Multimodality Imaging, Volume 2

Heart, lungs and peripheral organs

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Heart, lungs and peripheral organs

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To my late parents, my wife and daughter.

—Mainak Biswas

To all my collaborators around the world.

—Jasjit S Suri

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Part II An overview of deep learning and its applications in cardiovascular diseases

Preface

Deep learning and artificial intelligence (AI) is now as good for use as a general tool as other medical equipment and software. Having been deployed for some time now, it has been observed that inaccurate diagnosis cases (both false positives and false negatives) are decreasing with the usage of AI/DL aided tools. Medical practitioners are increasingly using diagnosis tools embedded with AI for coming to accurate decisions. With coming-of-age of AI platforms such as Google Health, DeepMind and OpenAI, the diagnosis will become more affordable and accessible than ever before. This book will look into some aspects of usage of deep learning for effective treatment.

Purpose

The book is written in the post-COVID-19 era and therefore a major section of this book is dedicated to deep learning (DL) and artificial intelligence (AI) applications in COVID-19 and respiratory diseases. This book discusses the effect on organs such as the brain and heart and how in the long term, AI will be able to detect the damage caused to vital organs. One single chapter is also dedicated to tuberculosis. AI also has made significant advances in the area of detection of cardiovascular diseases using multiple medical imaging modalities such as MRI, CT, and ultrasound. This book covers multiple areas where DL/AI technologies have been critical in accurate characterization of diseases.

Content and organization

The content of this book is divided into two sections: AI/DL in COVID-19/respiratory diseases and other cardiovascular diseases. In the first part, four chapters are dedicated to COVID-19 and one chapter to tuberculosis. In the second part, three chapters are dedicated to AI/DL in cardiovascular diseases. The description of each chapter in the first part is given as follows: Chapter 1 discusses the four pathways through which COVID-19 affects the heart and the brain, and how AI-assisted medical imaging can detect and diagnose the damage caused. Chapter 2 discusses critical AI technologies that have been applied to detection of COVID-19 induced Acute Respiratory Distress Syndrome (ARDS). In Chapter 3, eight pruned deep-learning models for COVID-19 CT lung segmentation and lesion localization are discussed in detail. An inter-variability study of the results of lung segmentation is done in Chapter 4. In Chapter 5, a segmentation study of tuberculosis-infected lung images using deep learning is discussed.

In the second part, there are three chapters. Chapter 6 presents a study of different applications of AI/DL in cardiovascular ultrasound. Chapter 7 discusses different segmentation/characterization studies related with atherosclerosis. Finally, Chapter 8 talks about different techniques for carotid disease management.

Editor biographies

Mainak Biswas

Mainak Biswas, PhD, is a computer scientist with specialization in the application of machine learning and deep learning in the biomedical domain. His research is inspired by providing an effective solution for computer-aided diagnosis for diverse diseases. His PhD specialization was in application of advanced machine learning and deep learning in complex tissue characterization and segmentation from ultrasound images of liver and carotid arteries. His other interests are development of advanced machine-learning architectures and early warning systems for risk estimation of both symptomatic and asymptomatic patients at high risk of CVDs. He also has keen interest in development of new metrics for machine learning algorithms based on statistical mechanics. He has published and presented more than 30 papers in the area of characterization and segmentation of ultrasound images through machine and deep learning platforms. His H-index is 13, and he has more than 1000 citations on his research. One of his review papers 'The Present and Future of Deep Learning in Radiology' has approximately 200 citations. Dr Mainak Biswas completed his BTech from the Government College of Engineering and Ceramic Technology under West Bengal University of Technology, Kolkata, MTech from Jadavpur University and his PhD from the National Institute of Technology Goa, India. Currently, he is serving as Associate Professor at Vignan's Foundation for Science, Technology and Research.

Jasjit S Suri

Jasjit S Suri (PhD, MBA, FIEEE, FAIMBE, FAIUM, FSVM, FAPVS) is an innovator, a visionary, a scientist, and an internationally known world leader. He has spent over 30 years in the field of biomedical engineering/sciences, software and hardware engineering and its management. During his career in biomedical industry/imaging, he has had an upstream growth and responsibilities from scientific engineer, scientist, manager, Director of R&D, Senior Director, Vice President, Chief Technology Officer (CTO), CEO level positions in industries like Siemens Medical Systems, Philips Medical Systems, Fisher Imaging Corporation and Eigen Inc., Global Biomedical Technologies Inc., AtheroPoint™, respectively, and managed up to a maximum of 100 people.

Dr Suri is a pioneer in the area of artificial intelligence (AI) and has published over 100+ papers in international journals covering several fields such as vascular, coronary, prostate, mammography, diabetes, and COVID-19 CT lung areas. He has developed products and worked extensively in the areas of breast, mammography, orthopedics (spine), neurology (brain), angiography (blood vessels), atherosclerosis (plaque), ophthalmology (eye), urology (prostate and ovarian), image-guided surgery (for neurology and orthopedics) and several kinds of biomedical devices from inception phase to commercialization, including 510(K)/FDA clearances. Under his leadership he has obtained over 5 FDA clearances in urology, angiography and image-guided surgery product lines ranging from 1000 page to 5000 page submissions. He has conducted *in vivo* and *ex vivo* validations on biomedical devices and surgery systems. Dr Suri has developed several collaboration programs between university–industry partnerships. He has managed funds ranging up to $10 million dollars. He has very successfully built IP portfolios during his career bringing attraction for larger OEMs spin-offs. Dr Suri has submitted over 100 US/European inventions, 20 trademarks, 50 books and over 750+ peer-reviewed Google Scholar articles, over 300+ journal articles with the National Library of Medicine (NLM), Washington DC, and currently holds over 38 000+ citations and an H-index of 90. Dr Suri has conducted over 50 national and international seminars around the globe. He received his Masters from the University of Illinois, Chicago, Doctorate from University of Washington, Seattle, and Masters in Business Administration (MBA) from Weatherhead School of Management, Case Western Reserve University (CWRU), Cleveland.

Dr Suri was crowned with Director General's President's gold medal (in 1980); one of the youngest Fellows of the American Institute of Medical and Biological Engineering (AIMBE, 2004) for his outstanding contributions in health imaging, a recipient of Marquis Life Time Achievement Award (2018) for his outstanding contributions in healthcare, Fellow of American Institute of Ultrasound in Medicine, Fellow of Asia Pacific Vascular Society, Fellow of Society of Vascular Medicine, and Fellow of IEEE, all for exceptional contributions. He believes in 'getting a job done' using his strengths of innovation, strategic partnerships and strong team collaborations by bringing cross-functional and multi-disciplinary teams together both in-house and outsourcing relationships. Dr Suri currently lives in California, USA.

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Part I

An overview of deep learning and its applications in COVID-19 and tuberculosis

Chapter 1

An overview of AI applications in medical imaging for COVID-19-related brain and heart injuries

Harshit Sharma, Radhakrishn Birla, Mainak Biswas and Jasjit S Suri

Artificial intelligence (AI) has significantly impacted the field of medicine, especially radiology, in recent years. The COVID-19 pandemic has caused a devastating impact, with over 416 million people infected and more than 5.8 million lives lost as of February 23, 2022. Although there have been approximately 228,391 publications on COVID-19, only a few articles have focused on the influence of AI and medical imaging on infected patients with comorbidities.

A comprehensive study has recently been conducted to investigate the various pathways that lead to heart and brain damage in individuals who have contracted COVID-19. This study has provided valuable insights into the importance of medical imaging in the management of patients with comorbid conditions, utilizing statistical data on COVID-19 symptoms. Common symptoms associated with COVID-19 include hypoxia, arrhythmias, plaque rupture, coronary thrombosis, encephalitis, ischemia, inflammation, venous and lung injury, as well as thromboembolism. The research primarily focuses on the application of AI in identifying specific tissues in COVID-19 patients and assessing the severity of their illness through the analysis of medical images. Given the limited medical resources available to governments worldwide in the fight against the pandemic, the use of image-based AI has become increasingly essential for the detection and diagnosis of COVID-19.

The integration of imaging and AI-based tissue classification, along with preliminary test probability and COVID-19 symptoms, has revealed a promising method to evaluate the potential danger posed by patients with comorbidities. Techniques like these can play a crucial role in monitoring and enhancing the healthcare system during and after the epidemic. Keywords such as COVID-19, comorbidity, pathophysiology, heart, brain, lung, imaging, artificial intelligence, and risk assessment have been identified as important factors in this context.

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1.1 Introduction

In December 2019, a new coronavirus called 'severe acute respiratory distress syndrome coronavirus 2' (SARS-CoV-2) was identified in Wuhan, the capital of Hubei Province in the People's Republic of China [1]. Initially, the Chinese government referred to the illness caused by the viral infection as 'new coronavirus pneumonia' (NCP), while the World Health Organization (WHO) named it 'coronavirus disease 2019' (COVID-19). A global public health emergency was declared on January 30, 2020 [2]. The primary mode of transmission for SARS-CoV-2 is believed to be by means of respiratory droplets or nasal secretions [3]. Interhuman transmission was first observed by Jasper Fuk-Woo Chan *et al* during their investigation at the University of Hong Kong-Shenzhen Hospital [4]. As of July 16, 2022, the pandemic had spread to more than 200 countries, resulting in over 416 million infections and 5.8 million deaths due to its high contagion rate (Ro = 2.7) [5], as shown in figure 1.1.

Recent studies have revealed that individuals with preexisting conditions face a higher risk of severe consequences due to COVID-19 [6–10]. In a specific study focused on COVID-19 patients, diabetic individuals (48, 24.9%) exhibited significantly higher mortality rates (81.3% vs. 47.6%) and ICU hospitalization rates (66.7% vs. 41.4%) compared to non-diabetic individuals (145, 75.1%) [11]. Diabetic individuals also experienced severe inflammatory reactions and coagulopathy in the heart, liver, and kidneys. Infected individuals with chronic disorders such as diabetes, renal disease, dyslipidemia, hypertension, cardiovascular diseases, and chronic obstructive pulmonary disease (COPD) had a higher prevalence of heart and

Figure 1.1. COVID-19 is distributed over 213 countries on a world map (courtesy: John Hopkins University).

brain (H&B) damage [12–16]. SARS-CoV-2 has been found to infect the thin lining of the epithelial cells that line the arteries, leading to atherosclerosis and arterial inflammatory disease, which are significant contributors to cardiovascular diseases (CVDs) and H&B damage [12, 17–21]. This may be attributed to a decrease in the production of angiotensin-converting enzyme 2 (ACE2), which results in endothelial dysfunction and exacerbates existing atherosclerosis [22, 23]. When individuals with comorbidities undergo image screening, it has been observed that they exhibit a wide range of preliminary test probabilities (PTPs) for COVID-19, ranging from mild to severe [24]. Conventional cardiovascular risk factors (CCVRFs), such as imaging techniques of the heart or alternative indicators used as substitutes for assessing coronary artery disease (e.g., carotid artery disease), are closely associated with comorbid patients. COVID-19 severity prediction models can benefit from the incorporation of both biomarkers and imaging [25–30]. Figure 1.2 illustrates the connections between SARS-CoV-2 and comorbidities, as well as the survival rates of COVID-19 individuals with and without diabetes.

The expression of ACE2 can lead to scarring and potential artery rupture [31–34]. Therefore, it is essential to evaluate CCVRF alongside imaging in individuals with COVID-19 and other comorbidities [35]. In stage two of the disease, when patients are severely affected by COVID-19, there is a higher risk of heart damage or the release of troponin T (TnT). Imaging has proven to be valuable in keeping track of tissue scarring caused by COVID-19 [35–39].

Different imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound can be employed to detect COVID-19 symptoms in patients [40–44]. These imaging techniques offer the advantage of visualizing the scar tissue caused by the disease. However, a drawback is their inability to provide a 'risk assessment' on their own. Artificial intelligence (AI) technologies have the potential to leverage information from imaging modalities and generate more precise predictions, enabling accurate identification of tissues and disease processes [45–51]. The combination of AI and medical imaging (MI) has demonstrated significant advancements in diagnosis, risk stratification, rapid patient

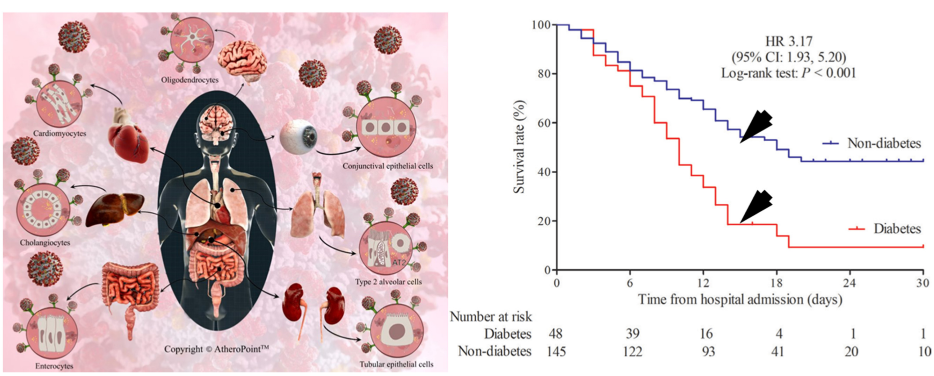

Figure 1.2. (a) SARS-CoV-2 and its link with other comorbidities, and (b) COVID-19 diabetes and non-diabetic patients' mortality rates compared (with permission to reprint [11]).

evaluation, disease monitoring, and early intervention [40, 48, 52–57]. Consequently, this review focuses on the utilization of AI-based tissue characterization through medical imaging in comorbid patients affected by COVID-19.

The chapter is organized as follows: section 1.2 examines the physiological mechanisms underlying the four pathways that result in heart and brain injuries. Section 1.3 presents an overview of the justification for utilizing imaging in the context of the COVID-19 pandemic. Section 1.4 provides an in-depth exploration of utilizing AI-based tissue characterization for risk assessment. Ultimately, the paper concludes with a thorough critical analysis.

1.2 SAR-CoV-2 pathophysiology in the context of heart and brain injury

Numerous studies indicate that SARS-CoV-2 relies on the ACE2 receptor for cell entry, achieved by binding to the spike protein (S protein) on the cell surface [58–60] (see figure 1.2). ACE1 and ACE2 are carboxypeptidase enzymes that are structurally similar but have distinct roles in the renin-angiotensin-aldosterone system (RAAS) [61]. The ACE2 is found in various cardiac cells, including, astrocytes (brain cells), enterocytes and type 2 pneumocytes [15, 61–63], and is recognized as a contributing factor to extrapulmonary complications. Figure 1.3 provides a comprehensive visual representation of how SARS-CoV-2 induces cardiac and brain damage through four

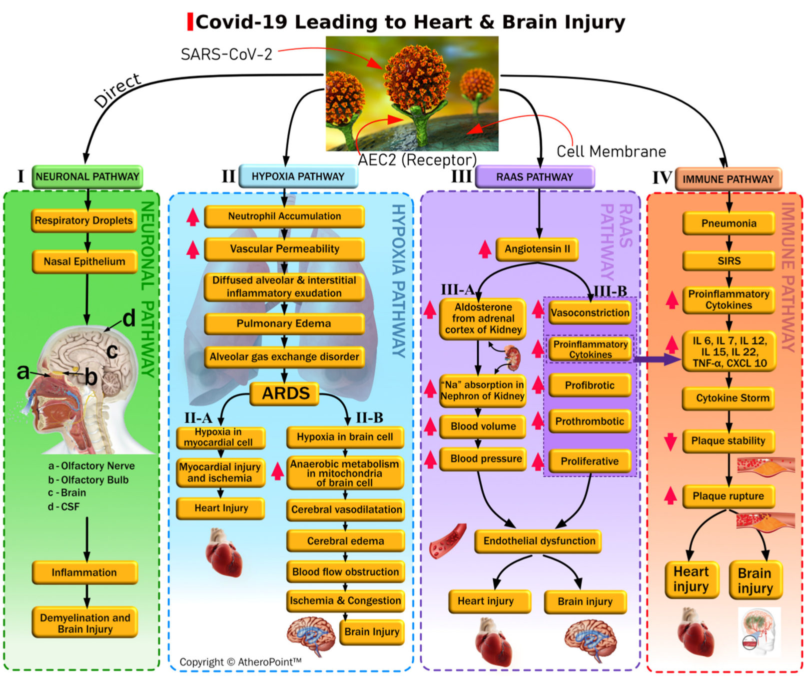

Figure 1.3. We have shown in four pathways how COVID-19 can cause brain and heart injury. Brain image in pathway I: http://debuglies.com/2020/01/23/olfactory-disturbances-have-implications-in-mental-and-emotional-well-being-health/ (courtesy of Debug Lies).

distinct paths: (i) the RAAS pathway, (ii) the immune pathway, (iii) the neural pathway, and (iv) the hypoxia pathway. These pathways will be further discussed, along with the resulting injuries, which may encompass infectious toxic encephalopathy, acute cerebrovascular diseases and viral encephalitis.

(i) The neural pathway (figure 1.3, the first pathway): Recent epidemiological investigations have highlighted genomic similarities between MERS, SARS-CoV-1, and SARS-CoV-2 [6, 64, 65]. Prior research has demonstrated that coronaviruses, including SARS-CoV-1, have the ability to enter the brain and directly infect it [66, 67]. In figure 1.3, the sagittal brain image representing the neural pathway illustrates the olfactory nerve and bulb, labeled as 'a' and 'b,' respectively [68–70]. It has been observed that individuals infected with SARS-CoV-2 may experience symptoms such as dysgeusia (taste loss) and anosmia (loss of smell) [64, 71–73]. Furthermore, a mouse experiment where the olfactory bulb was surgically removed demonstrated a limitation of CoV within the central nervous system (CNS) [74]. These findings suggest that the neural pathway could be one of the potential routes for SARS-CoV-2.

(ii) The hypoxia pathway (figure 1.3, the second pathway): Following the entry of the coronavirus into lung parenchyma cells, there is a reduction in ACE2 levels, leading to the accumulation of neutrophils, increased vascular permeability, and the release of diffuse alveolar and interstitial exudates. This process contributes to the development of acute respiratory distress syndrome (ARDS) and pulmonary edema [75]. ARDS is described by significant irregularities in the composition of blood gases, causing an imbalance of oxygen and carbon dioxide and leading to decreased blood oxygen levels [76, 77]. Prolonged hypoxia can induce myocardial ischemia and cardiac damage [78, 79] (see figure 1.3, pathway II-A). In the brain, hypoxia is the primary cause of cerebral vasodilation, edema, and reduced blood flow due to increased anaerobic metabolism in brain cell mitochondria. This can lead to cerebral ischemia and acute cerebrovascular disorders, such as acute ischemic stroke [71, 80] (see figure 1.3, pathway II-B).

(iii) The RAAS pathway (figure 1.3, the third pathway): The renin-angiotensin-aldosterone system (RAAS) pathway plays a critical role in regulating blood pressure and electrolyte balance. Disruption of this pathway can contribute to the development of cardiovascular disorders [15]. Prior to SARS-CoV-2 invasion, angiotensin I (Ang I) is converted to angiotensin II (Ang II) by ACE1. Ang II causes vasoconstriction and possesses pro-inflammatory, prothrombotic, and proliferative properties that can negatively impact the hemostasis and vascular tone [77, 80]. Conversely, ACE2 counteracts the effects of Ang II by converting it to Ang (1–7), which has mitigating effects [75, 78]. Both ACE2 and Ang (1–7) have protective effects on the cardiovascular and cerebrovascular systems [61]. SARS-CoV-2 infection disrupts the RAAS, leading to injuries in the heart and brain through two distinct pathways. The primary mechanism involves an increase in Ang II levels due to a decrease in ACE2 levels (figure 1.3, pathway III-A). Firstly, elevated Ang II levels stimulate the adrenal cortex in the kidney, resulting in increased aldosterone production. Aldosterone, a steroid hormone, facilitates the reabsorption of sodium and water in the distal tubule and collecting duct of the nephron [81]. This leads to an increase in blood volume and raises blood pressure, causing endothelial dysfunction and subsequent damage to the heart and brain [82]. Secondly, elevated Ang II levels and decreased ACE2 levels contribute to endothelial dysfunction in arterial walls, which can be observed in arterial wall images [21] (see figure 1.3, pathway III-B). High levels of Ang II can also trigger the release of pro-inflammatory cytokines, contributing to a cytokine storm.

(iv) The immune pathway (figure 1.3, the fourth pathway): In recent studies, SARS-CoV-2 viral pneumonia has been linked to an elevated inflammatory response known as a 'cytokine storm' [7, 77, 83, 84]. Advanced stages of severe COVID-19 are characterized by increased levels of inflammatory cytokines, which can contribute to multiple organ failure [85–87]. Inflammatory markers such as IL-6, IL-7, IL-12, IL-15, IL-22, TNF-α, and CXCL-10 have been associated with plaque destabilization. This increased inflammation can potentially lead to plaque rupture and subsequent damage to the heart and brain [37, 68–70, 80, 85–87, 89–91].

1.3 The role of imaging in patients with comorbidities and COVID-19

COVID-19 leads to significant damage to the heart and brain through four pathways (neuronal, hypoxia, RAAS, and immunological), as discussed earlier. This highlights the need for increased utilization of medical imaging (MI) to expedite assessments, differential diagnoses, and patient management [92] with appropriate safety measures. The choice of imaging modality depends on symptom severity, with consideration for portability and invasiveness. Portable and non-invasive ultrasound imaging in B-Mode is suitable for low-risk individuals, while x-rays, magnetic resonance imaging (MRI), and computed tomography (CT) are non-portable and can be used for patients with a medium risk level [40, 41]. Invasive imaging techniques like intravascular ultrasonography (IVUS) and ventriculography are reserved for life-threatening situations [42, 43, 98–100]. Ultrasound is particularly advantageous due to its rapidity, reproducibility, cost-effectiveness, radiation-free nature, and portability. It can be performed in isolation, minimizing the risk of COVID-19 transmission [101, 102].

Throughout the early and later stages of the pandemic, various imaging modalities have proven effective. X-ray imaging of the lungs has revealed different patterns, signaling the advancement of COVID-19 at different stages and aiding in treatment planning [103]. Chest CT scans have shown lung involvement in nearly 86% of COVID-19 patients, affecting at least one lobe [104]. Chest MRI scans have revealed pulmonary tissue consolidation, diffusion-restricted areas, and lung injury in COVID-19 patients [105]. MRI examinations of recovered patients have identified myocardial edema and late gadolinium augmentation, indicating long-term cardiac damage requiring ongoing care even after recovery [106]. MR scans of COVID-19 patients have demonstrated myocardial inflammation, highlighting cardiac damage caused by the cytokine storm associated with the infection (Pathway IV) [107]. Studies have also investigated the impact of COVID-19 on the brain, with MRI images showing hemorrhagic rim enhancing lesions in specific brain regions [108] (figure 1.4). Abnormal findings have been observed in brain MRI scans of COVID-19 patients, and combined CT and ultrasound investigations have revealed liver disease and gallbladder abnormalities [109, 110]. Recent MRI scans of COVID-19 patients' olfactory bulbs have revealed inflammatory occlusion caused by the interaction between SARS-CoV-2 and the ACE2 protein expressed in the olfactory epithelium, resulting in the loss of olfactory function [111].

Invasive imaging techniques are employed to ascertain the diagnosis of individuals with COVID-19 with significant comorbidities. One trial utilized intravascular ultrasonography (IVUS) in combination with stenting for a COVID-19 patient who experienced a myocardial infarction [112] (figure 1.5). Precautions regarding invasive imaging techniques are further explained in section 1.5. Another study employed ventriculography to detect takotsubo syndrome, a type of cardiac damage associated with COVID-19 [113]. In several trials, MI of COVID-19 patients played a critical role in assessing tissue damage and determining the severity of infection, even in the absence of obvious signs [39, 114]. Therefore, MI is recommended for evaluating the degree of damage to cardiac and cerebral tissues in individuals with

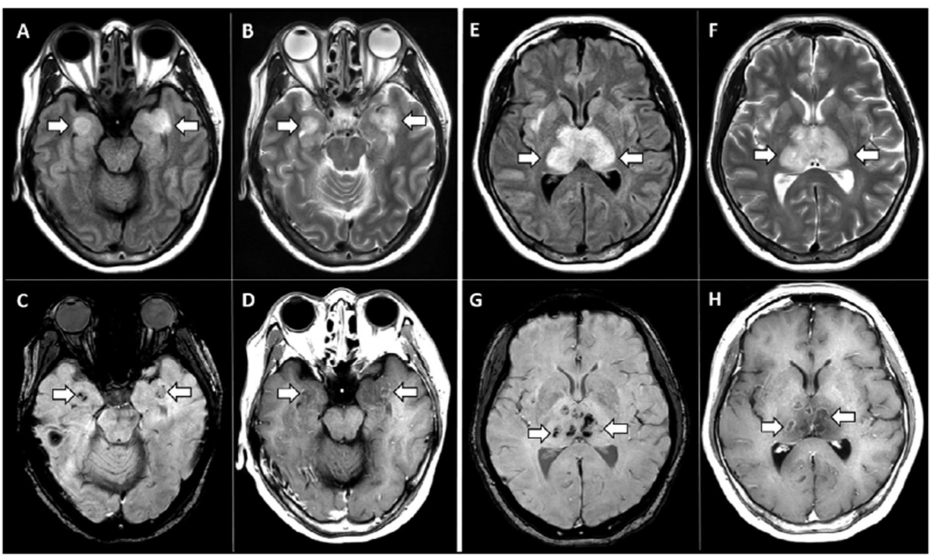

Figure 1.4. The MRI scan of a patient with COVID-19 showed evidence of bleeding. T2 FLAIR hyperintensity was observed in the paired medial temporal lobes and thalami (A, B, E, F), and the hemorrhage was identified by a hypointense signal intensity on susceptibility-weighted images (C, G). Additionally, postcontrast imaging revealed rim enhancement (D, H) (reprinted with permission [108]).

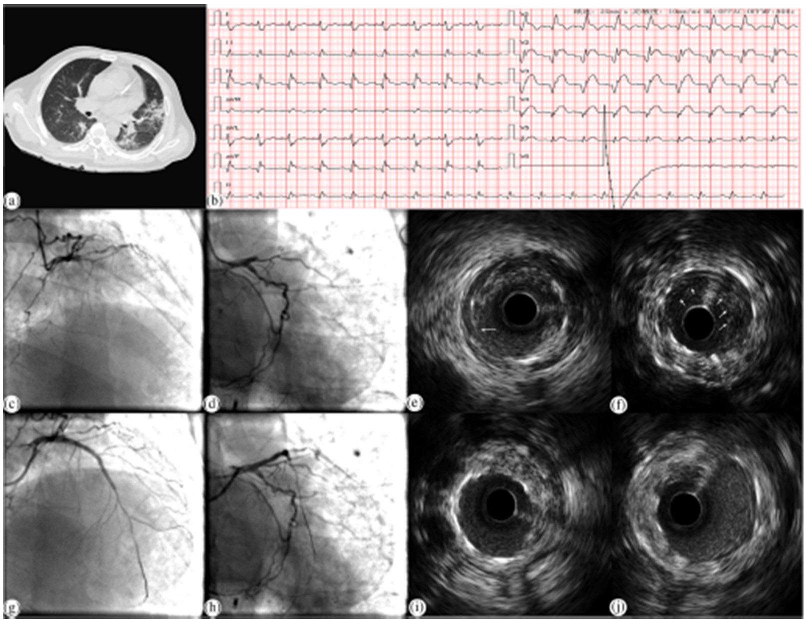

Figure 1.5. In a COVID-19 patient with myocardial infarction, both chest CT and intravascular ultrasound (IVUS) were utilized for diagnostic purposes. The findings from these imaging techniques are as follows: (a) Chest CT scan revealed localized fibrinous exudative alterations, which are associated with viral pneumonia. (b) ECG data showed ST-segment elevations in leads V1–V5 when the patient experienced chest pain. (c, d) Coronary angiography (CAG) indicated occlusion in the proximal segment of the left anterior descending artery (LAD). (e, f) Blood flow in the LAD was restored after the placement of two drug-eluting stents (DESs). (g) IVUS revealed a dissection distal to the stent in the LAD, specifically from the 7–12 o'clock position. (h) A low echogenic shadow with dispersed increased echogenic flicker was observed, indicating the presence of a thrombus. (i) The dissection was no longer visible after the DES was implanted and the stent was adequately inflated. (j) The thrombus disappeared following the intervention. These findings were obtained from a published study and are reprinted with permission [112].

COVID-19 throughout their lifetime. Individuals with preexisting medical conditions who have contracted COVID-19 are particularly vulnerable and should undergo MI examination from the time of diagnosis. MI can also be beneficial for COVID-19 patients with deep vein thrombosis (DVT). An analysis found that patients suffering from COVID-19 and DVT had a worse prognosis compared to those lacking DVT. The DVT group had a higher rate of ICU admission (18.2%), lower rate of discharge (48.5%), and higher mortality rate (38.5%) [115].

However, the evaluation, diagnosis, and monitoring processes for myocardial infarction imaging can be challenging due to the exponential nature of the pandemic, limited medical resources, and a shortage of radiologists. These factors contribute to time-consuming processes and a higher risk of errors [116–118]. To address these challenges, the utilization of artificial intelligence (AI) in medical imaging (MI) for tissue characterization can offer valuable support. AI-based systems have the potential to be scaled up to meet the demands of the pandemic, facilitating rapid MI assessments and diagnoses during the COVID-19 outbreak [119–121].

Based on the severity of symptoms and patient presentation, AI-driven assessments have the capability to classify or categorize the risk level into different categories, including zero-risk, low, low-medium, high-medium, low-high, or high-high risk [120, 122], as illustrated in figure 1.6. The choice of imaging modality depends on the assessed risk level. For zero-risk patients, no imaging is necessary.

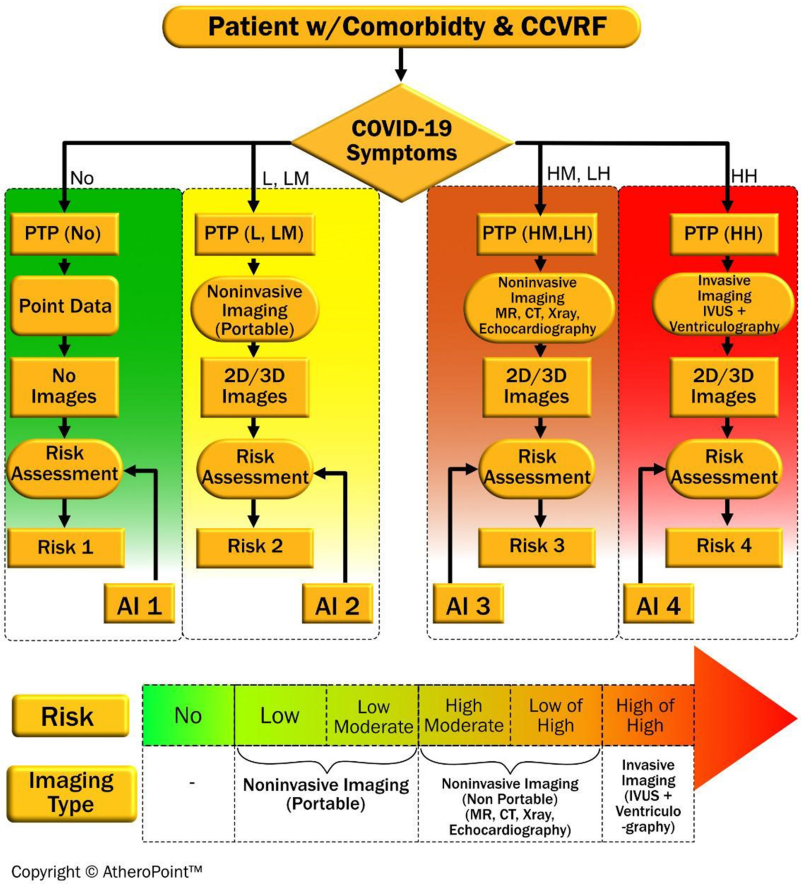

Figure 1.6. AI-based risk assessment plays a crucial role in managing comorbidity patients with COVID-19, offering valuable insights and aiding in healthcare administration [54, 55, 127–129]. The implementation of AI in healthcare encompasses various systems that enable accurate decision-making in patient monitoring, diagnosis, management, and treatment. In the field of medical imaging, artificial intelligence has gained significant importance due to the abundant volume of three-dimensional data accessible and the necessity to characterize and quantify diseases utilizing imaging observations [130–132]. Tissue imaging and classification are particularly vital as they directly impact decisions regarding the severity of COVID-19 in patients [133–135]. The key advantage of AI technologies lies in their ability to be trained to emulate the cognitive actions of physicians, allowing for the prediction of disease severity in asymptomatic patients. Several machine learning (ML)-based approaches have effectively utilized AI to combat COVID-19 within a short timeframe [136, 137].

Portable imaging modalities are suitable for patients at zero-risk and low-medium risk levels. Non-portable imaging techniques such as MRI, CT, x-ray, and echocardiography are appropriate for high-medium and low-high risk patients. Invasive imaging methods like IVUS and ventriculography are reserved for high-high risk patients. Precise evaluation of diagnostic results and patient categorization into specific risk groups can be achieved through pre-test probability (PTP) assessment [123–126]. Non-imaging biomarkers can be utilized by AI-based algorithms for risk assessment in zero-risk patients. Patients with low risk may undergo portable 2D/3D imaging modalities, such as ultrasound, while non-portable and invasive 2D/3D imaging modalities are suitable for low-medium risk patients. High-high risk patients may require invasive imaging techniques like ventriculography and IVUS. AI-driven MI plays a crucial role in assessing the risk level based on data obtained from multiple 2D/3D scans, and treatment decisions can be made accordingly. The subsequent section will focus on deep learning (DL)-based MI, particularly in the context of ultrasound scans for COVID-19 patients.

1.4 Machine learning and deep learning for tissue classification

The exponential rise in the number of patients during the pandemic and the limited availability of trained radiologists have presented challenges in achieving timely diagnoses. Nonetheless, the integration of AI and related technologies in healthcare holds significant promise in significantly reducing diagnosis times [119].

1.4.1 ML and DL architectures

The machine learning process consists of two stages. In stage I, various attributes from the images of COVID lesions are extracted and processed by a machine learning (ML) model to produce offline parameters. These parameters are then modified by test lesion photos, leading to intelligent categorization or inference. Figure 1.7 illustrates a typical machine learning system used for predicting risk class. The development of a CUSIP (image-based phenotype) relies on the event equivalent gold standard (EEGS) model [57, 138, 139]. Deep learning (DL) functions similarly to the visual cortex, employing multiple neural layers directly applied to tissue images for feature extraction and classification purposes [54]. Convolutional neural networks (CNN) [140], as shown in figure 1.8, are a common type of deep learning network used for medical image classification. Convolution and max-pooling operations are employed to extract features and carry out characterizations. Both ML and DL utilize a supervised learning method is employed, in which models are trained using preexisting data.

The previous sections have discussed how COVID-19 spreads through four distinct pathways and can cause damage to the heart and blood vessels (H&B). Myocardial infarction (MI) can be used to assess the level of tissue damage in these pathways, aiding healthcare professionals in developing appropriate treatment strategies for patients. The use of AI models for tissue classification based on medical images has been widely employed, both during the pandemic and in routine healthcare settings. In the subsequent sections, we will present a proposed approach

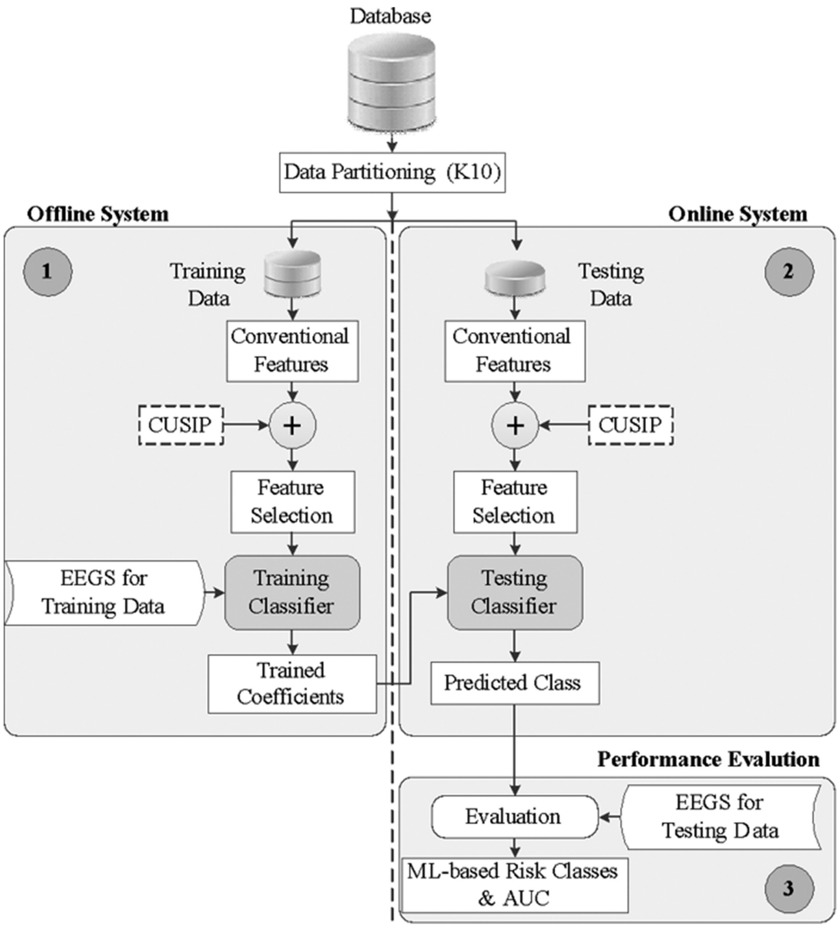

Figure 1.7. Classic ML model utilizing EEGS model.

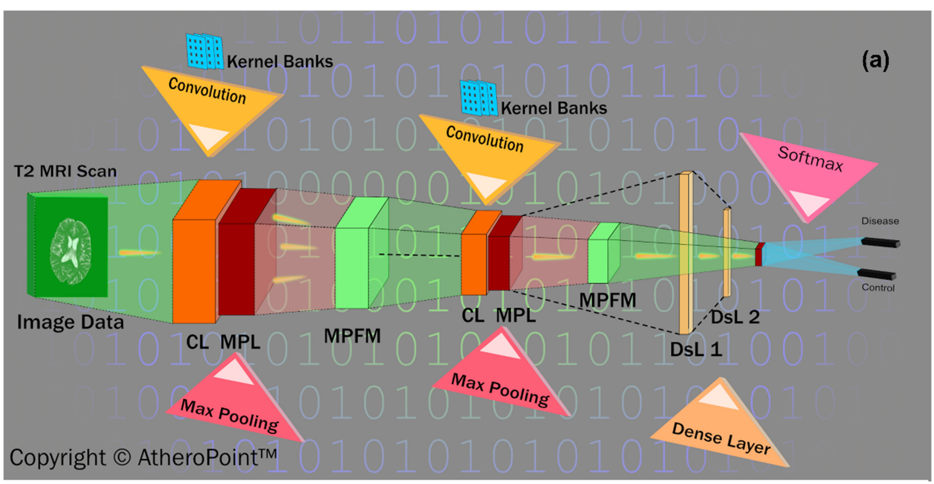

Figure 1.8. A convolution neural network (courtesy of AtheroPoint™, CA, USA).

for describing tissue classification using deep learning (DL) and provide specific examples of AI applications for each organ.

1.4.2 Tissue characterization ML system for stroke risk stratification

There are two primary types of AI-based approaches: (i) ML-based and (ii) DL-based methods [63, 141, 142]. ML-based techniques have been developed for the classification of symptomatic and asymptomatic plaques using ultrasound images. For instance, support vector machines (SVM), an ML-based method, were utilized to classify 346 carotid images into symptomatic and asymptomatic plaques [143, 144]. SVM classifiers create a hyperplane with the largest margin between points of two classes, known as support vectors. In the feature extraction step, texture analysis is employed to extract features such as entropy, symmetry, standard deviation, and run percentage [145, 146]. These features were then used to characterize plaque tissue lesions using SVM with a radial basis function (RBF) kernel, achieving an accuracy of 82.4%. Higher-order spectra (HOS) analysis has also been found to be significant in tissue characterization [130]. Another study combined HOS, discrete wavelet transformations (DWTs), and texture data from 146 patient images to create an SVM-RBF-based classifier [46, 130, 146–148]. This classifier achieved an accuracy of 91.7%. Additionally, DWT-based features were used with second-order kernels to differentiate tissues, resulting in an accuracy of 83.7%. To compare and evaluate various classifiers, a total of 346 scans from two distinct carotid plaque datasets (Portugal and the United Kingdom) were utilized. Various classifiers, including fuzzy classifier [154], k-nearest neighbor [152], radial basis probabilistic neural network [150], decision tree [151], Gaussian mixture model [149], naive Bayes classifier [153], and SVM [45] fuzzy classifier [154], were evaluated. The primary features employed encompassed trace transform [155], fuzzy gray level co-occurrence matrix [156], and fuzzy run-length matrix [157]. In the Portugal cohort, the fuzzy classifier attained the highest accuracy of 93.1%, while both the NBC and SVM-RBF kernels exhibited comparable performance at 85.3%. These AI models for plaque classification have been applied in various approaches for cardiovascular disease (CVD) risk stratification [27, 28, 158].

1.4.3 Vessel characterization, measurement, and risk stratification using ML/DL

1.4.3.1 Chest CT and liver disease classification using AI

During the COVID-19 pandemic, ML and DL techniques have been utilized for the classification of lung CT images, demonstrating varying degrees of effectiveness [159–164]. Kang *et al* achieved an accuracy of 95.5% by employing the utilization of representation learning to characterize chest CT scans without infection of data from COVID-19 patients [168]. Wang *et al* developed a DL-based system to differentiate CT scans of COVID-19 patients from those of non-infected individuals, yielding a receiver operating characteristic (ROC) curve with an area under the curve (AUC) of 0.959 [169].

Additionally, DL-based radiomics using shear wave elastography has been applied to distinguish diseased (fatty liver) ultrasound images and assess liver fibrosis stages with an impressive accuracy of 100% [170–172]. This technique proves valuable for the identification and categorization of COVID-19 patients.

1.4.3.2 Tissue characterization and risk stratification using artificial intelligence in lung CT

Over the past few decades, numerous studies have been conducted ML and DL algorithms for the classification of lung CT images. These studies can be categorized into two types based on the number of risk stratification classes involved. The initial set of research focused on distinguishing COVID-19 pneumonia patients from non-COVID-19 pneumonia patients, resulting in a two-class scenario. The subsequent collection of studies explored multi-class paradigms.

In one study, the DenseNet 121 model was employed to create and segment lung masks, achieving an area under the curve (AUC) of 0.9, a sensitivity of 78.93%, and a specificity of 89.93% for categorizing COVID-19 and control patients [173]. Zhang *et al* adopted a three-class classification system that encompassed lung segmentation and categorization, including COVID-19, community pneumonia, and normal cases. They utilized the DeepLabv3 model for lung segmentation and 3D ResNet-18 for classification, achieving an accuracy of 92.49% and an AUC of 0.98 [174].

Other researchers also incorporated AI techniques in their CT lung scan studies. For instance, Li *et al* developed a DL system for CT lung analysis capable of predicting COVID-19 severity and progression [175]. Chen *et al* devised a UNet++ architecture to segment COVID-19-infected lung regions in CT scans [176, 177]. In a similar manner, Yang *et al* conducted lung segmentation on CT images by identifying pulmonary parenchyma and employing DenseNet for classification. Their approach achieved an accuracy of 92% and an AUC of 0.98 [178]. In another study, Oh *et al* employed x-ray chest images for both classification and segmentation, achieving an accuracy of 88.9% by employing a patch-based technique with the same network [179].

1.4.3.3 AI-based plaque tissue characterization and risk stratification for cardiac health

A DL-based platform is proposed for the treatment of COVID-19 patients with comorbidities. The platform utilizes preexisting facts obtained by patients suffering from COVID-19 worldwide to train the DL system. This data includes multiple ultrasound scans by patients suffering from COVID-19 with comorbidities who underwent treatment according to strict guidelines [93–97]. The AtheroEdgeTM system, which is capable of distinguishing and fragmenting plaque regions, automatically extracts tissue regions of interest (ROIs) from the ultrasound scans. The same AtheroEdgeTM technique is applied to extract ROIs from online patients' ultrasound scans. The DL model is then used to estimate the susceptibility of plaque in the online data, which is collected from testing patients after being trained with the offline data. The predictions obtained from this process are utilized to evaluate and support the clinical feasibility of the DL system.

1.5 Summary

In this review, we conducted an analysis of various imaging investigations performed on COVID-19 patients to assess the impact of the infection on key organs such as the lungs [104, 105], heart [106, 107], brain [108, 109] and liver. These imaging investigations were crucial in guiding the medical team in providing appropriate treatment for COVID-19 patients with varying degrees of symptoms. Among the available imaging modalities, ultrasonography was found to be particularly advantageous due to its portability and the ability to perform scans in isolation rooms, minimizing the risk of infection transmission across different wards. Similar mobility recommendations were also given for MRI and CT scanning as a preventive measure to curb the transmission of infections [180–182]. The availability of mass scanning for admitting patients would enable healthcare professionals to promptly design treatment plans and potentially save lives. In serious cases of patients suffering from COVID-19, the use of IVUS [98] and ventriculography (with necessary preventive measures) is recommended [42, 43, 99, 100] (figure 1.9).

The exponential growth of the COVID-19 pandemic presents challenges in evaluating and analyzing medical images in light of resource constraints and a shortage of radiologists. To address this, AI-driven medical imaging (MI) can be utilized to assist in the analysis, diagnosis, and risk stratification of patients suffering from COVID-19. AI systems have the capability to process large volumes of images simultaneously, enabling mass diagnosis to keep up with the rapidly evolving pandemic curve.

There are two main types of AI: ML and DL [54]. ML models use feature mining algorithms to make predictions, while DL models directly extract features from medical images, resulting in clearer images. An AI-based imaging-based risk evaluation model is recommended, where patients are categorized into risk levels such as zero/no-risk, low-risk, low-medium, medium-high, low-high, or high-high based on pre-test probability (PTP) tests [120, 122–126]. MI is then performed based on the patient's risk level, followed by AI utilization to assess the risk in MI. DL-driven tissue characterization systems can be particularly useful for ultrasound examinations and other imaging modalities. These DL-driven systems are trained using training data and evaluated using test data, allowing for the evaluation of tissue damage caused by COVID-19 infection.

Telemedicine, combined with AI support, can play a significant role in monitoring the well-being of patients. Telemedicine enables the management of infections by monitoring patients' health through Internet of Things (IoT) devices [183]. Social media platforms can also contribute to tracking patients' health and sharing important research findings through the application of big data analytics [184–186].

1.5.1 A note on COVID-19 precautions

In order to prevent infection, medical personnel must strictly adhere to guidelines [187–189]. This includes wearing eye protection, disposable gowns that are water-resistant, and disposable gloves, among other necessary precautions. Portable equipment should be used to avoid the need for relocating patients. Any

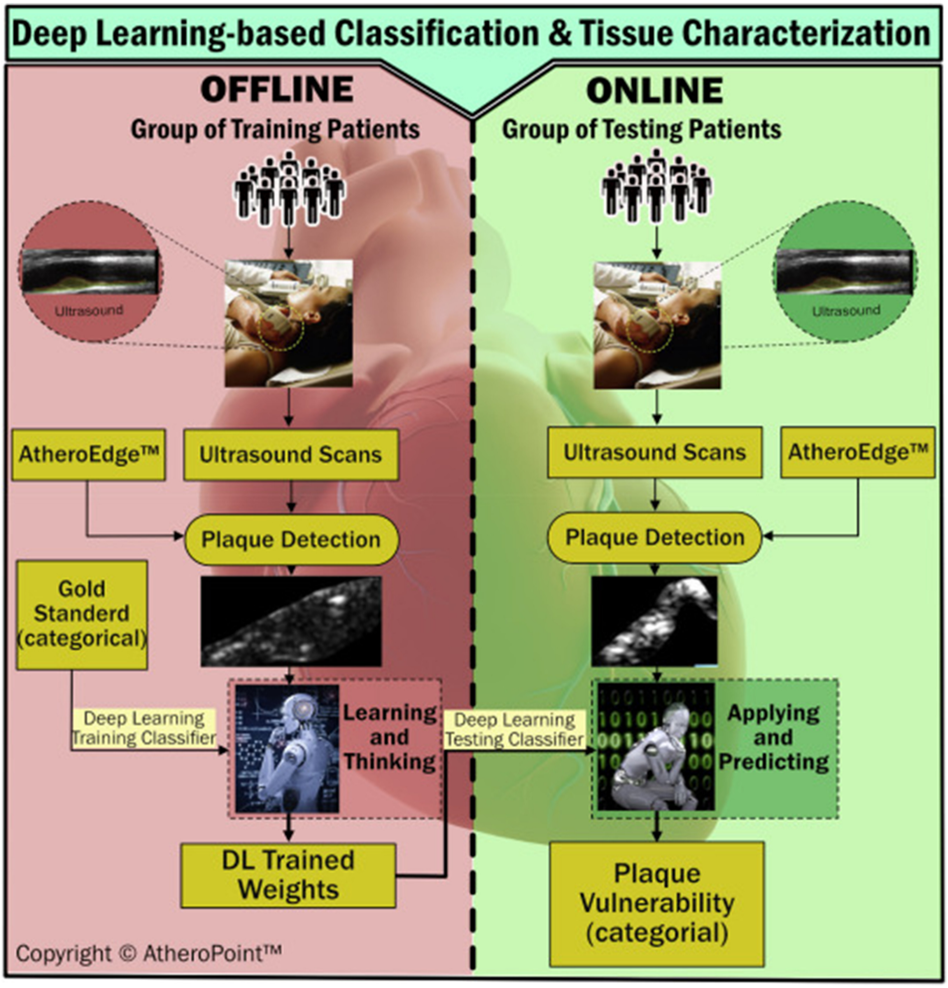

Figure 1.9. Proposed DL-based method for tissue characterization and classification of COVID-19 severity for patients with comorbidities (courtesy of AtheroPoint™, CA, USA).

medical imaging equipment that requires physical contact should be sterilized after each use, as shown in figure 1.10. Imaging equipment can be positioned outside the isolation room, allowing image acquisition through the window of the room to minimize direct interaction, as depicted in figure 1.10(b). When it is necessary to handle devices, a sterile protective disposable cover, such as an ultrasound probe cover as illustrated in figure 1.10(c), should be used.

1.6 Conclusion

COVID-19 can cause harm to the heart and blood vessels through four pathways: RAAS, neuronal, hypoxia, and immune. The severity of a patient's symptoms determines the level of risk associated with their condition, which in turn determines

Figure 1.10. (a) Before taking scans, clinical personnel should follow these protection measures (with permission to reprint [187]); (b) Images shot through a window (with permission to reprint [188]); (c) probe covered with disposable sterile sheath (with permission to reprint [189]).

the type of imaging modality that should be used. Portable or non-portable invasive imaging modalities are recommended depending on the risk level, and appropriate safety measures must be taken during the imaging process. However, the limited availability of qualified radiologists poses a challenge to the widespread use of MI for COVID-19 diagnosis and evaluation.

To address this challenge, AI approaches such as ML and DL can be employed to expedite MI-based clinical evaluation and diagnosis. These AI methodologies have the potential to improve the efficiency and speed of diagnosing COVID-19 and assessing the risk associated with the disease. In particular, a DL-based system has been developed for COVID-19 diagnosis and risk classification, which can aid in providing timely and accurate evaluations for individuals with comorbidities who are at a higher risk of experiencing severe health complications [190].

References

[1] Yuen K-S, Ye Z-W, Fung S-Y, Chan C-P and Jin D-Y 2020 SARS-CoV-2 and COVID-19: the most important research questions *Cell Biosci.* **10** 1–5

[2] Coronavirus (COVID-19) outbreak (https://who.int/westernpacific/emergencies/covid-19)

[3] Coronavirus (https://who.int/health-topics/coronavirus#tab=tab_1)

[4] Chan J F-W, Yuan S, Kok K-H, To K K-W, Chu H, Yang J, Xing F, Liu J, Yip C C-Y and Poon R W-S 2020 A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster *Lancet* **395** 514–23

[5] Coronavirus (https://worldometers.info/coronavirus/)

[6] Wang D, Hu B, Hu C, Zhu F, Liu X, Zhang J, Wang B, Xiang H, Cheng Z and Xiong Y 2020 Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China *JAMA* **323** 1061–9

[7] Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J and Gu X 2020 Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China *Lancet* **395** 497–506

[8] Shi S, Qin M, Shen B, Cai Y, Liu T, Yang F, Gong W, Liu X, Liang J and Zhao Q 2020 Association of cardiac injury with mortality in hospitalized patients with COVID-19 in Wuhan, China *JAMA Cardiol.* **5** 802–10

[9] Zhou F, Yu T, Du R, Fan G, Liu Y, Liu Z, Xiang J, Wang Y, Song B and Gu X 2020 Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study *Lancet* **395** 1054–62

[10] Gao F, Zheng K I, Wang X B, Yan H D, Sun Q F, Pan K H, Wang T Y, Chen Y P, George J and Zheng M H 2020 Metabolic associated fatty liver disease increases COVID-19 disease severity in non-diabetic patients *J. Gastroenterol. Hepatol* **36** 204–7

[11] Yan Y, Yang Y, Wang F, Ren H, Zhang S, Shi X, Yu X and Dong K 2020 Clinical characteristics and outcomes of patients with severe covid-19 with diabetes *BMJ Open Diabetes Res. Care* **8** e001343

[12] Virani S S, Alonso A, Benjamin E J, Bittencourt M S, Callaway C W, Carson A P, Chamberlain A M, Chang A R, Cheng S and Delling F N 2020 Heart disease and stroke statistics—2020 update: a report from the American heart association *Circulation* **141** E139–596

[13] Zheng Y-Y, Ma Y-T, Zhang J-Y and Xie X 2020 COVID-19 and the cardiovascular system *Nat. Rev. Cardiol.* **17** 259–60

[14] Chen L, Li X, Chen M, Feng Y and Xiong C 2020 The ACE2 expression in human heart indicates new potential mechanism of heart injury among patients infected with SARS-CoV-2 *Cardiovasc. Res.* **116** 1097–100

[15] Williams V R and Scholey J W 2018 Angiotensin-converting enzyme 2 and renal disease *Curr. Opi. Nephrol. Hypertens.* **27** 35–41

[16] Wang B, Li R, Lu Z and Huang Y 2020 Does comorbidity increase the risk of patients with COVID-19: evidence from meta-analysis *Aging (Albany NY)* **12** 6049

[17] Cheng H, Wang Y and Wang G Q 2020 Organ-protective effect of angiotensin-converting enzyme 2 and its effect on the prognosis of COVID-19 *J. Med. Virol* **92** 726–30

[18] Libby P 2020 The heart in COVID19: primary target or secondary bystander? *JACC: Basic Transl. Sci.* **5** 537–42

[19] Clerkin K J, Fried J A, Raikhelkar J, Sayer G, Griffin J M, Masoumi A, Jain S S, Burkhoff D, Kumaraiah D and Rabbani L 2020 Coronavirus disease 2019 (COVID-19) and cardiovascular disease *Circulation* **141** 1648–55

[20] Libby P, Ridker P M and Maseri A 2002 Inflammation and atherosclerosis *Circulation* **105** 1135–43

[21] Suri J S, Kathuria C and Molinari F 2010 *Atherosclerosis Disease Management* (New York: Springer Science & Business Media)

[22] South A M, Diz D I and Chappell M C 2020 COVID-19, ACE2, and the cardiovascular consequences *Am. J. Physiol-Heart Circ. Physiol.* **318** H1084–90

[23] Dong B, Zhang C, Feng J B, Zhao Y X, Li S Y, Yang Y P, Dong Q L, Deng B P, Zhu L and Yu Q T 2008 Overexpression of ACE2 enhances plaque stability in a rabbit model of atherosclerosis *Arter. Thromb. Vasc. Biol.* **28** 1270–6

[24] Mossa-Basha M, Meltzer C C, Kim D C, Tuite M J, Kolli K P and Tan B S 2020 Radiology department preparedness for COVID-19: radiology scientific expert panel *Radiology* **296** 200988

[25] Kotsis V, Jamthikar A D, Araki T, Gupta D, Laird J R, Giannopoulos A A, Saba L, Suri H S, Mavrogeni S and Kitas G D 2018 Echolucency-based phenotype in carotid atherosclerosis disease for risk stratification of diabetes patients *Diabetes Res. Clin. Pract.* **143** 322–31

[26] Khanna N N, Jamthikar A D, Gupta D, Araki T, Piga M, Saba L, Carcassi C, Nicolaides A, Laird J R and Suri H S 2019 Effect of carotid image-based phenotypes on cardiovascular risk calculator: AECRS1. 0 *Med. Biol. Eng. Comput.* **57** 1553–66

[27] Khanna N N, Jamthikar A D, Araki T, Gupta D, Piga M, Saba L, Carcassi C, Nicolaides A, Laird J R and Suri H S 2019 Nonlinear model for the carotid artery disease 10-year risk prediction by fusing conventional cardiovascular factors to carotid ultrasound image phenotypes: a japanese diabetes cohort study *Echocardiography* **36** 345–61

[28] Cuadrado-Godia E, Jamthikar A D, Gupta D, Khanna N N, Araki T, Maniruzzaman M, Saba L, Nicolaides A, Sharma A and Omerzu T 2019 Ranking of stroke and cardiovascular risk factors for an optimal risk calculator design: logistic regression approach *Comput. Biol. Med.* **108** 182–95

[29] Khanna N N, Jamthikar A D, Gupta D, Piga M, Saba L, Carcassi C, Giannopoulos A A, Nicolaides A, Laird J R and Suri H S 2019 Rheumatoid arthritis: atherosclerosis imaging and cardiovascular risk assessment using machine and deep learning–based tissue characterization *Curr. Atheroscler. Rep.* **21** 7

[30] Jamthikar A, Gupta D, Khanna N N, Araki T, Saba L, Nicolaides A, Sharma A, Omerzu T, Suri H S and Gupta A 2019 A special report on changing trends in preventive stroke/cardiovascular risk assessment via B-mode ultrasonography *Curr. Atheroscler Rep.* **21** 25

[31] Schnee J M and Hsueh W A 2000 Angiotensin II, adhesion, and cardiac fibrosis *Cardiovasc. Res.* **46** 264–8

[32] Wu L L, Yang N, Roe C J, Cooper M E, Gilbert R E, Atkins R C and Lan H Y 1997 Macrophage and myofibroblast proliferation in remnant kidney: role of angiotensin II *Kidney Int. Suppl.* **63** S221–5

[33] Sun Y, Ramires F J and Weber K T 1997 Fibrosis of atria and great vessels in response to angiotensin II or aldosterone infusion *Cardiovasc. Res.* **35** 138–47

[34] Morihara K, Takai S, Takenaka H, Sakaguchi M, Okamoto Y, Morihara T, Miyazaki M and Kishimoto S 2006 Cutaneous tissue angiotensin–converting enzyme may participate in pathologic scar formation in human skin *J. Am. Acad. Dermatol.* **54** 251–7
[35] Cosyns B, Lochy S, Luchian M L, Gimelli A, Pontone G, Allard S D, de Mey J, Rosseel P, Dweck M and Petersen S E 2020 The role of cardiovascular imaging for myocardial injury in hospitalized COVID-19 patients *Eur. Heart J. Cardiovasc. Imaging* **21** 709–14
[36] Inciardi R M, Lupi L, Zaccone G, Italia L, Raffo M, Tomasoni D, Cani D S, Cerini M, Farina D and Gavazzi E 2020 Cardiac involvement in a patient with coronavirus disease 2019 (COVID-19) *JAMA Cardiol* **5** 819–24
[37] Kim I-C, Kim J Y, Kim H A and Han S 2020 COVID-19-related myocarditis in a 21-year-old female patient *Eur. Heart J.* **41** 1859–9
[38] Kiamanesh O, Harper L, Wiskar K, Luksun W, McDonald M, Ross H, Woo A and Granton J 2020 Lung ultrasound for cardiologists in the time of COVID-19 *Can. J. Cardiol* **36** 1144–7
[39] Zieleskiewicz L, Duclos G, Dransart-Rayé O, Nowobilski N and Bouhemad B 2020 Ultrasound findings in patients with COVID-19 pneumonia in early and late stages: two case-reports *Anaesth. Crit. Care Pain Med* **39** 571–3
[40] Saba L, Tiwari A, Biswas M, Gupta S K, Godia-Cuadrado E, Chaturvedi A, Turk M, Suri H S, Orru S and Sanches J M 2019 Wilson's disease: a new perspective review on its genetics, diagnosis and treatment *Front. Biosci. (Elite edition)* **11** 166–85
[41] Collaborators NASCET 1991 Beneficial effect of carotid endarterectomy in symptomatic patients with high-grade carotid stenosis *New Engl. J. Med.* **325** 445–53
[42] Sanches J M, Laine A F and Suri J S 2012 *Ultrasound Imaging* (Berlin: Springer)
[43] Suri J S, Wilson D and Laxminarayan S 2005 *Handbook of Biomedical Image Analysis* vol 2 43 (New York: Springer Science & Business Media)
[44] Suri J S and Laxminarayan S 2003 *Angiography and Plaque Imaging: Advanced Segmentation Techniques* (Boca Raton, FL: CRC Press)
[45] Acharya U R, Mookiah M R K, Sree S V, Afonso D, Sanches J, Shafique S, Nicolaides A and Pedro L M 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23
[46] Acharya U R, Faust O, Sree S V, Alvin A P C, Krishnamurthi G, Sanches J and Suri J S 2011 Atheromatic™: symptomatic vs. asymptomatic classification of carotid ultrasound plaque using a combination of HOS, DWT & texture *2011 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 4489–92
[47] Acharya U R, Sree S V, Kulshreshtha S, Molinari F, Koh J E W, Saba L and Suri J S 2014 GyneScan: an improved online paradigm for screening of ovarian cancer via tissue characterization *Technol. Cancer Res. Treat.* **13** 529–39
[48] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M and Suri J S 2018 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Prog. Biomed.* **155** 165–77
[49] Acharya U R, Krishnan M M R, Sree S V, Sanches J, Shafique S, Nicolaides A, Pedro L M and Suri J S 2012 Plaque tissue characterization and classification in ultrasound carotid scans: a paradigm for vascular feature amalgamation *IEEE Trans. Instrum. Meas.* **62** 392–400
[50] Molinari F, Liboni W, Pavanelli E, Giustetto P, Badalamenti S and Suri J S 2007 Accurate and automatic carotid plaque characterization in contrast enhanced 2-D ultrasound images

2007 29th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (Piscataway, NJ: IEEE) pp 335–8
[51] Acharya U, Vinitha Sree S, Mookiah M, Yantri R, Molinari F, Zieleźnik W, Małyszek-Tumidajewicz J, Stępień B, Bardales R and Witkowska A 2013 Diagnosis of Hashimoto's thyroiditis in ultrasound using tissue characterization and pixel classification *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **227** 788–98
[52] Sharma A M, Gupta A, Kumar P K, Rajan J, Saba L, Nobutaka I, Laird J R, Nicolades A and Suri J S 2015 A review on carotid ultrasound atherosclerotic tissue characterization and stroke risk stratification in machine learning framework *Curr. Atheroscler. Rep.* **17** 55
[53] Ravì D, Wong C, Deligianni F, Berthelot M, Andreu-Perez J, Lo B and Yang G-Z 2016 Deep learning for health informatics *IEEE J. Biomed. Health Inform.* **21** 4–21
[54] Saba L, Biswas M, Kuppili V, Godia E C, Suri H S, Edla D R, Omerzu T, Laird J R, Khanna N N and Mavrogeni S 2019 The present and future of deep learning in radiology *Eur. J. Radiol* **114** 14–24
[55] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Cuadrado-Godia E, Laird J, Marinhoe R, Sanches J and Nicolaides A 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci. (Landmark Ed)* **24** 392–426
[56] Biswas M, Kuppili V, Araki T, Edla D R, Godia E C, Saba L, Suri H S, Omerzu T, Laird J R and Khanna N N 2018 Deep learning strategy for accurate carotid intima-media thickness measurement: an ultrasound study on Japanese diabetic cohort *Comput. Biol. Med.* **98** 100–17
[57] Jamthikar A, Gupta D, Khanna N N, Saba L, Araki T, Viskovic K, Suri H S, Gupta A, Mavrogeni S and Turk M 2019 A low-cost machine learning-based cardiovascular/stroke risk assessment system: integration of conventional factors with image phenotypes *Cardiovasc. Diagn. Ther.* **9** 420
[58] Hoffmann M, Kleine-Weber H, Schroeder S, Krüger N, Herrler T, Erichsen S, Schiergens T S, Herrler G, Wu N-H and Nitsche A 2020 SARS-CoV-2 cell entry depends on ACE2 and TMPRSS2 and is blocked by a clinically proven protease inhibitor *Cell* **181** 271–80
[59] de Wit E, van Doremalen N, Falzarano D and Munster V J 2016 SARS and MERS: recent insights into emerging coronaviruses *Nat. Rev. Microbiol.* **14** 523
[60] Wu K, Peng G, Wilken M, Geraghty R J and Li F 2012 Mechanisms of host receptor adaptation by severe acute respiratory syndrome coronavirus *J. Biol. Chem.* **287** 8904–11
[61] Patel V B, Zhong J-C, Grant M B and Oudit G Y 2016 Role of the ACE2/angiotensin 1–7 axis of the renin–angiotensin system in heart failure *Circ. Res.* **118** 1313–26
[62] Zou X, Chen K, Zou J, Han P, Hao J and Han Z 2020 Single-cell RNA-seq data analysis on the receptor ACE2 expression reveals the potential risk of different human organs vulnerable to 2019-nCoV infection *Front. Med.* **14** 185–192
[63] Hamming I, Timens W, Bulthuis M, Lely A, Navis G and van Goor H 2004 Tissue distribution of ACE2 protein, the functional receptor for SARS coronavirus. A first step in understanding SARS pathogenesis *J. Pathol.* **203** 631–7
[64] Giacomelli A, Pezzati L, Conti F, Bernacchia D, Siano M, Oreni L, Rusconi S, Gervasoni C, Ridolfo A L and Rizzardini G 2020 Self-reported olfactory and taste disorders in patients with severe acute respiratory coronavirus 2 infection: a cross-sectional study *Clin. Infect Dis.* **71** 889–90

[65] Wu A, Peng Y, Huang B, Ding X, Wang X, Niu P, Meng J, Zhu Z, Zhang Z and Wang J 2020 Genome composition and divergence of the novel coronavirus (2019-nCoV) originating in China *Cell Host Microbe* **27** 325–8

[66] Koyuncu O O, Hogue I B and Enquist L W 2013 Virus infections in the nervous system *Cell Host Microbe* **13** 379–93

[67] Desforges M, Le Coupanec A, Dubeau P, Bourgouin A, Lajoie L, Dubé M and Talbot P J 2020 Human coronaviruses and other respiratory viruses: underestimated opportunistic pathogens of the central nervous system? *Viruses* **12** 14

[68] McCray P B, Pewe L, Wohlford-Lenane C, Hickey M, Manzel L, Shi L, Netland J, Jia H P, Halabi C and Sigmund C D 2007 Lethal infection of K18-hACE2 mice infected with severe acute respiratory syndrome coronavirus *J. Virol.* **81** 813–21

[69] Li K, Wohlford-Lenane C, Perlman S, Zhao J, Jewell A K, Reznikov L R, Gibson-Corley K N, Meyerholz D K and McCray P B 2016 Middle East respiratory syndrome coronavirus causes multiple organ damage and lethal disease in mice transgenic for human dipeptidyl peptidase 4 *J. Infect. Dis.* **213** 712–22

[70] Netland J, Meyerholz D K, Moore S, Cassell M and Perlman S 2008 Severe acute respiratory syndrome coronavirus infection causes neuronal death in the absence of encephalitis in mice transgenic for human ACE2 *J. Virol.* **82** 7264–75

[71] Baig A M 2020 Neurological manifestations in COVID-19 caused by SARS-CoV-2 *CNS Neurosci. Ther.* **26** 499

[72] Ryan W 2020 There's a new symptom of coronavirus, doctors say: sudden loss of smell or taste

[73] Hopkins C and Kumar N 2020 Loss of sense of smell as marker of COVID-19 infection *ENT UK* **26** 2020 (https://www.entuk.org/sites/default/files/files/Loss_of_sense_of_smell_as_marker_of_COVID.pdf)

[74] Bohmwald K, Galvez N, Ríos M and Kalergis A M 2018 Neurologic alterations due to respiratory virus infections *Front. Cell. Neurosci.* **12** 386

[75] Zhang H and Baker A 2017 *Recombinant Human ACE2: Acing Out Angiotensin II in ARDS Therapy* (Berlin: Springer)

[76] Radermacher P, Maggiore S M and Mercat A 2017 Fifty years of research in ARDS. Gas exchange in acute respiratory distress syndrome *Am. J. Respir. Crit. Care Med.* **196** 964–84

[77] Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y and Wei Y 2020 Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study *Lancet* **395** 507–13

[78] Xiong T-Y, Redwood S, Prendergast B and Chen M 2020 Coronaviruses and the cardiovascular system: acute and long-term implications *Eur. Heart J.* **41** 1798–800

[79] Oudit G, Kassiri Z, Jiang C, Liu P, Poutanen S, Penninger J and Butany J 2009 SARS-coronavirus modulation of myocardial ACE2 expression and inflammation in patients with SARS *Eur. J. Clin. Investig.* **39** 618–25

[80] Abdennour L, Zeghal C, Deme M and Puybasset L 2012 Interaction brain-lungs *Ann. Fr. Anesth. Reanim.* e101–7

[81] Fountain J H and Lappin S L 2019 Physiology, Renin Angiotensin System *StatPearls* pp 81 (St Petersburg, FL: StatPearls Publishing)

[82] Rajendran P, Rengarajan T, Thangavel J, Nishigaki Y, Sakthisekaran D, Sethi G and Nishigaki I 2013 The vascular endothelium and human diseases *Int. J. Biol. Sci.* **9** 1057

[83] Lillie P J, Samson A, Li A, Adams K, Capstick R, Barlow G D, Easom N, Hamilton E, Moss P J and Evans A 2020 Novel coronavirus disease (Covid-19): the first two patients in the UK with person to person transmission *J. Infect.* **80** 578–606

[84] Bai Y, Yao L, Wei T, Tian F, Jin D-Y, Chen L and Wang M 2020 Presumed asymptomatic carrier transmission of COVID-19 *JAMA* **323** 1406–7

[85] Mehta P, McAuley D F, Brown M, Sanchez E, Tattersall R S and Manson J J 2020 COVID-19: consider cytokine storm syndromes and immunosuppression *Lancet* **395** 1033–4

[86] Siddiqi H K and Mehra M R 2020 COVID-19 illness in native and immunosuppressed states: a clinical-therapeutic staging proposal *J. Heart Lung Transp.* **39** 405–7

[87] Yin C, Wang C, Tang Z, Wen Y, Zhang S and Wang B 2004 Clinical analysis of multiple organ dysfunction syndrome in patients suffering from SARS *Zhongguo wei zhong bing ji jiu yi xue= Chin. Crit. Care Med.= Zhongguo weizhongbing jijiuyixue* **16** 646–50

[88] Schoenhagen P, Tuzcu E M and Ellis S G 2002 Plaque vulnerability, plaque rupture, and acute coronary syndromes: (multi)-focal manifestation of a systemic disease process *Circulation*

[89] Tisoncik J R, Korth M J, Simmons C P, Farrar J, Martin T R and Katze M G 2012 Into the eye of the cytokine storm *Microbiol. Mol. Biol. Rev.* **76** 16–32

[90] Tersalvi G, Vicenzi M, Calabretta D, Biasco L, Pedrazzini G and Winterton D 2020 Elevated troponin in patients with Coronavirus Disease 2019 (COVID-19): possible mechanisms *J. Cardiac Failure* **26** 470–75

[91] Gomes V A 2020 COVID-19 Cardiac repercussions *Rev. Bras. Fisiol. Exer.* **19**

[92] Zeng J H, Liu Y-X, Yuan J, Wang F-X, Wu W-B, Li J-X, Wang L-F, Gao H, Wang Y and Dong C-F 2020 *First Case of COVID-19 Infection with Fulminant Myocarditis Complication: Case Report and Insights*

[93] Cieszanowski A, Czekajska E, Giżycka B, Gruszczyńska K, Podgórska J, Oronowicz-Jaśkowiak A, Serafin Z, Szurowska E and Walecki J M 2020 Management of patients with COVID-19 in radiology departments, and indications regarding imaging studies–recommendations of the Polish Medical Society of Radiology *Pol. J. Radiol.* **85** e209

[94] Kim D J, Jelic T, Woo M Y, Heslop C and Olszynski P 2020 Just the facts: recommendations on point of care ultrasound use and machine infection control during the COVID-19 pandemic *Can. J. Emerg. Med.* **22** 1–7

[95] An X, Song Z, Gao Y, Tao J and Yang J 2020 To resume noninvasive imaging detection safely after peak period of COVID-19: experiences from Wuhan China *Dermatol. Ther.* **33** e13590

[96] Jakhar D, Kaur I and Kaul S 2020 Art of performing dermoscopy during the times of coronavirus disease (COVID-19): simple change in approach can save the day! *J. Eur. Acad. Dermatol. Venereol.*

[97] Skulstad H, Cosyns B, Popescu B A, Galderisi M, Salvo G D, Donal E, Petersen S, Gimelli A, Haugaa K H and Muraru D 2020 COVID-19 pandemic and cardiac imaging: EACVI recommendations on precautions, indications, prioritization, and protection for patients and healthcare personnel *Eur. Heart J.-Cardiovasc. Imaging* **21** 592–98

[98] Lo S, Yong A, Sinhal A, Shetty S, McCann A, Clark D, Galligan L, El-Jack S, Sader M and Tan R 2020 Consensus guidelines for interventional cardiology services delivery during COVID-19 pandemic in Australia and New Zealand *Heart Lung Circ* **29** 69–77

[99] El-Baz A, Jiang X and Suri J S 2016 *Biomedical Image Segmentation: Advances and Trends* (Boca Raton, FL: CRC Press)

[100] El-Baz A S, Acharya R, Mirmehdi M and Suri J S 2011 *Multi Modality State-of-the-Art Medical Image Segmentation and Registration Methodologies* vol 1 (New York: Springer Science & Business Media)

[101] Olusanya O 2020 Ultrasound in times of COVID-19 *ICU Management & Practice* **20** 43–50

[102] Smith M, Hayward S, Innes S and Miller A 2020 Point-of-care lung ultrasound in patients with COVID-19: a narrative review *Anaesthesia* **75** 1096–104

[103] Jacobi A, Chung M, Bernheim A and Eber C 2020 Portable chest X-ray in coronavirus disease-19 (COVID-19): a pictorial review *Clin. Imaging* **64** 35–42

[104] Chung M, Bernheim A, Mei X, Zhang N, Huang M, Zeng X, Cui J, Xu W, Yang Y and Fayad Z A 2020 CT imaging features of 2019 novel coronavirus (2019-nCoV) *Radiology* **295** 202–7

[105] Vasilev Y, Sergunova K, Bazhin A, Masri A, Vasileva Y, Suleumanov E, Semenov D, Kudryavtsev N, Panina O and Khoruzhaya A 2020 MRI of the lungs in patients with COVID-19: clinical case *JMRI* **79** 13–9

[106] Huang L, Zhao P, Tang D, Zhu T, Han R, Zhan C, Liu W, Zeng H, Tao Q and Xia L 2020 Cardiac involvement in recovered COVID-19 patients identified by magnetic resonance imaging *JACC: Cardiovasc. Imaging* **13** 2330–9

[107] Luetkens J A, Isaak A, Zimmer S, Nattermann J, Sprinkart A M, Boesecke C, Rieke G J, Zachoval C, Heine A and Velten M 2020 Diffuse myocardial inflammation in covid-19 associated myocarditis detected by multiparametric cardiac magnetic resonance imaging *Circ.: Cardiovasc. Imaging* **13** e010897

[108] Poyiadji N, Shahin G, Noujaim D, Stone M, Patel S and Griffith B 2020 COVID-19–associated acute hemorrhagic necrotizing encephalopathy: CT and MRI features *Radiology* **296** 201187

[109] Kandemirli S G, Dogan L, Sarikaya Z T, Kara S, Akinci C, Kaya D, Kaya Y, Yildirim D, Tuzuner F and Yildirim M S 2020 Brain MRI findings in patients in the intensive care unit with COVID-19 infection *Radiology* **297** 201697

[110] Bhayana R, Som A, Li M D, Carey D E, Anderson M A, Blake M A, Catalano O, Gee M S, Hahn P F and Harisinghani M 2020 Abdominal imaging findings in COVID-19: preliminary observations *Radiology* **297** 201908

[111] Eliezer M and Hautefort C 2020 MRI evaluation of the olfactory clefts in patients with SARS-CoV-2 infection revealed an unexpected mechanism for olfactory function loss *Acad. Radiol.* **27** 1191

[112] Xiao Z, Xu C, Wang D and Zeng H 2020 The experience of treating patients with acute myocardial infarction under the COVID-19 epidemic *Catheter. Cardiovasc. Interv.* **97** E244–8

[113] Meyer P, Degrauwe S, Van Delden C, Ghadri J-R and Templin C 2020 Typical takotsubo syndrome triggered by SARS-CoV-2 infection *Eur. Heart J.* **41** 1860–0

[114] Danzi G B, Loffi M, Galeazzi G and Gherbesi E 2020 Acute pulmonary embolism and COVID-19 pneumonia: a random association? *Eur. Heart J.* **41** 1858–8

[115] Zhang L, Feng X, Zhang D, Jiang C, Mei H, Wang J, Zhang C, Li H, Xia X and Kong S 2020 Deep vein thrombosis in hospitalized patients with coronavirus disease 2019 (COVID-19) in Wuhan, China: prevalence, risk factors, and outcome *Circulation* **142** 114–28

[116] Emanuel E J, Persad G, Upshur R, Thome B, Parker M, Glickman A, Zhang C, Boyle C, Smith M and Phillips J P 2020 Fair Allocation of Scarce Medical Resources in the Time of Covid-19 *N Engl. J. Med.* **382** 2049–55

[117] Rosenbaum L 2020 Facing Covid-19 in Italy—ethics, logistics, and therapeutics on the epidemic's front line *New Engl. J. Med.* **382** 1873–5

[118] Bhatt A S *et al* 2020 Declines in hospitalizations for acute cardiovascular conditions during the COVID-19 pandemic: a multicenter tertiary care experience *J. Am. Coll. Cardiol.* **76** 280–8

[119] Vaishya R, Haleem A, Vaish A and Javaid M 2020 Emerging technologies to combat COVID-19 pandemic *J. Clin. Exp. Hepatol* **10** 409–11

[120] Murphy K, Smits H, Knoops A J, Korst M B, Samson T, Scholten E T, Schalekamp S, Schaefer-Prokop C M, Philipsen R H and Meijers A 2020 COVID-19 on the chest radiograph: a multi-reader evaluation of an AI system *Radiology* **296** 201874

[121] Zheng N, Du S, Wang J, Zhang H, Cui W, Kang Z, Yang T, Lou B, Chi Y and Long H 2020 Predicting COVID-19 in China using hybrid AI model *IEEE Trans. Cybern* **50** 2891–904

[122] Chieffo A, Stefanini G G, Price S, Barbato E, Tarantini G, Karam N, Moreno R, Buchanan G L, Gilard M and Halvorsen S 2020 EAPCI position statement on invasive management of acute coronary syndromes during the COVID-19 pandemic *Eur. Heart J.* **41** 1839–51

[123] Salehi S, Abedi A, Balakrishnan S and Gholamrezanezhad A 2020 Coronavirus disease 2019 (COVID-19): a systematic review of imaging findings in 919 patients *Am. J. Roentgenol.* **215** 1–7

[124] Dangis A, Gieraerts C, Bruecker Y D, Janssen L, Valgaeren H, Obbels D, Gillis M, Ranst M V, Frans J and Demeyere A 2020 Accuracy and reproducibility of low-dose submillisievert chest CT for the diagnosis of COVID-19 *Radiol.: Cardiothorac. Imaging* **2** e200196

[125] Rubin G D, Ryerson C J, Haramati L B, Sverzellati N, Kanne J P, Raoof S, Schluger N W, Volpi A, Yim J-J and Martin I B 2020 The role of chest imaging in patient management during the COVID-19 pandemic: a multinational consensus statement from the Fleischner Society *Chest* **158** 106–16

[126] Nair A *et al* 2020 Society of Thoracic Imaging statement: considerations in designing local imaging diagnostic algorithms for the COVID-19 pandemic *Clin. Radiol.* **75** 329–34

[127] Laghi A 2020 Cautions about radiologic diagnosis of COVID-19 infection driven by artificial intelligence *Lancet Digit. Health* **2** e225

[128] Miotto R, Wang F, Wang S, Jiang X and Dudley J T 2018 Deep learning for healthcare: review, opportunities and challenges *Brief. Bioinform.* **19** 1236–46

[129] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S and Dean J 2019 A guide to deep learning in healthcare *Nat. Med.* **25** 24–9

[130] Hosny A, Parmar C, Quackenbush J, Schwartz L H and Aerts H J 2018 Artificial intelligence in radiology *Nat. Rev. Cancer* **18** 500–10

[131] Sinha JSS G R 2019 *Cognitive Informatics, Computer Modelling, and Cognitive Science: Volume 1: Theory, Case Studies, and Applications* (Netherlands: Elsevier)

[132] Tang X 2019 The role of artificial intelligence in medical imaging research *BJR| Open* **2** 20190031

[133] Saeian K, Rhyne T L and Sagar K B 1994 Ultrasonic tissue characterization for diagnosis of acute myocardial infarction in the coronary care unit *Am. J. Cardiol.* **74** 1211–5

[134] Mavrogeni S, Sfikakis P P, Gialafos E, Bratis K, Karabela G, Stavropoulos E, Spiliotis G, Sfendouraki E, Panopoulos S and Bournia V 2014 Cardiac tissue characterization and the

diagnostic value of cardiovascular magnetic resonance in systemic connective tissue diseases *Arthritis Care Res.* **66** 104–12
[135] Wu J, Pan J, Teng D, Xu X, Feng J and Chen Y-C 2020 Interpretation of CT signs of 2019 novel coronavirus (COVID-19) pneumonia *Eur. Radiol.* **30** 5455–62
[136] Alimadadi A, Aryal S, Manandhar I, Munroe P B, Joe B and Cheng X 2020 Artificial Intelligence and Machine Learning to Fight COVID-19 *Physiological Genomics* **52** 200–2
[137] Vaishya R, Javaid M, Khan I H and Haleem A 2020 Artificial intelligence (AI) applications for COVID-19 pandemic *Diabetes Metab. Syndr.: Clin. Res. Rev.* **14** 337–9
[138] Jamthikar A, Gupta D, Saba L, Khanna N N, Araki T, Viskovic K, Mavrogeni S, Laird J R, Pareek G and Miner M *et al* 2020 Cardiovascular/stroke risk predictive calculators: a comparison between statistical and machine learning models *Cardiovasc. Diagn. Ther* **10** 919–38
[139] Jamthikar A, Gupta D, Khanna N N, Saba L, Laird J R and Suri J S 2020 Cardiovascular/stroke risk prevention: a new machine learning framework integrating carotid ultrasound image-based phenotypes and its harmonics with conventional risk factors *Indian Heart J.* **72** 258–64
[140] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M and Suri J S 2017 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Prog. Biomed* **155** 165–77
[141] Bishop C M 2006 *Pattern Recognition and Machine Learning* (New York: Springer)
[142] LeCun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436–44
[143] Suri J S, Acharya U R, Faust O, Alvin A P C, Sree S V, Molinari F, Saba L and Nicolaides A 2011 Symptomatic vs. asymptomatic plaque classification in carotid ultrasound *J. Med. Syst.* **36** 1861–71
[144] Cortes C and Vapnik V 1995 Support-vector networks *Mach. Learn.* **20** 273–97
[145] Mirmehdi M 2008 *Handbook of Texture Analysis* (Singapore: Imperial College Press)
[146] Bharati M H, Liu J J and MacGregor J F 2004 Image texture analysis: methods and comparisons *Chemometr. Intell. Lab. Syst.* **72** 57–71
[147] Acharya U R, Chua C K, Lim T-C, Dorithy T and Suri J S 2009 Automatic identification of epileptic EEG signals using nonlinear parameters *J. Mech. Med. Biol.* **9** 539–53
[148] Acharya U R, Faust O, Sree S V, Molinari F and Suri J S 2012 ThyroScreen system: high resolution ultrasound thyroid image characterization into benign and malignant classes using novel combination of texture and discrete wavelet transform *Comput. Methods Programs Biomed.* **107** 233–41
[149] Reynolds D A 2009 Gaussian mixture models *Encyclopedia of Biometrics* (Berlin: Springer) 741
[150] Huang D-S 1999 Radial basis probabilistic neural networks: model and application *Int. J. Pattern Recognit Artif Intell.* **13** 1083–101
[151] Quinlan J R 1987 Generating production rules from decision trees *IJCAI* **87** 304–7
[152] Clark P J and Evans F C 1954 Distance to nearest neighbor as a measure of spatial relationships in populations *Ecology* **35** 445–53
[153] Rish I 2001 An empirical study of the naive Bayes classifier *IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence* pp 41–6
[154] Ross T J 2009 *Fuzzy Logic with Engineering Applications* (University of New Mexico: Wiley)

[155] Kadyrov A and Petrou M 2001 The trace transform and its applications *IEEE Trans. Pattern Anal. Mach. Intell.* **23** 811–28
[156] Jawahar C and Ray A 1996 Incorporation of gray-level imprecision in representation and processing of digital images *Pattern Recognit. Lett.* **17** 541–6
[157] Galloway M M 1974 Texture analysis using grey level run lengths *STIN* **75** 18555
[158] Boi A, Jamthikar A D, Saba L, Gupta D, Sharma A, Loi B, Laird J R, Khanna N N and Suri J S 2018 A survey on coronary atherosclerotic plaque tissue characterization in intravascular optical coherence tomography *Curr. Atheroscler. Rep.* **20** 33
[159] Jamthikar A, Gupta D, Khanna N N, Saba L, Araki T, Viskovic K, Suri H S, Gupta A, Mavrogeni S and Turk M *et al* 2019 A low-cost machine learning-based cardiovascular/stroke risk assessment system: integration of conventional factors with image phenotypes *Cardiovasc. Diagn. Ther.* **9** 420
[160] Jamthikar A, Gupta D, Khanna N N, Araki T, Saba L, Nicolaides A, Sharma A, Omerzu T, Suri H S and Gupta A *et al* 2019 A special report on changing trends in preventive stroke/cardiovascular risk assessment via B-Mode ultrasonography *Curr. Atheroscler. Rep.* 21 25
[161] Viswanathan V *et al* 2020 Does the carotid bulb offer a better 10-Year CVD/stroke risk assessment compared to the common carotid artery? A 1516 ultrasound scan study *Angiology* **71** 3319720941730
[162] Long J, Shelhamer E and Darrell T 2015 Fully convolutional networks for semantic segmentation *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition* pp 3431–40
[163] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Sharma A, Cuadrado-Godia E, Laird J R, Nicolaides A and Suri J S 2019 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 543–64
[164] Saba L, Biswas M, Suri H S, Viskovic K, Laird J R, Cuadrado-Godia E, Nicolaides A, Khanna N, Viswanathan V and Suri J S 2019 Ultrasound-based carotid stenosis measurement and risk stratification in diabetic cohort: a deep learning paradigm *Cardiovasc. Diagn. Ther.* **9** 439
[165] Dong D, Tang Z, Wang S, Hui H, Gong L, Lu Y, Xue Z, Liao H, Chen F and Yang F 2020 The role of imaging in the detection and management of COVID-19: a review *IEEE Rev. Biomed. Eng*
[166] Ito R I S and Naganawa S 2020 A review on the use of artificial intelligence for medical imaging of the lungs of patients with coronavirus disease 2019 *Diagn. Interv. Radiol*
[167] Lu W, Zhang S, Chen B, Chen J, Xian J, Lin Y, Shan H and Su Z Z 2020 A clinical study of noninvasive assessment of lung lesions in patients with coronavirus disease-19 (COVID-19) by bedside ultrasound *Ultraschall in der Medizin-Eur. J. Ultrasound* **41** 300–7
[168] Kang H, Xia L, Yan F, Wan Z, Shi F, Yuan H, Jiang H, Wu D, Sui H and Zhang C 2020 Diagnosis of coronavirus disease 2019 (covid-19) with structured latent multi-view representation learning *IEEE Trans. Med. Imaging* **39** 2606–14
[169] Xinggang Wang X D, Fu Q, Zhou Q, Zhou Q, Feng J, Ma H, Liu W and Zheng C 2020 A weakly-supervised framework for COVID-19 classification and lesion localization from chest CT *IEEE Trans. Med. Imaging* **39** 2615–25
[170] Krizhevsky A, Sutskever I and Hinton G E 2012 *Imagenet classification with deep convolutional neural networks Advances in Neural Information Processing Systems 25 (NIPS 2012)* F. Pereira *et al* (Cambridge, MA: MIT Press) 1097–105

[171] Szegedy C, Vanhoucke V, Ioffe S, Shlens J and Wojna Z 2016 Rethinking the inception architecture for computer vision *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition* pp 2818–26
[172] Wang K, Lu X, Zhou H, Gao Y, Zheng J, Tong M, Wu C, Liu C and Huang L 2019 Deep learning Radiomics of shear wave elastography significantly improved diagnostic performance for assessing liver fibrosis in chronic hepatitis B: a prospective multicentre study *Gut* **68** 729–41
[173] Wang S *et al* 2020 A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis *Eur. Respir. J.* **56** 2000775
[174] Zhang K *et al* 2020 Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis *Cell* **182** 1360
[175] Li Z *et al* 2020 from community acquired pneumonia to COVID-19: a deep learning based method for quantitative analysis of COVID-19 on thick-section CT scans *Medrxiv* 2020
[176] Chen J *et al* 2020 Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study *Sci. Rep.* **10** 19196
[177] Angel C T (http://121.40.75.149/znyx-ncov/index#/app/index) (accessed 24 July 2020)
[178] Yang S, Jiang L, Cao Z, Wang L, Cao J, Feng R, Zhang Z, Xue X, Shi Y and Shan F 2020 Deep learning for detecting corona virus disease 2019 (COVID-19) on high-resolution computed tomography: a pilot study *Ann. Transl. Med.* **8**
[179] Oh Y, Park S and Ye J C 2020 Deep learning Covid-19 features on CXR using limited training data sets *IEEE Trans. Med. Imaging* **39** 2688–700
[180] Ren Z H, Mu W C and Huang S Y 2018 Design and optimization of a ring-pair permanent magnet array for head imaging in a low-field portable MRI system *IEEE Trans. Magn.* **55** 1–8
[181] Cooley C Z, Stockmann J P, Armstrong B D, Sarracanie M, Lev M H, Rosen M S and Wald L L 2015 Two-dimensional imaging in a lightweight portable MRI scanner without gradient coils *Magn. Reson. Med.* **73** 872–83
[182] Mirvis S E 1999 Use of portable CT in the R Adams Cowley Shock Trauma Center: experiences in the admitting area, ICU, and operating room *Surg. Clin. North Am.* **79** 1317–30
[183] Wang X and Bhatt D L 2020 COVID-19: an unintended force for medical revolution *J. Invasive Cardiol.* **32** E81–2
[184] Thamman R, Gulati M, Narang A, Utengen A, Mamas M A and Bhatt D L 2020 Twitter-based learning for continuing medical education? *Eur. Heart J.*
[185] Li L, Zhang Q, Wang X, Zhang J, Wang T, Gao T-L, Duan W, Tsoi K K-F and Wang F-Y 2020 Characterizing the propagation of situational information in social media during COVID-19 epidemic: a case study on weibo *IEEE Trans. Comput. Soc. Syst.* **7** 556–62
[186] El-Baz A and Suri J S (ed) 2019 *Big Data in Multimodal Medical Imaging* (Boca Raton, FL: CRC Press)
[187] Kooraki S, Hosseiny M, Myers L and Gholamrezanezhad A 2020 Coronavirus (COVID-19) outbreak: what the department of radiology should know *J. Am. Coll. Radiol* **17** 447–51
[188] Mossa-Basha M, Medverd J, Linnau K, Lynch J B, Wener M H, Kicska G, Staiger T and Sahani D 2020 Policies and guidelines for COVID-19 preparedness: experiences from the University of Washington *Radiology* **296** 201326

[189] Buonsenso D, Piano A, Raffaelli F, Bonadia N, Donati K D G and Franceschi F 2020 novel coronavirus disease-19 pnemoniae: a case report and potential applications during COVID-19 outbreak *Eur. Rev. Med. Pharmacol. Sci.* **24** 2776–80
[190] Suri J S *et al* 2020 COVID-19 pathways for brain and heart injury in comorbidity patients: A role of medical imaging and artificial intelligence-based COVID severity classification: A review *Comput. Biol. Med.* **124** 103960

Full list of references

Chapter 1

[1] Yuen K-S, Ye Z-W, Fung S-Y, Chan C-P and Jin D-Y 2020 SARS-CoV-2 and COVID-19: the most important research questions *Cell Biosci.* **10** 1–5

[2] Coronavirus (COVID-19) outbreak (https://who.int/westernpacific/emergencies/covid-19)

[3] Coronavirus (https://who.int/health-topics/coronavirus#tab=tab_1)

[4] Chan J F-W, Yuan S, Kok K-H, To K K-W, Chu H, Yang J, Xing F, Liu J, Yip C C-Y and Poon R W-S 2020 A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster *Lancet* **395** 514–23

[5] Coronavirus (https://worldometers.info/coronavirus/)

[6] Wang D, Hu B, Hu C, Zhu F, Liu X, Zhang J, Wang B, Xiang H, Cheng Z and Xiong Y 2020 Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China *JAMA* **323** 1061–9

[7] Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J and Gu X 2020 Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China *Lancet* **395** 497–506

[8] Shi S, Qin M, Shen B, Cai Y, Liu T, Yang F, Gong W, Liu X, Liang J and Zhao Q 2020 Association of cardiac injury with mortality in hospitalized patients with COVID-19 in Wuhan, China *JAMA Cardiol.* **5** 802–10

[9] Zhou F, Yu T, Du R, Fan G, Liu Y, Liu Z, Xiang J, Wang Y, Song B and Gu X 2020 Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study *Lancet* **395** 1054–62

[10] Gao F, Zheng K I, Wang X B, Yan H D, Sun Q F, Pan K H, Wang T Y, Chen Y P, George J and Zheng M H 2020 Metabolic associated fatty liver disease increases COVID-19 disease severity in non-diabetic patients *J. Gastroenterol. Hepatol* **36** 204–7

[11] Yan Y, Yang Y, Wang F, Ren H, Zhang S, Shi X, Yu X and Dong K 2020 Clinical characteristics and outcomes of patients with severe covid-19 with diabetes *BMJ Open Diabetes Res. Care* **8** e001343

[12] Virani S S, Alonso A, Benjamin E J, Bittencourt M S, Callaway C W, Carson A P, Chamberlain A M, Chang A R, Cheng S and Delling F N 2020 Heart disease and stroke statistics—2020 update: a report from the American heart association *Circulation* **141** E139–596

[13] Zheng Y-Y, Ma Y-T, Zhang J-Y and Xie X 2020 COVID-19 and the cardiovascular system *Nat. Rev. Cardiol.* **17** 259–60

[14] Chen L, Li X, Chen M, Feng Y and Xiong C 2020 The ACE2 expression in human heart indicates new potential mechanism of heart injury among patients infected with SARS-CoV-2 *Cardiovasc. Res.* **116** 1097–100

[15] Williams V R and Scholey J W 2018 Angiotensin-converting enzyme 2 and renal disease *Curr. Opi. Nephrol. Hypertens.* **27** 35–41

[16] Wang B, Li R, Lu Z and Huang Y 2020 Does comorbidity increase the risk of patients with COVID-19: evidence from meta-analysis *Aging (Albany NY)* **12** 6049

[17] Cheng H, Wang Y and Wang G Q 2020 Organ-protective effect of angiotensin-converting enzyme 2 and its effect on the prognosis of COVID-19 *J. Med. Virol* **92** 726–30

[18] Libby P 2020 The heart in COVID19: primary target or secondary bystander? *JACC: Basic Transl. Sci.* **5** 537–42

[19] Clerkin K J, Fried J A, Raikhelkar J, Sayer G, Griffin J M, Masoumi A, Jain S S, Burkhoff D, Kumaraiah D and Rabbani L 2020 Coronavirus disease 2019 (COVID-19) and cardiovascular disease *Circulation* **141** 1648–55
[20] Libby P, Ridker P M and Maseri A 2002 Inflammation and atherosclerosis *Circulation* **105** 1135–43
[21] Suri J S, Kathuria C and Molinari F 2010 *Atherosclerosis Disease Management* (New York: Springer Science & Business Media)
[22] South A M, Diz D I and Chappell M C 2020 COVID-19, ACE2, and the cardiovascular consequences *Am. J. Physiol-Heart Circ. Physiol.* **318** H1084–90
[23] Dong B, Zhang C, Feng J B, Zhao Y X, Li S Y, Yang Y P, Dong Q L, Deng B P, Zhu L and Yu Q T 2008 Overexpression of ACE2 enhances plaque stability in a rabbit model of atherosclerosis *Arter. Thromb. Vasc. Biol.* **28** 1270–6
[24] Mossa-Basha M, Meltzer C C, Kim D C, Tuite M J, Kolli K P and Tan B S 2020 Radiology department preparedness for COVID-19: radiology scientific expert panel *Radiology* **296** 200988
[25] Kotsis V, Jamthikar A D, Araki T, Gupta D, Laird J R, Giannopoulos A A, Saba L, Suri H S, Mavrogeni S and Kitas G D 2018 Echolucency-based phenotype in carotid atherosclerosis disease for risk stratification of diabetes patients *Diabetes Res. Clin. Pract.* **143** 322–31
[26] Khanna N N, Jamthikar A D, Gupta D, Araki T, Piga M, Saba L, Carcassi C, Nicolaides A, Laird J R and Suri H S 2019 Effect of carotid image-based phenotypes on cardiovascular risk calculator: AECRS1. 0 *Med. Biol. Eng. Comput.* **57** 1553–66
[27] Khanna N N, Jamthikar A D, Araki T, Gupta D, Piga M, Saba L, Carcassi C, Nicolaides A, Laird J R and Suri H S 2019 Nonlinear model for the carotid artery disease 10-year risk prediction by fusing conventional cardiovascular factors to carotid ultrasound image phenotypes: a japanese diabetes cohort study *Echocardiography* **36** 345–61
[28] Cuadrado-Godia E, Jamthikar A D, Gupta D, Khanna N N, Araki T, Maniruzzaman M, Saba L, Nicolaides A, Sharma A and Omerzu T 2019 Ranking of stroke and cardiovascular risk factors for an optimal risk calculator design: logistic regression approach *Comput. Biol. Med.* **108** 182–95
[29] Khanna N N, Jamthikar A D, Gupta D, Piga M, Saba L, Carcassi C, Giannopoulos A A, Nicolaides A, Laird J R and Suri H S 2019 Rheumatoid arthritis: atherosclerosis imaging and cardiovascular risk assessment using machine and deep learning–based tissue characterization *Curr. Atheroscler. Rep.* **21** 7
[30] Jamthikar A, Gupta D, Khanna N N, Araki T, Saba L, Nicolaides A, Sharma A, Omerzu T, Suri H S and Gupta A 2019 A special report on changing trends in preventive stroke/cardiovascular risk assessment via B-mode ultrasonography *Curr. Atheroscler Rep.* **21** 25
[31] Schnee J M and Hsueh W A 2000 Angiotensin II, adhesion, and cardiac fibrosis *Cardiovasc. Res.* **46** 264–8
[32] Wu L L, Yang N, Roe C J, Cooper M E, Gilbert R E, Atkins R C and Lan H Y 1997 Macrophage and myofibroblast proliferation in remnant kidney: role of angiotensin II *Kidney Int. Suppl.* **63** S221–5
[33] Sun Y, Ramires F J and Weber K T 1997 Fibrosis of atria and great vessels in response to angiotensin II or aldosterone infusion *Cardiovasc. Res.* **35** 138–47

[34] Morihara K, Takai S, Takenaka H, Sakaguchi M, Okamoto Y, Morihara T, Miyazaki M and Kishimoto S 2006 Cutaneous tissue angiotensin–converting enzyme may participate in pathologic scar formation in human skin *J. Am. Acad. Dermatol.* **54** 251–7

[35] Cosyns B, Lochy S, Luchian M L, Gimelli A, Pontone G, Allard S D, de Mey J, Rosseel P, Dweck M and Petersen S E 2020 The role of cardiovascular imaging for myocardial injury in hospitalized COVID-19 patients *Eur. Heart J. Cardiovasc. Imaging* **21** 709–14

[36] Inciardi R M, Lupi L, Zaccone G, Italia L, Raffo M, Tomasoni D, Cani D S, Cerini M, Farina D and Gavazzi E 2020 Cardiac involvement in a patient with coronavirus disease 2019 (COVID-19) *JAMA Cardiol* **5** 819–24

[37] Kim I-C, Kim J Y, Kim H A and Han S 2020 COVID-19-related myocarditis in a 21-year-old female patient *Eur. Heart J.* **41** 1859–9

[38] Kiamanesh O, Harper L, Wiskar K, Luksun W, McDonald M, Ross H, Woo A and Granton J 2020 Lung ultrasound for cardiologists in the time of COVID-19 *Can. J. Cardiol* **36** 1144–7

[39] Zieleskiewicz L, Duclos G, Dransart-Rayé O, Nowobilski N and Bouhemad B 2020 Ultrasound findings in patients with COVID-19 pneumonia in early and late stages: two case-reports *Anaesth. Crit. Care Pain Med* **39** 571–3

[40] Saba L, Tiwari A, Biswas M, Gupta S K, Godia-Cuadrado E, Chaturvedi A, Turk M, Suri H S, Orru S and Sanches J M 2019 Wilson's disease: a new perspective review on its genetics, diagnosis and treatment *Front. Biosci. (Elite edition)* **11** 166–85

[41] Collaborators NASCET 1991 Beneficial effect of carotid endarterectomy in symptomatic patients with high-grade carotid stenosis *New Engl. J. Med.* **325** 445–53

[42] Sanches J M, Laine A F and Suri J S 2012 *Ultrasound Imaging* (Berlin: Springer)

[43] Suri J S, Wilson D and Laxminarayan S 2005 *Handbook of Biomedical Image Analysis*vol 2 43 (New York: Springer Science & Business Media)

[44] Suri J S and Laxminarayan S 2003 *Angiography and Plaque Imaging: Advanced Segmentation Techniques* (Boca Raton, FL: CRC Press)

[45] Acharya U R, Mookiah M R K, Sree S V, Afonso D, Sanches J, Shafique S, Nicolaides A and Pedro L M 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23

[46] Acharya U R, Faust O, Sree S V, Alvin A P C, Krishnamurthi G, Sanches J and Suri J S 2011 Atheromatic™: symptomatic vs. asymptomatic classification of carotid ultrasound plaque using a combination of HOS, DWT & texture *2011 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 4489–92

[47] Acharya U R, Sree S V, Kulshreshtha S, Molinari F, Koh J E W, Saba L and Suri J S 2014 GyneScan: an improved online paradigm for screening of ovarian cancer via tissue characterization *Technol. Cancer Res. Treat.* **13** 529–39

[48] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M and Suri J S 2018 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Prog. Biomed.* **155** 165–77

[49] Acharya U R, Krishnan M M R, Sree S V, Sanches J, Shafique S, Nicolaides A, Pedro L M and Suri J S 2012 Plaque tissue characterization and classification in ultrasound carotid scans: a paradigm for vascular feature amalgamation *IEEE Trans. Instrum. Meas.* **62** 392–400

[50] Molinari F, Liboni W, Pavanelli E, Giustetto P, Badalamenti S and Suri J S 2007 Accurate and automatic carotid plaque characterization in contrast enhanced 2-D ultrasound images *2007 29th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 335–8
[51] Acharya U, Vinitha Sree S, Mookiah M, Yantri R, Molinari F, Zieleźnik W, Małyszek-Tumidajewicz J, Stępień B, Bardales R and Witkowska A 2013 Diagnosis of Hashimoto's thyroiditis in ultrasound using tissue characterization and pixel classification *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **227** 788–98
[52] Sharma A M, Gupta A, Kumar P K, Rajan J, Saba L, Nobutaka I, Laird J R, Nicolades A and Suri J S 2015 A review on carotid ultrasound atherosclerotic tissue characterization and stroke risk stratification in machine learning framework *Curr. Atheroscler. Rep.* **17** 55
[53] Ravì D, Wong C, Deligianni F, Berthelot M, Andreu-Perez J, Lo B and Yang G-Z 2016 Deep learning for health informatics *IEEE J. Biomed. Health Inform.* **21** 4–21
[54] Saba L, Biswas M, Kuppili V, Godia E C, Suri H S, Edla D R, Omerzu T, Laird J R, Khanna N N and Mavrogeni S 2019 The present and future of deep learning in radiology *Eur. J. Radiol* **114** 14–24
[55] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Cuadrado-Godia E, Laird J, Marinhoe R, Sanches J and Nicolaides A 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci. (Landmark Ed)* **24** 392–426
[56] Biswas M, Kuppili V, Araki T, Edla D R, Godia E C, Saba L, Suri H S, Omerzu T, Laird J R and Khanna N N 2018 Deep learning strategy for accurate carotid intima-media thickness measurement: an ultrasound study on Japanese diabetic cohort *Comput. Biol. Med.* **98** 100–17
[57] Jamthikar A, Gupta D, Khanna N N, Saba L, Araki T, Viskovic K, Suri H S, Gupta A, Mavrogeni S and Turk M 2019 A low-cost machine learning-based cardiovascular/stroke risk assessment system: integration of conventional factors with image phenotypes *Cardiovasc. Diagn. Ther.* **9** 420
[58] Hoffmann M, Kleine-Weber H, Schroeder S, Krüger N, Herrler T, Erichsen S, Schiergens T S, Herrler G, Wu N-H and Nitsche A 2020 SARS-CoV-2 cell entry depends on ACE2 and TMPRSS2 and is blocked by a clinically proven protease inhibitor *Cell* **181** 271–80
[59] de Wit E, van Doremalen N, Falzarano D and Munster V J 2016 SARS and MERS: recent insights into emerging coronaviruses *Nat. Rev. Microbiol.* **14** 523
[60] Wu K, Peng G, Wilken M, Geraghty R J and Li F 2012 Mechanisms of host receptor adaptation by severe acute respiratory syndrome coronavirus *J. Biol. Chem.* **287** 8904–11
[61] Patel V B, Zhong J-C, Grant M B and Oudit G Y 2016 Role of the ACE2/angiotensin 1–7 axis of the renin–angiotensin system in heart failure *Circ. Res.* **118** 1313–26
[62] Zou X, Chen K, Zou J, Han P, Hao J and Han Z 2020 Single-cell RNA-seq data analysis on the receptor ACE2 expression reveals the potential risk of different human organs vulnerable to 2019-nCoV infection *Front. Med.* **14** 185–192
[63] Hamming I, Timens W, Bulthuis M, Lely A, Navis G and van Goor H 2004 Tissue distribution of ACE2 protein, the functional receptor for SARS coronavirus. A first step in understanding SARS pathogenesis *J. Pathol.* **203** 631–7
[64] Giacomelli A, Pezzati L, Conti F, Bernacchia D, Siano M, Oreni L, Rusconi S, Gervasoni C, Ridolfo A L and Rizzardini G 2020 Self-reported olfactory and taste disorders in patients with severe acute respiratory coronavirus 2 infection: a cross-sectional study *Clin. Infect Dis.* **71** 889–90

[65] Wu A, Peng Y, Huang B, Ding X, Wang X, Niu P, Meng J, Zhu Z, Zhang Z and Wang J 2020 Genome composition and divergence of the novel coronavirus (2019-nCoV) originating in China *Cell Host Microbe* **27** 325–8
[66] Koyuncu O O, Hogue I B and Enquist L W 2013 Virus infections in the nervous system *Cell Host Microbe* **13** 379–93
[67] Desforges M, Le Coupanec A, Dubeau P, Bourgouin A, Lajoie L, Dubé M and Talbot P J 2020 Human coronaviruses and other respiratory viruses: underestimated opportunistic pathogens of the central nervous system? *Viruses* **12** 14
[68] McCray P B, Pewe L, Wohlford-Lenane C, Hickey M, Manzel L, Shi L, Netland J, Jia H P, Halabi C and Sigmund C D 2007 Lethal infection of K18-hACE2 mice infected with severe acute respiratory syndrome coronavirus *J. Virol.* **81** 813–21
[69] Li K, Wohlford-Lenane C, Perlman S, Zhao J, Jewell A K, Reznikov L R, Gibson-Corley K N, Meyerholz D K and McCray P B 2016 Middle East respiratory syndrome coronavirus causes multiple organ damage and lethal disease in mice transgenic for human dipeptidyl peptidase 4 *J. Infect. Dis.* **213** 712–22
[70] Netland J, Meyerholz D K, Moore S, Cassell M and Perlman S 2008 Severe acute respiratory syndrome coronavirus infection causes neuronal death in the absence of encephalitis in mice transgenic for human ACE2 *J. Virol.* **82** 7264–75
[71] Baig A M 2020 Neurological manifestations in COVID-19 caused by SARS-CoV-2 *CNS Neurosci. Ther.* **26** 499
[72] Ryan W 2020 There's a new symptom of coronavirus, doctors say: sudden loss of smell or taste
[73] Hopkins C and Kumar N 2020 Loss of sense of smell as marker of COVID-19 infection *ENT UK* **26** 2020 (https://www.entuk.org/sites/default/files/files/Loss_of_sense_of_smell_as_marker_of_COVID.pdf)
[74] Bohmwald K, Galvez N, Ríos M and Kalergis A M 2018 Neurologic alterations due to respiratory virus infections *Front. Cell. Neurosci.* **12** 386
[75] Zhang H and Baker A 2017 *Recombinant Human ACE2: Acing Out Angiotensin II in ARDS Therapy* (Berlin: Springer)
[76] Radermacher P, Maggiore S M and Mercat A 2017 Fifty years of research in ARDS. Gas exchange in acute respiratory distress syndrome *Am. J. Respir. Crit. Care Med.* **196** 964–84
[77] Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y and Wei Y 2020 Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study *Lancet* **395** 507–13
[78] Xiong T-Y, Redwood S, Prendergast B and Chen M 2020 Coronaviruses and the cardiovascular system: acute and long-term implications *Eur. Heart J.* **41** 1798–800
[79] Oudit G, Kassiri Z, Jiang C, Liu P, Poutanen S, Penninger J and Butany J 2009 SARS-coronavirus modulation of myocardial ACE2 expression and inflammation in patients with SARS *Eur. J. Clin. Investig.* **39** 618–25
[80] Abdennour L, Zeghal C, Deme M and Puybasset L 2012 Interaction brain-lungs *Ann. Fr. Anesth. Reanim.* e101–7
[81] Fountain J H and Lappin S L 2019 Physiology, Renin Angiotensin System *StatPearls* pp 81 (St Petersburg, FL: StatPearls Publishing)
[82] Rajendran P, Rengarajan T, Thangavel J, Nishigaki Y, Sakthisekaran D, Sethi G and Nishigaki I 2013 The vascular endothelium and human diseases *Int. J. Biol. Sci.* **9** 1057

[83] Lillie P J, Samson A, Li A, Adams K, Capstick R, Barlow G D, Easom N, Hamilton E, Moss P J and Evans A 2020 Novel coronavirus disease (Covid-19): the first two patients in the UK with person to person transmission *J. Infect.* **80** 578–606

[84] Bai Y, Yao L, Wei T, Tian F, Jin D-Y, Chen L and Wang M 2020 Presumed asymptomatic carrier transmission of COVID-19 *JAMA* **323** 1406–7

[85] Mehta P, McAuley D F, Brown M, Sanchez E, Tattersall R S and Manson J J 2020 COVID-19: consider cytokine storm syndromes and immunosuppression *Lancet* **395** 1033–4

[86] Siddiqi H K and Mehra M R 2020 COVID-19 illness in native and immunosuppressed states: a clinical-therapeutic staging proposal *J. Heart Lung Transp.* **39** 405–7

[87] Yin C, Wang C, Tang Z, Wen Y, Zhang S and Wang B 2004 Clinical analysis of multiple organ dysfunction syndrome in patients suffering from SARS *Zhongguo wei zhong bing ji jiu yi xue= Chin. Crit. Care Med.= Zhongguo weizhongbing jijiuyixue* **16** 646–50

[88] Schoenhagen P, Tuzcu E M and Ellis S G 2002 Plaque vulnerability, plaque rupture, and acute coronary syndromes: (multi)-focal manifestation of a systemic disease process *Circulation*

[89] Tisoncik J R, Korth M J, Simmons C P, Farrar J, Martin T R and Katze M G 2012 Into the eye of the cytokine storm *Microbiol. Mol. Biol. Rev.* **76** 16–32

[90] Tersalvi G, Vicenzi M, Calabretta D, Biasco L, Pedrazzini G and Winterton D 2020 Elevated troponin in patients with Coronavirus Disease 2019 (COVID-19): possible mechanisms *J. Cardiac Failure* **26** 470–75

[91] Gomes V A 2020 COVID-19 Cardiac repercussions *Rev. Bras. Fisiol. Exer.* **19**

[92] Zeng J H, Liu Y-X, Yuan J, Wang F-X, Wu W-B, Li J-X, Wang L-F, Gao H, Wang Y and Dong C-F 2020 *First Case of COVID-19 Infection with Fulminant Myocarditis Complication: Case Report and Insights*

[93] Cieszanowski A, Czekajska E, Giżycka B, Gruszczyńska K, Podgórska J, Oronowicz-Jaśkowiak A, Serafin Z, Szurowska E and Walecki J M 2020 Management of patients with COVID-19 in radiology departments, and indications regarding imaging studies–recommendations of the Polish Medical Society of Radiology *Pol. J. Radiol.* **85** e209

[94] Kim D J, Jelic T, Woo M Y, Heslop C and Olszynski P 2020 Just the facts: recommendations on point of care ultrasound use and machine infection control during the COVID-19 pandemic *Can. J. Emerg. Med.* **22** 1–7

[95] An X, Song Z, Gao Y, Tao J and Yang J 2020 To resume noninvasive imaging detection safely after peak period of COVID-19: experiences from Wuhan China *Dermatol. Ther.* **33** e13590

[96] Jakhar D, Kaur I and Kaul S 2020 Art of performing dermoscopy during the times of coronavirus disease (COVID-19): simple change in approach can save the day! *J. Eur. Acad. Dermatol. Venereol.*

[97] Skulstad H, Cosyns B, Popescu B A, Galderisi M, Salvo G D, Donal E, Petersen S, Gimelli A, Haugaa K H and Muraru D 2020 COVID-19 pandemic and cardiac imaging: EACVI recommendations on precautions, indications, prioritization, and protection for patients and healthcare personnel *Eur. Heart J.-Cardiovasc. Imaging* **21** 592–98

[98] Lo S, Yong A, Sinhal A, Shetty S, McCann A, Clark D, Galligan L, El-Jack S, Sader M and Tan R 2020 Consensus guidelines for interventional cardiology services delivery during COVID-19 pandemic in Australia and New Zealand *Heart Lung Circ* **29** 69–77

[99] El-Baz A, Jiang X and Suri J S 2016 *Biomedical Image Segmentation: Advances and Trends* (Boca Raton, FL: CRC Press)

[100] El-Baz A S, Acharya R, Mirmehdi M and Suri J S 2011 *Multi Modality State-of-the-Art Medical Image Segmentation and Registration Methodologies*vol 1 (New York: Springer Science & Business Media)

[101] Olusanya O 2020 Ultrasound in times of COVID-19 *ICU Management & Practice* **20** 43–50

[102] Smith M, Hayward S, Innes S and Miller A 2020 Point-of-care lung ultrasound in patients with COVID-19: a narrative review *Anaesthesia* **75** 1096–104

[103] Jacobi A, Chung M, Bernheim A and Eber C 2020 Portable chest X-ray in coronavirus disease-19 (COVID-19): a pictorial review *Clin. Imaging* **64** 35–42

[104] Chung M, Bernheim A, Mei X, Zhang N, Huang M, Zeng X, Cui J, Xu W, Yang Y and Fayad Z A 2020 CT imaging features of 2019 novel coronavirus (2019-nCoV) *Radiology* **295** 202–7

[105] Vasilev Y, Sergunova K, Bazhin A, Masri A, Vasileva Y, Suleumanov E, Semenov D, Kudryavtsev N, Panina O and Khoruzhaya A 2020 MRI of the lungs in patients with COVID-19: clinical case *JMRI* **79** 13–9

[106] Huang L, Zhao P, Tang D, Zhu T, Han R, Zhan C, Liu W, Zeng H, Tao Q and Xia L 2020 Cardiac involvement in recovered COVID-19 patients identified by magnetic resonance imaging *JACC: Cardiovasc. Imaging* **13** 2330–9

[107] Luetkens J A, Isaak A, Zimmer S, Nattermann J, Sprinkart A M, Boesecke C, Rieke G J, Zachoval C, Heine A and Velten M 2020 Diffuse myocardial inflammation in covid-19 associated myocarditis detected by multiparametric cardiac magnetic resonance imaging *Circ.: Cardiovasc. Imaging* **13** e010897

[108] Poyiadji N, Shahin G, Noujaim D, Stone M, Patel S and Griffith B 2020 COVID-19–associated acute hemorrhagic necrotizing encephalopathy: CT and MRI features *Radiology* **296** 201187

[109] Kandemirli S G, Dogan L, Sarikaya Z T, Kara S, Akinci C, Kaya D, Kaya Y, Yildirim D, Tuzuner F and Yildirim M S 2020 Brain MRI findings in patients in the intensive care unit with COVID-19 infection *Radiology* **297** 201697

[110] Bhayana R, Som A, Li M D, Carey D E, Anderson M A, Blake M A, Catalano O, Gee M S, Hahn P F and Harisinghani M 2020 Abdominal imaging findings in COVID-19: preliminary observations *Radiology* **297** 201908

[111] Eliezer M and Hautefort C 2020 MRI evaluation of the olfactory clefts in patients with SARS-CoV-2 infection revealed an unexpected mechanism for olfactory function loss *Acad. Radiol.* **27** 1191

[112] Xiao Z, Xu C, Wang D and Zeng H 2020 The experience of treating patients with acute myocardial infarction under the COVID-19 epidemic *Catheter. Cardiovasc. Interv.* **97** E244–8

[113] Meyer P, Degrauwe S, Van Delden C, Ghadri J-R and Templin C 2020 Typical takotsubo syndrome triggered by SARS-CoV-2 infection *Eur. Heart J.* **41** 1860–0

[114] Danzi G B, Loffi M, Galeazzi G and Gherbesi E 2020 Acute pulmonary embolism and COVID-19 pneumonia: a random association? *Eur. Heart J.* **41** 1858–8

[115] Zhang L, Feng X, Zhang D, Jiang C, Mei H, Wang J, Zhang C, Li H, Xia X and Kong S 2020 Deep vein thrombosis in hospitalized patients with coronavirus disease 2019 (COVID-19) in Wuhan, China: prevalence, risk factors, and outcome *Circulation* **142** 114–28

[116] Emanuel E J, Persad G, Upshur R, Thome B, Parker M, Glickman A, Zhang C, Boyle C, Smith M and Phillips J P 2020 Fair Allocation of Scarce Medical Resources in the Time of Covid-19 *N Engl. J. Med.* **382** 2049–55
[117] Rosenbaum L 2020 Facing Covid-19 in Italy—ethics, logistics, and therapeutics on the epidemic's front line *New Engl. J. Med.* **382** 1873–5
[118] Bhatt A S *et al* 2020 Declines in hospitalizations for acute cardiovascular conditions during the COVID-19 pandemic: a multicenter tertiary care experience *J. Am. Coll. Cardiol.* **76** 280–8
[119] Vaishya R, Haleem A, Vaish A and Javaid M 2020 Emerging technologies to combat COVID-19 pandemic *J. Clin. Exp. Hepatol* **10** 409–11
[120] Murphy K, Smits H, Knoops A J, Korst M B, Samson T, Scholten E T, Schalekamp S, Schaefer-Prokop C M, Philipsen R H and Meijers A 2020 COVID-19 on the chest radiograph: a multi-reader evaluation of an AI system *Radiology* **296** 201874
[121] Zheng N, Du S, Wang J, Zhang H, Cui W, Kang Z, Yang T, Lou B, Chi Y and Long H 2020 Predicting COVID-19 in China using hybrid AI model *IEEE Trans. Cybern* **50** 2891–904
[122] Chieffo A, Stefanini G G, Price S, Barbato E, Tarantini G, Karam N, Moreno R, Buchanan G L, Gilard M and Halvorsen S 2020 EAPCI position statement on invasive management of acute coronary syndromes during the COVID-19 pandemic *Eur. Heart J.* **41** 1839–51
[123] Salehi S, Abedi A, Balakrishnan S and Gholamrezanezhad A 2020 Coronavirus disease 2019 (COVID-19): a systematic review of imaging findings in 919 patients *Am. J. Roentgenol.* **215** 1–7
[124] Dangis A, Gieraerts C, Bruecker Y D, Janssen L, Valgaeren H, Obbels D, Gillis M, Ranst M V, Frans J and Demeyere A 2020 Accuracy and reproducibility of low-dose submillisievert chest CT for the diagnosis of COVID-19 *Radiol.: Cardiothorac. Imaging* **2** e200196
[125] Rubin G D, Ryerson C J, Haramati L B, Sverzellati N, Kanne J P, Raoof S, Schluger N W, Volpi A, Yim J-J and Martin I B 2020 The role of chest imaging in patient management during the COVID-19 pandemic: a multinational consensus statement from the Fleischner Society *Chest* **158** 106–16
[126] Nair A *et al* 2020 Society of Thoracic Imaging statement: considerations in designing local imaging diagnostic algorithms for the COVID-19 pandemic *Clin. Radiol.* **75** 329–34
[127] Laghi A 2020 Cautions about radiologic diagnosis of COVID-19 infection driven by artificial intelligence *Lancet Digit. Health* **2** e225
[128] Miotto R, Wang F, Wang S, Jiang X and Dudley J T 2018 Deep learning for healthcare: review, opportunities and challenges *Brief. Bioinform.* **19** 1236–46
[129] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S and Dean J 2019 A guide to deep learning in healthcare *Nat. Med.* **25** 24–9
[130] Hosny A, Parmar C, Quackenbush J, Schwartz L H and Aerts H J 2018 Artificial intelligence in radiology *Nat. Rev. Cancer* **18** 500–10
[131] Sinha JSS G R 2019 *Cognitive Informatics, Computer Modelling, and Cognitive Science: Volume 1: Theory, Case Studies, and Applications* (Netherlands: Elsevier)
[132] Tang X 2019 The role of artificial intelligence in medical imaging research *BJR| Open* **2** 20190031
[133] Saeian K, Rhyne T L and Sagar K B 1994 Ultrasonic tissue characterization for diagnosis of acute myocardial infarction in the coronary care unit *Am. J. Cardiol.* **74** 1211–5

[134] Mavrogeni S, Sfikakis P P, Gialafos E, Bratis K, Karabela G, Stavropoulos E, Spiliotis G, Sfendouraki E, Panopoulos S and Bournia V 2014 Cardiac tissue characterization and the diagnostic value of cardiovascular magnetic resonance in systemic connective tissue diseases *Arthritis Care Res.* **66** 104–12
[135] Wu J, Pan J, Teng D, Xu X, Feng J and Chen Y-C 2020 Interpretation of CT signs of 2019 novel coronavirus (COVID-19) pneumonia *Eur. Radiol.* **30** 5455–62
[136] Alimadadi A, Aryal S, Manandhar I, Munroe P B, Joe B and Cheng X 2020 Artificial Intelligence and Machine Learning to Fight COVID-19 *Physiological Genomics* **52** 200–2
[137] Vaishya R, Javaid M, Khan I H and Haleem A 2020 Artificial intelligence (AI) applications for COVID-19 pandemic *Diabetes Metab. Syndr.: Clin. Res. Rev.* **14** 337–9
[138] Jamthikar A, Gupta D, Saba L, Khanna N N, Araki T, Viskovic K, Mavrogeni S, Laird J R, Pareek G and Miner M *et al* 2020 Cardiovascular/stroke risk predictive calculators: a comparison between statistical and machine learning models *Cardiovasc. Diagn. Ther* **10** 919–38
[139] Jamthikar A, Gupta D, Khanna N N, Saba L, Laird J R and Suri J S 2020 Cardiovascular/stroke risk prevention: a new machine learning framework integrating carotid ultrasound image-based phenotypes and its harmonics with conventional risk factors *Indian Heart J.* **72** 258–64
[140] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M and Suri J S 2017 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Prog. Biomed* **155** 165–77
[141] Bishop C M 2006 *Pattern Recognition and Machine Learning* (New York: Springer)
[142] LeCun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436–44
[143] Suri J S, Acharya U R, Faust O, Alvin A P C, Sree S V, Molinari F, Saba L and Nicolaides A 2011 Symptomatic vs. asymptomatic plaque classification in carotid ultrasound *J. Med. Syst.* **36** 1861–71
[144] Cortes C and Vapnik V 1995 Support-vector networks *Mach. Learn.* **20** 273–97
[145] Mirmehdi M 2008 *Handbook of Texture Analysis* (Singapore: Imperial College Press)
[146] Bharati M H, Liu J J and MacGregor J F 2004 Image texture analysis: methods and comparisons *Chemometr. Intell. Lab. Syst.* **72** 57–71
[147] Acharya U R, Chua C K, Lim T-C, Dorithy T and Suri J S 2009 Automatic identification of epileptic EEG signals using nonlinear parameters *J. Mech. Med. Biol.* **9** 539–53
[148] Acharya U R, Faust O, Sree S V, Molinari F and Suri J S 2012 ThyroScreen system: high resolution ultrasound thyroid image characterization into benign and malignant classes using novel combination of texture and discrete wavelet transform *Comput. Methods Programs Biomed.* **107** 233–41
[149] Reynolds D A 2009 Gaussian mixture models *Encyclopedia of Biometrics* (Berlin: Springer) 741
[150] Huang D-S 1999 Radial basis probabilistic neural networks: model and application *Int. J. Pattern Recognit Artif Intell.* **13** 1083–101
[151] Quinlan J R 1987 Generating production rules from decision trees *IJCAI* **87** 304–7
[152] Clark P J and Evans F C 1954 Distance to nearest neighbor as a measure of spatial relationships in populations *Ecology* **35** 445–53
[153] Rish I 2001 An empirical study of the naive Bayes classifier *IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence* pp 41–6

[154] Ross T J 2009 *Fuzzy Logic with Engineering Applications* (University of New Mexico: Wiley)
[155] Kadyrov A and Petrou M 2001 The trace transform and its applications *IEEE Trans. Pattern Anal. Mach. Intell.* **23** 811–28
[156] Jawahar C and Ray A 1996 Incorporation of gray-level imprecision in representation and processing of digital images *Pattern Recognit. Lett.* **17** 541–6
[157] Galloway M M 1974 Texture analysis using grey level run lengths *STIN* **75** 18555
[158] Boi A, Jamthikar A D, Saba L, Gupta D, Sharma A, Loi B, Laird J R, Khanna N N and Suri J S 2018 A survey on coronary atherosclerotic plaque tissue characterization in intravascular optical coherence tomography *Curr. Atheroscler. Rep.* **20** 33
[159] Jamthikar A, Gupta D, Khanna N N, Saba L, Araki T, Viskovic K, Suri H S, Gupta A, Mavrogeni S and Turk M *et al* 2019 A low-cost machine learning-based cardiovascular/ stroke risk assessment system: integration of conventional factors with image phenotypes *Cardiovasc. Diagn. Ther.* **9** 420
[160] Jamthikar A, Gupta D, Khanna N N, Araki T, Saba L, Nicolaides A, Sharma A, Omerzu T, Suri H S and Gupta A *et al* 2019 A special report on changing trends in preventive stroke/cardiovascular risk assessment via B-Mode ultrasonography *Curr. Atheroscler. Rep.* 21 25
[161] Viswanathan V *et al* 2020 Does the carotid bulb offer a better 10-Year CVD/stroke risk assessment compared to the common carotid artery? A 1516 ultrasound scan study *Angiology* **71** 3319720941730
[162] Long J, Shelhamer E and Darrell T 2015 Fully convolutional networks for semantic segmentation *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition* pp 3431–40
[163] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Sharma A, Cuadrado-Godia E, Laird J R, Nicolaides A and Suri J S 2019 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 543–64
[164] Saba L, Biswas M, Suri H S, Viskovic K, Laird J R, Cuadrado-Godia E, Nicolaides A, Khanna N, Viswanathan V and Suri J S 2019 Ultrasound-based carotid stenosis measurement and risk stratification in diabetic cohort: a deep learning paradigm *Cardiovasc. Diagn. Ther.* **9** 439
[165] Dong D, Tang Z, Wang S, Hui H, Gong L, Lu Y, Xue Z, Liao H, Chen F and Yang F 2020 The role of imaging in the detection and management of COVID-19: a review *IEEE Rev. Biomed. Eng*
[166] Ito R I S and Naganawa S 2020 A review on the use of artificial intelligence for medical imaging of the lungs of patients with coronavirus disease 2019 *Diagn. Interv. Radiol*
[167] Lu W, Zhang S, Chen B, Chen J, Xian J, Lin Y, Shan H and Su Z Z 2020 A clinical study of noninvasive assessment of lung lesions in patients with coronavirus disease-19 (COVID-19) by bedside ultrasound *Ultraschall in der Medizin-Eur. J. Ultrasound* **41** 300–7
[168] Kang H, Xia L, Yan F, Wan Z, Shi F, Yuan H, Jiang H, Wu D, Sui H and Zhang C 2020 Diagnosis of coronavirus disease 2019 (covid-19) with structured latent multi-view representation learning *IEEE Trans. Med. Imaging* **39** 2606–14
[169] Xinggang Wang X D, Fu Q, Zhou Q, Zhou Q, Feng J, Ma H, Liu W and Zheng C 2020 A weakly-supervised framework for COVID-19 classification and lesion localization from chest CT *IEEE Trans. Med. Imaging* **39** 2615–25

[170] Krizhevsky A, Sutskever I and Hinton G E 2012 *Imagenet classification with deep convolutional neural networks Advances in Neural Information Processing Systems 25 (NIPS 2012)* F. Pereira *et al* (Cambridge, MA: MIT Press) 1097–105
[171] Szegedy C, Vanhoucke V, Ioffe S, Shlens J and Wojna Z 2016 Rethinking the inception architecture for computer vision *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition* pp 2818–26
[172] Wang K, Lu X, Zhou H, Gao Y, Zheng J, Tong M, Wu C, Liu C and Huang L 2019 Deep learning Radiomics of shear wave elastography significantly improved diagnostic performance for assessing liver fibrosis in chronic hepatitis B: a prospective multicentre study *Gut* **68** 729–41
[173] Wang S *et al* 2020 A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis *Eur. Respir. J.* **56** 2000775
[174] Zhang K *et al* 2020 Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis *Cell* **182** 1360
[175] Li Z *et al* 2020 from community acquired pneumonia to COVID-19: a deep learning based method for quantitative analysis of COVID-19 on thick-section CT scans *Medrxiv* 2020
[176] Chen J *et al* 2020 Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study *Sci. Rep.* **10** 19196
[177] Angel C T (http://121.40.75.149/znyx-ncov/index#/app/index) (accessed 24 July 2020)
[178] Yang S, Jiang L, Cao Z, Wang L, Cao J, Feng R, Zhang Z, Xue X, Shi Y and Shan F 2020 Deep learning for detecting corona virus disease 2019 (COVID-19) on high-resolution computed tomography: a pilot study *Ann. Transl. Med.* **8**
[179] Oh Y, Park S and Ye J C 2020 Deep learning Covid-19 features on CXR using limited training data sets *IEEE Trans. Med. Imaging* **39** 2688–700
[180] Ren Z H, Mu W C and Huang S Y 2018 Design and optimization of a ring-pair permanent magnet array for head imaging in a low-field portable MRI system *IEEE Trans. Magn.* **55** 1–8
[181] Cooley C Z, Stockmann J P, Armstrong B D, Sarracanie M, Lev M H, Rosen M S and Wald L L 2015 Two-dimensional imaging in a lightweight portable MRI scanner without gradient coils *Magn. Reson. Med.* **73** 872–83
[182] Mirvis S E 1999 Use of portable CT in the R Adams Cowley Shock Trauma Center: experiences in the admitting area, ICU, and operating room *Surg. Clin. North Am.* **79** 1317–30
[183] Wang X and Bhatt D L 2020 COVID-19: an unintended force for medical revolution *J. Invasive Cardiol.* **32** E81–2
[184] Thamman R, Gulati M, Narang A, Utengen A, Mamas M A and Bhatt D L 2020 Twitter-based learning for continuing medical education? *Eur. Heart J.*
[185] Li L, Zhang Q, Wang X, Zhang J, Wang T, Gao T-L, Duan W, Tsoi K K-F and Wang F-Y 2020 Characterizing the propagation of situational information in social media during COVID-19 epidemic: a case study on weibo *IEEE Trans. Comput. Soc. Syst.* **7** 556–62
[186] El-Baz A and Suri J S (ed) 2019 *Big Data in Multimodal Medical Imaging* (Boca Raton, FL: CRC Press)
[187] Kooraki S, Hosseiny M, Myers L and Gholamrezanezhad A 2020 Coronavirus (COVID-19) outbreak: what the department of radiology should know *J. Am. Coll. Radiol* **17** 447–51

[188] Mossa-Basha M, Medverd J, Linnau K, Lynch J B, Wener M H, Kicska G, Staiger T and Sahani D 2020 Policies and guidelines for COVID-19 preparedness: experiences from the University of Washington *Radiology* **296** 201326
[189] Buonsenso D, Piano A, Raffaelli F, Bonadia N, Donati K D G and Franceschi F 2020 novel coronavirus disease-19 pnemoniae: a case report and potential applications during COVID-19 outbreak *Eur. Rev. Med. Pharmacol. Sci.* **24** 2776–80
[190] Suri J S *et al* 2020 COVID-19 pathways for brain and heart injury in comorbidity patients: A role of medical imaging and artificial intelligence-based COVID severity classification: A review *Comput. Biol. Med.* **124** 103960

Chapter 2

[1] Shereen M A, Khan S, Kazmi A, Bashir N and Siddique R 2020 COVID-19 infection: origin, transmission, and characteristics of human coronaviruses *J. Adv. Res.* **24** 91–8
[2] Guo Y-R, Cao Q-D, Hong Z-S, Tan Y-Y, Chen S-D, Jin H-J, Tan K-S, Wang D-Y and Yan Y 2020 The origin, transmission and clinical therapies on coronavirus disease 2019 (COVID-19) outbreak - an update on the status *Mil Med Res.* **7** 11–1
[3] Horton R J L 2020 Offline: COVID-19 is not a pandemic *Lancet* **396** 874
[4] Cucinotta D and Vanelli M 2020 WHO declares COVID-19 a pandemic *Acta Biomed* **91** 157–60
[5] https://worldometers.info/coronavirus/
[6] D'Arienzo M and Coniglio A 2020 Assessment of the SARS-CoV-2 basic reproduction number, R (0), based on the early phase of COVID-19 outbreak in Italy *Biosaf Health* **2** 57–9
[7] Ravalli S and Musumeci G 2020 *Coronavirus Outbreak in Italy: Physiological Benefits of Home-Based Exercise During Pandemic* (Multidisciplinary Digital Publishing Institute)
[8] Wilder-Smith A, Chiew C J and Lee V J 2020 Can we contain the COVID-19 outbreak with the same measures as for SARS? *Lancet Infect Dis* **20** e102–7
[9] Maugeri G, Castrogiovanni P, Battaglia G, Pippi R, D'Agata V, Palma A, Di Rosa M and Musumeci G J H 2020 The impact of physical activity on psychological health during Covid-19 pandemic in Italy **6** e04315
[10] Lesser I A, Nienhuis C P J I J O E R and Health P 2020 The impact of COVID-19 on physical activity behavior and well-being of Canadians *Int. J. Environ. Res. Public Health* **17** 3899
[11] Viswanathan V, Puvvula A and Jamthikar A D A pathophysiological bidirectional association between diabetes mellitus and COVID-19 leading to heart and brain injury: a mini-review
[12] Saba L, Gerosa C, Wintermark M, Hedin U, Fanni D, Suri J S, Balestrieri A and Faa G 2020 Can COVID19 trigger the plaque vulnerability—a Kounis syndrome warning for 'asymptomatic subjects' *Cardiovasc. Diagn. Ther.* **10** 1352–5
[13] Pubmed COVID-19 publicatons
[14] Skandha S S *et al* 2020 3-D optimized classification and characterization artificial intelligence paradigm for cardiovascular/stroke risk stratification using carotid ultrasound-based delineated plaque: Atheromatic™ 2.0 *Comput. Biol. Med.* **125** 103958
[15] https://ourworldindata.org/grapher/total-confirmed-cases-of-covid-19-per-million-people
[16] Saba L *et al* 2019 The present and future of deep learning in radiology *Eur. J. Radiol.* **114** 14–24

[17] Biswas M *et al* 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci.* **24** 392–426
[18] Suri J S *et al* 2020 COVID-19 pathways for brain and heart injury in comorbidity patients: a role of medical imaging and artificial intelligence-based COVID severity classification: a review *Comput. Biol. Med.* **124** 103960
[19] Gatto M, Bertuzzo E, Mari L, Miccoli S, Carraro L, Casagrandi R and Rinaldo A 2020 Spread and dynamics of the COVID-19 epidemic in Italy: effects of emergency containment measures *Proc. Natl Acad. Sci. U S A.* **117** 10484–91
[20] Rekha Hanumanthu S J C 2020 Solitons, fractals, role of intelligent computing in COVID-19 prognosis: a state-of-the-art review *Chaos Solit. Fractals.* **138** 109947
[21] Deng Y, Lei L, Chen Y and Zhang W 2020 The potential added value of FDG PET/CT for COVID-19 pneumonia *Eur. J. Nucl. Med. Mol. Imaging* **47** 1634–5
[22] Liu C, Zhou J, Xia L, Cheng X and Lu D 2020 18F-FDG PET/CT and serial chest CT findings in a COVID-19 patient With dynamic clinical characteristics in different period *Clin. Nucl. Med.* **45** 495–6
[23] Maurea S, Mainolfi C G, Bombace C, Annunziata A, Attanasio L, Petretta M, Del Vecchio S and Cuocolo A 2020 FDG-PET/CT imaging during the Covid-19 emergency: a southern Italian perspective *Eur. J. Nucl. Med. Mol. Imaging* **47** 2691–7
[24] Verdecchia P, Cavallini C, Spanevello A and Angeli F 2020 The pivotal link between ACE2 deficiency and SARS-CoV-2 infection *Eur. J. Intern. Med.* **76** 14–20
[25] Mossel E C *et al* 2008 SARS-CoV replicates in primary human alveolar type II cell cultures but not in type I-like cells *Virology* **372** 127–35
[26] Saba L *et al* 2020 Molecular pathways triggered by COVID19 in different organs: ACE2 receptor-expressing cells under attack? A review *Eur Rev Med Pharmacol Sci.* **24** 12609–22
[27] Zhou P *et al* 2020 A pneumonia outbreak associated with a new coronavirus of probable bat origin *Nature* **579** 270–3
[28] Qian Z, Travanty E A, Oko L, Edeen K, Berglund A, Wang J, Ito Y, Holmes K V and Mason R J 2013 Innate immune response of human alveolar type II cells infected with severe acute respiratory syndrome-coronavirus *Am. J. Respir. Cell Mol. Biol.* **48** 742–8
[29] Ding Y *et al* 2003 The clinical pathology of severe acute respiratory syndrome (SARS): a report from China *J. Pathol.* **200** 282–9
[30] Liu J, Zheng X, Tong Q, Li W, Wang B, Sutter K, Trilling M, Lu M, Dittmer U and Yang D 2020 Overlapping and discrete aspects of the pathology and pathogenesis of the emerging human pathogenic coronaviruses SARS-CoV, MERS-CoV, and 2019-nCoV *J. Med. Virol* **92** 491–4
[31] Wang S, Le T Q, Kurihara N, Chida J, Cisse Y, Yano M and Kido H 2010 Influenza virus-cytokine-protease cycle in the pathogenesis of vascular hyperpermeability in severe influenza *J. Infect. Dis.* **202** 991–1001
[32] Huang C *et al* 2020 Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China *Lancet* **395** 497–506
[33] Matthay M A, Ware L B and Zimmerman G A 2012 The acute respiratory distress syndrome *J. Clin. Invest.* **122** 2731–40
[34] Katzenstein A L, Bloor C M and Leibow A A 1976 Diffuse alveolar damage–the role of oxygen, shock, and related factors. A review *Am. J. Pathol.* **85** 209–28
[35] Nuckton T J, Alonso J A, Kallet R H, Daniel B M, Pittet J-F, Eisner M D and Matthay M A 2002 Pulmonary dead-space fraction as a risk factor for death in the acute respiratory distress syndrome *New Engl. J. Med.* **346** 1281–6

[36] Wu C *et al* 2020 Risk factors associated with acute respiratory distress syndrome and death in patients with coronavirus disease 2019 pneumonia in Wuhan, China *JAMA Intern. Med.* **180** 934–43

[37] Lian J *et al* 2020 Analysis of epidemiological and clinical features in older patients with coronavirus disease 2019 (COVID-19) outside Wuhan *Clin. Infect. Dis* **71** 740–7

[38] Liu Y, Sun W, Li J, Chen L, Wang Y, Zhang L and Yu L 2020 *Clinical Features And Progression of Acute Respiratory Distress Syndrome in Coronavirus Disease 2019* (Cold Spring Harbor Laboratory)

[39] Khan A, Chatterjee A and Singh S 2020 *Comorbidities and Disparities in Outcomes of COVID-19 Among African American and White Patients* (Cold Spring Harbor Laboratory)

[40] Zhang P *et al* 2020 Association of inpatient use of angiotensin-converting enzyme inhibitors and angiotensin II receptor blockers with mortality among patients with hypertension hospitalized with COVID-19 *Circ. Res.* **126** 1671–81

[41] Maniruzzaman M, Kumar N, Menhazul Abedin M, Shaykhul Islam M, Suri H S, El-Baz A S and Suri J S 2017 Comparative approaches for classification of diabetes mellitus data: machine learning paradigm *Comput. Methods Programs Biomed.* **152** 23–34

[42] Dreher M *et al* 2020 The characteristics of 50 hospitalized COVID-19 patients with and without ARDS *Dtsch. Arztebl Int* **117** 271–8

[43] Palaiodimos L, Kokkinidis D G, Li W, Karamanis D, Ognibene J, Arora S, Southern W N and Mantzoros C S 2020 Severe obesity, increasing age and male sex are independently associated with worse in-hospital outcomes, and higher in-hospital mortality, in a cohort of patients with COVID-19 in the Bronx, New York *Metabolism* **108** 154262–2

[44] Yu T, Cai S, Zheng Z, Cai X, Liu Y, Yin S, Peng J and Xu X 2020 Association between clinical manifestations and prognosis in patients with COVID-19 *Clin Ther* **42** 964–72

[45] Bandyopadhyay D *et al* 2020 COVID-19 Pandemic: cardiovascular complications and future implications *Am. J. Cardiovasc. Drugs : Drugs, Devices, and Other Interventions* **20** 311–24

[46] Doyen D, Moceri P, Ducreux D and Dellamonica J 2020 Myocarditis in a patient with COVID-19: a cause of raised troponin and ECG changes *Lancet* **395** 1516

[47] Madjid M, Safavi-Naeini P, Solomon S D and Vardeny O 2020 Potential effects of coronaviruses on the cardiovascular system: a review *JAMA Cardiol* **5** 831–40

[48] Suleyman G *et al* 2020 Clinical characteristics and morbidity associated with coronavirus disease 2019 in a series of patients in metropolitan detroit *JAMA Netw. Open* **3** e2012270

[49] Meyerowitz E A *et al* 2020 Disproportionate burden of coronavirus disease 2019 among racial minorities and those in congregate settings among a large cohort of people with *HIV, AIDS* **34** 1781–7

[50] Chandran M, Chan Maung A, Mithal A and Parameswaran R 2020 Vitamin D in COVID - 19: dousing the fire or averting the storm?—A perspective from the Asia-Pacific *Osteoporosis and Sarcopenia* **6** 97–105

[51] Chang T S *et al* 2020 Prior diagnoses and medications as risk factors for COVID-19 in a Los Angeles health system *Medrxiv*

[52] Sanyaolu A, Okorie C, Marinkovic A, Patidar R, Younis K, Desai P, Hosein Z, Padda I, Mangat J and Altaf M 2020 Comorbidity and its impact on patients with COVID-19 *SN. Compr. Clin. Med.* **2** 1069–76

[53] Takemoto M *et al* 2020 C. Brazilian group for studies of, pregnancy, clinical characteristics and risk factors for mortality in obstetric patients with severe COVID-19 in Brazil: a surveillance database analysis *BJOG* **127** 1618–26

[54] Gudipati S, Brar I, Murray S, McKinnon J E, Yared N and Markowitz N J J O A I D S 2020 Descriptive analysis of patients living with HIV affected by COVID-19 *JAIDS* **85** 123–6
[55] Bornstein S R *et al* 2020 Practical recommendations for the management of diabetes in patients with COVID-19 *Lancet Diabetes Endocrinol.* **8** 546–50
[56] Guzik T J *et al* 2020 COVID-19 and the cardiovascular system: implications for risk assessment, diagnosis, and treatment options *Cardiovasc Res.* **116** 1666–87
[57] Bassendine M F, Bridge S H, McCaughan G W and Gorrell M D 2020 COVID-19 and comorbidities: a role for dipeptidyl peptidase 4 (DPP4) in disease severity? *J. Diabetes* **12** 649–58
[58] Bode B, Garrett V, Messler J, McFarland R, Crowe J, Booth R and Klonoff D C 2020 Glycemic characteristics and clinical outcomes of COVID-19 patients hospitalized in the United States *J. Diabetes Sci. Technol.* **14** 813–21
[59] Akram J, Azhar S, Shahzad M, Latif W and Khan K S 2020 Pakistan randomized and observational trial to evaluate coronavirus treatment (PROTECT) of hydroxychloroquine, oseltamivir and azithromycin to treat newly diagnosed patients with COVID-19 infection who have no comorbidities like diabetes mellitus: a structured summary of a study protocol for a randomized controlled trial *Trials* **21** 702
[60] Yang Q *et al* 2020 Analysis of the clinical characteristics, drug treatments and prognoses of 136 patients with coronavirus disease 2019 *J. Clin. Pharm. Ther.* **45** 609–16
[61] Halaji M, Farahani A, Ranjbar R, Heiat M and Dehkordi F J L I I M 2020 Emerging coronaviruses: first SARS, second MERS and third SARS-CoV-2: epidemiological updates of COVID-19 *Infez. Med.* **28** 6–17
[62] Grimaldi D *et al* 2020 Characteristics and outcomes of acute respiratory distress syndrome related to COVID-19 in Belgian and French intensive care units according to antiviral strategies: the COVADIS multicentre observational study *Ann. Intensive Care.* **10** 131
[63] Zaim S, Chong J H, Sankaranarayanan V and Harky A 2020 COVID-19 and multiorgan response *Curr. Probl. Cardiol.* **45** 100618
[64] Ponziani F R, Del Zompo F, Nesci A, Santopaolo F, Ianiro G, Pompili M and Gasbarrini A'Gemelli against COVID-19' group 2020 Liver involvement is not associated with mortality: results from a large cohort of SARS-CoV-2 positive patients *Aliment Pharmacol Ther* **52** 1060–8
[65] Brandt J S, Hill J, Reddy A, Schuster M, Patrick H S, Rosen T, Sauer M V, Boyle C and Ananth C V 2020 Epidemiology of coronavirus disease 2019 in pregnancy: risk factors and associations with adverse maternal and neonatal outcomes *Am. J. Obstet. Gynecol.* **224** 389. E1–9
[66] Cheng L L *et al* 2020 Effect of recombinant human granulocyte colony-stimulating factor for patients with coronavirus disease 2019 (COVID-19) and lymphopenia: a randomized clinical trial *JAMA Intern. Med.* **181** 71–8
[67] Cummings M J *et al* 2020 Epidemiology, clinical course, and outcomes of critically ill adults with COVID-19 in New York City: a prospective cohort study *Lancet* **395** 1763–70
[68] Nakeshbandi M *et al* 2020 The impact of obesity on COVID-19 complications: a retrospective cohort study *Int. J. Obes. (Lond)* **44** 1832–7
[69] Zhao J, Li X, Gao Y and Huang W J I J O M S 2020 Risk factors for the exacerbation of patients with 2019 Novel Coronavirus: a meta-analysis *Int. J. Med. Sci.* **17** 1744

[70] Chen T *et al* 2020 Clinical characteristics of 113 deceased patients with coronavirus disease 2019: retrospective study *Brit. Med. J.* **368** m1091
[71] Qin C, Zhou L, Hu Z, Yang S, Zhang S, Chen M, Yu H, Tian D S and Wang W 2020 Clinical characteristics and outcomes of COVID-19 patients with a history of stroke in Wuhan, China *Stroke* **51** 2219–23
[72] Shi S *et al* 2020 Association of cardiac injury with mortality in hospitalized patients with COVID-19 in Wuhan, China *JAMA Cardiol* **5** 802–10
[73] Deng Y *et al* 2020 Clinical characteristics of fatal and recovered cases of coronavirus disease 2019 in Wuhan, China: a retrospective study *Chin. Med. J. (Engl)* **133** 1261–7
[74] Yang F, Shi S, Zhu J, Shi J, Dai K and Chen X 2020 Clinical characteristics and outcomes of cancer patients with COVID-19 *J. Med. Virol* **92** 2067–73
[75] Del Sole F, Farcomeni A, Loffredo L, Carnevale R, Menichelli D, Vicario T, Pignatelli P and Pastori D 2020 Features of severe COVID-19: a systematic review and meta-analysis *Eur. J. Clin. Invest.* **50** e13378–8
[76] Ciceri F *et al* 2020 Early predictors of clinical outcomes of COVID-19 outbreak in Milan, Italy *Clin. Immunol.* **217** 108509
[77] Kutluhan M A, Taş A, Şahin A, Ürkmez A, Topaktas R, Ataç Ö and Verit A J I J O C P 2020 Assessment of clinical features and renal functions in Coronavirus disease-19: a retrospective analysis of 96 patients *Int. J. Clin. Pract.* **74** e13636
[78] Derespina K R, Kaushik S, Plichta A, Conway E E, Bercow A, Choi J, Eisenberg R, Gillen J, Sen A I and Hennigan C M J T J O P 2020 Clinical manifestations and outcomes of critically ill children and adolescents with coronavirus disease 2019 in New York City *J. Pediatr.* **226** 55–63
[79] Blumfield E and Levin T L J P R 2020 COVID-19 in pediatric patients: a case series from the Bronx, NY *Pediatr. Radiol.* **50** 1369–74
[80] Jazieh A-R, Alenazi T H, Alhejazi A, Al Safi F and Al Olayan A J J G O 2020 Outcome of oncology patients infected with coronavirus *LCO Glob. Oncol.* **6** 471–5
[81] Al-Wahaibi K, Al-Wahshi Y and Mohamed O 2020 Elfadil, myocardial injury is associated with higher morbidity and mortality in patients with 2019 Novel Coronavirus Disease (COVID-19) *SN. Compr. Clin. Med.* **2** 1–7
[82] Chand S, Kapoor S, Orsi D, Fazzari M J, Tanner T G, Umeh G C, Islam M and Dicpinigaitis P V 2020 COVID-19-associated critical illness-report of the first 300 patients admitted to intensive care units at a New York City medical center *J. Intensive Care Med.* **35** 963–70
[83] Lee Y R *et al* 2020 Clinical outcomes of coronavirus disease 2019 in patients with pre-existing liver diseases: a multicenter study in South Korea *Clin. Mol. Hepatol.* **26** 562–76
[84] Wang L, He W, Yu X, Hu D, Bao M, Liu H, Zhou J and Jiang H 2020 Coronavirus disease 2019 in elderly patients: characteristics and prognostic factors based on 4-week follow-up *J. Infect.* **80** 639–45
[85] Du Y *et al* 2020 Clinical features of 85 fatal cases of COVID-19 from Wuhan. A retrospective observational study *Am. J. Respir. Crit. Care Med.* **201** 1372–9
[86] Ziehr D R, Alladina J, Petri C R, Maley J H, Moskowitz A, Medoff B D, Hibbert K A, Thompson B T and Hardin C C 2020 Respiratory pathophysiology of mechanically ventilated patients with COVID-19: a cohort study *Am. J. Respir. Crit. Care Med.* **201** 1560–4

[87] Garcia-Cruz E *et al* 2020 Critical care ultrasonography during COVID-19 pandemic: the ORACLE protocol *Echocardiography* **37** 1353–61
[88] Huang Y, Guo H, Zhou Y, Guo J, Wang T, Zhao X, Li H, Sun Y, Bian X and Fang C 2020 The associations between fasting plasma glucose levels and mortality of COVID-19 in patients without diabetes *Diabetes Res. Clin. Pract.* **169** 108448
[89] Arrieta J, Galwankar S, Lattanzio N, Ray D and Agrawal A 2020 Studying the clinical data of COVID positive patients admitted to a tertiary care academic hospital *J. Emerg. Trauma Shock.* **13** 131–4
[90] Oltean M, Søfteland J M, Bagge J, Ekelund J, Felldin M, Schult A, Magnusson J, Friman V and Karason K J I D 2020 Covid-19 in kidney transplant recipients: a systematic review of the case series available three months into the pandemic *Infect. Dis.* **52** 830–7
[91] Marinaki S, Tsiakas S, Korogiannou M, Grigorakos K, Papalois V and Boletis I J J O C M 2020 A systematic review of COVID-19 infection in kidney transplant recipients: a universal effort to preserve patients' lives and allografts *J. Clin. Med.* **9** 2986
[92] Rajpal A, Rahimi L and Ismail-Beigi F J J O D 2020 Factors leading to high morbidity and mortality of COVID-19 in patients with type 2 diabetes *J. Diabetes* **12** 895–908
[93] Huang I, Lim M A and Pranata R 2020 Diabetes mellitus is associated with increased mortality and severity of disease in COVID-19 pneumonia—a systematic review, meta-analysis, and meta-regression *Diabetes Metab. Syndr.* **14** 395–403
[94] Salerno M, Sessa F, Piscopo A, Montana A, Torrisi M, Patanè F, Murabito P, Volti G L and Pomara C 2020 No autopsies on COVID-19 deaths: a missed opportunity and the lockdown of science *J. Clin. Med.* **9** 1472
[95] Arrieta J, Galwankar S, Lattanzio N, Ray D and Agrawal A 2020 Common clinical characteristics and complications determining the outcome in a COVID-positive predominantly geriatric population *J. Emerg. Trauma Shock.* **13**
[96] Tomazini B M *et al* 2020 Effect of dexamethasone on days alive and ventilator-free in patients with moderate or severe acute respiratory distress syndrome and COVID-19: the codex randomized clinical trial *JAMA* **324** 1307–16
[97] Nasir N, Farooqi J, Mahmood S F and Jabeen K 2020 COVID-19-associated pulmonary aspergillosis (CAPA) in patients admitted with severe COVID-19 pneumonia: an observational study from pakistan *Mycoses* **63** 766–70
[98] Antoun L, Taweel N E, Ahmed I, Patni S and Honest H 2020 Maternal COVID-19 infection, clinical characteristics, pregnancy, and neonatal outcome: a prospective cohort study *Eur. J. Obstet. Gynecol. Reprod. Biol.* **252** 559–62
[99] Khan M, Khan H, Khan S and Nawaz M 2020 Epidemiological and clinical characteristics of coronavirus disease (COVID-19) cases at a screening clinic during the early outbreak period: a single-centre study *J. Med. Microbiol.* **69** 1114–23
[100] Xie J *et al* 2020 Metabolic syndrome and COVID-19 mortality among adult black patients in New Orleans *Diabetes Care*
[101] Li T, Lu L, Zhang W, Tao Y, Wang L, Bao J, Liu B and Duan J 2020 Clinical characteristics of 312 hospitalized older patients with COVID-19 in Wuhan, China *Arch. Gerontol. Geriatr.* **91** 104185
[102] Saba L, Agarwal M, Sanagala S, Gupta S, Sinha G, Johri A, Khanna N, Mavrogeni S, Laird J and Pareek G J E L 2020 Brain MRI-based Wilson disease tissue classification: an optimised deep transfer learning approach *Electron. Lett.* **56** 1395–8

[103] Tandel G S, Biswas M, Kakde O G, Tiwari A, Suri H S, Turk M, Laird J R, Asare C K, Ankrah A A and Khanna N J C 2019 A review on a deep learning perspective in brain cancer classification *Cancers* **11** 111

[104] Saba L, Tiwari A, Biswas M, Gupta S K, Godia-Cuadrado E, Chaturvedi A, Turk M, Suri H S, Orru S and Sanches J M J F I B 2019 Wilson's disease: a new perspective review on its genetics, diagnosis and treatment *FBE* **11** 166–85

[105] Acharya U R, Mookiah M R K, Sree S V, Afonso D, Sanches J, Shafique S, Nicolaides A, Pedro L M, Fernandes J F E and Suri J S J M 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23

[106] Sharma A M, Gupta A, Kumar P K, Rajan J, Saba L, Nobutaka I, Laird J R, Nicolades A and Suri J S J C A R 2015 A review on carotid ultrasound atherosclerotic tissue characterization and stroke risk stratification in machine learning framework *Curr. Atheroscler. Rep.* **17** 55

[107] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Sharma A, Cuadrado-Godia E, Laird J R, Nicolaides A and Suri J S J M 2019 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 543–64

[108] Saba L, Jain P K, Suri H S, Ikeda N, Araki T, Singh B K, Nicolaides A, Shafique S, Gupta A and Laird J R J J O M S 2017 Plaque tissue morphology-based stroke risk stratification using carotid ultrasound: a polling-based PCA learning paradigm *J. Med. Syst.* **41** 98

[109] Acharya U, Sree S V, Mookiah M, Saba L, Gao H, Mallarini G and Suri J S 2013 Computed tomography carotid wall plaque characterization using a combination of discrete wavelet transform and texture features: a pilot study *J. Med. Eng.* **227** 643–54

[110] Acharya U R, Molinari F, Saba L, Nicolaides A, Shafique S and Suri J S 2012 Carotid ultrasound symptomatology using atherosclerotic plaque characterization: a class of Atheromatic systems *2012 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 3199–202

[111] Prasad H, Martis R J, Acharya U R, Min L C and Suri J S 2013 Application of higher order spectra for accurate delineation of atrial arrhythmia *2013 35th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (EMBC)* (Piscataway, NJ: IEEE) pp 57–60

[112] Saba L *et al* 2016 Automated stratification of liver disease in ultrasound: an online accurate feature classification paradigm *Comput. Methods Programs Biomed.* **130** 118–134

[113] Acharya U R, Sree S V, Ribeiro R, Krishnamurthi G, Marinho R T, Sanches J and Suri J S J M P 2012 Data mining framework for fatty liver disease classification in ultrasound: a hybrid feature extraction paradigm *Med. Phys.* **39** 4255–64

[114] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M, Suri J S J C M and biomedicine p i 2018 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Programs Biomed.* **155** 165–77

[115] Boi A, Jamthikar A D, Saba L, Gupta D, Sharma A, Loi B, Laird J R, Khanna N N and Suri J S J C A R 2018 A survey on coronary atherosclerotic plaque tissue characterization in intravascular optical coherence tomography *Curr. Atheroscler. Rep.* **20** 33

[116] Acharya U R, Faust O, Kadri N A, Suri J S and Yu W J C I B 2013 Medicine, Automated identification of normal and diabetes heart rate signals using nonlinear measures *Comput. Biol. Med.* **43** 1523–9

[117] Pareek G, Acharya U R, Sree S V, Swapna G, Yantri R, Martis R J, Saba L, Krishnamurthi G, Mallarini G and El-Baz A J T I C R 2013 Treatment, prostate tissue characterization/classification in 144 patient population using wavelet and higher order spectra features from transrectal ultrasound images *Technol. Cancer Res. Treat.* **12** 545–57
[118] Acharya U R, Molinari F, Sree S V, Swapna G, Saba L, Guerriero S and Suri J S J T I C R 2015 Treatment, ovarian tissue characterization in ultrasound: a review *Technol. Cancer Res. Treat.* **14** 251–61
[119] Acharya U R, Sree S V, Kulshreshtha S, Molinari F, Koh J E W, Saba L and Suri J S J T I C R 2014 Treatment, GyneScan: an improved online paradigm for screening of ovarian cancer via tissue characterization**13** 529–39
[120] Viswanathan V, Jamthikar A D, Gupta D, Shanu N, Puvvula A, Khanna N N, Saba L, Omerzum T, Viskovic K and Mavrogeni S J F I B 2020 Low-cost preventive screening using carotid ultrasound in patients with diabetes *Front. Biosci.* **25** 1132–71
[121] Acharya U R, Swapna G, Sree S V, Molinari F, Gupta S, Bardales R H, Witkowska A and Suri J S J T I C R 2014 Treatment, a review on ultrasound-based thyroid cancer tissue characterization and automated classification *Technol. Cancer Res. Treat.* **13** 289–301
[122] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S J C M 2016 Computer-aided diagnosis of psoriasis skin images with HOS, texture and color features: a first comparative study of its kind *Comput. Methods Programs Biomed.* **126** 98–109
[123] Shrivastava V K, Londhe N D, Sonawane R S, Suri J S J C M and biomedicine p i 2017 A novel and robust Bayesian approach for segmentation of psoriasis lesions and its risk stratification *Comput. Methods Programs Biomed.* **150** 9–22
[124] Acharya U R, Joseph K P, Kannathal N, Lim C M, Suri J S J M and Engineering B 2006 Computing, heart rate variability: a review *Med. Bio. Eng. Comput.* **44** 1031–51
[125] Corrias G, Cocco D, Suri J S, Meloni L, Cademartiri F and Saba L J C D 2020 Therapy, Heart applications of 4D flow**10** 1140
[126] Acharya U R, Sree S V, Krishnan M M R, Krishnananda N, Ranjan S, Umesh P and Suri J S 2013 Automated classification of patients with coronary artery disease using grayscale features from left ventricle echocardiographic images *Comput. Methods Programs Biomed.* **112** 624–32
[127] Maniruzzaman M *et al* 2019 Statistical characterization and classification of colon microarray gene expression data using multiple machine learning paradigms**176** 173–93
[128] Khanna N N, Jamthikar A D, Gupta D, Piga M, Saba L, Carcassi C, Giannopoulos A A, Nicolaides A, Laird J R and Suri H S J C A R 2019 Rheumatoid arthritis: atherosclerosis imaging and cardiovascular risk assessment using machine and deep learning–based tissue characterization**21** 7
[129] Jiang J, Hu Y C, Tyagi N, Zhang P, Rimner A, Deasy J O and Veeraraghavan H 2019 Cross-modality (CT-MRI) prior augmented deep learning for robust lung tumor segmentation from small MR datasets *Med. Phys.* **46** 4392–404
[130] Aresta G, Jacobs C, Araujo T, Cunha A, Ramos I, van Ginneken B and Campilho A 2019 iW-Net: an automatic and minimalistic interactive lung nodule segmentation deep network *Sci Rep.* **9** 11591
[131] Anthimopoulos M, Christodoulidis S, Ebner L, Geiser T, Christe A and Mougiakakou S 2019 Semantic segmentation of pathological lung tissue with dilated fully convolutional networks *IEEE J. Biomed. Health Inform.* **23** 714–22

[132] Weikert T, Akinci D'Antonoli T, Bremerich J, Stieltjes B, Sommer G and Sauter A W 2019 Evaluation of an AI-powered lung nodule algorithm for detection and 3d segmentation of primary lung tumors *Contrast Media Mol. Imaging.* **2019** 1545747

[133] Liu H, Cao H, Song E, Ma G, Xu X, Jin R, Jin Y and Hung C C 2019 A cascaded dual-pathway residual network for lung nodule segmentation in CT images *Phys. Med.* **63** 112–21

[134] Wong Yuzhen N and Barrett S 2019 A review of automatic lung tumour segmentation in the era of 4DCT *Rep. Pract. Oncol. Radiother.* **24** 208–20

[135] Park B, Park H, Lee S M, Seo J B and Kim N 2019 Lung segmentation on HRCT and volumetric CT for diffuse interstitial lung disease using deep convolutional neural networks *J. Digit. Imaging.* **32** 1019–26

[136] Nasrullah N, Sang J, Alam M S, Mateen M, Cai B and Hu H 2019 Automated lung nodule detection and classification using deep learning combined with multiple strategies *Sensors (Basel)* **19**

[137] Xu M, Qi S, Yue Y, Teng Y, Xu L, Yao Y and Qian W 2019 Segmentation of lung parenchyma in CT images using CNN trained with the clustering algorithm generated dataset *Biomed. Eng. Online.* **18** 2

[138] Baek S *et al* 2019 Deep segmentation networks predict survival of non-small cell lung cancer *Sci. Rep.* **9** 17286

[139] Pang T, Guo S, Zhang X and Zhao L 2019 Automatic lung segmentation based on texture and deep features of HRCT images with interstitial lung disease *BioMed. Res. Int.* **2019** 2045432

[140] Chen G, Xiang D, Zhang B, Tian H, Yang X, Shi F, Zhu W, Tian B and Chen X 2019 Automatic pathological lung segmentation in low-dose CT image using eigenspace sparse shape composition *IEEE Trans. Med. Imaging* **38** 1736–49

[141] Senthil Kumar K, Venkatalakshmi K and Karthikeyan K 2019 Lung cancer detection using image segmentation by means of various evolutionary algorithms *Comput. Math. Methods Med.* **2019** 4909846

[142] Liu C, Zhao R and Pang M 2020 A fully automatic segmentation algorithm for CT lung images based on random forest *Med. Phys.* **47** 518–29

[143] Geng L, Zhang S, Tong J and Xiao Z 2019 Lung segmentation method with dilated convolution based on VGG-16 network *Comput. Assist. Surg. (Abingdon)* **24** 27–33

[144] Sousa A M, Martins S B, Falcao A X, Reis F, Bagatin E and Irion K 2019 ALTIS: a fast and automatic lung and trachea CT-image segmentation method *Med. Phys.* **46** 4970–82

[145] Souza J C, Bandeira Diniz J O, Ferreira J L, Franca da Silva G L, Correa Silva A and de Paiva A C 2019 An automatic method for lung segmentation and reconstruction in chest x-ray using deep neural networks *Comput. Methods Programs Biomed.* **177** 285–96

[146] Noor N M, Than J C M, Rijal O M, Kassim R M, Yunus A, Zeki A A, Anzidei M, Saba L and Suri J S 2015 Automatic lung segmentation using control feedback system: morphology and texture paradigm *J. Med. Syst.* **39**

[147] Ni Q *et al* 2020 A deep learning approach to characterize 2019 coronavirus disease (COVID-19) pneumonia in chest CT images *Eur. Radiol* **30** 6517–27

[148] Shan F, Gao Y, Wang J, Shi W, Shi N, Han M, Xue Z and Shi Y J A P A 2020 Lung infection quantification of covid-19 in CT images with deep learning

[149] Hwang E J, Kim H, Yoon S H, Goo J M and Park C M 2020 Implementation of a deep learning-based computer-aided detection system for the interpretation of chest radiographs in patients suspected for COVID-19 *Korean J. Radiol* **21** 1150–60

[150] Roy S *et al* 2020 Deep learning for classification and localization of COVID-19 markers in point-of-care lung ultrasound *IEEE Trans. Med. Imaging.* **39** 2676–87

[151] Signoroni A, Savardi M, Benini S, Adami N, Leonardi R, Gibellini P, Vaccher F, Ravanelli M, Borghesi A and Maroldi R J A P A 2020 End-to-end learning for semiquantitative rating of COVID-19 severity on chest x-rays

[152] Li Z *et al* 2020 From community-acquired pneumonia to COVID-19: a deep learning-based method for quantitative analysis of COVID-19 on thick-section 2.CT scans *Eur Radiol* **30** 6828–37

[153] Chaganti S *et al* 2020 Automated quantification of CT patterns associated with COVID-19 from chest CT *Radiol.: Artif. Intell.* **2** e200048

[154] Li L *et al* 2020 Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy *Radiology* **296** E65–71

[155] Yang S, Jiang L, Cao Z, Wang L, Cao J, Feng R, Zhang Z, Xue X, Shi Y and Shan F 2020 Deep learning for detecting corona virus disease 2019 (COVID-19) on high-resolution computed tomography: a pilot study *Ann. Transl. Med.* **8** 450–0

[156] Hu S *et al* 2020 Weakly supervised deep learning for COVID-19 infection detection and classification from CT images *IEEE Access.* **8** 118869–83

[157] Zhang K *et al* 2020 Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography *Cell* **181** 1423–33 e1411

[158] Carrer L *et al* 2020 Automatic pleural line extraction and COVID-19 scoring from lung ultrasound data *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **67** 2207–17

[159] Tang Z, Zhao W, Xie X, Zhong Z, Shi F, Liu J and Shen D J A P A 2020 Severity assessment of coronavirus disease 2019 (COVID-19) using quantitative features from chest CT images *Med Image Anal.* arXiv:2003.11988

[160] Rajaraman S, Siegelman J, Alderson P O, Folio L S, Folio L R and Antani S K 2020 Iteratively pruned deep learning ensembles for COVID-19 detection in chest x-rays *IEEE Access* **8** 115041–50

[161] Born J, Brändle G, Cossio M, Disdier M, Goulet J, Roulin J and Wiedemann N J A P A 2020 POCOVID-Net: automatic detection of COVID-19 from a new lung ultrasound imaging dataset (POCUS) arXiv:2004.12084

[162] Jaiswal A, Gianchandani N, Singh D, Kumar V and Kaur M 2020 Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning *J. Biomol. Struct. Dyn.* 1–8

[163] Tsiknakis N *et al* 2020 Interpretable artificial intelligence framework for COVID-19 screening on chest x-rays *Exp. Ther. Med.* **20** 727–35

[164] Maghdid H S, Asaad A T, Ghafoor K Z, Sadiq A S and Khan M K J A P A 2020 Diagnosing COVID-19 pneumonia from x-ray and CT images using deep learning and transfer learning algorithms *Proc. IEEE* **11734** 117340E

[165] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2016 Computer-aided diagnosis of psoriasis skin images with HOS, texture and color features: a first comparative study of its kind *Comput. Methods Programs Biomed.* **126** 98–109

[166] Chen A, Karwoski R A, Gierada D S, Bartholmai B J and Koo C W 2020 Quantitative CT analysis of diffuse lung disease *Radiographics* **40** 28–43

[167] Than J C M, Saba L, Noor N M, Rijal O M, Kassim R M, Yunus A, Suri H S, Porcu M and Suri J S 2017 Lung disease stratification using amalgamation of Riesz and Gabor transforms in machine learning framework *Comput. Biol. Med.* **89** 197–211

[168] Hattori A, Takamochi K, Oh S and Suzuki K 2019 New revisions and current issues in the eighth edition of the TNM classification for non-small cell lung cancer *Jpn. J. Clin. Oncol.* **49** 3–11

[169] Saba T 2019 Automated lung nodule detection and classification based on multiple classifiers voting *Microsc. Res. Tech.* **82** 1601–9

[170] Zhang G, Yang Z, Gong L, Jiang S and Wang L 2019 Classification of benign and malignant lung nodules from CT images based on hybrid features *Phys. Med. Biol.* **64** 125011

[171] Singh D, Kumar V, Vaishali and Kaur M 2020 Classification of COVID-19 patients from chest CT images using multi-objective differential evolution-based convolutional neural networks *Eur. J. Clin. Microbiol. Infect. Dis.* **39** 1379–89

[172] Mahmud T, Rahman M A and Fattah S A 2020 CovXNet: a multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest x-ray images with transferable multi-receptive feature optimization *Comput. Biol. Med.* **122** 103869–9

[173] Das D, Santosh K C and Pal U 2020 Truncated inception net: COVID-19 outbreak screening using chest x-rays, research Square *Phys. Eng. Sci. Med.* **43** 915–25

[174] Ozturk T, Talo M, Yildirim E A, Baloglu U B, Yildirim O and Rajendra U 2020 Automated detection of COVID-19 cases using deep neural networks with x-ray images *Comput. Biol. Med.* **121** 103792–2

[175] Brunese L, Mercaldo F, Reginelli A and Santone A 2020 Explainable deep learning for pulmonary disease and coronavirus COVID-19 detection from x-rays *Comput. Methods Programs Biomed.* **196** 105608

[176] Suri J S, Singh S and Reden L J P A 2002 Applications, fusion of region and boundary/surface-based computer vision and pattern recognition techniques for 2-D and 3-D MR cerebral cortical segmentation (part-II): a state-of-the-art review**5** 77–98

[177] Suri J S, Singh S and Reden L J P A 2002 Applications, computer vision and pattern recognition techniques for 2-D and 3-D MR cerebral cortical segmentation (Part I): a state-of-the-art review**5** 46–76

[178] Suri J S, Liu K, Reden L and Laxminarayan S 2002 A review on MR vascular image processing: skeleton versus nonskeleton approaches: part II *IEEE Trans. Inf. Technol. Biomed.* **6** 338

[179] https://xmedcon.sourceforge.io/

[180] Sahu S P, Kamble B and Doriya R 2020 3D lung segmentation using thresholding and active contour method *Advances in Intelligent Systems and Computing* (Singapore: Springer) pp 369–80

[181] Taylor M E 2009 Transfer between different reinforcement learning methods *Transfer in Reinforcement Learning Domains* (Berlin: Springer) pp 139–79

[182] Acharya U R, Swapna G, Sree S V, Molinari F, Gupta S, Bardales R H, Witkowska A and Suri J S 2014 A review on ultrasound-based thyroid cancer tissue characterization and automated classification *Technol. Cancer Res. Treat.* **13** 289–301

[183] Shih A R *et al* 2019 Problems in the reproducibility of classification of small lung adenocarcinoma: an international interobserver study *Histopathology* **75** 649–59
[184] LeNail A 2019 NN-SVG: publication-ready neural network architecture schematics *J. Open Source Softw.* **4** 747
[185] Iqbal H 2018 HarisIqbal88/PlotNeuralNet v1.0.0
[186] Ye F, Pu J, Wang J, Li Y and Zha H 2017 Glioma grading based on 3D multimodal convolutional neural network and privileged learning *2017 IEEE Int. Conf. on Bioinformatics and Biomedicine (BIBM)* (Piscataway, NJ: IEEE)
[187] Wang S *et al* 2020 A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis *Eur. Res. J.* **56**
[188] Yoo S H *et al* 2020 Deep learning-based decision-tree classifier for COVID-19 diagnosis from chest x-ray imaging *Front. Med. (Lausanne)* **7** 427
[189] Zhu J, Shen B, Abbasi A, Hoshmand-Kochi M, Li H and Duong T Q 2020 Deep transfer learning artificial intelligence accurately stages COVID-19 lung disease severity on portable chest radiographs *PLoS One* **15** e0236621
[190] Joseph J. C and Howard P. F The Economic Impact of the COVID-19 Pandemic on Radiology Practices
[191] Yasar H and Ceylan M 2020 A novel comparative study for detection of Covid-19 on CT lung images using texture analysis, machine learning, and deep learning methods *Multimed. Tools Appl.* **80** 1–25
[192] Setti L, Kirienko M, Dalto S C, Bonacina M and Bombardieri E 2020 FDG-PET/CT findings highly suspicious for COVID-19 in an Italian case series of asymptomatic patients *Eur. J. Nucl. Med. Mol. Imaging* **47** 1649–56
[193] Alonso Sanchez J, García Prieto J, Galiana Morón A and Pilkington-Woll J P 2020 PET/CT of COVID-19 as an organizing pneumonia *Clin. Nucl. Med.* **45** 642–3
[194] Castanheira J, Mascarenhas Gaivão A, Mairos Teixeira S, Pereira P J and Costa D C 2020 Asymptomatic COVID-19 positive patient suspected on FDG-PET/CT *Nucl. Med. Commun.* **41** 598–9
[195] Cohen J P *et al* 2020 Predicting COVID-19 pneumonia severity on chest x-ray with deep learning *Cureus* **12** e9448
[196] Galougahi M K, Ghorbani J, Bakhshayeshkaram M, Naeini A S and Haseli S J A R 2020 Olfactory bulb magnetic resonance imaging in SARS-CoV-2-induced anosmia: the first report *Acad. Radiol.* **27** 892–3
[197] Gunraj H, Wang L and Wong A J A P A 2020 Covidnet-CT: a tailored deep convolutional neural network design for detection of covid-19 cases from chest CT images *Front. Med.* **7** 608525
[198] Ismael A M and Sengur A 2021 Deep learning approaches for COVID-19 detection based on chest x-ray images *Expert Syst. Appl.* **164** 114054
[199] Kandemirli S G *et al* 2020 Brain MRI findings in patients in the intensive care unit with COVID-19 infection *Radiology* **297** E232–5
[200] Kay F and Abbara S 2020 The many faces of COVID-19: spectrum of imaging manifestations *Radiol. Soc. North Am.* **2** 1–2
[201] Litjens G, Kooi T, Bejnordi B E, Setio A A A, Ciompi F, Ghafoorian M, van der Laak J A W M, van Ginneken B and Sánchez C I 2017 A survey on deep learning in medical image analysis *Med. Image Anal.* **42** 60–88

[202] Minaee S, Kafieh R, Sonka M, Yazdani S and Jamalipour G 2020 Deep-COVID: predicting COVID-19 from chest x-ray images using deep transfer learning *Med. Image Anal.* **65** 101794

[203] Shi F, Xia L, Shan F, Wu D, Wei Y, Yuan H, Jiang H, Gao Y, Sui H and Shen D J A P A 2020 Large-scale screening of Covid-19 from community acquired pneumonia using infection size-aware classification *Phys. Med. Biol.* **66** 065031

[204] Panwar H, Gupta P K, Siddiqui M K, Morales-Menendez R, Bhardwaj P and Singh V 2020 A deep learning and grad-CAM based color visualization approach for fast detection of COVID-19 cases using chest x-ray and CT-Scan images *Chaos Solit. Fractals.* **140** 110190–0

[205] Ouchicha C, Ammor O and Meknassi M 2020 CVDNet: a novel deep learning architecture for detection of coronavirus (Covid-19) from chest x-ray images *Chaos Solit. Fractals* **140** 110245–5

[206] Farooq M and Hafeez A J A P A 2020 Covid-resnet: a deep learning framework for screening of covid19 from radiographs arXiv:2003.14395

[207] Cozzi D, Albanesi M, Cavigli E, Moroni C, Bindi A, Luvarà S, Lucarini S, Busoni S, Mazzoni L N and Miele V 2020 Chest x-ray in new Coronavirus Disease 2019 (COVID-19) infection: findings and correlation with clinical outcome *Radiol. Med.* **125** 730–7

[208] Pereira R M, Bertolini D, Teixeira L O, Silla C N and Costa Y M G 2020 COVID-19 identification in chest x-ray images on flat and hierarchical classification scenarios *Comput. Methods Programs Biomed.* **194** 105532–2

[209] Ardakani A A, Kanafi A R, Acharya U R, Khadem N and Mohammadi A 2020 Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks *Comput. Biol. Med.* **121** 103795–5

[210] Zheng C, Deng X, Fu Q, Zhou Q, Feng J, Ma H, Liu W and Wang X 2020 *Deep Learning-Based Detection for COVID-19 from Chest CT using Weak Label* (Cold Spring Harbor Laboratory)

[211] Yang X, He X, Zhao J, Zhang Y, Zhang S and Xie P J A E-P 2020 Covid-CT-dataset: a CT scan dataset about covid-19 arXiv:2003.13865

[212] Gozes O, Frid-Adar M, Sagie N, Kabakovitch A, Amran D, Amer R and Greenspan H 2020 A weakly supervised deep learning framework for COVID-19 CT detection and analysis *Thoracic Image Analysis* (Springer International Publishing) pp 84–93

[213] Liu B, Gao X, He M, Liu L and Yin G 2020 A fast online COVID-19 diagnostic system with chest CT scans *Proc. of KDD*

[214] Hemdan E E-D, Shouman M A and Karar M E J A P A 2020 Covidx-net: a framework of deep learning classifiers to diagnose covid-19 in x-ray images

[215] Zhang J, Xie Y, Liao Z, Pang G, Verjans J, Li W, Sun Z, He J and Yi Li C S J A P A 2020 Viral pneumonia screening on chest x-ray images using confidence-aware anomaly detection *IEEE Trans. on Med. Imag.* **40** 879–90

[216] Narayan Das N, Kumar N, Kaur M, Kumar V and Singh D 2020 Automated deep transfer learning-based approach for detection of COVID-19 infection in chest x-rays *Ing Rech Biomed.* **43** 114–9

[217] Wu Y-H, Gao S-H, Mei J, Xu J, Fan D-P, Zhao C-W and Cheng M-M 2020 JCS: an explainable COVID-19 diagnosis system by joint classification and segmentation *IEEE Trans. on Imag. Proc.* **30** 3113–26

[218] Toğaçar M, Ergen B and Cömert Z 2020 COVID-19 detection using deep learning models to exploit social mimic optimization and structured chest x-ray images using fuzzy color and stacking approaches *Comput. Biol. Med.* **121** 103805–5
[219] Basu S and Mitra S J A P A 2020 Deep learning for screening COVID-19 using chest x-ray images *MedRxiv* IEEE - PMC COVID-19 Collection
[220] Gozes O, Frid-Adar M, Greenspan H, Browning P D, Zhang H, Ji W, Bernheim A and Siegel E J A P A 2020 Rapid AI development cycle for the coronavirus (covid-19) pandemic: initial results for automated detection & patient monitoring using deep learning CT image analysis
[221] Yan T, Wong P K, Ren H, Wang H, Wang J and Li Y J C 2020 Solitons, fractals, automatic distinction between Covid-19 and common pneumonia using multi-scale convolutional neural network on chest CT scans *Chaos Solit. Fractals* **140** 110153
[222] Oh Y, Park S and Ye J C 2020 Deep learning COVID-19 features on CXR using limited training data sets *IEEE Trans. on Med. Imag.* **39** 2688–700
[223] Saba L, Than J C M, Noor N M, Rijal O M, Kassim R M, Yunus A, Ng C R and Suri J S 2016 Inter-observer variability analysis of automatic lung delineation in normal and disease patients *J. Med. Syst.* **40**
[224] Liu K and Suri J S 2005 Automatic vessel indentification for angiographic screening, Google Patents
[225] Ambale-Venkatesh B *et al* 2017 Cardiovascular event prediction by machine learning: the multi-ethnic study of atherosclerosis *Circ. Res.* **121** 1092–101
[226] Tandel G S, Balestrieri A, Jujaray T, Khanna N N, Saba L and Suri J S 2020 Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm *Comput. Biol. Med.* **122** 103804
[227] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2017 A novel and robust Bayesian approach for segmentation of psoriasis lesions and its risk stratification *Comput. Methods Programs Biomed.* **150** 9–22
[228] Jamthikar A, Gupta D, Saba L, Khanna N N, Viskovic K, Mavrogeni S, Laird J R, Sattar N, Johri A M and Pareek G J C I B 2020 Medicine, artificial intelligence framework for predictive cardiovascular and stroke risk assessment models: a narrative review of integrated approaches using carotid ultrasound *Comput. Biol. Med.* **126** 104043
[229] Wu X *et al* 2020 Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: a multicentre study *Eur. J. Radiol.* **128** 109041–1
[230] Organization W H 2020 *Use of Chest Imaging in COVID-19* 1–56
[231] Yusuf G T, Wong A, Rao D, Tee A, Fang C and Sidhu P S 2020 The use of contrast-enhanced ultrasound in COVID-19 lung imaging *J. Ultrasound* **25** 319–23
[232] Ni Q, Sun Z Y, Qi L, Chen W, Yang Y, Wang L, Zhang X, Yang L, Fang Y and Xing Z J E R 2020 A deep learning approach to characterize 2019 coronavirus disease (COVID-19) pneumonia in chest CT images**30** 6517–27
[233] Wang S, Zha Y, Li W, Wu Q, Li X, Niu M, Wang M, Qiu X, Li H and Yu H J E R J 2020 A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis *Eur. Respir. J.* **56** 2000775
[234] Narayanan R, Werahera P N, Barqawi A, Crawford E D, Shinohara K, Simoneau A R and Suri J S 2008 Adaptation of a 3D prostate cancer atlas for transrectal ultrasound guided target-specific biopsy *Phys. Med. Biol.* **53** N397–406

[235] Shen F, Narayanan R and Suri J S 2008 Rapid motion compensation for prostate biopsy using GPU *Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society* 2008 3257–60
[236] State of the Art in Neural Networks and Their Applications 1st edn
[237] Acharya U R *et al* 2013 Diagnosis of Hashimoto's thyroiditis in ultrasound using tissue characterization and pixel classification *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **227** 788–98
[238] Kandemirli S G, Altundag A, Yildirim D, Tekcan Sanli D E and Saatci O 2020 Olfactory bulb MRI and paranasal sinus CT findings in persistent COVID-19 Anosmia *Acad. Radiol.* **28** 28–35
[239] Cuadrado-Godia E, Dwivedi P, Sharma S, Santiago A O, Gonzalez J R, Balcells M, Laird J, Turk M, Suri H S and Nicolaides A J J O S 2018 Cerebral small vessel disease: a review focusing on pathophysiology, biomarkers, and machine learning strategies *J. Stroke* **20** 302
[240] Maniruzzaman M, Kumar N, Abedin M M, Islam M S, Suri H S, El-Baz A S, Suri J S J C M and biomedicine p i 2017 Comparative approaches for classification of diabetes mellitus data: machine learning paradigm *Comput. Methods Programs Biomed.* **152** 23–34
[241] Acharya R, Ng Y E and Suri J S 2008 *Image Modeling of the Human Eye* (Norwood, MA: Artech House)
[242] El-Baz A and Suri J 2019 *Lung Imaging and CADx* (Boca Raton, FL: CRC Press)
[243] El-Baz A and Suri J S 2011 *Lung Imaging and Computer Aided Diagnosis* (Boca Raton, FL: CRC Press)
[244] 2020 *Online COVID-19 Diagnosis with Chest CT Images: Lesion-Attention Deep Neural Networks* (Boston, MA: Rescognito, Inc.)
[245] Suri J S, Agarwal S and Gupta S K *et al* 2021 A narrative review on characterization of acute respiratory distress syndrome in COVID-19-infected lungs using artificial intelligence *Comput. Biol. Med.* **130** 104210

Chapter 3

[1] Cucinotta D and Vanelli M 2020 WHO declares COVID-19 a pandemic *Acta Biomed. Atenei Parm.* **91** 157–60
[2] WHO coronavirus (COVID-19) dashboard, (https://covid19.who.int/) (24 Janurary 2022
[3] Saba L *et al* 2020 Molecular pathways triggered by COVID-19 in different organs: ACE2 receptor-expressing cells under attack? A review *Eur. Rev. Med. Pharmacol. Sci.* **24** 12609–22
[4] Suri J S *et al* 2020 COVID-19 pathways for brain and heart injury in comorbidity patients: a role of medical imaging and artificial intelligence-based COVID severity classification: a review *Comput. Biol. Med.* **124** 103960
[5] Cau R, Bassareo P P, Mannelli L, Suri J S and Saba L 2021 Imaging in COVID-19-related myocardial injury *Int. J. Cardiovasc. Imaging.* **37** 1349–60
[6] Onnis C *et al* 2022 Non-invasive coronary imaging in patients with COVID-19: a narrative review *Eur. J. Radiol.* **149** 110188
[7] Viswanathan V, Puvvula A, Jamthikar A D, Saba L, Johri A M, Kotsis V, Khanna N N, Dhanjil S K, Majhail M and Misra D P 2021 Bidirectional link between diabetes mellitus and coronavirus disease 2019 leading to cardiovascular disease: a narrative review *World J. Diabetes* **12** 215

[8] Fanni D *et al* 2021 Vaccine-induced severe thrombotic thrombocytopenia following COVID-19 vaccination: a report of an autoptic case and review of the literature *Eur. Rev. Med. Pharmacol. Sci.* **25** 5063–9
[9] Gerosa C, Faa G, Fanni D, Manchia M, Suri J, Ravarino A, Barcellona D, Pichiri G, Coni P and Congiu T 2021 Fetal programming of COVID-19: may the Barker hypothesis explain the susceptibility of a subset of young adults to develop severe disease? *Eur. Rev. Med. Pharmacol Sci.* **25** 5876–84
[10] Congiu T, Demontis R, Cau F, Piras M, Fanni D, Gerosa C, Botta C, Scano A, Chighine A and Faedda E 2021 Scanning electron microscopy of lung disease due to COVID-19-a case report and a review of the literature *Eur. Rev. Med Pharmacol. Sci.* **25** 7997–8003
[11] Suri J S and Laxminarayan S 2003 *Angiography and Plaque Imaging: Advanced Segmentation Techniques* (Boca Raton, FL: CRC Press)
[12] Faa G, Gerosa C, Fanni D, Barcellona D, Cerrone G, Orrù G, Scano A, Marongiu F, Suri J and Demontis R 2021 Aortic vulnerability to COVID-19: is the microvasculature of vasa vasorum a key factor? A case report and a review of the literature *Eur. Rev. Med. Pharmacol. Sci.* **25** 6439–42
[13] Munjral S, Ahluwalia P, Jamthikar A D, Puvvula A, Saba L, Faa G, Singh I M, Chadha P S, Turk M and Johri A M 2021 Nutrition, atherosclerosis, arterial imaging, cardiovascular risk stratification, and manifestations in COVID-19 framework: a narrative review *Front. Biosci. (Landmark Edition)* **26** 1312–39
[14] Congiu T, Fanni D, Piras M, Gerosa C, Cau F, Barcellona D, D'Aloja E, Demontis R, Chighine F and Nioi M 2022 Ultrastructural findings of lung injury due to vaccine-induced immune thrombotic thrombo-cytopenia (VITT) following COVID-19 vaccination: a scanning electron microscopic study *Eur. Rev. Med. Pharmacol Sci.* **26** 270–7
[15] Fang Y, Zhang H, Xie J, Lin M, Ying L, Pang P and Ji W 2020 Sensitivity of chest CT for COVID-19: comparison to RT-PCR *Radiology* **296** E115–7
[16] Dram´e M, Teguo M T, Proye E, Hequet F, Hentzien M, Kanagaratnam L and Godaert L 2020 Should RT-PCR be considered a gold standard in the diagnosis of COVID-19? *J. Med. Virol.* **92** 2312–3
[17] Xiao A T, Tong Y X and Zhang S 2020 False negative of RT-PCR and prolonged nucleic acid conversion in COVID-19: rather than recurrence *J. Medi. Virol.* **92** 1755–6
[18] Suri J S, Agarwal S, Gupta S K, Puvvula A, Biswas M, Saba L, Bit A, Tandel G S, Agarwal M and Patrick A 2021 A narrative review on characterization of acute respiratory distress syndrome in COVID-19-infected lungs using artificial intelligence *Comput. Biol. Med.* **130** 104210
[19] Biswas M *et al* 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci. (Landmark Ed)* **24** 392–426
[20] Saba L *et al* 2019 The present and future of deep learning in radiology *Eur. J. Radiol.* **114** 14–24
[21] Kuppili V, Biswas M, Sreekumar A, Suri H S, Saba L, Edla D R, Marinhoe R T, Sanches J M and Suri J S 2017 Extreme learning machine framework for risk stratification of fatty liver disease using ultrasound tissue characterization *J. Med. Syst.* **41** 1–20
[22] Chen X, Tang Y, Mo Y, Li S, Lin D, Yang Z, Yang Z, Sun H, Qiu J and Liao Y 2020 A diagnostic model for coronavirus disease 2019 (COVID-19) based on radiological semantic and clinical features: a multi-center study *Eur. Radiol.* **30** 4893–902

[23] Jain P K, Sharma N, Giannopoulos A A, Saba L, Nicolaides A and Suri J S 2021 Hybrid deep learning segmentation models for atherosclerotic plaque in internal carotid artery B-mode ultrasound *Comput. Biol. Med.* **136** 104721
[24] Jena B, Saxena S, Nayak G K, Saba L, Sharma N and Suri J S 2021 Artificial intelligence-based hybrid deep learning models for image classification: the first narrative review *Comput. Biol. Med.* **137** 104803
[25] Suri J S, Agarwal S, Pathak R, Ketireddy V, Columbu M, Saba L, Gupta S K, Faa G, Singh I M and Turk M 2021 Covlias 1.0: lung segmentation in COVID-19 computed tomography scans using hybrid deep learning artificial intelligence models *Diagnostics* **11** 1405
[26] Jain P K, Sharma N, Saba L, Paraskevas K I, Kalra M K, Johri A, Nicolaides A N and Suri J S 2022 Automated deep learning-based paradigm for high-risk plaque detection in B-mode common carotid ultrasound scans: an asymptomatic Japanese cohort study *Int. Angiol.* **41** 9–23
[27] Suri J S, Agarwal S, Carriero A, Pasch'e A, Danna P S, Columbu M, Saba L, Viskovic K, Mehmedovi´c A and Agarwal S 2021 COVLIAS 1.0 vs. MedSeg: artificial intelligence-based comparative study for automated COVID-19 computed tomography lung segmentation in Italian and Croatian cohorts *Diagnostics* **11** 2367
[28] Suri J S *et al* 2021 Inter-variability study of COVLIAS 1.0: hybrid deep learning models for COVID-19 lung segmentation in computed tomography *Diagnostics (Basel)* **11** 2025
[29] Skandha S S, Nicolaides A, Gupta S K, Koppula V K, Saba L, Johri A M, Kalra M S and Suri J S 2022 A hybrid deep learning paradigm for carotid plaque tissue characterization and its validation in multicenter cohorts using a supercomputer framework *Comput. Biol. Med.* **141** 105131
[30] Gupta N, Gupta S K, Pathak R K, Jain V, Rashidi P and Suri J S 2022 Human activity recognition in artificial intelligence framework: a narrative review *Artif. Intell. Rev.* **55** 4755–808
[31] Saba L, Biswas M, Suri H S, Viskovic K, Laird J R, Cuadrado-Godia E, Nicolaides A, Khanna N N, Viswanathan V and Suri J S 2019 Ultrasound-based carotid stenosis measurement and risk stratification in diabetic cohort: a deep learning paradigm *Cardiovasc. Diagn. Ther.* **9** 439–61
[32] Agarwal M, Saba L, Gupta S K, Johri A M, Khanna N N, Mavrogeni S, Laird J R, Pareek G, Miner M and Sfikakis P P 2021 Wilson disease tissue classification and characterization using seven artificial intelligence models embedded with 3D optimization paradigm on a weak training brain magnetic resonance imaging datasets: a supercomputer application *Med. Biol. Eng. Comput.* **59** 511–33
[33] Sanagala S S, Nicolaides A, Gupta S K, Koppula V K, Saba L, Agarwal S, Johri A M, Kalra M S and Suri J S 2021 Ten fast transfer learning models for carotid ultrasound plaque tissue characterization in augmentation framework embedded with heatmaps for stroke risk stratification *Diagnostics* **11** 2109
[34] LeCun Y, Denker J and Solla S 1989 Optimal brain damage *Adv. Neural Inf. Process. Systems* 2
[35] Zhu M and Gupta S 2017 To prune, or not to prune: exploring the efficacy of pruning for model compression Arxiv Preprint arXiv:1710.01878
[36] Band S S, Janizadeh S, Chandra Pal S, Saha A, Chakrabortty R, Shokri M and Mosavi A 2020 Novel ensemble approach of deep learning neural network (DLNN) model and

particle swarm optimization (PSO) algorithm for prediction of gully erosion susceptibility *Sensors* **20** 5609
[37] Brodzicki A, Piekarski M and Jaworek-Korjakowska J 2021 The whale optimization algorithm approach for deep neural networks *Sensors* **21** 8003
[38] Ashraf N M, Mostafa R R, Sakr R H and Rashad M 2021 Optimizing hyperparameters of deep reinforcement learning for autonomous driving based on whale optimization algorithm *PLoS One* **16** e0252754
[39] Acharya U R, Mookiah M R, Vinitha Sree S, Yanti R, Martis R J, Saba L, Molinari F, Guerriero S and Suri J S 2014 Evolutionary algorithm-based classifier parameter tuning for automatic ovarian cancer tissue characterization and classification *Ultraschall Med.* **35** 237–45
[40] Horry M, Chakraborty S, Pradhan B, Paul M, Zhu J, Loh H W, Barua P D and Arharya U R 2022 Debiasing pipeline improves deep learning model generalization for X-ray based lung nodule detection Arxiv Preprint arXiv:2201.09563
[41] MedSeg 2022 https://htmlsegmentation.s3.eu-north-1.amazonaws.com/index.html
[42] Eelbode T, Bertels J, Berman M, Vandermeulen D, Maes F, Bisschops R and Blaschko M B 2020 Optimization for medical image segmentation: theory and practice when evaluating with dice score or jaccard index *IEEE Trans. Med. Imaging* **39** 3679–90
[43] Giavarina D 2015 Understanding bland Altman analysis *Biochem. Med.* **25** 141–51
[44] Dewitte K, Fierens C, Stockl D and Thienpont L M 2002 Application of the bland–altman plot for interpretation of method-comparison studies: a critical investigation of its practice *Clin. Chem.* **48** 799–801
[45] Asuero A G, Sayago A and Gonzalez A 2006 The correlation coefficient: an overview *Crit. Rev. Anal. Chem.* **36** 41–59
[46] Taylor R 1990 Interpretation of the correlation coefficient: a basic review *J. Diagn. Med. Sonogr.* **6** 35–9
[47] El-Baz A, Gimel'farb G and Suri J S 2015 *Stochastic Modeling for Medical Image Analysis* 1st edn (Boca Raton, FL: CRC Press)
[48] El-Baz A, Jiang X and Suri J S 2016 *Biomedical Image Segmentation: Advances and Trends* (Boca Raton, FL: CRC Press)
[49] El-Baz A S, Acharya R, Mirmehdi M and Suri J S 2011 *Multi Modality State-Of-The-Art Medical Image Segmentation and Registration Methodologies* vol 2 (Berlin: Springer Science & Business Media)
[50] Maniruzzaman M, Rahman M J, Al-MehediHasan M, Suri H S, Abedin M M, El-Baz A and Suri J S 2018 Accurate diabetes risk stratification using machine learning: role of missing value and outliers *J. Med. Syst.* **42** 1–17
[51] Maniruzzaman M, Kumar N, Abedin M M, Islam M S, Suri H S, El-Baz A S and Suri J S 2017 Comparative approaches for classification of diabetes mellitus data: machine learning paradigm *Comput. Methods Programs Biomed.* **152** 23–34
[52] Maniruzzaman M, Suri H S, Kumar N, Abedin M M, Rahman M J, El-Baz A, Bhoot M, Teji J S and Suri J S 2018 Risk factors of neonatal mortality and child mortality in Bangladesh *J. Glob. Health* **8**
[53] Maniruzzaman M, Jahanur Rahman M, Ahammed B, Abedin M M, Suri H S, Biswas M, El-Baz A, Bangeas P, Tsoulfas G and Suri J S 2019 Statistical characterization and classification of colon microarray gene expression data using multiple machine learning paradigms *Comput. Methods Programs Biomed.* **176** 173–93

[54] Noor N M, Than J C, Rijal O M, Kassim R M, Yunus A, Zeki A A, Anzidei M, Saba L and Suri J S 2015 Automatic lung segmentation using control feedback system: morphology and texture paradigm *J. Med. Syst.* **39** 1–18

[55] Acharya R U, Faust O, Alvin A P, Sree S V, Molinari F, Saba L, Nicolaides A and Suri J S 2012 Symptomatic vs. asymptomatic plaque classification in carotid ultrasound *J. Med. Syst.* **36** 1861–71

[56] Acharya U R, Faust O, Alvin V S S A P, Krishnamurthi G, Seabra J C, Sanches J and Suri J S 2013 Understanding symptomatology of atherosclerotic plaque by image-based tissue characterization *Comput. Methods Programs Biomed.* **110** 66–75

[57] Acharya U R, Faust O, Sree S V, Alvin A P C, Krishnamurthi G, Sanches J and Suri J S 2011 Atheromatic™: symptomatic vs. asymptomatic classification of carotid ultrasound plaque using a combination of HOS, DWT and texture *2011 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 4489–92

[58] Acharya U R, Mookiah M R, Vinitha Sree S, Afonso D, Sanches J, Shafique S, Nicolaides A, Pedro L M, Fernandes E F J and Suri J S 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23

[59] Molinari F, Liboni W, Pavanelli E, Giustetto P, Badalamenti S and Suri J S 2007 Accurate and automatic carotid plaque characterization in contrast enhanced 2-D ultrasound images *2007 29th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 335–8

[60] Acharya U, Vinitha Sree S, Mookiah M, Yantri R, Molinari F, Ziele´znik W, Małyszek-Tumidajewicz J, Stępie´n B, Bardales R and Witkowska A 2013 Diagnosis of Hashimoto's thyroiditis in ultrasound using tissue characterization and pixel classification *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **227** 788–98

[61] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M and Suri J S 2018 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Programs Biomed.* **155** 165–77

[62] Saba L *et al* 2021 Multimodality carotid plaque tissue characterization and classification in the artificial intelligence paradigm: a narrative review for stroke application *Ann. Transl. Med.* **9** 1206

[63] Banchhor S K, Londhe N D, Araki T, Saba L, Radeva P, Laird J R and Suri J S 2017 Wall-based measurement features provides an improved IVUS coronary artery risk assessment when fused with plaque texture-based features during machine learning paradigm *Comput. Biol. Med.* **91** 198–212

[64] Acharya U R, Saba L, Molinari F, Guerriero S and Suri J S 2012 Ovarian tumor characterization and classification: a class of GyneScan™ systems *2012 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 4446–9

[65] Pareek G, Acharya U R, Sree S V, Swapna G, Yantri R, Martis R J, Saba L, Krishnamurthi G, Mallarini G and El-Baz A 2013 Prostate tissue characterization/classification in 144 patient population using wavelet and higher order spectra features from transrectal ultrasound images *Technol. Cancer Res. Treat.* **12** 545–57

[66] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2015 Exploring the color feature power for psoriasis risk stratification and classification: a data mining paradigm *Comput. Biol. Med.* **65** 54–68

[67] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2017 A novel and robust Bayesian approach for segmentation of psoriasis lesions and its risk stratification *Comput. Methods Prog. Biomed.* **150** 9–22
[68] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2015 Reliable and accurate psoriasis disease classification in dermatology images using comprehensive feature space in machine learning paradigm *Expert Syst. Appl.* **42** 6184–95
[69] Acharya U R, Kannathal N, Ng E, Min L C and Suri J S 2006 Computer-based classification of eye diseases *2006 Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 6121–4
[70] Saba L and Suri J S 2013 *Multi-Detector CT Imaging: Principles, Head, Neck, and Vascular Systems* (Boca Raton, FL: CRC Press)
[71] Murgia A, Erta M, Suri J S, Gupta A, Wintermark M and Saba L 2020 CT imaging features of carotid artery plaque vulnerability *Ann. Transl. Med.* **8**
[72] Saba L, di Martino M, Siotto P, Anzidei M, Argiolas G M, Porcu M, Suri J S and Wintermark M 2018 Radiation dose and image quality of computed tomography of the supra-aortic arteries: a comparison between single-source and dual-source CT scanners *J. Neuroradiol.* **45** 136–41
[73] Wu J, Pan J, Teng D, Xu X, Feng J and Chen Y -C 2020 Interpretation of CT signs of 2019 novel coronavirus (COVID-19) pneumonia *Eur. Radiol.* **30** 5455–62
[74] De Wever W, Meersschaert J, Coolen J, Verbeken E and Verschakelen J A 2011 The crazy-paving pattern: a radiological-pathological correlation *Insights into Imaging* **2** 117–32
[75] Niu R, Ye S, Li Y, Ma H, Xie X, Hu S, Huang X, Ou Y and Chen J 2021 Chest CT features associated with the clinical characteristics of patients with COVID-19 pneumonia *Ann. Med.* **53** 169–80
[76] Salehi S, Abedi A, Balakrishnan S and Gholamrezanezhad A 2020 Coronavirus disease 2019 (COVID-19): a systematic review of imaging findings in 919 patients *AJR Am. J. Roentgenol* **215** 87–93
[77] Xie X, Zhong Z, Zhao W, Zheng C, Wang F and Liu J 2020 Chest CT for typical coronavirus disease 2019 (COVID-19) pneumonia: relationship to negative RT-PCR testing *Radiology* **296** E41–5
[78] Gozes O, Frid-Adar M, Greenspan H, Browning P D, Zhang H, Ji W, Bernheim A and Siegel E 2020 Rapid AI development cycle for the coronavirus (Covid-19) pandemic: initial results for automated detection and patient monitoring using deep learning CT image analysis Arxiv Preprint arXiv:2003.05037
[79] Shalbaf A and Vafaeezadeh M 2021 Automated detection of COVID-19 using ensemble of transfer learning with deep convolutional neural network based on CT scans *Int. J. Comput. Assist. Radiol. Surg.* **16** 115–23
[80] Yang X, He X, Zhao J, Zhang Y, Zhang S and Xie P 2020 COVID-CT-dataset: a CT Scan Dataset about COVID-19 arXiv Preprint arXiv:2003.13865
[81] Cau R *et al* 2021 Computed tomography findings of COVID-19 pneumonia in intensive care unit-patients *J. Public Health Res.* **10**
[82] Yang X, He X, Zhao J, Zhang Y, Zhang S and Xie P 2020 COVID-CT-dataset: a CT Scan Dataset about COVID-19 arXiv Preprint arXiv:2003.13865
[83] Setio A A A, Traverso A, De Bel T, Berens M S, Van Den Bogaard C, Cerello P, Chen H, Dou Q, Fantacci M E and Geurts B 2017 Validation, comparison, and combination of

algorithms for automatic detection of pulmonary nodules in computed tomography images: the LUNA16 challenge *Med. Image Anal.* **42** 1–13

[84] Kogilavani S, Prabhu J, Sandhiya R, Kumar M S, Subramaniam U, Karthick A, Muhibbullah M and Imam S B S 2022 COVID-19 detection based on lung ct scan using deep learning techniques *Comput. Math. Methods Med.* **2022** 7672196

[85] Simonyan K and Zisserman A 2014 very deep convolutional networks for large-scale image recognition arXiv preprint arXiv:

[86] Iandola F, Moskewicz M, Karayev S, Girshick R, Darrell T and Keutzer K 2014 Densenet: implementing efficient convnet descriptor pyramids arXiv Preprint arXiv:1404.1869

[87] Howard A G, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, Andreetto M and Adam H 2017 Mobilenets, efficient convolutional neural networks for mobile vision applications arXiv Preprint arXiv:1704.04861

[88] Chollet F 2017 Xception: deep learning with depthwise separable convolutions *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition* pp 1251–8

[89] Zoph B, Vasudevan V, Shlens J and Le Q V 2018 Learning transferable architectures for scalable image recognition *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition* pp 8697–710

[90] Tan M and Le Q 2019 Efficientnet: rethinking model scaling for convolutional neural networks *Int. Conf. on Machine Learning, PMLR* pp 6105–14

[91] Paluru N, Dayal A, Jenssen H B, Sakinis T, Cenkeramaddi L R, Prakash J, Yalavarthy P K and Systems L 2021 Anam-Net: anamorphic depth embedding-based lightweight CNN for segmentation of anomalies in COVID-19 chest CT images *IEEE Transact. Neural Networks Learn. Syst.* **32** 932–46 3rd ed

[92] COVID-19 database, 10 February 2022, 2022 (https://radiopaedia.org/articles/covid-19-4?lang=gb)

[93] Paszke A, Chaurasia A, Kim S and Culurciello E 2016 Enet: a deep neural network architecture for real-time semantic segmentation arXiv preprint arXiv: 1606.02147

[94] Zhou Z, Siddiquee M M R, Tajbakhsh N and Liang J 2020 UNet++: redesigning skip connections to exploit multiscale features in image segmentation *IEEE Trans. Med. Imaging* **39** 1856–67

[95] Wang Y, Zhou Q, Liu J, Xiong J, Gao G, Wu X and Latecki L J 2019 Lednet: a lightweight encoder-decoder network for real-time semantic segmentation *2019 IEEE Int. Conf. on Image Processing (ICIP)* (Piscataway, NJ: IEEE) pp 1860–4

[96] Cai W, Liu T, Xue X, Luo G, Wang X, Shen Y, Fang Q, Sheng J, Chen F and Liang T 2020 CT quantification and machine-learning models for assessment of disease severity and prognosis of COVID-19 patients *Acad. Radiol.* **27** 1665–78

[97] Saood A and Hatem I 2021 COVID-19 lung CT image segmentation using deep learning methods: U-Net versus SegNet *BMC Med. Imaging* **21** 1–10

[98] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Sharma A, Cuadrado- Godia E, Laird J R, Nicolaides A and Suri J S 2019 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 543–64

[99] Badrinarayanan V, Kendall A and Cipolla R 2017 SegNet: a deep convolutional encoder-decoder architecture for image segmentation *IEEE Trans. Pattern Anal. Mach. Intell.* **39** 2481–95

[100] Fleetwood K 2004 An introduction to differential evolution *Proc. of Mathematics and Statistics of Complex Systems (MASCOS) One Day Symp.* pp 785–91 *(Brisbane, Australia)*

[101] Price K V 2013 *Differential Evolution, Handbook of Optimization* (Berlin: Springer) pp 187–214

[102] Singh D, Kumar V and Kaur M 2020 Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks *Eur. J. Clin. Microbiol. Infect Dis.* **39** 1379–89

[103] Bas¸türk A and Günay E 2009 Efficient edge detection in digital images using a cellular neural network optimized by differential evolution algorithm *Expert Syst. Appl.* **36** 2645–50

[104] Ruse M 1975 Charles Darwin's theory of evolution: an analysis *J. Hist. Biol.* **8** 219–41

[105] Kozek T, Roska T and Chua L O 1993 Genetic algorithm for CNN template learning *IEEE Trans. Circuits Syst.* I **40** 392–402

[106] Sun Y, Xue B, Zhang M, Yen G G and Lv J 2020 Automatically designing CNN architectures using the genetic algorithm for image classification *IEEE Trans. Cybern.* **50** 3840–54

[107] Kennedy J and Eberhart R 1995 Particle swarm optimization *Proc. of ICNN'95-Int. Conf. on Neural Networks* (Piscataway, NJ: IEEE) pp 1942–8

[108] Navaneeth B and Suchetha M 2019 PSO optimized 1-D CNN-SVM architecture for real-time detection and classification applications *Comput. Biol. Med.* **108** 85–92

[109] Wang Y, Zhang H and Zhang G 2019 cPSO-CNN, An efficient PSO-based algorithm for fine-tuning hyper-parameters of convolutional neural networks *Swarm. Evol. Comput.* **49** 114–23

[110] Mirjalili S and Lewis A 2016 The whale optimization algorithm *Adv. Eng. Software* **95** 51–67

[111] Dixit U, Mishra A, Shukla A and Tiwari R 2019 Texture classification using convolutional neural network optimized with whale optimization algorithm *SN Appl. Sci.* **1** 1–11

[112] Rana N, Latiff M S A, Abdulhamid S I M and Chiroma H 2020 Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments *Neural Comput. Appl.* **32** 16245–77

[113] Yuan T, Liu W, Han J and Lombardi F 2020 High performance CNN accelerators based on hardware and algorithm co-optimization *IEEE Trans. Circuits Syst.* I **68** 250–63

[114] Zhang J, Raj P, Zarar S, Ambardekar A and Garg S 2019 CompAct: on-chip com pression of act ivations for low power systolic array based CNN acceleration *ACM Trans. Embed. Comput. Syst. (TECS)* **18** 1–24

[115] Saba L, Banchhor S K, Londhe N D, Araki T, Laird J R, Gupta A, Nicolaides A and Suri J S 2017 Web-based accurate measurements of carotid lumen diameter and stenosis severity: an ultrasound-based clinical tool for stroke risk assessment during multicenter clinical trials *Comput. Biol. Med.* **91** 306–17

[116] Saba L, Than J C, Noor N M, Rijal O M, Kassim R M, Yunus A, Ng C R and Suri J S 2016 Inter-observer variability analysis of automatic lung delineation in normal and disease patients *J. Med. Syst.* **40** 142

[117] Molinari F, Meiburger K M, Saba L, Acharya U R, Famiglietti L, Georgiou N, Nicolaides A, Mamidi R S, Kuper H and Suri J S 2014 Automated carotid IMT measurement and its validation in low contrast ultrasound database of 885 patient indian population epidemiological study: results of atheroedge® software *Multi-Modality Atherosclerosis Imaging and Diagnosis* (Berlin: Springer) pp 209–19

[118] Mirmehdi M 2008 *Handbook of Texture Analysis* (Imperial College Press)
[119] He G, Ping A, Wang X and Zhu Y 2019 Alzheimer's disease diagnosis model based on three-dimensional full convolutional DenseNet *2019 10th Int. Conf. on Information Technology in Medicine and Education (ITME)* (Piscataway, NJ: IEEE) pp 13–7
[120] Ouhami M, Es-Saady Y, Hajji M E, Hafiane A, Canals R and Yassa M E 2020 Deep Transfer learning models for tomato disease detection *Int. Conf. on Image and Signal Processing (Berlin)* (Springer) pp 65–73
[121] Ruiz J, Mahmud M, Modasshir M, Shamim Kaiser M and Alzheimer's Disease Neuroimaging Initiative 2020 3D densenet ensemble in 4-way classification of Alzheimer's disease *Int. Conf. on Brain Informatics* (Berlin: Springer) 85–96
[122] Saba L, Sanagala S S, Gupta S K, Koppula V K, Laird J R, Viswanathan V, Sanches M J, Kitas G D, Johri A M and Sharma N 2021 A multicenter study on carotid ultrasound plaque tissue characterization and classification using six deep artificial intelligence models: a stroke application *IEEE Trans. Instrum. Meas.* **70** 1–12
[123] Jain P K, Sharma N, Saba L, Paraskevas K I, Kalra M K, Johri A, Laird J R, Nicolaides A N and Suri J S 2021 Unseen artificial intelligence—deep learning paradigm for segmentation of low atherosclerotic plaque in carotid ultrasound: a multicenter cardiovascular study *Diagnostics* **11** 2257
[124] El-Baz A and Suri J S 2019 *Big Data in Multimodal Medical Imaging* (Boca Raton, FL: CRC Press)
[125] Sudeep P, Palanisamy P, Rajan J, Baradaran H, Saba L, Gupta A and Suri J S 2016 Speckle reduction in medical ultrasound images using an unbiased non-local means method *Biomed. Signal Process. Control* **28** 1–8
[126] Suri J S, Liu K, Singh S, Laxminarayan S N, Zeng X and Reden L 2002 Shape recovery algorithms using level sets in 2-D/3-D medical imagery: a state-of-the-art review *IEEE Trans. Inf. Technol. Biomed.* **6** 8–28
[127] Suri J S *et al* 2021 Systematic review of artificial intelligence in acute respiratory distress syndrome for COVID-19 lung patients: a biomedical imaging perspective *IEEE J. Biomed. Health Inform.* **25** 4128–39
[128] Paul S, Maindarkar M, Saxena S, Saba L, Turk M, Kalra M, Krishnan P R and Suri J S 2022 Bias investigation in artificial intelligence systems for early detection of Parkinson's disease: a narrative review *Diagnostics* **12** 166
[129] Suri J S, Bhagawati M, Paul S, Protogeron A, Sfikakis P P, Kitas G D, Khanna N N, Ruzsa Z, Sharma A M and Saxena S 2022 Understanding the bias in machine learning systems for cardiovascular disease risk assessment: the first of its kind review *Comput. Biol. Med.* **142** 105204
[130] Agarwal M, Agarwal S, Saba L, Chabert G L, Gupta S, Carriero A and Suri J S 2022 Eight pruning deep learning models for low storage and high-speed COVID-19 computed tomography lung segmentation and heatmap-based lesion localization: a multicenter study using COVLIAS 2.0 *Comput. Biol. Med.* **146** 105571

Chapter 4

[1] Agarwal M, Saba L, Gupta S K, Johri A M, Khanna N N, Mavrogeni S, Laird J R, Pareek G, Miner M and Sfikakis P P 2021 Wilson disease tissue classification and characterization using seven artificial intelligence models embedded with 3D optimization paradigm on a weak training brain magnetic resonance imaging datasets: a supercomputer application *Med. Biol. Eng. Comput.* **59** 511–33

[2] Cau R, Pacielli A, Fatemeh H, Vaudano P, Arru C, Crivelli P, Stranieri G, Suri J S, Mannelli L and Conti M *et al* 2021 Complications in COVID-19 patients: characteristics of pulmonary embolism *Clin. Imaging* **77** 244–9
[3] Saba L, Gerosa C, Fanni D, Marongiu F, La Nasa G, Caocci G, Barcellona D, Balestrieri A, Coghe F and Orru G *et al* 2020 Molecular pathways triggered by COVID-19 in different organs: ACE2 receptor-expressing cells under attack? A review *Eur. Rev. Med. Pharmacol. Sci.* **24** 12609–22
[4] Cau R, Bassareo P P, Mannelli L, Suri J S and Saba L 2021 Imaging in COVID-19-related myocardial injury *Int. J. Cardiovasc. Imaging* **37** 1349–60
[5] Viswanathan V, Viswanathan V, Puvvula A, Jamthikar A D, Saba L, Johri A M, Kotsis V, Khanna N N, Dhanjil S K and Majhail M *et al* 2021 Bidirectional link between diabetes mellitus and coronavirus disease 2019 leading to cardiovascular disease: a narrative review *World J. Diabetes* **12** 215–37
[6] Suri J S, Agarwal S, Gupta S K, Puvvula A, Biswas M, Saba L, Bit A, Tandel G S, Agarwal M and Patrick A *et al* 2021 A narrative review on characterization of acute respiratory distress syndrome in COVID-19-infected lungs using artificial intelligence *Comput. Biol. Med.* **130** 104210
[7] Cau R, Falaschi Z, Paschè A, Danna P, Arioli R, Arru C D, Zagaria D, Tricca S, Suri J S and Karla M K *et al* 2021 Computed tomography findings of COVID-19 pneumonia in Intensive Care Unit-patients *J. Public Health Res.* **10** 2270
[8] Emery S L, Erdman D D, Bowen M D, Newton B R, Winchell J M, Meyer R F, Tong S, Cook B T, Holloway B P and McCaustland K A *et al* 2004 Real-time reverse transcription–polymerase chain reaction assay for SARS-associated coronavirus *Emerg. Infect. Dis.* **10** 311–6
[9] Wu X, Hui H, Niu M, Li L, Wang L, He B, Yang X, Li L, Li H and Tian J *et al* 2020 Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: a multicentre study *Eur. J. Radiol.* **128** 109041
[10] Pathak Y, Shukla P K, Tiwari A, Stalin S and Singh S 2020 Deep transfer learning based classification model for COVID-19 disease *IRBM* **43** 87–92
[11] Saba L and Suri J S 2013 *Multi-Detector CT Imaging: Principles, Head, Neck, and Vascular Systems* vol 1 (Boca Raton, FL: CRC Press)
[12] Gozes O, Frid-Adar M, Greenspan H, Browning P D, Zhang H, Ji W, Bernheim A and Siegel E 2020 Rapid ai development cycle for the coronavirus (COVID-19) pandemic: initial results for automated detection & patient monitoring using deep learning ct image analysis *arXiv* arXiv:05037
[13] Shalbaf A and Vafaeezadeh M 2021 Automated detection of COVID-19 using ensemble of transfer learning with deep convolutional neural network based on CT scans *Int. J. Comput. Assist. Radiol. Surg.* **16** 115–23
[14] Yang X, He X, Zhao J, Zhang Y, Zhang S and Xie P 2020 COVID-CT-dataset: a CT scan dataset about COVID-19 *arXiv* arXiv:13865
[15] Alqudah A M, Qazan S, Alquran H, Qasmieh I A and Alqudah A 2020 COVID-2019 Detection using X-ray images and artificial intelligence hybrid systems *Phys. Sci.* **2** 1
[16] Aslan M F, Unlersen M F, Sabanci K and Durdu A 2021 CNN-based transfer learning–BiLSTM network: a novel approach for COVID-19 infection detection *Appl. Soft Comput.* **98** 10691

[17] Wu Y H, Gao S H, Mei J, Xu J, Fan D P, Zhang R G and Cheng M M 2021 Jcs: an explainable COVID-19 diagnosis system by joint classification and segmentation *IEEE Trans. Image Process.* **30** 3113–26

[18] Xu X, Jiang X, Ma C, Du P, Li X, Lv S, Yu L, Ni Q, Chen Y and Su J *et al* 2020 A deep learning system to screen novel coronavirus disease 2019 pneumonia *Engineering* **6** 1122–9

[19] El-Baz A and Suri J 2021 *Machine Learning in Medicine* (Boca Raton, FL: CRC Press)

[20] Suri J S and Rangayyan R M 2006 *Recent Advances in Breast Imaging, Mammography, and Computer-Aided Diagnosis of Breast Cancer* (Bellingham, WA: SPIE Publications)

[21] Biswas M, Kuppili V, Edla D R, Suri H S, Saba L, Marinhoe R T, Sanches J M and Suri J S 2018 Symtosis: a liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm *Comput. Methods Programs Biomed.* **155** 165–77

[22] Acharya U R, Sree S V, Ribeiro R, Krishnamurthi G, Marinho R T, Sanches J and Suri J S 2012 Data mining framework for fatty liver disease classification in ultrasound: a hybrid feature extraction paradigm *Med. Phys.* **39** 4255–64

[23] Acharya U R, Sree S V, Krishnan M M R, Molinari F, Garberoglio R and Suri J S 2012 Non-invasive automated 3D thyroid lesion classification in ultrasound: a class of ThyroScan™ systems *Ultrasonics* **52** 508–20

[24] Acharya U R, Swapna G, Sree S V, Molinari F, Gupta S, Bardales R H, Witkowska A and Suri J S 2014 A review on ultrasound based thyroid cancer tissue characterization and automated classification *Technol. Cancer Res. Treat.* **13** 289–301

[25] Molinari F, Mantovani A, Deandrea M, Limone P, Garberoglio R and Suri J S 2010 Characterization of single thyroid nodules by contrast-enhanced 3-D ultrasound *Ultrasound Med. Biol.* **36** 1616–25

[26] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2016 Computer-aided diagnosis of psoriasis skin images with HOS, texture and color features: a first comparative study of its kind *Comput. Methods Programs Biomed.* **126** 98–109

[27] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2015 Reliable and accurate psoriasis disease classification in dermatology images using comprehensive feature space in machine learning paradigm *Expert Syst. Appl.* **42** 6184–95

[28] Pareek G, Acharya U R, Sree S V, Swapna G, Yantri R, Martis R J, Saba L, Krishnamurthi G, Mallarini G and El-Baz A *et al* 2013 Prostate tissue characterization/classification in 144 patient population using wavelet and higher order spectra features from transrectal ultrasound images *Technol. Cancer Res. Treat.* **12** 545–57

[29] McClure P, Elnakib A, El-Ghar M A, Khalifa F, Soliman A, El-Diasty T, Suri J S, Elmaghraby A and El-Baz A 2014 In-vitro and in-vivo diagnostic techniques for prostate cancer: a review *J. Biomed. Nanotechnol.* **10** 2747–77

[30] Mookiah M R K, Acharya U R, Martis R J, Chua C K, Lim C M, Ng E Y K and Laude A 2013 Evolutionary algorithm based classifier parameter tuning for automatic diabetic retinopathy grading: a hybrid feature extraction approach *Knowl.-Based Syst.* **39** 9–22

[31] Than J C, Saba L, Noor N M, Rijal O M, Kassim R M, Yunus A, Suri H S, Porcu M and Suri J S 2017 Lung disease stratification using amalgamation of Riesz and Gabor transforms in machine learning framework *Comput. Biol. Med.* **89** 197–211

[32] El-Baz A, Jiang X and Suri J S 2016 *Biomedical Image Segmentation: Advances and Trends* (Boca Raton, FL: CRC Press)

[33] Than J C, Saba L, Noor N M, Rijal O M, Kassim R M, Yunus A, Suri H S, Porcu M and Suri J S 2002 Shape recovery algorithms using level sets in 2-D/3-D medical imagery: a state-of-the-art review *IEEE Trans. Inf. Technol. Biomed.* **6** 8–28
[34] El-Baz A S, Acharya R, Mirmehdi M and Suri J S 2011 *Multi Modality State-of-the-Art Medical Image Segmentation and Registration Methodologies* vol 2 (Berlin: Springer Science & Business Media)
[35] El-Baz A and Suri J S 2019 *Level Set Method in Medical Imaging Segmentation* (Boca Raton, FL: CRC Press)
[36] Saba L *et al* 2021 Multimodality carotid plaque tissue characterization and classification in the artificial intelligence paradigm: a narrative review for stroke application *Ann. Transl. Med.* **9** 1206
[37] Acharya U R, Sree S V, Krishnan M M R, Krishnananda N, Ranjan S, Umesh P and Suri J S 2013 Automated classification of patients with coronary artery disease using grayscale features from left ventricle echocardiographic images *Comput. Methods Programs Biomed.* **112** 624–32
[38] Agarwal M, Saba L, Gupta S K, Carriero A, Falaschi Z, Paschè A, Danna P, El-Baz A, Naidu S and Suri J S 2021 A novel block imaging technique using nine artificial intelligence models for COVID-19 disease classification, characterization and severity measurement in lung computed tomography scans on an Italian cohort *J. Med. Syst.* **45** 1–30
[39] Saba L, Agarwal M, Patrick A, Puvvula A, Gupta S K, Carriero A, Laird J R, Kitas G D, Johri A M and Balestrieri A *et al* 2021 Six artificial intelligence paradigms for tissue characterisation and classification of non-COVID-19 pneumonia against COVID-19 pneumonia in computed tomography lungs *Int. J. Comput. Assist. Radiol. Surg.* **16** 423–34
[40] Skandha S S, Gupta S K, Saba L, Koppula V K, Johri A M, Khanna N N, Mavrogeni S, Laird J R, Pareek G and Miner M *et al* 2020 3-D optimized classification and characterization artificial intelligence paradigm for cardiovascular/stroke risk stratificationusing carotid ultrasound-based delineated plaque: Atheromatic™ 2.0 *Comput. Biol. Med.* **125** 103958
[41] Tandel G S, Balestrieri A, Jujaray T, Khanna N N, Saba L and Suri J S 2020 Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm *Comput. Biol. Med.* **122** 103804
[42] Sarker M M K, Makhlouf Y, Banu S F, Chambon S, Radeva P and Puig D 2020 Web-based efficient dual attention networks to detect COVID-19 from x-ray images *Electron. Lett.* **56** 1298–301
[43] Sarker M M K, Makhlouf Y, Craig S G, Humphries M P, Loughrey M, James J A, Salto-Tellez M, O'Reilly P and Maxwell P 2021 A means of assessing deep learning-based detection of ICOS protein expression in colon cancer *Cancers* **13** 3825
[44] Jain P K, Sharma N, Giannopoulos A A, Saba L, Nicolaides A and Suri J S 2021 Hybrid deep learning segmentation models for atherosclerotic plaque in internal carotid artery B-mode ultrasound *Comput. Biol. Med.* **136** 104721
[45] Jena B, Saxena S, Nayak G K, Saba L, Sharma N and Suri J S 2021 Artificial intelligence-based hybrid deep learning models for image classification: the first narrative review *Comput. Biol. Med.* **137** 104803
[46] Suri J, Agarwal S, Gupta S K, Puvvula A, Viskovic K, Suri N, Alizad A, El-Baz A, Saba L and Fatemi M *et al* 2021 Systematic review of artificial intelligence in acute respiratory distress syndrome for COVID-19 lung patients: a biomedical imaging perspective *IEEE J. Biomed. Health Inform* **25** 4128–39

[47] Saba L, Banchhor S K, Araki T, Viskovic K, Londhe N D, Laird J R, Suri H S and Suri J S 2018 Intra- and inter-operator reproducibility of automated cloud-based carotid lumen diameter ultrasound measurement *Indian Heart J.* **70** 649–64

[48] Saba L, Than J C, Noor N M, Rijal O M, Kassim R M, Yunus A, Ng C R and Suri J S 2016 Inter-observer variability analysis of automatic lung delineation in normal and disease patients *J. Med. Syst.* **40** 142

[49] Zhang S, Suri J S, Salvado O, Chen Y, Wacker F K, Wilson D L, Duerk J L and Lewin J S 2005 Inter-and intra-observer variability assessment of *in vivo* carotid plaque burden quantification using multi-contrast dark blood MR images *Stud. Health Technol.Inform.* **113** 384–93

[50] Aggarwal D and Saini V 2020 Factors limiting the utility of bronchoalveolar lavage in the diagnosis of COVID-19 *Eur. Respir. J.* **56** 2003116

[51] Saba L, Banchhor S K, Suri H S, Londhe N D, Araki T, Ikeda N, Viskovic K, Shafique S, Laird J R and Gupta A *et al* 2016 Accurate cloud-based smart IMT measurement, its validation and stroke risk stratification in carotid ultrasound: a web-based point-of-care tool for multicenter clinical trial *Comput. Biol. Med.* **75** 217–34

[52] Zhao H, Shi J, Qi X, Wang X and Jia J 2017 Pyramid scene parsing network *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition (Honolulu, HI, USA, 21–26 July 2017)* pp 2881–90

[53] Simonyan K and Zisserman A 2014 Very deep convolutional networks for large-scale image recognition *arXiv* arXiv:1409.1556

[54] Suri J S, Agarwal S, Pathak R, Ketireddy V, Columbu M, Saba L, Gupta S K, Faa G, Singh I M and Turk M *et al* 2021 COVLIAS 1.0: lung segmentation in COVID-19 computed tomography scans using hybrid deep learning artificial intelligence models *Diagnostics* **11** 1405

[55] He K, Zhang X, Ren S and Sun J 2016 Deep residual learning for image recognition *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition (Las Vegas, NV, 27–30 June 2016)* (Piscataway, NJ: IEEE) pp 770–8

[56] Acharya U R, Faust O, Sree S V, Molinari F, Saba L, Nicolaides A and Suri J S 2012 An accurate and generalized approach to plaque characterization in 346 carotid ultrasound scans *IEEE Trans. Instrum. Meas.* **61** 1045–53

[57] Acharya U R, Saba L, Molinari F, Guerriero S and Suri J S 2012 Ovarian tumor characterization and classification: a class of GyneScan™ systems *Proc. of the 2012 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (San Diego, CA, 28 August–1 September 2012)* (Piscataway, NJ: IEEE)

[58] Araki T, Ikeda N, Dey N, Acharjee S, Molinari F, Saba L, Godia E C, Nicolaides A and Suri J S 2015 Shape-based approach for coronary calcium lesion volume measurement on intravascular ultrasound imaging and its association with carotid intima-media thickness *J. Ultrasound Med.* **34** 469–82

[59] Barqawi A B, Li L, Crawford E D, Fenster A, Werahera P N, Kumar D, Miller S and Suri J S 2007 Three different strategies for real-time prostate capsule volume computation from 3-D end-fire transrectal ultrasound *Proc. of the 2007 29th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (Lyon, France, 22–26 August 2007)* (Piscataway, NJ: IEEE)

[60] Suri J S, Haralick R M and Sheehan F H 1997 Left ventricle longitudinal axis fitting and its apex estimation using a robust algorithm and its performance: a parametric apex model

Proc. of the Int. Conf. on Image Processing (Santa Barbara, CA, 14–17 July 1997) (Piscataway, NJ: IEEE)

[61] Singh B K, Verma K, Thoke A S and Suri J S 2017 Risk stratification of 2D ultrasound-based breast lesions using hybrid feature selection in machine learning paradigm *Measurement* **105** 146–57

[62] Riffenburgh R H and Gillen D L 2020 Contents *Statistics in Medicine* (Cambridge, MA: Academic) pp ix–xvi

[63] Acharya R U, Faust O, Alvin A P C, Sree S V, Molinari F, Saba L, Nicolaides A and Suri J S 2012 Symptomatic vs. asymptomatic plaque classification in carotid ultrasound *J. Med. Syst.* **36** 1861–71

[64] Acharya U R, Vinitha Sree S, Mookiah M R K, Yantri R, Molinari F, Ziele´znik W, Małyszek-Tumidajewicz J, St˛epie ´ n B, Bardales R H and Witkowska A *et al* 2013 Diagnosis of Hashimoto's thyroiditis in ultrasound using tissue characterization and pixel classification *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **227** 788–98

[65] Acharya U R, Faust O, Alvin A P C, Krishnamurthi G, Seabra J C, Sanches J and Suri J S 2013 Understanding symptomatology of atherosclerotic plaque by image-based tissue characterization *Comput. Methods Programs Biomed.* **110** 66–75

[66] Acharya U R, Faust O, Sree S V, Alvin A P C, Krishnamurthi G, Sanches J and Suri J S 2011 Atheromatic™: symptomatic vs. asymptomatic classification of carotid ultrasound plaque using a combination of HOS, DWT & texture *Proc. of the 2011 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (Boston, MA, 3 August–3 September 2011)* (Piscataway, NJ: IEEE)

[67] Acharya U R, Mookiah M R K, Sree S V, Afonso D, Sanches J, Shafique S, Nicolaides A, Pedro L M, Fernandes J F E and Suri J S 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23

[68] Molinari F, Liboni W, Pavanelli E, Giustetto P, Badalamenti S and Suri J S 2007 Accurate and automatic carotid plaque characterization in contrast enhanced 2-D ultrasound images *Proc. of the 29th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (Lyon, France, 22–26 August 2007)* (Piscataway, NJ: IEEE)

[69] Saba L, Biswas M, Suri H S, Viskovic K, Laird J R, Cuadrado-Godia E, Nicolaides A, Khanna N N, Viswanathan V and Suri J S 2019 Ultrasound-based carotid stenosis measurement and risk stratification in diabetic cohort: a deep learning paradigm *Cardiovasc. Diagn. Ther.* **9** 439–61

[70] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Sharma A, Cuadrado-Godia E, Laird J R, Nicolaides A and Suri J S 2019 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 543–64

[71] Chaddad A, Hassan L and Desrosiers C 2021 Deep CNN models for predicting COVID-19 in CT and x-ray images *J. Med. Imaging* **8** 014502

[72] Gunraj H, Wang L and Wong A 2020 COVIDNet-CT: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest CT images *Front. Med.* **7** 608525

[73] Iyer T J, Raj A N J, Ghildiyal S and Nersisson R 2021 Performance analysis of lightweight CNN models to segment infectious lung tissues of COVID-19 cases from tomographic images *PeerJ Comput. Sci.* **7** e368

[74] Ranjbarzadeh R, Jafarzadeh Ghoushchi S, Bendechache M, Amirabadi A, Ab Rahman M N, Baseri Saadi S, Aghamohammadi A and Kooshki Forooshani M 2021 Lung infection segmentation for COVID-19 pneumonia based on a cascade convolutional network from CT images *BioMed Res. Int.* **2021** 5544742
[75] Erasmus J J, Gladish G W, Broemeling L, Sabloff B S, Truong M T, Herbst R S and Munden R F 2003 Interobserver and intraobserver variability in measurement of non–small-cell carcinoma lung lesions: implications for assessment of tumor response *J. Clin. Oncol.* **21** 2574–82
[76] Joskowicz L, Cohen D, Caplan N and Sosna J 2019 Inter-observer variability of manual contour delineation of structures in CT *Eur. Radiol.* **29** 1391–9
[77] El-Baz A and Suri J 2019 *Lung Imaging and CADx* (Boca Raton, FL: CRC Press)
[78] El-Baz A and Suri J S 2011 *Lung Imaging and Computer Aided Diagnosis* (Boca Raton, FL: CRC Press)
[79] Sudeep P V, Palanisamy P, Rajan J, Baradaran H, Saba L, Gupta A and Suri J S 2016 Speckle reduction in medical ultrasound images using an unbiased non-local means method *Biomed. Signal Process. Control* **28** 1–8
[80] Sarker M M K, Rashwan H A, Akram F, Singh V K, Banu S F, Chowdhury F U, Choudhury K A, Chambon S, Radeva P and Puig D *et al* 2021 SLSNet: skin lesion segmentation using a lightweight generative adversarial network *Expert Syst. Appl.* **183** 115433
[81] Saba L, Agarwal M, Sanagala S S, Gupta S K, Sinha G R, Johri A M, Khanna N N, Mavrogeni S, Laird J R and Pareek G *et al* 2020 Brain MRI-based Wilson disease tissue classification: an optimised deep transfer learning approach *Electron. Lett.* **56** 1395–8
[82] El-Baz A and Suri J S 2019 *Big Data in Multimodal Medical Imaging* (Boca Raton, FL: CRC Press)

Chapter 5

[1] Chakaya J *et al* 2022 The WHO global tuberculosis 2021 report—not so good news and turning the tide back to End TB *Int. J. Infect. Dis.* **124** S26–9
[2] Corbett E L *et al* 2003 The growing burden of tuberculosis: global trends and interactions with the HIV epidemic *Arch. Intern. Med.* **163** 1009
[3] LeCun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436–44
[4] Saba L *et al* 2019 The present and future of deep learning in radiology *Eur. J. Radiol.* **114** 14–24
[5] Tandel G S *et al* 2019 A review on a deep learning perspective in brain cancer classification *Cancers* **11** 111
[6] Albawi S, Mohammed T A and Al-Zawi S 2017 Understanding of a convolutional neural network *2017 Int. Conf. on Engineering and Technology (ICET) (Antalya)* (IEEE) pp 1–6
[7] Suri J S 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci.* **24** 392–426
[8] Ronneberger O, Fischer P and Brox T 2015 U-Net: convolutional networks for biomedical image segmentation arXiv:1505.04597 (accessed 20 May 2023)
[9] Biswas M *et al* 2018 Deep learning strategy for accurate carotid intima-media thickness measurement: an ultrasound study on Japanese diabetic cohort *Comput. Biol. Med.* **98** 100–17

[10] Saba L *et al* 2019 Ultrasound-based carotid stenosis measurement and risk stratification in diabetic cohort: a deep learning paradigm *Cardiovasc. Diagn. Ther.* **9** 439–61
[11] Fu X and Qu H 2018 Research on semantic segmentation of high-resolution remote sensing image based on full convolutional neural network *2018 12th Int. Symp. on Antennas, Propagation and EM Theory (ISAPE) (Hangzhou, China)* (IEEE) pp 1–4
[12] Zhou Z, Siddiquee M M R, Tajbakhsh N and Liang J 2018 U-Net++: a nested U-Net architecture for medical image segmentation arXiv:1807.10165
[13] Stirenko S *et al* 2018 Chest x-ray analysis of tuberculosis by deep learning with segmentation and augmentation *2018 IEEE 38th Int. Conf. on Electronics and Nanotechnology (ELNANO) (Kiev)* (IEEE) pp 422–8
[14] Yang F *et al* 2022 Annotations of lung abnormalities in the shenzhen chest x-ray dataset for computer-aided screening of pulmonary diseases *Data* **7** 95
[15] Bahdanau D, Cho K and Bengio Y 2016 Neural machine translation by jointly learning to align and translate arXiv:1409.0473 (accessed 20 May 2023)

Chapter 6

[1] Benjamin E J, Muntner P, Alonso A, Bittencourt M S, Callaway C W, Carson A P, Chamberlain A M, Chang A R, Cheng S and Das S R 2019 Heart disease and stroke Statistics-2019 update a report from the American heart association *Circulation* **139** e56–528
[2] Mozaffarian D, Benjamin E J, Go A S, Arnett D K, Blaha M J, Cushman M, De Ferranti S, Després J-P, Fullerton H J and Howard V J 2015 Executive summary: heart disease and stroke statistics—2015 update: a report from the American Heart Association *Circulation* **131** 434–41
[3] Mozaffarian D, Benjamin E J, Go A S, Arnett D K, Blaha M J, Cushman M, Das S R, De Ferranti S, Després J-P and Fullerton H J 2016 Executive summary: heart disease and stroke statistics—2016 update: a report from the American Heart Association *Circulation* **133** 447–54
[4] Suri J S, Kathuria C and Molinari F 2010 *Atherosclerosis Disease Management* (Springer Science & Business Media)
[5] Libby P, Ridker P M and Maseri A 2002 Inflammation and atherosclerosis *Circulation* **105** 1135–43
[6] Acharya U R, Joseph K P, Kannathal N, Lim C M and Suri J S 2006 Heart rate variability: a review *Med. Biol. Eng. Comput.* **44** 1031–51
[7] Greenstein A J, Chassin M R, Wang J, Rockman C B, Riles T S, Tuhrim S and Halm E A 2007 Association between minor and major surgical complications after carotid endarterectomy: results of the New York Carotid Artery Surgery study *J. Vasc. Surg.* **46** 1138–46
[8] Naylor A, Payne D, London N, Thompson M, Dennis M, Sayers R and Bell P 2002 Prosthetic patch infection after carotid endarterectomy *Eur. J. Vasc. Endovasc. Surg.* **23** 11–6
[9] Wolk M J, Allen J M and Raskin I E 2005 ACCF proposed method for evaluating the appropriateness of cardiovascular imaging *J. Am. Coll. Cardiol.* **46**
[10] Budoff M J, Achenbach S, Blumenthal R S, Carr J J, Goldin J G, Greenland P, Guerci A D, Lima J A, Rader D J and Rubin G D 2006 Assessment of coronary artery disease by cardiac computed tomography: a scientific statement from the American heart association committee on cardiovascular imaging and intervention, council on cardiovascular radiology and intervention, and committee on cardiac imaging, council on clinical cardiology *Circulation* **114** 1761–91

[11] Sanches J M, Laine A F and Suri J S 2012 *Ultrasound Imaging* (Berlin: Springer)
[12] Suri J S, Wilson D and Laxminarayan S 2005 *Handbook of Biomedical Image Analysis*vol 2 (Springer Science & Business Media)
[13] Preiss D and Kristensen S L 2015 The new pooled cohort equations risk calculator *Can. J. Cardiol.* **31** 613–9
[14] Lloyd-Jones D M, Wilson P W, Larson M G, Beiser A, Leip E P, D'Agostino R B and Levy D 2004 Framingham risk score and prediction of lifetime risk for coronary heart disease *The Am. J. Cardiol.* **94** 20–4
[15] Board J B S 2014 Joint British Societies' consensus recommendations for the prevention of cardiovascular disease (JBS3) *Heart* **100** ii1–ii67
[16] Tillin T, Hughes A D, Whincup P, Mayet J, Sattar N, McKeigue P M, Chaturvedi N and Group S S 2014 Ethnicity and prediction of cardiovascular disease: performance of QRISK2 and Framingham scores in a UK tri-ethnic prospective cohort study (SABRE—Southall And Brent REvisited) *Heart* **100** 60–7
[17] Ridker P M, Buring J E, Rifai N and Cook N R 2007 Development and validation of improved algorithms for the assessment of global cardiovascular risk in women: the Reynolds risk score *JAMA* **297** 611–9
[18] Stevens R J, Kothari V, Adler A I, Stratton I M and Holman R RGroup UKPDS 2001 The UKPDS risk engine: a model for the risk of coronary heart disease in Type II diabetes (UKPDS 56) *Clin. Sci.* **101** 671–9
[19] Kothari V, Stevens R J, Adler A I, Stratton I M, Manley S E, Neil H A and Holman R R 2002 UKPDS 60: risk of stroke in type 2 diabetes estimated by the UK Prospective Diabetes Study risk engine *Stroke* **33** 1776–81
[20] Khanna N N, Jamthikar A D, Gupta D, Piga M, Saba L, Carcassi C, Giannopoulos A A, Nicolaides A, Laird J R and Suri H S 2019 Rheumatoid arthritis: atherosclerosis imaging and cardiovascular risk assessment using machine and deep learning–based tissue characterization *Curr. Atheroscler. Rep.* **21** 7
[21] Viswanathan V, Jamthikar A D, Gupta D, Puvvula A, Khanna N N, Saba L, Viskovic K, Mavrogeni S, Turk M and Laird J R 2020 Integration of eGFR biomarker in image-based CV/stroke risk calculator: a south Asian-Indian diabetes cohort with moderate chronic kidney disease *Int. Angiol.* **39** 290–306
[22] Saba L, Sanches J M, Pedro L M and Suri J S 2014 *Multi-Modality Atherosclerosis Imaging and Diagnosis* (Berlin: Springer)
[23] Seabra J and Sanches J 2012 *Ultrasound Imaging: Advances and Applications* (New York: Springer)
[24] Suri J S and Laxminarayan S 2003 *Angiography and Plaque Imaging: Advanced Segmentation Techniques* (Boca Raton, FL: CRC Press)
[25] Molinari F, Meiburger K M, Acharya U R, Zeng G, Rodrigues P S, Saba L, Nicolaides A and Suri J S 2011 CARES 3.0: a two stage system combining feature-based recognition and edge-based segmentation for CIMT measurement on a multi-institutional ultrasound database of 300 images *2011 Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society* (Piscataway, NJ: IEEE) pp 5149–52
[26] Wendelhag I, Liang Q, Gustavsson T and Wikstrand J 1997 A new automated computerized analyzing system simplifies readings and reduces the variability in ultrasound measurement of intima-media thickness *Stroke* **28** 2195–200

[27] Cheng D-c, Schmidt-Trucksäss A, Cheng K-s and Burkhardt H 2002 Using snakes to detect the intimal and adventitial layers of the common carotid artery wall in sonographic images *Comput. Methods Programs Biomed.* **67** 27–37

[28] Kumar P K, Araki T, Rajan J, Saba L, Lavra F, Ikeda N, Sharma A M, Shafique S, Nicolaides A and Laird J R 2017 Accurate lumen diameter measurement in curved vessels in carotid ultrasound: an iterative scale-space and spatial transformation approach *Med. Biol. Eng. Comput.* **55** 1415–34

[29] Bishop C M 2006 *Pattern Recognition and Machine Learning* (Berlin: Springer)

[30] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S, Cuadrado-Godia E, Laird J R, Marinhoe R T, Sanches J M and Nicolaides A 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci. (Landmark edition)* **24** 392–426

[31] LeCun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436–44

[32] Sutton R S and Barto A G 2018 *Reinforcement Learning: An Introduction* (Cambridge, MA: MIT Press)

[33] Kaelbling L P, Littman M L and Moore A W 1996 Reinforcement learning: a survey *J. Artif. Intell. Res.* **4** 237–85

[34] Rosenblatt F 1958 The perceptron: a probabilistic model for information storage and organization in the brain *Psychol. Rev.* **65** 386

[35] Hart P 1968 The condensed nearest neighbor rule (Corresp.) *IEEE Trans. Inf. Theory* **14** 515–6

[36] Bayes T 1968 *Naive Bayes Classifier* Article Sources and Contributors 1–9

[37] Cortes C and Vapnik V 1995 Support-vector networks *Mach. Learn.* **20** 273–97

[38] Huang G-B, Wang D H and Lan Y 2011 Extreme learning machines: a survey *Int. J. Mach. Learn. Cybern.* **2** 107–22

[39] Kuppili V, Biswas M, Sreekumar A, Suri H S, Saba L, Edla D R, Marinhoe R T, Sanches J M and Suri J S 2017 Extreme learning machine framework for risk stratification of fatty liver disease using ultrasound tissue characterization *J. Med. Syst.* **41** 152

[40] Saba L, Biswas M, Kuppili V, Godia E C, Suri H S, Edla D R, Omerzu T, Laird J R, Khanna N N and Mavrogeni S 2019 The present and future of deep learning in radiology *Eur. J. Radiol.* **114** 14–24

[41] Coenen A, Kim Y-H, Kruk M, Tesche C, De Geer J, Kurata A, Lubbers M L, Daemen J, Itu L and Rapaka S 2018 Diagnostic accuracy of a machine-learning approach to coronary computed tomographic angiography-based fractional flow reserve: result from the MACHINE consortium *Circ: Cardiovasc. Imaging* **11** e007217

[42] Kissas G, Yang Y, Hwuang E, Witschey W R, Detre J A and Perdikaris P 2020 Machine learning in cardiovascular flows modeling: predicting arterial blood pressure from non-invasive 4D flow MRI data using physics-informed neural networks *Comput. Meth. Appl. Mech. Eng.* **358** 112623

[43] Kusunose K, Abe T, Haga A, Fukuda D, Yamada H, Harada M and Sata M 2020 A deep learning approach for assessment of regional wall motion abnormality from echocardiographic images *JACC: Cardiovascular Imaging* **13** 374–81

[44] Narula S, Shameer K, Omar A M S, Dudley J T and Sengupta P P 2016 Machine-learning algorithms to automate morphological and functional assessments in 2D echocardiography *J. Am. Coll. Cardiol.* **68** 2287–95

[45] Yuan B, Chitturi S R, Iyer G, Li N, Xu X, Zhan R, Llerena R, Yen J T and Bertozzi A L 2017 Machine learning for cardiac ultrasound time series data *Medical Imaging 2017:*

Biomedical Applications in Molecular, Structural, and Functional Imaging (International Society for Optics and Photonics) pp 101372D
[46] Ghorbani A, Ouyang D, Abid A, He B, Chen J H, Harrington R A, Liang D H, Ashley E A and Zou J Y 2020 Deep learning interpretation of echocardiograms *NPJ Digit. Med.* **3** 1–10
[47] Acharya R U, Faust O, Alvin A P C, Sree S V, Molinari F, Saba L, Nicolaides A and Suri J S 2012 Symptomatic vs. asymptomatic plaque classification in carotid ultrasound *J. Med. Syst.* **36** 1861–71
[48] Acharya U R, Faust O, Sree S V, Molinari F, Saba L, Nicolaides A and Suri J S 2011 An accurate and generalized approach to plaque characterization in 346 carotid ultrasound scans *IEEE Trans. Instrum. Meas.* **61** 1045–53
[49] Acharya U R, Mookiah M R K, Sree S V, Afonso D, Sanches J, Shafique S, Nicolaides A, Pedro L M, Fernandes J F and Suri J S 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23
[50] Lekadir K, Galimzianova A, Betriu À, del Mar Vila M, Igual L, Rubin D L, Fernández E, Radeva P and Napel S 2016 A convolutional neural network for automatic characterization of plaque composition in carotid ultrasound *IEEE J. Biomed. Health Inform* **21** 48–55
[51] Carneiro G and Nascimento J C 2013 Combining multiple dynamic models and deep learning architectures for tracking the left ventricle endocardium in ultrasound data *IEEE Trans. Pattern Anal. Mach. Intell.* **35** 2592–607
[52] Avendi M, Kheradvar A and Jafarkhani H 2016 A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI *Med. Image Anal.* **30** 108–19
[53] Romaguera L V, Costa M G F, Romero F P and Costa Filho C F F 2017 Left ventricle segmentation in cardiac MRI images using fully convolutional neural networks *Medical Imaging 2017: Computer-Aided Diagnosis* (International Society for Optics and Photonics) 101342Z
[54] Menchón-Lara R-M, Bastida-Jumilla M-C, Morales-Sánchez J and Sancho-Gómez J-L 2014 Automatic detection of the intima-media thickness in ultrasound images of the common carotid artery using neural networks *Med. Biol. Eng. Comput.* **52** 169–81
[55] Menchón-Lara R-M and Sancho-Gómez J-L 2014 Ultrasound image processing based on machine learning for the fully automatic evaluation of the Carotid Intima-Media Thickness *2014 12th Int. Workshop on Content-Based Multimedia Indexing (CBMI)* (Piscataway, NJ: IEEE) pp 1–4
[56] Molinari F, Zeng G and Suri J S 2010 Intima-media thickness: setting a standard for a completely automated method of ultrasound measurement *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **57** 1112–24
[57] Menchón-Lara R-M and Sancho-Gómez J-L 2015 Fully automatic segmentation of ultrasound common carotid artery images based on machine learning *Neurocomputing* **151** 161–7
[58] Biswas M, Kuppili V, Araki T, Edla D R, Godia E C, Saba L, Suri H S, Omerzu T, Laird J R and Khanna N N 2018 Deep learning strategy for accurate carotid intima-media thickness measurement: an ultrasound study on Japanese diabetic cohort *Comput. Biol. Med.* **98** 100–17
[59] Cuadrado-Godia E, Srivastava S K, Saba L, Araki T, Suri H S, Giannopolulos A, Omerzu T, Laird J, Khanna N N and Mavrogeni S 2018 Geometric total plaque area is an equally powerful phenotype compared with carotid intima-media thickness for stroke risk assessment: a deep learning approach *J. Vasc. Ultrasound* **42** 162–88

[60] Biswas M, Saba L, Chakrabartty S, Khanna N N, Song H, Suri H S, Sfikakis P P, Mavrogeni S, Viskovic K and Laird J R 2020 Two-stage artificial intelligence model for jointly measurement of atherosclerotic wall thickness and plaque burden in carotid ultrasound: a screening tool for cardiovascular/stroke risk assessment *Comput. Biol. Med.* **123** 103847

[61] Biswas M, Saba L and Chakrabartty S *et al* 2020 Two-stage artificial intelligence model for jointly measurement of atherosclerotic wall thickness and plaque burden in carotid ultrasound: a screening tool for cardiovascular/stroke risk assessment *Comput. Biol. Med.* **123** 103847

[62] Su S, Hu Z, Lin Q, Hau W K, Gao Z and Zhang H 2017 An artificial neural network method for lumen and media-adventitia border detection in IVUS *Comput. Med. Imaging Graph.* **57** 29–39

[63] Sofian H, Ming J T C, Mohamad S and Noor N M 2018 *Calcification Detection Using Deep Structured Learning in Intravascular Ultrasound Image for Coronary Artery Disease 2018 2nd Int. Conf. on BioSignal Analysis, Processing and Systems (ICBAPS) (Piscataway, NJ)* (IEEE) pp 47–52

[64] Olender M L, Athanasiou L S, Michalis L K, Fotiadis D I, Edelman E and Domain A 2020 Enriched deep learning approach to classify atherosclerosis using intravascular ultrasound imaging *IEEE J. Sel. Top. Signal Process* **14** 1210–20

Chapter 7

[1] Benjamin E J, Muntner P, Alonso A, Bittencourt M S, Callaway C W and Carson A P *et al* 2019 Heart disease and stroke statistics—2019 update: a report from the american heart association *Circulation* **139** 897–9

[2] WHO Reference https://who.int/topics/cerebrovascular_accident/en/

[3] Kamalakannan S, Gudlavalleti A V, Gudlavalleti V M, Goenka S and Kuper H 2017 Incidence and prevalence of stroke in india: a systematic review *Indian J. Med. Res.* **146** 175

[4] Chauhan S A B T 2015 The rising incidence of cardiovascular disease in India *J. Prev. Cardiol* **4** 735–40 http://journalofpreventivecardiology.com/pdf/Last-pdp/rising_incidence_4_2015.pdf

[5] Prabhakaran D, Jeemon P and Roy A 2016 Cardiovascular diseases in India: current epidemiology and future directions *Circulation* **133** 1605–20

[6] Benjamin E J, Virani S S, Callaway C W, Chamberlain A M, Chang A R and Cheng S *et al* 2018 Heart disease and stroke statistics – 2018 update: a report from the American Heart Association. *Circulation* **137** 67 492

[7] Suri J S 2011 *Atherosclerosis Disease Management* ed J S Suri, C Kathuria and F Molinari (New York: Springer)

[8] Molinari F, Zeng G and Suri J S 2010 A state of the art review on intima-media thickness (IMT) measurement and wall segmentation techniques for carotid ultrasound *Comput. Methods Programs Biomed.* **100** 201–21

[9] Park T H 2016 Evaluation of carotid plaque using ultrasound imaging *J. Cardiovasc. Ultrasound* **24** 91–5

[10] Togay-Işikay C, Kim J, Betterman K, Andrews C, Meads D and Tesh P *et al* 2005 Carotid artery tortuosity, kinking, coiling: stroke risk factor, marker, or curiosity? *Acta Neurol. Belg.* **105** 68–72 http://ncbi.nlm.nih.gov/pubmed/16076059

[11] Tracqui P, Broisat A, Toczek J, Mesnier N, Ohayon J and Riou L 2011 Mapping elasticity moduli of atherosclerotic plaque *in situ* via atomic force microscopy *J. Struct. Biol.* **174** 115–23

[12] Teng Z, Zhang Y, Huang Y, Feng J, Yuan J and Lu Q *et al* 2014 Material properties of components in human carotid atherosclerotic plaques: a uniaxial extension study *Acta Biomater.* **10** 5055–63

[13] Patel A K, Suri H S, Singh J, Kumar D, Shafique S and Nicolaides A *et al* 2016 A review on atherosclerotic biology, wall stiffness, physics of elasticity, and its ultrasound-based measurement *Curr. Atheroscler Rep.* (Berlin: Springer)18 83

[14] Polak J F and O'Leary D H 2016 Carotid intima-media thickness as surrogate for and predictor of CVD *Glob. Heart* **11** 295–312

[15] Rothwell P M and Warlow C P 2011 Low risk of ischemic stroke in patients with reduced internal carotid artery lumen diameter distal to severe symptomatic carotid stenosis *Stroke* **31** 622–30

[16] Kumar P K, Araki T, Rajan J, Laird J R, Nicolaides A and Suri J S 2018 State-of-the-art review on automated lumen and adventitial border delineation and its measurements in carotid ultrasound *Comput. Methods Programs Biomed.* **163** 155–68

[17] Araki T, Ikeda N, Shukla D, Jain P K, Londhe N D and Shrivastava V K *et al* 2016 PCA-based polling strategy in machine learning framework for coronary artery disease risk assessment in intravascular ultrasound: a link between carotid and coronary grayscale plaque morphology *Comput. Methods Programs Biomed.* **128** 137–58

[18] Araki T, Jain P K, Suri H S, Londhe N D, Ikeda N and El-Baz A *et al* 2017 Stroke risk stratification and its validation using ultrasonic echolucent carotid wall plaque morphology: a machine learning paradigm *Comput. Biol. Med.* **80** 77–96

[19] Saba L, Banchhor S K, Araki T, Viskovic K, Londhe N D and Laird J R *et al* 2018 Intra- and inter-operator reproducibility of automated cloud-based carotid lumen diameter ultrasound measurement *Indian Heart J.* **70** 649–64

[20] Bots M L, Baldassarre D, Simon A, De Groot E, O'Leary D H and Riley W *et al* 2007 Carotid intima-media thickness and coronary atherosclerosis: weak or strong relations? *Eur. Heart J.* **28** 398–406

[21] Ikeda N, Araki T, Dey N, Bose S, Shafique S and El-Baz A *et al* 2014 Automated and accurate carotid bulb detection, its verification and validation in low quality frozen frames and motion video *Int. Angiol.* **33** 573–89 http://ncbi.nlm.nih.gov/pubmed/24658129

[22] Biswas M, Kuppili V, Araki T, Edla D R, Godia E C and Saba L *et al* 2018 Deep learning strategy for accurate carotid intima-media thickness measurement: an ultrasound study on Japanese diabetic cohort *Comput. Biol. Med.* **98** 100–17

[23] Sudha S, Jayanthi K B, Rajasekaran C, Madian N and Sunder T 2018 Convolutional neural network for segmentation and measurement of intima media thickness *J. Med. Syst.* **42**

[24] Molinari F, Meiburger K M, Saba L, Zeng G, Acharya U R and Ledda M *et al* 2012 Fully automated dual-snake formulation for carotid intima-media thickness measurement: a new approach *J. Ultrasound Med* **31** 1123–36

[25] Molinari F, Meiburger K M, Nicolaides A and Suri J S 2012 CAUDLES-EF: carotid automated ultrasound double line extraction system using edge flow *Ultrasound Imaging Adv. Appl.* **24** 129–62

[26] Molinari F, Pattichis C S, Guang Z, Saba L, Acharya U R and Sanfilippo R *et al* 2012 Completely automated multiresolution edge snapper—a new technique for an accurate carotid ultrasound imt measurement: clinical validation and benchmarking on a multi-institutional database *IEEE Tran.s Image Process.* **21** 1211–22

[27] Kim G H and Youn H J 2017 Is carotid artery ultrasound still useful method for evaluation of atherosclerosis? *Korean Circ. J.* **47** 1–8

[28] Naim C, Douziech M, Therasse É, Robillard P, Giroux M F and Arsenault F *et al* 2014 Vulnerable atherosclerotic carotid plaque evaluation by ultrasound, computed tomography angiography, and magnetic resonance imaging: an overview *Can. Assoc. Radiol. J.* **65** 275–86

[29] Naim C, Cloutier G, Mercure E, Destrempes F, Qin Z and El-Abyad W *et al* 2013 Characterisation of carotid plaques with ultrasound elastography: feasibility and correlation with high-resolution magnetic resonance imaging *Eur. Radiol* **23** 2030–41

[30] Lee W 2014 General principles of carotid doppler ultrasonography *Ultrason (Seoul, Korea)* **33** 11–7

[31] Christopher B 2006 *Pattern Recognition and Machine Learning* (New York: Springer) 1st

[32] Saba L, Araki T, Krishna Kumar P, Rajan J, Lavra F and Ikeda N *et al* 2016 Carotid inter-adventitial diameter is more strongly related to plaque score than lumen diameter: an automated tool for stroke analysis. *J. Clin. Ultrasound* **44** 210–20

[33] Saba L, Banchhor S K, Suri H S, Londhe N D, Araki T and Ikeda N *et al* 2016 Accurate cloud-based smart IMT measurement, its validation and stroke risk stratification in carotid ultrasound : a web-based point-of-care tool for multicenter clinical trial. *Comput. Biol. Med.* **75** 217–34

[34] Molinari F, Acharya R U, Zeng G, Meiburger K M, Rodrigues P S and Saba L *et al* 2011 CARES 2.0: completely automated robust edge snapper for CIMT measurement in 300 ultrasound images—a two stage paradigm *J. Med. Imaging Heal Inform.* **1** 150–63

[35] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S and Sharma A *et al* 2019 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 543–64

[36] Cootes T F, Taylor C J, Cooper D H and Graham J 1995 Active shape models-their training and application *Comput. Vis. Image Underst.* **61** 38–59

[37] Yang X, Jin J, Xu M, Wu H, He W and Yuchi M *et al* 2013 Ultrasound common carotid artery segmentation based on active shape model. *Comput. Math. Methods Med* **2013** 1–11

[38] Araki T, Ikeda N, Dey N, Acharjee S, Molinari F and Saba L *et al* 2015 Shape-based approach for coronary calcium lesion volume measurement on intravascular ultrasound imaging and its association with carotid intima-media thickness *J. Ultrasound Med* **34** 469–82

[39] Loizou C P, Pattichis C S, Pantziaris M, Tyllis T and Nicolaides A 2007 Snakes based segmentation of the common carotid artery intima media *Med. Biol. Eng. Comput.* **45** 35–49

[40] Saba L, Jain P K, Suri H S, Ikeda N, Araki T and Singh B K *et al* 2017 Plaque tissue morphology-based stroke risk stratification using carotid ultrasound: a polling-based PCA learning paradigm *J. Med. Syst.* **41**

[41] Araki T, Ikeda N, Shukla D, Saba L, Nicolaides A and Shafique S *et al* 2015 A new method for IVUS-based coronary artery disease risk stratification: a link between coronary and carotid ultrasound plaque burdens *Comput. Methods Programs Biomed* **124** 161–79

[42] Tandel G S, Biswas M, Kakde O G, Tiwari A, Suri H S and Turk M *et al* 2019 A review on a deep learning perspective in brain cancer classification *Cancers (Basel)* **11** 111

[43] Klang E 2018 Deep learning and medical imaging *J. Thorac. Dis* **10** 1325–8

[44] Vieira S, Pinaya W H L and Mechelli A 2017 Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: methods and applications. *Neurosci. Biobehav. Rev.* **74** 58–75

[45] Gibson E, Li W, Sudre C, Fidon L, Shakir D I and Wang G *et al* 2018 NiftyNet: a deep-learning platform for medical imaging *Comput. Methods Programs Biomed* **158** 113–22

[46] Hoo-Chang Member S, Roth hoochangshin H R, Gao M, Lu Senior Member L, Xu Z and Nogues I *et al* 2016 Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning and daniel mollura are with center for infectious disease imaging HHS public access *IEEE Trans. Med. Imag* **35** 1285–98

[47] Lundervold A S and Lundervold A 2019 An overview of deep learning in medical imaging focusing on MRI *Z Med. Phys.* **29** 102–27

[48] Meyer P, Noblet V, Mazzara C and Lallement A 2018 Survey on deep learning for radiotherapy *Comput. Biol. Med.* **98** 126–46

[49] Razzak M I, Naz S and Zaib A 2018 Deep learning for medical image processing: overview, challenges and the future *Classification in BioApps* (Berlin: Springer) 323–50

[50] Ker J, Wang L, Rao J and Lim T 2017 Deep learning applications in medical image analysis *IEEE Access* **6** 9375–9

[51] Menchón-Lara R M, Sancho-Gómez J L and Bueno-Crespo A 2016 Early-stage atherosclerosis detection using deep learning over carotid ultrasound images *Appl. Soft. Comput. J.* **49** 616–28

[52] Zreik M, van Hamersvelt R W, Wolterink J M, Leiner T, Viergever M A and Isgum I 2018 A Recurrent CNN for automatic detection and classification of coronary artery plaque and stenosis in coronary CT angiography. arXiv:1804.04360

[53] Liu S, Wang Y, Yang X, Lei B, Liu L and Li S X *et al* 2019 Deep learning in medical ultrasound analysis: a review *Engineering* **5** 261–75

[54] Saba L, Biswas M, Kuppili V, Cuadrado Godia E, Suri H S and Edla D R *et al* 2019 The present and future of deep learning in radiology *Eur. J. Radiol.* **114** 14–24

[55] Libby P 2002 Inflammation in atherosclerosis *Nature* **420** 868–74

[56] Naghavi M, Libby P, Falk E, Casscells S W, Litovsky S and Rumberger J *et al* 2003 From vulnerable plaque to vulnerable patient. *Circulation* **108** 1664–72

[57] Ross R 1995 Cell biology of atherosclerosis *Annu. Rev. Physiol.* **57** 791–804

[58] Hopkins P N 2013 Molecular biology of atherosclerosis *Physiol. Rev.* **93** 1317–542

[59] Mannarino E and Pirro M 2008 Molecular biology of atherosclerosis *Clin. Cases Miner Bone Metab.* **5** 57–62 http://ncbi.nlm.nih.gov/pubmed/22460847

[60] Lo J and Plutzky J 2012 The biology of atherosclerosis: general paradigms and distinct pathogenic mechanisms among HIV-infected patients *J. Infect. Dis.* **205** S368–74

[61] Mohebali J, Patel V I, Romero J M, Hannon K M, Jaff M R and Cambria R P *et al* 2015 Acoustic shadowing impairs accurate characterization of stenosis in carotid ultrasound examinations presented at the plenary session of the 2014 joint annual meeting of the New England society for vascular surgery and Eastern Vascular Society, Boston, Mass. *J. Vasc. Surg.* **62** 1236–44

[62] Chiu B, Shamdasani V, Entrekin R, Yuan C and Kerwin W S 2012 Characterization of carotid plaques on 3-dimensional ultrasound imaging by registration with multicontrast magnetic resonance imaging *J. Ultrasound Med* **31** 1567–80
[63] Pedro L M, Sanches J M, Seabra J, Suri J S, Fernandes E and Fernandes J 2014 Asymptomatic carotid disease: a new tool for assessing neurological risk *Echocardiography* **31** 353–61
[64] Ho S S Y 2016 Current status of carotid ultrasound in atherosclerosis *Quant. Imaging Med. Surg* **6** 285–96
[65] Mirek A M and Wolińska-Welcz A 2013 Is the lumen diameter of peripheral arteries a good marker of the extent of coronary atherosclerosis? *Kardiol. Pol* **71** 810–7
[66] Nambi V, Brunner G and Ballantyne C M 2013 Ultrasound in cardiovascular risk prediction: don't forget the plaque! *J. Am. Heart Assoc.* **2** 1–3
[67] Picano E and Paterni M 2015 Ultrasound tissue characterization of vulnerable atherosclerotic plaque *Int. J. Mol. Sci.* **16** 10121–33
[68] Cuadrado-Godia E, Dwivedi P, Sharma S, Ois Santiago A, Roquer Gonzalez J and Balcells M *et al* 2018 Cerebral small vessel disease: a review focusing on pathophysiology, biomarkers, and machine learning strategies *J. Stroke* **20** 302–20
[69] De Korte C L, Fekkes S, Nederveen A J, Manniesing R and Hansen H R H G 2016 Review: mechanical characterization of carotid arteries and atherosclerotic plaques *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **63** 1613–23
[70] Acharya U R 2012 Plaque tissue characterization and classification in ultrasound carotid scans: a paradigm for vascular *IEEE Trans. Instrum. Meas.* **62** 392–400
[71] Acharya U R 2012 Atherosclerotic risk stratification strategy for carotid arteries using texture-based features *Ultrasound Med. Biol.* **38** 899–915
[72] Cheng J, Yu Y and Chiu B 2016 Direct 3D segmentation of carotid plaques from 3D ultrasound images *Proc. 2016 IEEE Biomed. Circuits Syst. Conf. BioCAS 2016* pp 123–6
[73] Dong Y, Pan Y, Zhao X, Li R, Yuan C and Xu W 2017 Identifying carotid plaque composition in MRI with convolutional neural networks *2017 IEEE Int. Conf. Smart Comput. SMARTCOMP* 2017
[74] Jones W, Alasoo K, Fishman D and Parts L 2017 Computational biology: deep learning *Emerg. Top. Life Sci.* **1** 257–74
[75] Turan T N, Lematty T, Martin R, Chimowitz M I, Rumboldt Z and Spampinato M V *et al* 2015 Characterization of intracranial atherosclerotic stenosis using high-resolution MRI study – rationale and design *Brain Behav* **5** 1–9
[76] Gupta A, Kesavabhotla K, Baradaran H, Kamel H, Pandya A and Giambrone A E *et al* 2015 Plaque echolucency and stroke risk in asymptomatic carotid stenosis *Stroke* **46** 91–7
[77] Hunt K J, Evans G W, Folsom A R, Sharrett A R, Chambless L E and Tegeler C H *et al* 2001 Acoustic shadowing on B-mode ultrasound of the carotid artery predicts ischemic stroke. The Atherosclerosis Risk in Communities (ARIC) study *Stroke* **32** 1120–6
[78] Araki T, Banchhor S K, Londhe N D, Ikeda N, Radeva P and Shukla D *et al* 2016 Reliable and accurate calcium volume measurement in coronary artery using intravascular ultrasound videos *J. Med. Syst.* **40** 1–20
[79] Chu B, Kampschulte A, Ferguson M S, Kerwin W S, Yarnykh V L and O'Brien K D *et al* 2004 Hemorrhage in the atherosclerotic carotid plaque: a high-resolution MRI study *Stroke* **35** 1079–84

[80] Kamenskiy A V, Pipinos I I, Carson J S, Mactaggart J N and Baxter B T 2015 Age and disease-related geometric and structural remodeling of the carotid artery *J. Vasc. Surg.* **62** 1521–8

[81] Londhe N D and Suri J S 2016 Superharmonic imaging for medical ultrasound: a review *J. Med. Syst.* **40** 279

[82] Grønholdt M L M, Nordestgaard B G, Schroeder T V, Vorstrup S and Sillesen H 2001 Ultrasonic echolucent carotid plaques predict future strokes *Circulation* **104** 68–73

[83] Jashari F, Ibrahimi P, Bajraktari G, Grönlund C, Wester P and Henein M Y 2016 Carotid plaque echogenicity predicts cerebrovascular symptoms: a systematic review and meta-analysis *Eur. J. Neurol.* **23** 1241–7

[84] Madore B and Meral F C 2012 Reconstruction algorithm for improved ultrasound image quality *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **59** 217–30

[85] Remington L A 2012 Orbital blood supply *Clinical Anatomy and Physiology of the Visual System* (Amsterdam: Elsevier) 202–17

[86] Binning M J 2018 Internal carotid artery aneurysms introduction *Intracranial Aneurysms* (Amsterdam: Elsevier) 479–81

[87] Webb W G 2017 Organization of the nervous system II *Neurology for the Speech-Language Pathologist* (Amsterdam: Elsevier) 44–73

[88] Love B B and Biller J 2007 Neurovascular system *Textbook of Clinical Neurology* (Amsterdam: Elsevier) 405–34

[89] Hong J T, Kim T H, Kim I S, Yang S H, Sung J H and Son B C *et al* 2010 The effect of patient age on the internal carotid artery location around the atlas *J. Neurosurg. Spine* **12** 613–8

[90] Banchhor S K, Londhe N D, Araki T, Saba L, Radeva P and Khanna N N *et al* 2018 Calcium detection, its quantification, and grayscale morphology-based risk stratification using machine learning in multimodality big data coronary and carotid scans: a review *Comput. Biol. Med.* **101** 184–98

[91] Biswas M, Kuppili V, Saba L, Edla D R, Suri H S and Cuadrado-Godia E *et al* 2019 State-of-the-art review on deep learning in medical imaging *Front. Biosci. (Landmark Ed)* **24** 392–426

[92] Ren S, He K, Girshick R and Sun J 2015 Faster R-CNN: Towards real-time object detection with region proposal networks arXiv:1506.01497

[93] Girshick R 2015 *Fast R-CNN IEEE Int. Conf. on Computer Vision (ICCV)* 2015 (IEEE) 1440–8

[94] He K, Zhang X, Ren S and Sun J 2015 Delving deep into rectifiers: surpassing human-level performance on imagenet classification arXiv:1502.01852

[95] Lal B K, Hobson R W, Pappas P J, Kubicka R, Hameed M and Chakhtura E Y *et al* 2002 Pixel distribution analysis of B-mode ultrasound scan images predicts histologic features of atherosclerotic carotid plaques *J. Vasc. Surg.* **35** 1210–7

[96] Broomhead D and David L 1988 Multivariable Functional Interpolation and Adaptive Networks *Complex Systems* **2** 321–55

[97] Gonzalez R C and Woods R E 2002 *Digital Image Processing* (Hoboken, NJ: Prentice-Hall)

[98] Qian C and Yang X 2018 Computer methods and programs in biomedicine An integrated method for atherosclerotic carotid plaque segmentation in ultrasound image *Comput. Methods Programs Biomed.* **153** 19–32

[99] Lekadir K, Galimzianova A, Betriu A, Del Mar Vila M, Igual L and Rubin D L *et al* 2017 A convolutional neural network for automatic characterization of plaque composition in carotid ultrasound *IEEE J. Biomed. Heal Inform.* **21** 48–55

[100] Barnett H J M, Taylor D W, Eliasziw M, Fox A J, Ferguson G G and Haynes R B *et al* 1998 Benefit of carotid endarterectomy in patients with symptomatic moderate or severe stenosis *N. Engl. J. Med.* **339** 1415–25

[101] Vapnik V N 1999 An overview of statistical learning theory *IEEE Trans. Neural Networks* **10** 988–99

[102] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2016 A novel approach to multiclass psoriasis disease risk stratification: machine learning paradigm. *Biomed. Signal. Process. Control* **28** 27–40

[103] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2015 Exploring the color feature power for psoriasis risk stratification and classification: a data mining paradigm *Comput. Biol. Med.* **65** 54–68

[104] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2016 Computer-aided diagnosis of psoriasis skin images with HOS, texture and color features: a first comparative study of its kind *Comput. Methods Prog. Biomed.* **126** 98–109

[105] Shrivastava V K, Londhe N D, Sonawane R S and Suri J S 2015 Reliable and accurate psoriasis disease classification in dermatology images using comprehensive feature space in machine learning paradigm *Expert. Syst. Appl.* **42** 6184–95

[106] Srivastava R K, Greff K and Schmidhuber J 2015 Training very deep networks arXiv:1507.06228

[107] Bianchini M and Scarselli F 2014 On the complexity of neural network classifiers: a comparison between shallow and deep architectures *IEEE Trans. Neural. Networks Learn. Syst.* **25** 1553–65

[108] Yu D, Seltzer M L, Li J, Huang J T and Seide F 2013 Feature learning in deep neural networks – studies on speech recognition tasks arXiv:1301.3605

[109] Ciresan D, Meier U and Schmidhuber J 2012 Multi-column deep neural networks for image classification *IEEE Conf. on Computer Vision and Pattern Recognition* 2012 (IEEE) 3642–9

[110] Simonyan K and Zisserman A 2014 Very deep convolutional networks for large-scale image recognition arXiv:1409.1556

[111] He K, Zhang X, Ren S and Sun J 2015 Deep residual learning for image recognition arXiv:1512.03385

[112] Alex K and Ilya S G E H 2012 ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems* **25** pp 1097–105 https://cs.toronto.edu/~fritz/absps/imagenet.pdf

[113] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S and Anguelov D *et al* 2014 Going deeper with convolutions arXiv:1409.4842

[114] Lecun Y, Bottou L, Bengio Y and Haffner P 1998 Gradient-based learning applied to document recognition *Proc IEEE* **86** 2278–324

[115] Avendi M R, Kheradvar A and Jafarkhani H 2016 A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI *Med. Image Anal.* **30** 108–19

[116] Havaei M, Davy A, Warde-Farley D, Biard A, Courville A and Bengio Y *et al* 2017 Brain tumor segmentation with deep neural networks *Med. Image Anal.* **35** 18–31

[117] Tajbakhsh N, Shin J Y, Gurudu S R, Hurst R T, Kendall C B and Gotway M B *et al* 2016 Convolutional neural networks for medical image analysis: full training or fine tuning? *IEEE Trans. Med. Imaging* **35** 1299–312
[118] Alom M Z, Taha T M, Yakopcic C, Westberg S, Sidike P and Nasrin M S *et al* 2018 The history began from AlexNet: a comprehensive survey on deep learning approaches arXiv:1803.01164
[119] Bianco S, Cadene R, Celona L and Napoletano P 2018 Benchmark analysis of representative deep neural network architectures *IEEE Access* **6** 64270–7
[120] LeCun Y, Haffner P, Bottou L and Bengio Y 1999 Object recognition with gradient-based learning *Shape, Contour and Grouping in Computer Vision* (Berlin: Springer) 319–45
[121] He K, Zhang X, Ren S and Sun J 2014 Spatial pyramid pooling in deep convolutional networks for visual recognition *Computer Vision – ECCV 2014* (Springer) 346–61
[122] Özdemir H, Artaş H and Serhatlioğlu S 2006 Oğur E. Effects of overweight on luminal diameter, flow velocity and intima-media thickness of carotid arteries *Diagnost. Interv. Radiol* **12** 142–6
[123] Lloyd K D, Barinas-Mitchell E, Kuller L H, Mackey R H, Wong E A and Sutton-Tyrrell K 2012 Common carotid artery diameter and cardiovascular risk factors in overweight or obese postmenopausal women *Int. J. Vasc. Med* **2012** 1–7
[124] Krejza J, Arkuszewski M, Kasner S E, Weigele J, Ustymowicz A and Hurst R W *et al* 2006 Carotid artery diameter in men and women and the relation to body and neck size *Stroke* **37** 1103–5
[125] Ruan L, Chen W, Srinivasan S R, Sun M, Wang H and Toprak A *et al* 2009 Correlates of common carotid artery lumen diameter in black and white younger adults: the Bogalusa heart study *Stroke* **40** 702–7
[126] Mancini G B J 2004 Surrogate markers for cardiovascular disease: structural markers *Circulation* **109** IV-22–30
[127] Cohn J N 2004 Surrogate markers for cardiovascular disease: functional markers *Circulation* **109** IV-31–46
[128] Amato M, Montorsi P, Ravani A, Oldani E, Galli S and Ravagnani P M *et al* 2007 Carotid intima-media thickness by B-mode ultrasound as surrogate of coronary atherosclerosis: correlation with quantitative coronary angiography and coronary intravascular ultrasound findings *Eur. Heart J.* **28** 2094–101
[129] O'Leary D H, Polak J F, Wolfson S K, Bond M G, Bommer W and Sheth S *et al* 2011 Use of sonography to evaluate carotid atherosclerosis in the elderly. the cardiovascular health study. CHS collaborative research group *Stroke* **22** 1155–63
[130] Smistad E 2016 Deep learning and data labeling for medical applications. *First International Workshop, LABELS 2016, and Second International Workshop, DLMIA 2016, Held in Conjunction with MICCAI 2016, Athens, Greece, October 21, 2016, Proceedings* 10008 (Springer) 30–8
[131] Bastida-Jumilla M C, Menchón-Lara R M, Morales-Sánchez J, Verdú-Monedero R, Larrey-Ruiz J and Sancho-Gómez J L 2015 Frequency-domain active contours solution to evaluate intima–media thickness of the common carotid artery *Biomed. Signal Process. Control* **16** 68–79
[132] Ilea D E, Duffy C, Kavanagh L, Stanton A and Whelan P F 2013 Fully automated segmentation and tracking of the intima media thickness in ultrasound video sequences of the common carotid artery. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **60** 158–77

[133] Loizou C P, Kasparis T, Spyrou C and Pantziaris M 2013 Integrated system for the complete segmentation of the common carotid artery bifurcation in ultrasound images. *AIAI 2013: Artificial Intelligence Applications and Innovations* (Springer) 292–301
[134] Razzak M I, Naz S and Zaib A 2018 Deep learning for medical image processing: overview, challenges and the future *Lect. Notes Comput. Vis. Biomech* **26** 323–50
[135] Agarap A F 2017 An architecture combining convolutional neural network (CNN) and support vector machine (SVM) for image classification arXiv:1712.03541
[136] Lipton Z C 2016 The mythos of model interpretability arXiv:1606.03490
[137] Kane A G, Dillon W P, Barkovich A J, Norman D, Dowd C F and Kane T T 1996 Reduced caliber of the internal carotid artery: a normal finding with ipsilateral absence or hypoplasia of the A1 segment *Am. J. Neuroradiol* **17** 1295–301
[138] Ascher E, Markevich N, Hingorani A and Kallakuri S 2002 Pseudo-occlusions of the internal carotid artery: a rationale for treatment on the basis of a modified carotid duplex scan protocol *J. Vasc. Surg.* **35** 340–5
[139] Bartlett E S, Symons S P and Fox A J 2006 Correlation of carotid stenosis diameter and cross-sectional areas with CT angiography *AJNR Am. J. Neuroradiol.* **27** 638–42 http://ncbi.nlm.nih.gov/pubmed/16552008
[140] Hyde D E, Fox A J, Gulka I, Kalapos P, Lee D H and Pelz D M *et al* 2004 Internal carotid artery stenosis measurement: comparison of 3D computed rotational angiography and conventional digital subtraction angiography *Stroke* **35** 2776–81
[141] Baradaran X H, Patel P, Gialdini G, Al-Dasuqi K, Giambrone A and Kamel H *et al* 2017 Quantifying intracranial internal carotid artery stenosis on MR angiography *Am. J. Neuroradiol* **38** 986–90
[142] Lu N, Wu Y, Feng L and Song J 2019 Deep learning for fall detection: three-dimensional CNN combined with LSTM on video kinematic data *IEEE J. Biomed. Heal Informatics* **23** 314–23
[143] Savioli N, Visentin S, Cosmi E, Grisan E, Lamata P and Montana G 2018 Temporal convolution networks for real-time abdominal fetal aorta analysis with ultrasound 1–10 arXiv:1807.04056
[144] Babalyan K, Sultanov R, Generozov E, Sharova E, Kostryukova E and Larin A *et al* 2018 LogLoss-BERAF: an ensemble-based machine learning model for constructing highly accurate diagnostic sets of methylation sites accounting for heterogeneity in prostate cancer; A Elofsson *PLoS One* **13** e0204371

Chapter 8

[1] National Center for Health Statistics 2018 https://www.cdc.gov/nchs/nhanes/index.htm accessed 2 October 2018
[2] MEMBERS, WRITING GROUPEmelia J B, Michael J B, Stephanie E C, Mary C, Sandeep R D and Rajat D *et al* 2017 Heart disease and stroke statistics—2017 update: a report from the American Heart Association *Circulation* **135** e146
[3] National Center for Health Statistics 2014 Mortality multiple cause micro-data files, 2014: public-use data file and documentation: NHLBI tabulations http://cdc.gov/nchs/data_access/Vitalstatsonline.htm#Mortality_Multiple accessed 2 October 2018
[4] Heidenreich P A, Justin G T, Olga A K, Javed B, Kathleen D, Michael D E and Finkelstein E A *et al* 2011 Forecasting the future of cardiovascular disease in the United States: a policy statement from the American Heart Association *Circulation* **123** 933–44

[5] Suri J S, Kathuria C and Molinari F 2010 *Atherosclerosis Disease Management* (Berlin: Springer Science & Business Media)

[6] Libby P, Karin E B and Alan R T 2016 Atherosclerosis: successes, surprises, and future challenges *Circ. Res.* **118** 531–4

[7] https://mayfieldclinic.com/pe-carotidstenosis.htm

[8] Sato K, Ogoh S, Hirasawa A, Oue A and Sadamoto T 2011 The distribution of blood flow in the carotid and vertebral arteries during dynamic exercise in humans *J. Physiol.* **589** 2847–56

[9] Dhawan S S *et al* 2010 Shear stress and plaque development *Expert Rev. Cardiovasc. Ther.* **8** 545–56

[10] He X, Peter P C, Kischell E R and Chiang A M 2003 Ultrasound imaging system *U.S. Patent 6,638,226 issued*

[11] Punchard W F B and Robert D P 1988 Magnetic resonance imaging systems *U.S. Patent 4,733,189 issued*

[12] Hsieh J 2009 *Computed Tomography: Principles, Design, Artifacts, and Recent Advances* (Bellingham, WA: SPIE)

[13] Narayanan R, Kurhanewicz J, Shinohara K, David Crawford E, Simoneau A and Suri J S 2009 MRI-ultrasound registration for targeted prostate biopsy *Biomedical Imaging: From Nano to Macro, 2009. ISBI'09. IEEE Int. Symp. on* (Piscataway, NJ: IEEE) pp 991–4

[14] Saba L, Montisci R, Molinari F, Tallapally N, Zeng G, Mallarini G and Suri J S 2012 Comparison between manual and automated analysis for the quantification of carotid wall by using sonography. A validation study with CT *Eur. J. Radiol.* **81** 911–8

[15] El-Baz A and Jasjit S S (ed) 2011 *Lung Imaging and Computer Aided Diagnosis* (Boca Raton, FL: CRC Press)

[16] Haykin S S 2009 *Neural Networks and Learning Machines* 3 (Upper Saddle River, NJ: Pearson)

[17] Cortes C and Vladimir V 1995 Support-vector networks *Mach. Learn.* **20** 273–97

[18] Huang G B, Zhu Q Y and Siew C K 2006 Extreme learning machine: theory and applications *Neurocomputing* **70** 489–501

[19] Yegnanarayana B 2009 *Artificial Neural Networks* (Delhi: PHI Learning Pvt. Ltd)

[20] Hopfield J J 1988 Artificial neural networks *IEEE Circuits Dev. Mag.* **4** 3–10

[21] LeCun Y, Yoshua B and Geoffrey H 2015 Deep learning *Nature* **521** 436

[22] Goodfellow I, Bengio Y, Courville A and Bengio Y 2016 *Deep Learning* 1 (Cambridge, MA: MIT Press)

[23] Virmani R, Allen P B, Kolodgie F D and Farb A 2003 Pathology of the thin-cap fibroatheroma: a type of vulnerable plaque *J. Interv. Cardiol.* **16** 267–72

[24] Torvik A, Svindland A and Lindboe C F 1989 Pathogenesis of carotid thrombosis *Stroke* **20** 1477–83

[25] Roux S, Carteaux J P, Hess P, Falivene L and Clozel J P 1994 Experimental carotid thrombosis in the guinea pig *Thromb. Haemost.* **71** 252–6

[26] Molinari F, Zeng G and Suri J S 2010 A state of the art review on intima–media thickness (IMT) measurement and wall segmentation techniques for carotid ultrasound *Comput. Methods Prog. Biomed.* **100** 201–21

[27] Molinari F, Zeng G and Suri J S 2010 An integrated approach to computer-based automated tracing and its validation for 200 common carotid arterial wall ultrasound images: a new technique *J. Ultrasound Med.* **29** 399–418

[28] Huang Z and Ng M K 1999 A fuzzy k-modes algorithm for clustering categorical data *IEEE Trans. Fuzzy Syst.* **7** 446–52
[29] Araki T, Kumar P K, Harman S S, Nobutaka I, Ajay G, Luca S and Jeny R *et al* 2016 Two automated techniques for carotid lumen diameter measurement: regional versus boundary approaches *J. Med. Syst.* **40** 182
[30] Suri J S, Liu K, Reden L and Laxminarayan S 2002 A review on MR vascular image processing algorithms: acquisition and prefiltering: part I *IEEE Trans. Inform. Technol. Biomed.* **6** 324–37
[31] Suri J S, Haralick R M and Florence H S 2000 Greedy algorithm for error correction in automatically produced boundaries from low contrast ventriculograms *Pattern Anal. Appl.* **3** 39–60
[32] Li C, Xu C, Gui C and Fox M D 2010 Distance regularized level set evolution and its application to image segmentation *IEEE Trans. Image Process.* **19** 3243
[33] LeCun Y, Yoshua B and Geoffrey H 2015 Deep learning *Nature* **521** 436
[34] Long J, Shelhamer E and Darrell T 2015 Fully convolutional networks for semantic segmentation *Proc. IEEE Conf. on Computer Vision and Pattern Recognition* (IEEE) 3431–40
[35] Biswas M, Kuppili V, Saba L, Reddy Edla D, Suri H S, Sharma A, Cuadrado-Godia E, Laird J R, Nicolaides A and Suri J S 2018 Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk *Med. Biol. Eng. Comput.* **57** 1–22
[36] Simonyan K and Zisserman A 2014 Very deep convolutional networks for large-scale image recognition arXiv preprint arXiv:1409.1556
[37] Biswas M *et al* 2018 Deep learning strategy for accurate carotid intima-media thickness measurement: an ultrasound study on Japanese diabetic cohort *Comput. Biol. Med.* **98** 100–17
[38] Molinari F, Kristen M M, Saba L, Zeng G, Rajendra Acharya U, Ledda M, Nicolaides A and Suri J S 2012 Fully automated dual-snake formulation for carotid intima-media thickness measurement: a new approach *J. Ultrasound Med.* **31** 1123–36
[39] Sharma A M, Gupta A, Krishna Kumar P, Rajan J, Saba L, Nobutaka I, Laird J R, Nicolades A and Suri J S 2015 A review on carotid ultrasound atherosclerotic tissue characterization and stroke risk stratification in machine learning framework *Curr. Atheroscler. Rep.* **17** 55
[40] Acharya R U, Faust O, Peng Chuan Alvin A, Vinitha Sree S, Molinari F, Saba L, Nicolaides A and Suri J S 2012 Symptomatic vs. asymptomatic plaque classification in carotid ultrasound *J. Med. Syst.* **36** 1861–71
[41] Hastie T, Rosset S, Zhu J and Zou H 2009 Multi-class adaboost *Stat. Interface* **2** 349–60
[42] 1963 Whittle, Peter, Peter Whittle, Peter Whittle, Nouvelle-Zélande Mathématicien, Peter Whittle, New Zealand Mathematician, and Great Britain *Prediction and Regulation by Linear Least-Square Methods* (London: English Universities Press)
[43] Chakravarti A, Laura K L and Jillian E 1991 Reefer. ‘a maximum likelihood method for estimating genome length using genetic linkage data *Genetics* **128** 175–82
[44] Fraley C and Adrian E R 2002 Model-based clustering, discriminant analysis, and density estimation *J. Am. Stat. Assoc.* **97** 611–31
[45] Gallant S I and Stephen I G 1993 *Neural Network Learning and Expert Systems* (Cambridge, MA: MIT Press)

[46] Iba W and Langley P 1992 Induction of one-level decision trees *Machine Learning Proceedings* (Morgan Kaufmann) 233–40
[47] Acharya U *et al* 2013 Atherosclerotic plaque tissue characterization in 2D ultrasound longitudinal carotid scans for automated classification: a paradigm for stroke risk assessment *Med. Biol. Eng. Comput.* **51** 513–23
[48] Shi Z and Govindaraju V 2004 Line separation for complex document images using fuzzy runlength *First International Workshop on Document Image Analysis for Libraries* (Piscataway, NJ: IEEE) pp 306–12
[49] Reynolds D 2015 Gaussian mixture models *Encyclopedia of Biometrics* (Berlin: Springer) 827–32
[50] Huang D 1999 Radial basis probabilistic neural networks: model and application *Int. J. Pattern Recognit. Artif. Intell.* **13** 1083–101
[51] Safavian S, Rasoul and Landgrebe D 1991 A survey of decision tree classifier methodology *IEEE Trans. Syst. Man Cybern.* **21** 660–74
[52] Peterson L E 2009 K-nearest neighbor *Scholarpedia* **4** 1883
[53] Murphy K P 2006 *Naive Bayes Classifiers* (Vancouver: University of British Columbia) 18
[54] Kuncheva L 2000 *Fuzzy Classifier Design* 49 (Berlin: Springer Science & Business Media)
[55] Lekadir K, Alfiia G, Àngels B, Vila M, Igual L, Daniel L R, Elvira F, Petia R and Sandy N 2017 A convolutional neural network for automatic characterization of plaque composition in carotid ultrasound *IEEE J. Biomed. Health Inform.* **21** 48–55
[56] Xu B, Wang N, Chen T and Li M 2015 Empirical evaluation of rectified activations in convolutional network arXiv preprint arXiv:1505.00853
[57] Tofler G *et al* 1987 Concurrent morning increase in platelet aggregability and the risk of myocardial infarction and sudden cardiac death *New Engl. J. Med.* **316** 1514–8
[58] Falk E 1992 Why do plaques rupture? *Circulation* **86** III30–42
[59] Stone G W, Gary S M and Virmani R 2018 Vulnerable plaques, vulnerable patients, and intravascular imaging *J. Am. Coll. Cardiol.* **72** 2022–6
[60] Muller , James E, Geoffrey and Tofler H 1992 Triggering and hourly variation of onset of arterial thrombosis *Ann. Epidemiol.* **2** 393–405
[61] Saba L, Michele A, Marincola B C, Mario P, Eytan R, Pier Paolo B, Alessandro N, Lorenzo M, Carlo C and Max W 2014 Imaging of the carotid artery vulnerable plaque *Cardiovasc. Interv. Radiol.* **37** 572–85