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# BettaNet: A Deep Learning Architecture for Classification of Wild Siamese Betta Species

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**Abstract.** Fish classification is a mix of animal sciences and artificial intelligence. With the advent of machine learning in artificial intelligence, classification has been done using computer vision algorithms and now deep learning is gaining prominence. Betta fish classification is not much explored. The wild species of Betta Splendens which are native to the Kingdom of Thailand are taken in the research reported in this paper. BettaNet architecture, a modified version of ResNet 152 is used to classify 6 species of wild species of betta. The experimental results show that the proposed BettaNet architecture holds better in performance in terms of accuracy and F1-scores. Two different datasets were used and the performance obtained by the proposed architecture reduced the cross-entropy loss over different experimental configurations.

**Keywords:** Fish Classification, Deep Learning, BettaNet, Betta Fish Classification, Wild Species Classification

## 1. Introduction

### 1.1 *Betta splendens*

This is a less scientifically known fish (Monvises et al., 2009) which is native to the Kingdom of Thailand. There are around five main species of betta fish classified as wild. They are *Betta imbellis*, *Betta mahachaiensis*, *Betta samaragdina*, *Betta siamorientalis*, *Betta samaragdina guitar* and *Betta splendens*. This does not include the hybrid of these wild species or fancy betta species. Classification of these wild species of betta is necessary to group them for various competitions held all over Thailand. The five species taken for classification in this paper are listed in the Figure 1. below. These species are mouth brooding and bubble nesting, used for ornamental and fighting purpose (Kowasupat et al., 2014).

These wild species of betta are highly aggressive in nature (Ichihashi et al., 2004) and the males are raised in isolation and less lighting conditions. This aggressive nature is why they are used in fish fighting competitions and are relatively more expensive than the fancy betta sold worldwide. Data for



the experiments reported in this paper are collected from uncontrolled environment with varying light intensity and through randomly transparent glass.



**Figure 1.** Wild Betta Species from Thailand

## 2. Related Work

Machine Learning Based approach has been done in (Spampinato et al., 2010) and proposed a classification using discriminant analysis on Ecogrid images dataset. Feature selection based system was developed for machine learning systems in (Nery et al., 2005). Features are tried using the hoVer representation and it became ambiguous in huge image dataset (John Joseph et al 2011). Object recognition methods using genetic algorithm is available but it is computationally expensive (John Joseph and Auwatanamongol., 2016). Deep Learning methods have been gaining popularity in many biological domains. Fish classification also uses deep learning. Especially for the surveillance of underwater fish species and classification of fish in various regions. Fish4Knowledge dataset by (Boom et al., 2012) has given a source of underwater fish dataset. This was collected to analyze the trajectory of fish species in underwater environment. A combination of CNN and ReLu was used on this dataset (Rathi et al., 2017) which gave some convincing results. A variant of this method is also used in the experiments mentioned in the results reported in this paper. A fully connected CNN architecture was used to classify Covid 19 X Ray images using fully connected CNN (Bhoumik et al., 2020). This architecture was tried on the dataset collected for wild Siamese Betta species.

**Table 1.** Experimental analysis on Fish4Knowledge dataset (Boom et al., 2012)

S.No	Dataset	Methodology	Testing Accuracy
1	Fish4Knowledge (Boom et al., 2012)	<b>Separable Conv CNN + ReLu</b>	<b>99.96%</b>
2	Fish4Knowledge	CNN + ReLu (Rathi et al., 2017)	96.29%

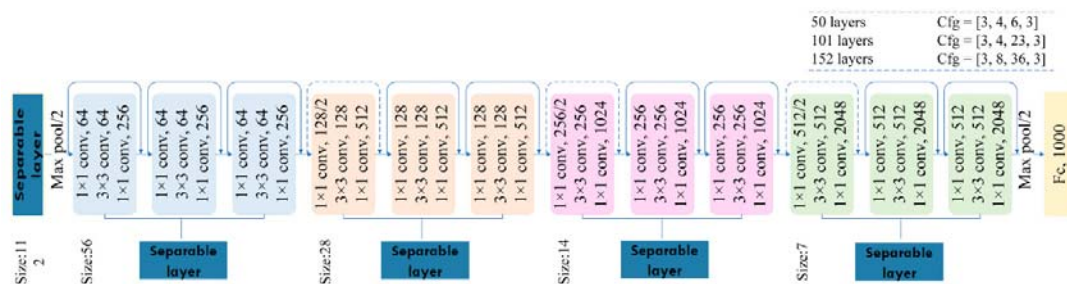
Separable Conv CNN + ReLu is used to compare with the proposed methodology.

## 3. Proposed Methodology

### 3.1 Dataset

Two datasets were collected for the performance reported in the results section. Chatuchak Dataset which was collected in a pet market in Mochit, Bangkok and ICON SIAM Dataset which was collected on occasion of a Betta Fish contest conducted at ICON SIAM, Bangkok. Both the datasets

are split in the ratio of 90:10 for training and testing. Keras API in Tensorflow library of Python was used to evaluate the performance of the existing and proposed methodologies. A terminal with NVIDIA GEFORCE RTX 2060 6GB GPU and 16 GB RAM were used for all the experiments reported in Table 2 and 3. The Keras and Tensorflow setup was done as per the instructions provided in (John Joseph et al., 2020). ResNet 152(He et al., 2016) is overhauled and a new architecture named BetaNet is constructed and proposed in this paper. The proposed BetaNet architecture is given in the Figure 2 below. Convolution 2D layers in ResNet 50 are replaced with Separable Convolution 2D layers.



**Figure 2.** BetaNet Architecture

## 4. Results

### 4.1 Quantitative Results

The experiments mentioned in the proposed methodology are performed with the given hardware and software specifications. The data set is split in the ratio of 90:10 for training and testing respectively. The performance evaluation of various existing deep learning architectures against the proposed BetaNet is given in the tables 2 and 3.

**Table 2.** Performance Evaluation of Chatuchak Dataset

S.No	Methodology	Epochs	Training Accuracy	Cross Entropy Loss	Testing Accuracy
1	LeNet (LeCun & others, 2015)	100	72.63	4.209	36.36
		200			
		300			
		400			
		500			
2	AlexNet (Krizhevsky et al., 2012)	100	72.63	4.209	36.36
		200			
		300			
		400			
		500			
3	CsBio Fully Connected (Bhoumik et al., 2020)	100	92.63	0.1868	72.72
		200	98.42	0.026	81.81
		300	97.37	0.0895	81.81
		400	100	0.0093	90.91
		500	100	0.00089927	90.91
4	Separable Convolution in Fish4Knowledge (Rathi et al., 2017)	100	100	0.000018282	90.91
		200	100	0.000042198	81.81
		300	100	0.000029009	90.91
		400	100	0.00002419	90.91
		500	100	0.00000261	90.91
5	ResNet 152 (He et al., 2016)	100	100	0.02598	81.81
		200	100	0.018977	81.81

6	<b>BettaNet</b> <b>(Proposed Methodology)</b>	300	100	0.002347	81.81
		400	100	0.002256	90.91
		500	100	0.00058963	90.91
		100	100	0.000035245	90.91
		200	100	0.000021689	90.91
		300	100	0.004987	90.91
		400	100	0.000001189	90.91
		<b>500</b>	<b>100</b>	<b>0.000000003</b>	<b>90.91</b>

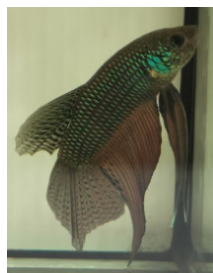
**Table 3.** Performance Evaluation of ICONSIAM Dataset

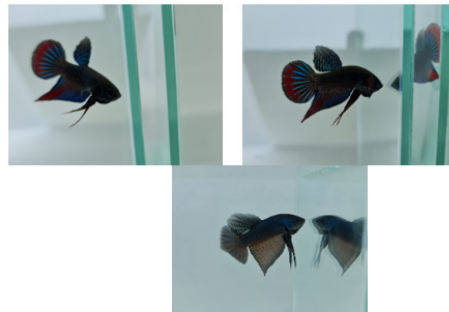
S.No	Methodology	Epochs	Training Accuracy	Cross Entropy Loss	Testing Accuracy
1	CsBio Fully Connected (Bhoumik et al., 2020)	100	93.59	0.1497	20
		200	100	0.0043	30
		300	100	0.0015	40
		400	100	0.000624	50
		500	100	0.0000412	40
2	Separable Convolution in Fish4Knowledge (Rathi et al., 2017)	100	100	0.0000136	20
		200	100	0.0000411	50
		300	100	0.0000347	40
		400	100	0.000000728	40
		500	100	0.000000326	40
3	ResNet 152 (He et al., 2016)	100	100	0.7582	40
		200	100	0.138	10
		300	100	0.0785	50
		400	100	0.0466	20
		500	100	0.013	50
4	<b>BettaNet (Proposed Methodology)</b>	100	100	0.0005242	30
		200	100	0.0648	30
		<b>300</b>	<b>100</b>	<b>0.000050613</b>	<b>70</b>
		400	100	0.0132	30
		500	100	0.000698	60

**Table 4.** BettaNet's best performance over the datasets

S.No	Dataset	Precision	Recall	F1-Score
1	Chatuchak	0.90	0.95	0.91
2	ICONSIAM	0.701	0.71	0.75

#### 4.2 Qualitative Results

**Figure 3.** Wrongly classified image in Chatuchak dataset



**Figure 4.** Wrongly classified images (sample) in ICONSIAM dataset

The wrong classification in ICONSIAM dataset is due to the availability of *B. siamorientalis* and their similarity with *B. smaragdina guitar* species. Chatuchak dataset classified few instances of *B. smaragdina guitar* as *B. mahachaiensis*.

## 5. Conclusion

It is evident from the performance evaluation given in Tables 2 and 3, it is evident that the proposed BettaNet architecture performs better than the existing methodologies. The cross-entropy loss and its related testing accuracy are better than the existing methodologies. This method has to be expanded to bigger datasets and needs to be validated against those images captured in controlled and uncontrolled environment. The preliminary results from our research leads a promising horizon towards the problem addressed in this paper. Table 4 shows enough evidence to back the performance of the proposed architecture. In future, the dataset will be created with a huge magnitude and the BettaNet architecture will be refined to suit the controlled and uncontrolled environments.

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