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Classification of Nile Tilapia using Convolutional Neural Network

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Abstract—**Nile Tilapia (Oreochromis niloticus) is widely known as finfish that is available in the wet market in the whole year-round. Its price and supply is the main reason why consumers buy them. However, some consumers are unmindful of whether the Nile tilapia is free from hibay or not. This paper presents an application of Convolutional Neural Network using the Inception Model V3 in classifying Nile Tilapia whether it was harvested alive or Hibay. Adam optimization was injected in the last two layers of the inception model by adjusting the weights and biases through increasing the number of iterations, the accuracy-test set rate increases. The result shows a significant leap in the accuracy rate of the classification of hibay among Nile tilapia. This research brings forward an extension of using the convolutional neural network in classifying Nile tilapia. Practical and research implications are presented.**

Keywords—nile tilapia, convolutional neural network, inception model, hibay, adam optimizer.

I. INTRODUCTION

Aquaculture is a practice of aquatic organism farming, which includes finfish, mollusks, shellfish, crustaceans, and some aquatic plants. Farming involves some type of production-enhancing interventions in the rearing process, such as periodic storage, feeding, predator protection [1]. Philippines' aquaculture practice has a long history and origin, [2] [3] involving many species and farming method in various ecosystems. The majority of the supply comes from the cultivation of milkfish, tilapia, shrimp, mussels, oyster, seaweeds, and carp [4] [5]. Aquaculture makes an essential and significant contribution to the food safety, jobs, and foreign exchange income of the country. Aquaculture is growing much faster than capture fisheries. However, the Philippines' worldwide position in aquaculture manufacturing has continuously declined from four seats in 1985 to 12th today. The Philippines now accounts for just over one percent of global farmed fish production compared to five percent in the past years [5].

Today, as the Nile Tilapia farming has spread throughout the country and second farmed finfish [6]. According to the Fisheries Statistics of the Philippines, from 2015-2017, CALABARZON Region, as the leader in tilapia production in the entire country. Producing almost 18 percent of the entire three years record of 2015-2017 in terms of the volume harvested [7]. However, there is a problem arising in the harvesting and selling of Nile Tilapia in the market; Consumer Tend to buy unmindfully a sick fish called “Hibay.” Streptococcus agalactiae in Tilapia [8] causes "Hibay," regarded to be the most catastrophic disease because it can lead to huge losses of large-scale fish and serious financial losses. [9] [10] [11]. Disoriented fish with Swirling behavior, bent bodies, and lethargy are frequently reported characteristics due to the tropism of the bacteria of the fish's central nervous system [12]. One of the major concerns in group B streptococcus (GBS) or Streptococcus agalactiae is that it serves a frequent rectovaginal colonizer, a serious problem that causes a primary contributor of neonatal infectious disease [13], and an evolving cause of disease in human non-pregnant adults [14] and causing infection in infants [15].

In order to address the issues, this paper aims to use image processing and machine learning by pointing out how knowledge and science can provide a grasp against the problem's complexities in nature, and thus merely trying to point out the motivation underneath technology-based systems. Convolutional Neural Network (ConvNet / CNN) [16] [17] [18] is an artificial Deep Learning algorithm capable of capturing an input pictures and images, assigning importance (learnable weights and biases) to various elements / features in the image, and being able to distinguish and give a demarcation point of classification between them [19].

Thus, this study contributes by extending knowledge on the use of machine learning to classify Live and Nile Tilapia.

II. RELATED LITERATURE

A. Convolutional Neural Network

Guo et al. (2017) have constructed an image classification using a convolutional neural network. By the Convolutional

Neural Network, various learning rate set techniques and separate optimization algorithms were primarily evaluated to solve the appropriate parameters of impact on image classification. The network design and method are simple compared to the current techniques, although the recognition rate is not the best, and parameters take up memory are low. It has been confirmed that the shallow network also has a comparatively excellent recognition impact [20].

Albawi et al. (2017) explain and describe all CNN-related aspects and critical problems and how they operate. The research also noted that the number of levels increases the amount of time needed in training and testing the network. Today the CNN sees many applications such as face detection and picture, video recognition, and natural language processing as a reliable instrument within machine learning [21].

Lee et al. (2016) propose a fine-grained classification technique based on convolutional neural networks for huge-scale plankton databases. CNN pre-training with class-normalized information and fine-tuning with initial information integrated transfer learning. Class-normalized information built by lowering the amount of information through random sampling for large classes showing superior classification precision compared to both CNN without transferring learning and CNN with transferring learning through other methods of information augmentation [22].

Ji et al. (2016) achieved an excellent experimental result after applying an iterative ref nement method and back-projection algorithm to reconstruct the high-resolution image and construct a multilayer convolutional neural network [23].

Chang et al. (2018) implemented the Convolutional Neural Network model with a single convolutional layer. It also compares the efficiency of our streamlined Convolutional Neural Network model, an Artificial Neural Network model, and the traditional ITA Fitzpatrick classification procedure with a 90% rate of accuracy [24].

B. *Classification*

Hayat et al. (2018) based on linear L2-SVM classifier, examine and compare CNN outcomes with final function vectors obtained from BOW variant methods. On this basis, adequate tests confirm the efficacy and robustness of our CNN model with an accuracy rate of 90.12 %. With normalized normal initialization, the convolutional neural network used to developed and trained with a training dataset of sample pictures from 9 distinct object categories plus sample test pictures using extensively different datasets. All findings were introduced within the framework of python tensor flow [25].

Qian et al. (2016) presented a visual attribute classification scheme based on choice of features and CNNs, the suggested visual attribute classification scheme comprises primarily three components: extraction of features, choice of features and classification. [26].

In combination with feature extraction methods based on Scale Invariant Feature Transform (SIFT) and Speed Up Robust Features (SURF) algorithms, Fouad et al. (2013) present an automated classification method for Nile Tilapia fish using support vector machines (SVMs) algorithms. Experimental findings acquired shows that the support vector machine algorithm outscored other machine learning methods in terms of general classification precision, such as k-nearest neighbor (k-NN) algorithms and artificial neural networks (ANN) [27].

Artificial neural networks have achieved popularity by being used in various ways, such as application detection of malware and medical diagnosis. Neural network models, however, may have a rate of mistake indicating their efficiency. Thus, algorithms involving optimization can reduce the rate of a mistake by updating the specifications of the neural network to achieve an optimal and ideal solution [28].

C. *Convolutional Neural Network*

Convolution neural network is an algorithm with multiple layer perceptron which has a distinctive model for identifying two-dimensional image information [16]. It always has more layers: an output layer, a sample layer, an input layer, and a layer of convolution [17]. Also, the test layer and the convolution layer can have various applications in an extensive network [18].

Convolution Neural Network is not as limited like Boltzmann machine, need to be for all links before and after the neuron layer in the convolution neural network algorithms, neighboring layer, each neuron need not feel global images, inspect the local area of the picture. Besides, every neuron variable placed to the same; weight sharing, namely each neuron of the same convolution kernels to deconvolution image [29] [37].

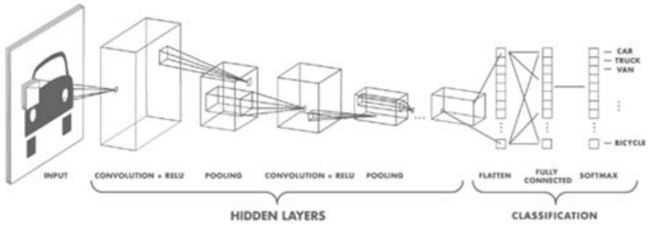

Figure 1. CNN Architecture

Convolution is the very first layer in an input image to obtain features. Convolution maintains the connection between pixels using tiny squares of input information to learn picture characteristics. It is a mathematical procedure that requires two inputs like a filter or kernel and the image matrix.

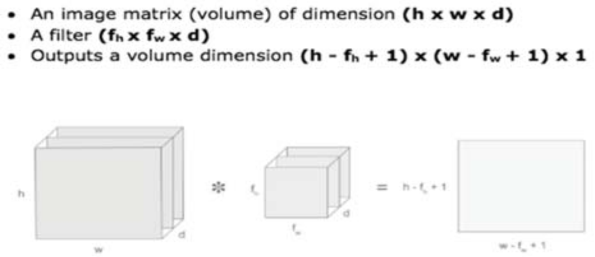

Figure 2. Image Metrix multiplies kernel or filter matrix

Then the convolution of 4 x 4 image matrix added with 4 x 4 filter matrix, which is known as the "Feature Map" as the output shown in figure 3.

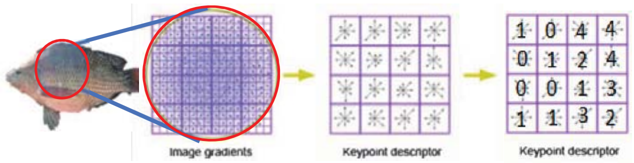

Figure 3. Convolving Process

It is also possible to convert a picture with distinct filters by adding filters to conduct activities such as edge detection, blur, and sharpening.

III. MATERIALS AND METHODS

A. Image Data Acquisition

Images were gathered and taken using high definition mobile phones equipped with no less than 5-megapixel camera phones. To ensure the best quality of image per subject, several photos were taken and chosen among the collected images.

The images were taken at the fish ports in Laurel, Talisay, Agoncillo and Taal, Batangas during a whole month duration of harvesting. Two classes of harvested nile tilapia were taken photos (Table 1) guided and technically observed by the fish farmers in identifying nile tilapia class.

Table 1. Classes of Harvested Nile Tilapia

Class	Description
Alive	The fish was harvested alive. Physical Feature: No skin damage, the body is intact; the color of eyes is black. Fins are intact.
Hibay	The fish suffers from bacterial attack and parasite. Physical Feature: Swollen Abdomen, Popped Eye, Gray discoloration in the eyes.

B. Dataset

In total, 2000 images were used, categorized as Hibay and Live. 900 or 90% out of the total number of Hibay were used as training data, and the remaining 100 or 10% for testing data as presented in Table 2.

Table 2. Dataset Distribution

Criteria	Count	Percentage
Hibay	1000	50.00 %
Live	1000	50.00 %
Total data set	2000	100.00%
HIBAY		
Training set	900	90%
Test set	100	10%
LIVE		
Training set	900	90%
Test set	100	10%

C. Classification

For the classification, Inception V3 Model [30] was used. The Inception models are types of Convolutional Neural Networks designed by Google mainly for image classification. Each new version (v1, v2, v3, etc.) marks improvements they make upon the previous architecture (Figure 4).

The main difference between the Inception models and regular CNNs model are the inception blocks [30][31]. These involve convolving the same input tensor with multiple filters and concatenating their results—such a block, as shown in figure 4. In contrast, regular CNNs performs single convolution operation on each tensor. Moreover, the inception model is based on the classic Convolutional Neural Network that delivers a higher number of convolutions.

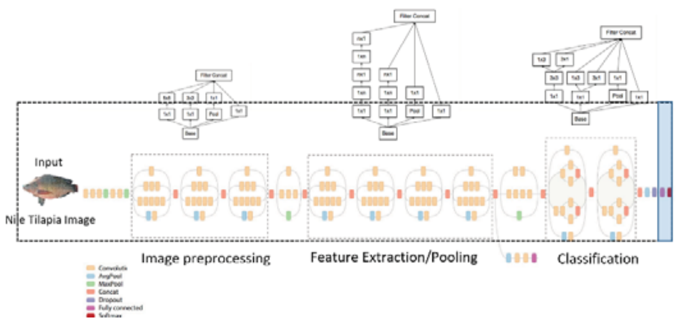

Figure 4. CNN Algorithm in Inception Model

D. Transfer Learning

One of the major issues with deep learning is the classification of images [32]. The primary goal in the method of image classification is to classify a specific image by a collection of feasible classifications.

The issue of image classification can be fixed from a deep learning view by transfer learning. Several kinds of research have some state-of-the-art research results in the classification of images based on transfer learning solutions [33] [34] demonstrates an excellent outcome. Transfer learning in this paper, instead of starting the learning method from scratch, the process begins with practices acquired or patterns when solving unique issues and problem. This takes advantage of prior training and avoids beginning from scratch. Example of actual generated transfer values of selected images from the data set to be processed in the newly created fully connected and SoftMax layer with specifications can be seen in **Figure 5**.

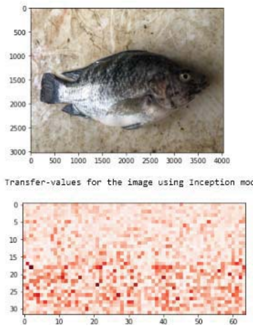

Figure 5. Generated Transfer Values

Figure 5 shows the example of actual generated transfer values of selected images from the data set. The transfer values passed through several convolutions and cross-entropy in the softmax layer it is then wrapped as a pretty tensor object to allow optimization.

Once the TensorFlow graph has been created, a TensorFlow session has been created, which is used to execute the graph. The variables for the new network must be initialized before starting to optimize them.

E. Optimization

In the last two layers of the inception model v3, Adam optimization [35] was used. Adam incorporates the edge of and RM-SProp and Adagrad. It is an algorithm for optimizing stochastic objective features based on first-order gradation-based optimization oriented on adaptive assessments of low-order times. The technique is simple to execute, is computationally effective and has a little storage requirement, is equivalent to a diagonal gradient rescaling, but is well adapted for issues that are huge in terms of data and parameters [36]. To get a higher accuracy-test set rate of the classification, weights and baizes were adjusted using Adam optimization.

F. Confusion Matrix

Confusion Matrix is a standard model performance representation [36]. The chart of the matrix in **Figure 6.** displays the number of cases grouped accurately and inaccurately relative to the actual results (target value) in the test data.

One of the benefits of using confusion matrix as an assessment and evaluation instrument is that it enables more thorough assessment (such as if the model confuses two categories) than a simple number of accurately categorized samples (accuracy) that can yield inaccurate scores when the dataset is uneven (i.e., when there are substantial differences in array of different classes).

	Predicted: NO	Predicted: YES
Actual: NO	TN = ??	FP = ??
Actual: YES	FN = ??	TP = ??

Figure 6. Confusion Matrix

True Negative (TN): anticipating the other tag correctly (we predicted ' no,' and it's ' no '), True Positive (TP): anticipating a tag correctly (we predicted ' yes,' and it's ' yes '), False Positive (FP): anticipating a tag falsely (we predicted ' yes,' but it's ' no '), False Negative (FN): missing and incoming tag (we expected ' no,' but it's ' yes ').

III. EXPERIMENTAL RESULTS

A. Confusion Matrix

This section presents the outcomes of the training process and sample information for the test data result. Inception Model V3 has been utilized in this study. Inception model V3 significantly shows a remarkably high result in image classifications. The initial results of the process, which is presented in Figure 4.a shows that the accuracy of the detection is 56%. Based on the generated output of the confusion matrix, there are 88 images in both classes, which are incorrectly classified that accounts with 44% misclassification.

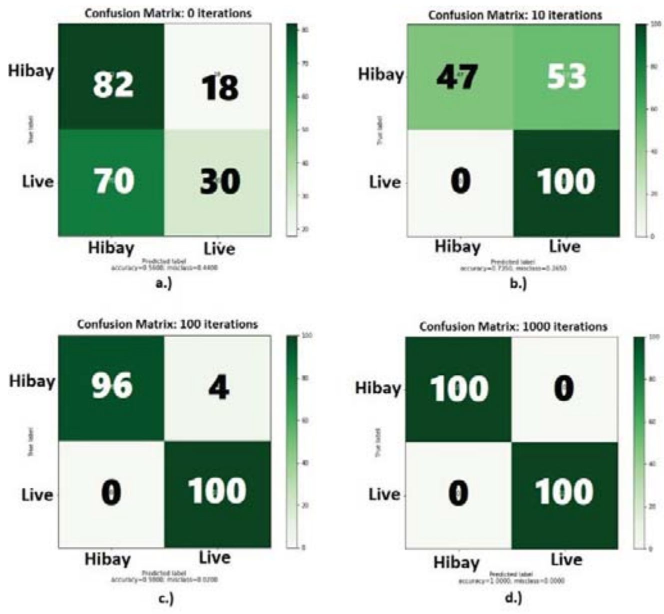

Figure 7. Confusion Matrix Result. **a)** 0 iteration, **b)** 10 iteration, **c)** 100 iteration, **d)** 1000 iteration

On the first accuracy classification test from the inception model it shows a relatively low accuracy having only 56% rate in the combined test-sets of Hibay and Live class while the Confusion Matrix shows that among 100 Hibay test dataset only 82 were classified correctly and significantly low in Live class which is only 30 correctly identified out of 100 test-set for live class.

The model is then optimized using the adaptive moment optimizer with multiple numbers of iterations. The first trial Figure 7. b) uses ten iterations/epoch. It generates a classification accuracy-test set of 73.5% which is 17.5% higher than the previous test with the training time of less than a second as shown in Figure 7. a) The model is pushed further to perform 20 up to 100 iterations, which processed in 1 second, and it gives a much higher classification accuracy, shown in Figure 7. c). The model result in these numbers of epoch is 98%, 24.5% above the previous iteration test result, and 42% higher than the first test result. Any additional iteration did not affect the accuracy, which shows that there is something in the dataset that confuses the neural network.

Finally, after 1000 iterations and with 100 test dataset, the classification model correctly classified all the data set as can be seen in Figure 7. d).

Table 3. Selected Misclassified Images.

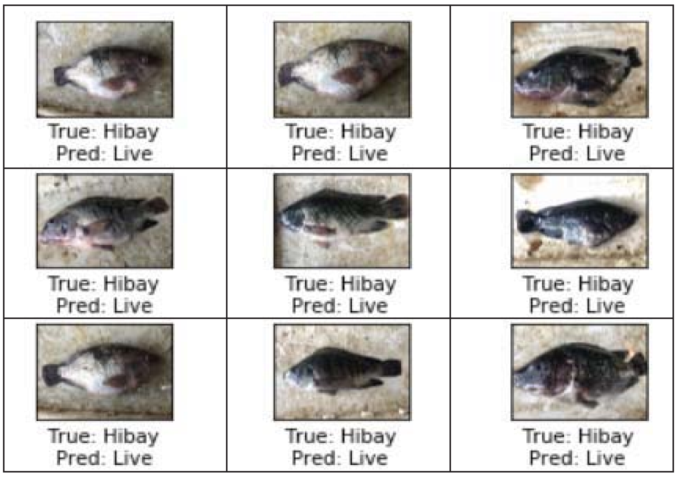

Table 3 shows the sample images of misclassified tilapia in under ten iterations. The value of the Fish are Hibay but predicted as Live.

B. Evaluation Metrics.

An essential aspect of this study is to evaluate the algorithm of the model. When assessed using a metric Confusion Matrix, the model provides satisfactory outcomes but may yield poor results when assessed against other metrics. Classification accuracy is most often used to evaluate a model's performance. It is not enough, however, to judge the model based on the accuracy-test alone.

Table 4 illustrates the generated value of different results measures and metrics; Accuracy, Negative Predicted Value, Specificity, Precision, False Positive Rate, False Discovery Rate, Sensitivity, F1 Score, and False Negative Rate, were used to evaluate the template used in this paper. Table 5. Metrics used to evaluate the Model.

Table 4. Model Evaluation Result

MEASURE	DERIVATIONS	VALUE			
		0 Iteration	10 Iteration	100 Iteration	1000 Iteration
Sensitivity	TPR = TP / (TP + FN)	53.95%	100.00%	100.00%	100.00%
Specificity	SPC – TN / (FP + TN)	62.50%	65.36%	96.15%	100%
Precision	PPV = TP / (TP + FP)	82.00%	47.00%	96.00%	100.00%
Negative Predictive Value	NPV = TN / (TN + FN)	30.00%	100.00%	100.00%	100.00%
False Positive Rate	FPR – FP / (FP – TN)	37.50%	34.64%	03.85%	00.00%
False Discovery Rate	FDR = FP / (FP + TP)	18.00%	53.00%	04.00%	00.00%
False Negative Rate	FNR = FN / (FN - TP)	46.05%	00.00%	00.00%	00.00%
Accuracy	ACC – (TP + TN) / (P + N)	56.00%	73.50%	98.00%	100.00%
F1 Score	F1 = 2TP / (2TP + FP + FN)	65.08%	63.95%	97.96%	100.00%

The values presented in Table 4 were computed using the generated output of the confusion matrix in different iterations. Each metric has a corresponding derivation formula that can be computed using the generated result of the confusion matrix's, TN means True Negative value, FP means False Positive value, FN means False Negative value, and TP means True Positive value.

In terms of metrics results in the 0 iterations, FDR register a result merely stating that the model under the initial state of training has identified 18% of the test data set are truly null, and the Precision result registered the highest value in the initial training result. When iteration increased by ten global steps, NPV, FNR, and TPR already showed the significantly highest result among other metrics.

However, the FDR shows an increase of percentage in nulling the test data set together with the decreasing result of PPV; with this result, ten global step iteration was optimized again up to 100 iterations. During 100 iterations, the results of the metrics registered a significantly high value meaning that adjusting the biases and weight in the fully connected level makes a significant contribution to the results. The highest result was registered when iterations increased to 1000.

It can also be seen in Table 5 of per batch training accuracy of the result. As the step global increases. It can be seen that in 200 iterations, the classification works in 100 percent accurately in a span of 0:00:02 millisecond to 0:00:15 second in 1000 iterations.

Table 5. Global Step Iteration Increments and Accuracy.

Global Step	Training Batch Accuracy:	Time Usage
200	100	0:00:02
300	100	0:00:03
400	100	0:00:04
500	100	0:00:06
600	100	0:00:07
700	100	0:00:08
800	100	0:00:09
900	100	0:00:11
1000	100	0:00:13
1011	100	0:00:15

IV. CONCLUSION

The classification of harvested Nile Tilapia shows an essential process in ensuring the quality of the farmed fish. Even consumers who have no knowledge in identifying whether the Nile Tilapia is a Hibay or not. After using inception model and Adam Optimizer, the result of several test-sets gradually improves as the iterations are being increased. The result shows a significant and high accuracy in identifying Hibay among harvested tilapia. Moreover. CNN and Inception model in this research work could also be utilized to perform classification and identification on other species of fish.

To further this study, model validation activities should be conducted, and other testing activities could be performed to improve the overall performance of the model. The potential use of the model developed could further users and experts in decision-making activities. Likewise, develop a consumer application based on the model to guide in identifying the characteristics of live and nile tilapia.

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