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# Design Methods of Detecting Atrial Fibrillation Using the Recurrent Neural Network Algorithm on the Arduino AD8232 ECG Module

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**Abstract.** Atrial fibrillation (AF) is part of a type of heart disease characterized by a rhythmic irregular heartbeat. AF conditions that occur continuously can potentially cause a stroke for sufferers. The method of reading and detecting the possibility of AF is needed to prevent the risk of stroke due to AF. In this research, the Recurrent Neural Network (RNN) method is used in classifying electrocardiogram readings to obtain accuracy in the assessment of AF. The data information used in the study was obtained from physicians who were the bases of ECG result image data, and data information was also obtained by implementing directly through a simple and low-cost ECG using Arduino AD8232 to test user information directly related to AF conditions at the user's heart. RNN method that is tested can obtain more accurate accuracy values in detecting AF heart rate abnormalities, and the Arduino AD8232 module can be a good ECG in reading low-cost but high-accuracy heart records.

## 1. Introduction

AF is an uncoordinated condition of electrical and mechanical activity atrium [1]. ECG is a medical technology tool that is used in reading the electrical activity of the heart. Knowing the electrical activity of the heart is very important in knowing the condition of the heart, because the heart is the most important part of the body where the heart is a part of the body that functions for human life. A progressive increase every year is seen in the prevalence of AF cases which is considered quite high [1]. AF becomes one of the important things to consider related to the detection of heart disease because the effect that can result from AF is to increase the likelihood of stroke and be able to bring death [2].

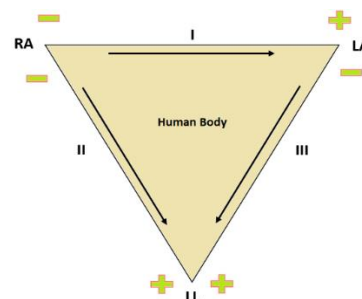
One way to find out AF is by knowing the peak of high amplitude Heart beat (R Peak) in the ECG pattern. In processing information R peak from ECG, there are many methods to process them including Recurrent Neural Network (RNN), Back Propagation Neural Network (BPNN). Utilization of RNN is carried out reviewing in previous studies where the use of RNN methods in detecting neurodegenerative diseases can detect and classify above 95% - 100% [3]. When compared with other algorithmic methods, RNN in previous studies had carried out a study related to A Comparative Study of Supervised Learning Techniques for Human Activity Monitoring Using Smart Sensors and in the research it was obtained that the RNN accuracy comparison results were better than the other methods tested namely 97.55 %, while accuracy on the BPNN of 94.7%, Probabilistic Neural Network of 94.1%, and Support Vector Machine of 59.11% [4].



## 2. Method

Information on ECG data used in this study was obtained from PhysioNet. PhysioNet is a website that provides information on data collection related to physiologic signals, which are signal record data. Accuracy related to data from information contained in the physio net is supported by the National Institute of General Medical Sciences (NIGMS) and the National Institute of Biomedical Imaging and Bioengineering (NIBIB) which is a research body related to Biomedical.

The signal that the ECG receives comes from electrodes mounted on the patient's body. The electrode installation system follows the existing principles such as 12 leads and the Einthoven Triangle. The Einthoven Triangle is a delusion triangle connecting the three lead vectors. The Einthoven Triangle is the basis for developing the Trihexial Reference System to calculate the axis of direction and electrical force of the heart (a combination of two or more lead vector diagrams) in the frontal plane. The electrocardiogram does not directly assess cardiac contractility. However, the ECG can provide a comprehensive indication of the ups and downs of contractility.



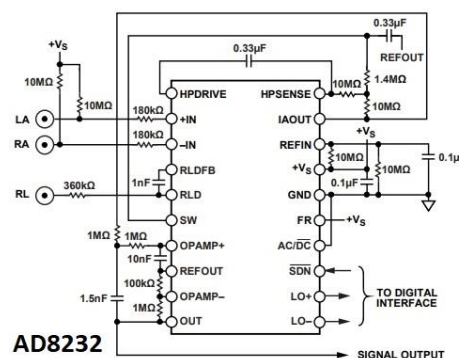
**Figure 1.** Einthoven Triangle

Lead I — This axis goes from shoulder to shoulder, with the negative electrode placed on the right shoulder and the positive electrode placed on the left shoulder. This results in a 0 degree angle of orientation. [5] Lead I = Left Arm – Right Arm.

Lead II — This axis goes from the right arm to the left leg, with the negative electrode on the shoulder and the positive one on the leg. This results in a +60 degree angle of orientation. Lead II = Left Leg – Right Arm.

Lead III — This axis goes from the left shoulder (negative electrode) to the right or left leg (positive electrode). This results in a +120 degree angle of orientation. Lead III = Left Leg – Left Arm.

AD8232 is a tool for measuring electrical signals in the body of living things. This tool technically performs electrical signal extraction, amplifies the signal, and filters electrical signals of little value to living things even under conditions of obstacles, such as a movement or misplacement of electrodes placed too far away. The design of the use of AD8232 in figure number 2 below aims as an analog-to-digital converter (ADC) ultralow-power or microcontroller embedded in obtaining an electrical output signal easily in the body [6].

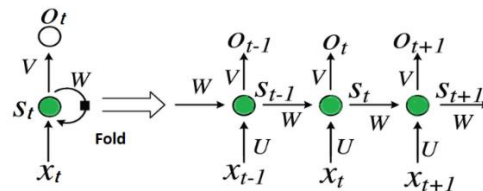


**Figure 2.** AD8232 Functional Block Diagram [6]

**TABEL 1. ABSOLUTE RATING AD8232**

PARAMETER	RATING
SUPPLY VOLTAGE	3.6 V
OUTPUT SHORT – CIRCUIT CURRENT DURATION	INDEFINITE
MAXIMUM VOLTAGE	+Vs + 0,3 V
MINIMUM VOLTAGE	-0.3 V
STORAGE TEMPERATURE RANGE	-65 °C TO 125 °C
OPERATING TEMPERATURE RANGE	-40 °C TO 85 °C
MINIMUM JUNCTION TEMPERATURE	140°C
THERMAL IMPEDANCE	48°C
ESD RATING	
HUMAN BODY MODEL	8 kV
CHARGED DEVICE MODEL	1.25 kV
MACHINE MODEL	200 V

RNN is a method that is classified in artificial intelligence in terms of engineering neural networks (NN). NN is divided into two groups, namely the Feedforward Neural Network (FFNN) and RNN. The advantage of RNN compared to the FFNN group is that RNN can perform repetition or feedback which is characterized by the presence of reverse connection loops where the closed-loop signal pathway from the neuron returns to itself.

**Figure 3. RNN Architecture [7]**

Based on the formula from the figure 3:

- $x_t$  is input in the time step. For example,  $x_1$  can be a one-hot vector that corresponds to the second word of a sentence being processed.
- $s_t$  is the hidden state at each time step  $t$ . Hidden state can be referred to as "memory" of a network that functions to store the results of calculations and records that have been made.  $s_t$  is calculated based on the previous hidden state and based on the current state input:

$$s_t = f(Ux_t + Ws_{t-1})$$

The function  $f$  is usually non-linear like tanh or ReLU.  $s_{t-1}$  is used to calculate the first hidden state, usually, the initialization always starts with 0 (zero).

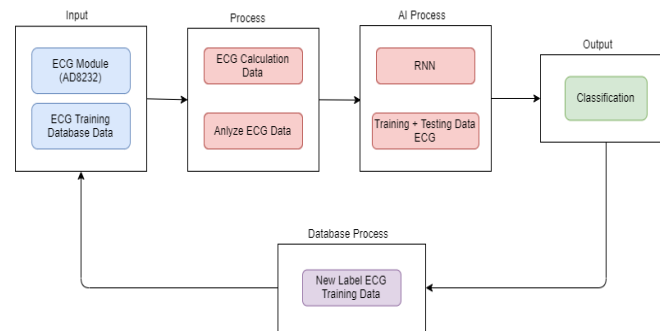
- $o_t$  is the output in step  $t$ . For example, if we want to predict the "next word" in a sentence, then  $o_t$  is a probability vector throughout the vocabulary in the database that we have.

$$o_t = \text{softmax}(Vs_t)$$

Several things need to be considered, namely:

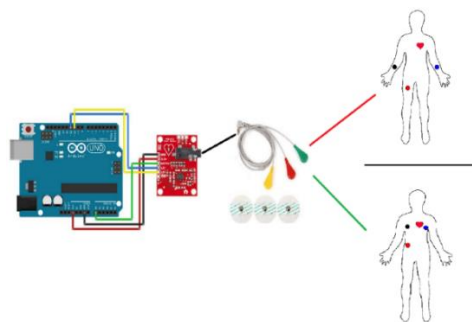
- Hidden state,  $s_t$ , as the memory of the network (network).  $s_t$  records the information that occurred in the previous time step. The output step,  $o_t$ , is calculated only based on each time  $t$  in memory. But in practice, often  $s_t$  cannot capture information from too many time steps.

- Unlike ordinary deep neural networks that use different parameters for each layer, the RNN evenly divides the parameters (U,V,W above) at all steps. This means that all perform the same tasks at each step.
- The diagram above has output at each time step but depends on unnecessary tasks. For example, when predicting sentiment in a sentence we might only need to see the final output, not the sentiment of each word. Likewise, we don't need input at every time step. But keep in mind that the main feature of RNN is the hidden layer, which captures information from each sequence.



**Figure 4.** Block Diagram System

In testing the ECG data set, the information obtained is converted into numerical figures before processing. Confirmation in this research is conducted by 2 methods of choice of converting, namely through the application of converting ECG image data into numbers or in other terms referred to as ECG generators and then producing numeric numbers or in numeric ASCII (Standard Numeric) means tangible numbers (numbers), and the next option is to translate manually through numerical data management software to generate numerical numbers through graph plotting.



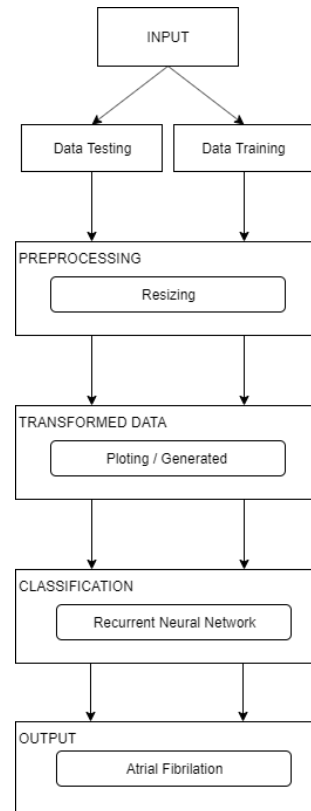
**Figure 5.** Hardware application

AD8232 cardiograph hardware installation on the body following the method described above, namely by The Einthoven method where the installation is done by attaching the cardiograph in a triangle-shaped position on the right chest, left chest and left leg.

**Table 2.** Pin Connection

BOARD LABEL	PIN FUNCTION	ARDUINO CONNECTION
<b>GND</b>	GROUND	GND
<b>3.3 V</b>	3.3 V POWER SUPPLY	3.3 V
<b>OUTPUT</b>	OUTPUT SIGNAL	A0
<b>LO-</b>	LEADS-OFF DETECT -	11
<b>LO+</b>	LEADS-OFF DETECT +	10
<b>SDN</b>	SHUTDOWN	NOT USED

The data are grouped into 2 parts, namely training dataset which aims to provide knowledge and information from data that is processed and testing dataset which aims to show the accuracy of the algorithm incorrectly classifying new data.



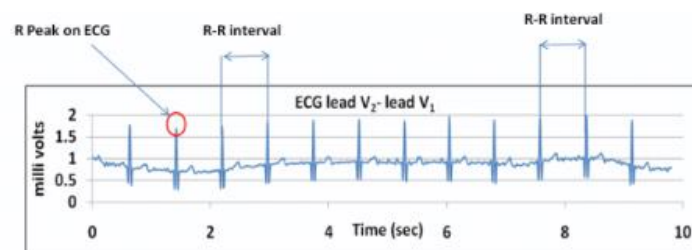
**Figure 6.** Arcitecture Process

### *Preprocessing*

At the first stage of preprocessing, filtration is carried out, which aims to separate the error data before it is processed. Data errors have the potential to occur when testing new data using AD8232, errors that occur can be in the form of electronic wave interference. After filtration is done resizing to equalize many R values in the graph so that it has the same data length. In this research we use 10 second data length to get the peak from R to another R peak and it calls as RR interval.

### *Plotting / Generated*

At the Transformed Data stage, a Plotting / Generated process is used which aims to translate the image results into numerical figures. Plotting is a manual method that is conducted by using a numerical processing application to get the value of each point on the cell. Plotting at the process it will be find the numer of all the R peak. Generated is a direct and practical way to get the value of each reading point.

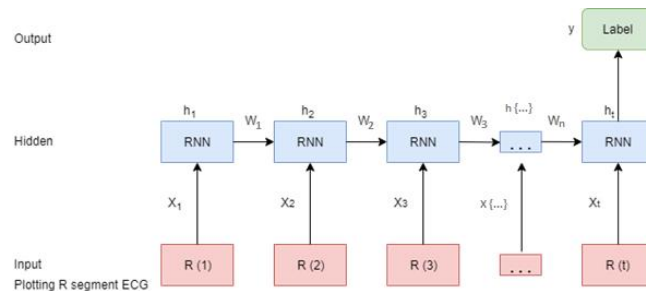
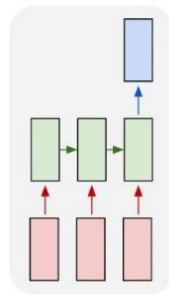


**Figure 7.** R – R Interval 10s [8]

### RNN Implementation

After the plotting value obtained classification is done using the RNN method. The Process Sequence used in RNN implementation is Many-to-One aims to find classification.

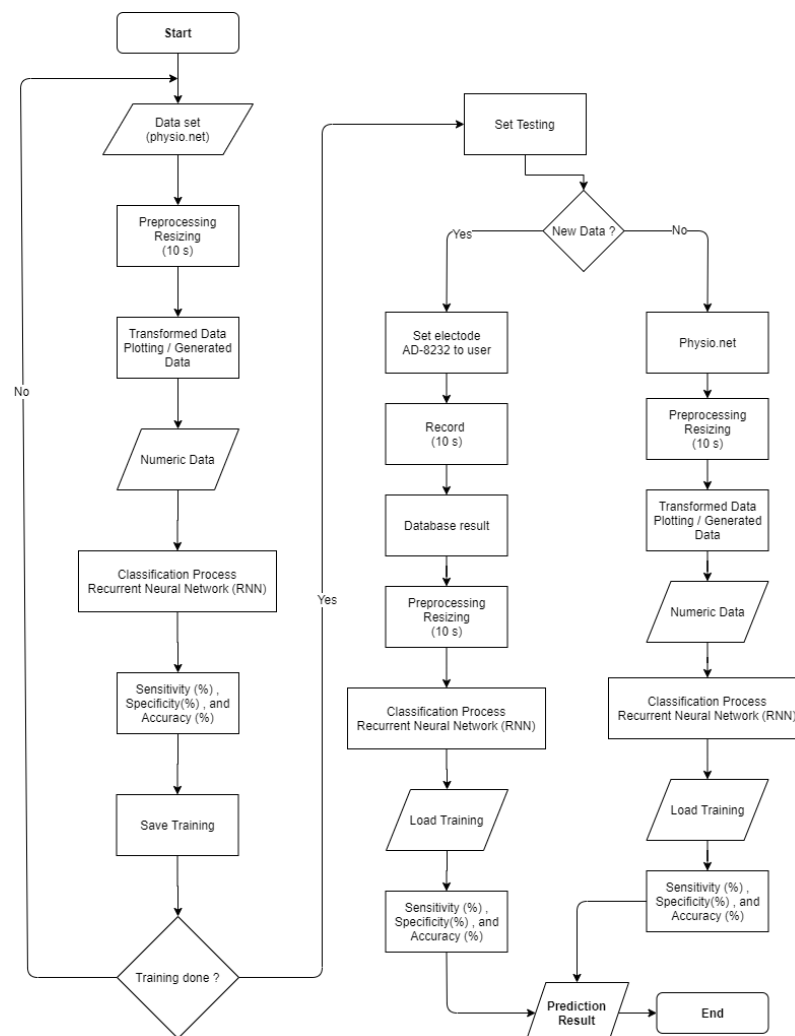
many to one



**Figure 8.** Many to One Classification

**Figure 9.** RNN Process Manny to One

AD8232 is used to obtain new data for testing. After the training data set is generated by experts and accuracy, it is expected that the system can provide an opinion regarding whether or not AF indications. The structure of the system that will be implemented include:



**Figure 10.** Structure Model Result



### 3. Conclusions

Based on the objectives of the research in this paper, we obtain a design of how AD8232 can be applied using in reading the condition of the heart beat and can classify it based on an artificial intelligence model that is RNN. The results of the study obtained a design structure that can be implemented in the training and testing process that is connected directly to realtime data through AD8232. The RNN method might be applied to the determination of AF by training and testing data both from the database and through direct data AD8232. Through this research it was also found that RNN can be applied designed to AD8232 data and how recurrent data designs are. It is hoped that in future design studies, the methods designed in this paper can be applied directly because this paper has found the best way to process AD8232 data into artificial intelligence with the RNN model.

### Conflicts of Interest

This research was made in terms of the final project at the Sumatra Institute of Technology in the Informatics Engineering study program, and is in the process of developing implementation. All authors have participated in conception and design, or analysis. This manuscript has never been sent, is not being reviewed in another journal or other place of publication.

### Acknowledgements

This project was formed by J E S Simanjuntak as an ITERA Informatics Engineering student, and assisted by M L Khodra and M C T Manullang who were the supervisors in the Final Project at the Sumatra Institute of Technology. In the future, you can contact the first author's email at [jonathaneprilio@gmail.com](mailto:jonathaneprilio@gmail.com).

### References

- [1] Rahman F and Benjamin E J 2015 Classification and Epidemiology of Atrial Fibrillation *Atrial Fibrillation: A Multidisciplinary Approach to Improving Patient Outcomes* Estes M and Waldo A L Eds (Minneapolis Minnesota USA: Cardiotext Publishing) vol 4 ch 1
- [2] Crandall M A et al 2009 Atrial Fibrillation Significantly Increases Total Mortality and Stroke Risk Beyond that Conveyed by the CHADS2 Risk Factors *Pacing Clin. Electrophysiol.* **32** (8) pp 981–986
- [3] Ruffini G, Ibanez D, Castellano M, Dunne S and Soria-Frisch A 2016 EEG-driven RNN Classification for Prognosis of Neurodegeneration in At-Risk Patients *Int. Conf. Artif. Neural Networks* **1** pp 314–321
- [4] Bhattacharjee S, Kishore S and Swetapadma A 2018 A Comparative Study of Supervised Learning Techniques for Human Activity Monitoring Using Smart Sensors” *Proc. 2nd Int. Conf. Adv. Electron. Comput. Commun. ICAECC* pp 1–4
- [5] Williams L and Wilkins 2007 *The Only EKG Book You’ll Ever Need* p 319
- [6] 2018 Single-Lead, Heart Rate Monitor Front End (Analog Devices Inc Norwood) pp 28
- [7] Prijono B 2018 *Pengenalan Recurrent Neural Network (RNN) – Bagian 1 – Belajar Pembelajaran Mesin Indonesia* [Online]. Available: <https://indoml.com/2018/04/04/pengenalan-rnn-bag-1/> [Accessed: 17-Oct-2019].
- [8] Shyamkumar S, Rai P, Oh S, Ramasamy M, Harbaugh R E and Varadan V 2014 Wearable wireless cardiovascular monitoring using textile-based nanosensor and nanomaterial systems *Electron* **3** (3) pp 504–520