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Improved Classification Model for Fish Species Based on Deep Learning Techniques

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Abstract: **Accurate classification of fish species plays a crucial role in biodiversity conservation, fisheries management, and aquatic ecosystem monitoring. Traditionally, fish classification methods, rely on manual identification, which are time-consuming, error-prone, and often depend heavily on expert knowledge. To overcome these limitations, this study presents an Improved Classification Model for Fish Species Based on Deep Learning Techniques. The proposed model integrates Convolutional Neural Networks (CNNs) with advanced deep learning architectures such as VGG16, ResNet50 and optimized through transfer learning and fine-tuning strategies to enhance feature extraction and classification accuracy. Fish Image Dataset containing multiple species acquired from kaggle.com was utilized. The dataset was preprocessed using image augmentation techniques including rotation, scaling, flipping, and brightness adjustments. Images were normalized and resized to 224×224 pixels to fit the model input requirements. The study adopted a comparative experimental design where three CNN architectures were trained, validated, and tested on the same dataset. Each model was evaluated using accuracy, precision, recall and F1-score metrics to ensure robust performance assessment. Training was conducted using Python and TensorFlow/Keras frameworks. The experimental results revealed that the Improved ResNet50-based model achieved superior classification performance compared to baseline CNN and VGG16 models, attaining an overall accuracy of 96.2%, precision of 97.4%, recall of 96.2%,** and an **F1-score of 96.4% on the test set. The improved deep learning model provides a robust, scalable, and automated approach for fish species classification, offering substantial potential for applications in marine biology, aquaculture, and ecological research.**

Keywords: **Fish Image Recognition, Classification, CNN, VGG16, ResNet, Deep Learning.**

I. INTRODUCTION

According to [1], recent research indicates that, there are over 33,000 fish species all over the world, and over 3 trillion of individual fish in the oceans, making them the most diverse group of vertebrates About halve of these species live in water, and a significant portion of freshwater fish populations are at risk of extinction (see Figure 1 for some common freshwater fish species). The fish population is constantly changing due to factors like fishing, breeding, and environmental conditions. The importance of fish for both nutritional and economic values is enormous. All over the world, consumption of fish species is a source of human diet which provides protein, vitamins and minerals. Other important roles include ecosystem balance, biodiversity, climatic regulation, and so on [2]. The ability to classifying various fish species plays an essential role in protecting its population, as well as fishery industry.

Fish classification is the act of identifying and classifying fish species based on their inherent features. It is the process of identifying and classifying the target fish species based on similarity with representative of fish specimen images [3], [4]. Fish classification is necessary for identification, marketability, pricing, consumption, scientific research and so on [3].

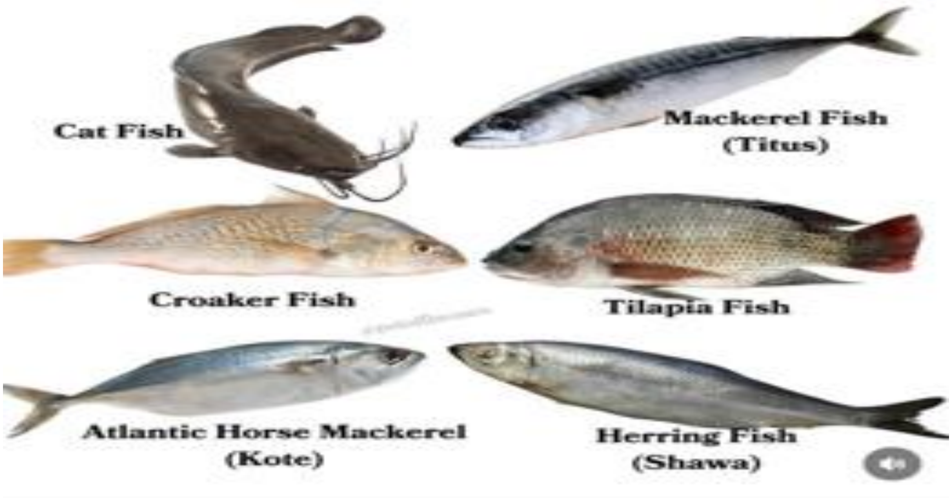

Fig. 1: Common Freshwater Fish Species

Statistical classification methods such as Principal Component Analysis (PCA), Discriminant Function Analysis (DFA) and classification tree have been used in fish classification with inherent limitations which have motivated the shift to Machine Learning, with preferable choice of deep learning [3]. The choice of deep learning technique encompasses its powerful and efficient approach to classification, providing high accurate, automated feature extraction, scalability and efficiency solutions across various domains for classification, regression, clustering and recommendation.

II. LITERATURE REVIEW

2.0 Overview of Deep Learning

Deep learning is a subset of machine learning which has the capable of leaning complex patterns and it has become increasingly popular in recent years due to the advances in processing power and noted for exceptional accuracy when trained on large datasets [5], [6]. Deep learning has achieved significant success in various fields, including image classification/recognition, natural language processing, speech recognition, recommendation systems, and so on. Some of the popular deep learning architectures include Convolutional Neural Networks (CNNs) [7],[8],[9],10], Recurrent Neural Networks (RNNs), Deep Belief Networks (DBNs), Random Forest, and auto-encoder [5, 11].

One of the most pronounced deep learning techniques is the Convolutional Neural Network (CNN) which has been established for excellent image recognition/classification compared to other deep learning algorithms. CNN uses its classification structure to categorize images into labelled classes, noted for high performances in spatial data analysis, computer vision, natural language processing, and signal processing, among others [5].

2.1 Convolutional Neural Network (CNN)

The adopted CNN architecture for the fish classification is depicted in Figure 2. The convolutional neural network (CNN) is a multi-layered deep neural network primarily designed to detect virtual patterns using minimum pre-processing image's pixel [8]. This architecture consists of two components namely, convolutional and pooling layers. Prominent among the CNN architectures adopted for this work are VGG16 and ResNet [8], [23]. The major reason for adopting VGG16 for the study is its support for large scale data set with deeper network layers with smaller filter to produce a better performance. Also, classification of fish species is complex; hence it requires an effective modeling approach as most of the fish species have similar shapes and features. VGG16 version of the CNN has been widely used in this regard because of its performance. When an image of a fish is fed into a CNN, it is processed through convolutional, activation, pooling, and fully connected layers. In convolutional layer, a filter or kernel is applied to the input image to create a feature map which detects specific features like the curvature of the fins edges, colors, and textures of the scales. The process is presented as follows:

$$S(i,j) = \sum_m \sum_n I(i+m, j+n).K(m,n) \qquad (1)$$

Where S is the output feature map, I is the input image, K is the kernel or filter, while m, n are the coordinates within the kernel.

After convolution, the ReLU activation function is introduced. This allows the network to learn non-linear relationships, which are necessary for distinguishing between different fish species using Equation:

$$f(x) = \max(0, x) \quad (2)$$

Where x is the value from the feature map. The function outputs the value itself if it is positive, otherwise, it output zero.

The result is passed to the pooling layer, this makes the model more robust to changes in the image, such as slight shift in the fish's position, ensuring a stable classification. The max pooling is expressed as:

$$y_{i,j=max_{a,b\epsilon window}}(x_{a,b}) \quad (3)$$

Where x is the input feature, y is the output pooled feature map.

The output of the pooling layer is passed into the fully connected layer and softmax for classification. The output layer, a fully connected layer with a softmax activation function, produces the final classification. The softmax function for a given output Z_i, its probability p_i is expressed as:

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (4)$$

Where z_i is the raw output for class i, k is the total number of fish species classes.

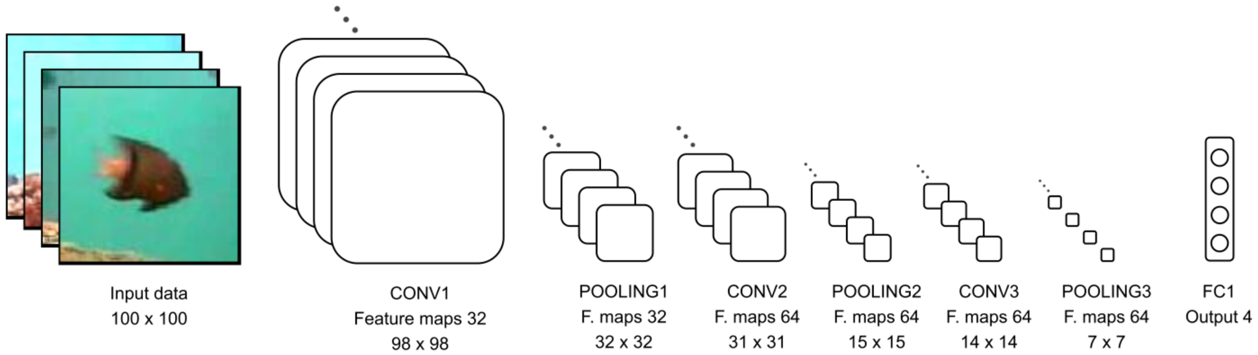

Fig. 2: The CNN Architecture

The VGG16 architecture model is presented in Figure 3. VGG16 is a convolutional neural network architecture for image classification that was developed by the Virtual Geometric Group (VGG) at the University of Oxford [2]. The architecture is characterized by a design which employs a series of convolutional and max-pooling layers followed by fully connected layers. VGG16 receives an input of 224x224x3, containing 13 convolutional layers, 5 pooling layers, and 3 fully connected layers, and the size of the resulted feature map is 224x224x64. The fish images serve as input to the convolutional layer. Each convolutional layer applies a set of learnable filters (kernels) to the input feature map X of size HxWxD (height, width, depth), and filter K of size FxFxD (filter size, filter size, depth), the output image Y as a specific location (i,j) is computed by:

$$Y(i,j) = \sum[X(i+m, j+n, d) * K(m,n,d)] \quad (5)$$

Where $\sum$ is performed over all spatial positions (m,n) of the filter and all channels (d) of the input image.

These layers are arranged in blocks, each starting with convolutional layers (kernels) and end with a max-pooling layer, which allows it to effectively capture the spatial hierarchy of features in an image. The max-pooling layer accepts output images from the convolutional layers and resizing the spatial dimensions of the feature maps by taking the maximum value within a specified 2x2 window stride. The output image Y is computed as follows:

$$Y(i,j) = \max\big(X(i*S+m, j*S+n, d)\big) \quad (6)$$

Where m and n range from 0 to P-1

The final layers are fully connected layers which perform a linear transformation on the images using a softmax activation function. The output vector is computed using

$$Y = WX + b \qquad (7)$$

where X is an input vector, W is a weight matrix, and b is a bias vector.

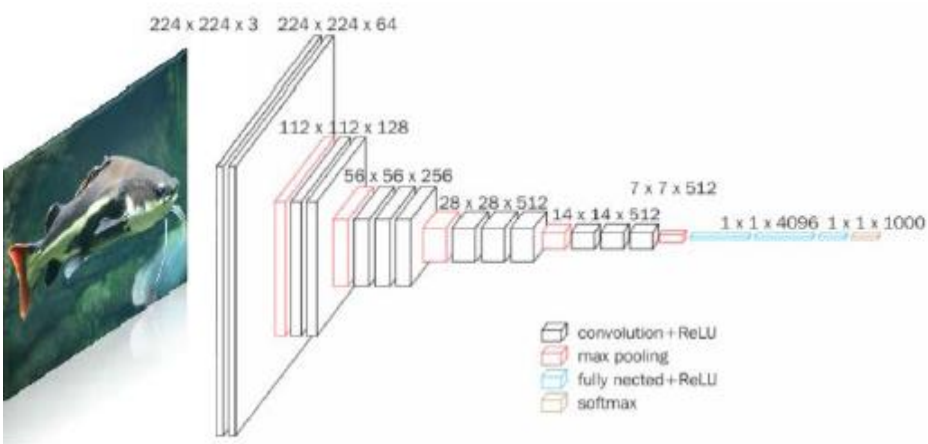

Fig. 3: The VGG16 Architecture

2.2 ResNet

The ResNet (architecture show in Figure 4), is a deep convolutional neural network consist of the initial convolution (conv) layer, several residual blocks and the final fully connected layer [10]. The first convolutional layer does not require normalization of images and ReLU nonlinear activation, while Conv layer in residual block normalizes images using mean and standard deviation, as ReLU nonlinear activation is used as the activation function. Then the initial 3x3 convolution operation is performed on the fish images and the results of the convolution are batch normalization. The ReLU nonlinear activation prompt the next 3x3 convolution operation, and the implementation of a long jump connection pass the activation of the initial layer to the next residual block after the sixth layer. The residual block takes an input X and applies a series of transformations, typically convolutional layers, followed by a non-linear activation function. The output of these transformations is then added to the original input X and the result is passed to another activated function as presented in the formula:

$$y = F(x, \{w_i\}) + x \qquad (8)$$

Where y is the output of the residual block, x is the input to the residual block, F(x, {W_i}) represents the learned mapping with a series of convolutional layers with weights {W_i}, and +x is the shortcut connection.

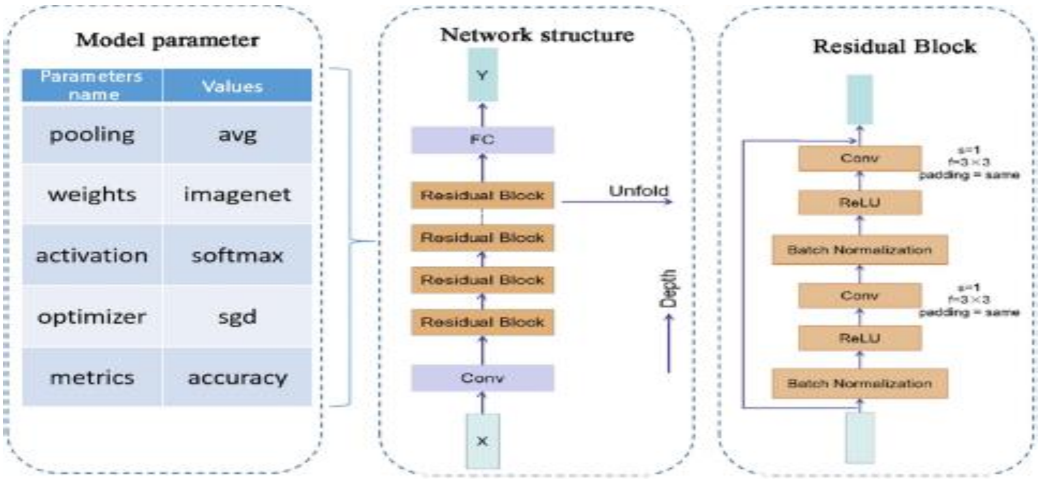

Fig. 4: The ResNet Architecture

Several literatures have been reported in this domain: A machine learning-based fish classification technique utilizing morphometric measurement and mathematical transform data was presented in [1]. The authors focused on the integration of morphometric and transform data with machine learning algorithms namely, SVM, ANN, random forest (RF) and CNN for the fish classification process. Feature selection technique was carried out to optimize classification performance and reduced dimensionality. The experimental result shown encouraging classification accuracy in the automation and improvement of fish species categorization, but failed to used large dataset.

In [2], fish classification using deep learning was presented. The authors incorporated CNN model based on VGG16. The fish dataset acquired from Kaggle website containing 9000 images of different types of fish was used, with 6300 images for training, 1350 images for validation and 1350 images for testing. The classification accuracy rate of 99.68%, precision 99.69%, recall 99.68% and F1-Score 99.68% was achieved. Though, the model exhibited high accuracy, but failed with distorted and noisy fish images. A fish classification technique with salient object detection based on shape and texture is presented in [12]. The model involves preprocessing layer with segmentation making use of U^2-net to remove background and other contaminants, histogram of orientation gradient (HOG) is used as feature extractor, while ensemble layer is used for the classification. A fish dataset containing 2678 comprising 5 classes of fish was used with tested classification accuracy of 99.77% on model-1and 100% on model-2. The experimental results revealed the high performance of this technique but enhancement in feature detection, dimensionality reduction and morphometric analysis are needed. An algorithm for classification of fish species with image data using K-nearest neighbor was presented in [13]. The framework extracted color, texture and shape features with fish dataset contain 4 types fishes of 160 fishes. The algorithm was implemented using WEKA application which produced best classification accuracy of 77.70% with K=7. The algorithm proved suitable for its ability to classify fish images with low fish dataset but failed with large dataset and exhibited high computational complexity. A fish detection and recognition approach based on convolutional neural network (CNN) is presented in [14]. The methodology comprises image processing, feature extraction and classification. The study revealed its promising high speed for detection and categorization of fish species but unable to detect underwater fish species. Also, failed on large dataset. In [15], a consumable fish classification using KNN model was developed. The model incorporated four classes of fish by extracting their texture using Hue, Saturation and Value (HSV) model and color features using Gray Level Co-occurrence Matrix (GLCM). KNN was used as classifier with 320 fish images and obtained classification accuracy of 90% for Tilapia, 97.5% for mackerel. However, the model failed with large dataset. In [16], fish species classification using a collaborative technique of firefly algorithm and neural network was presented. The technique involved a combination of morphological-operators for preprocessing of the underwater fishes, followed by speedup robust feature algorithm for extracting features. The extracted features were optimized using firefly algorithm. PatternNet approach is employed for the categorization of the 10,000 marine fish species into 5 categories. The efficiency of the approach was performed in terms of classification accuracy, execution time, precision value, F-measurement and recall factors with respect to various fish categories. Though, the approach proved suitable for enhancing accuracy and advancing fish species classification but failed for the cases of video datasets and other constraints. Fish species recognition using an improved AlexNet model was presented in [17]. The model incorporated item-based soft attention mechanism which consists of four convolutional layers with one item-based soft attention layer and two fully-connected layers. Transfer layer was then implemented to achieve a shorter training time. The model proved suitable for achieving high accuracy and less computational complexity compared with other models, but failed when apply a simultaneous detection of multiple objects for real-time underwater fish species classification in complex background environments and murky waters. A convolutional neural network-based fish detection model was presented in [18]. The CNN framework incorporated data augmentation approach to support the training process with enough data, Dropout algorithm to solve the over-fitting problem and loss function to update the parameter inside the network. Data was collected using digital camera. Experimental result shown the proposed model performed well has the potential to be extended to other underwater objects. In [19], fish species recognition using transfer learning technique was presented. The technique involved extracting salient features using Google Inception V3 model followed by classifying all the test images using SoftMax classifier. Fine-tuning was carried out using input images, followed by classification by ensembling both Google Inception V3 and SVM classifiers. Evaluation of the model was performed on the acquired Fish4Knowledge (F4K) dataset, and obtained an impressive accuracy. The model is suitable for identifying fish existence and quantity for marine biologist use. However, an improved classification accuracy would be obtained by using deep learning approach. A deep CNN-based fish identification and classification using deep learning and machine learning was presented in [20]. The authors adopted the combination of deep learning (DL) and machine learning (ML) techniques, which comprise of seven CNN architectures used to extract salient fish features while seven ML classifiers were implemented to identify the two classes of fish species namely freshwater and salinity. denseNet121, EfficienNetBO, ResNet50, VGG16and VGG19 of the CNN architecture were implemented for the classification process while and SVC ML technique was used to generate F1-score, precision, and recall for binary classification (freshwater/salinity) of the fish images, with an improved classification accuracy. However, the model is characterized with inadequate and low dataset, cannot produce accurate result with unknown fish species, badly affected mage quality, background and noise. Also, there was no trained model used. Automatic labelling of Fish Species using deep Learning across different classification strategies was presented in [21]. The model was conducted in five steps, namely, (1) image acquisition and preprocessing, (2) application of the following CNN algorithms, ResNet152V2, VGG16, EfficientNeL and Xception for image classification, (3) ally fine-tunning to obtain final CNN models, 4. Substitute classification layer with 21 different classifiers to obtain multiple F1-scores for each model, and final step is by applying post-hoc statistical analysis for performance accuracy comparison. Experimental results indicated an increase model performance when combining the feature extraction capabilities of CNN with other supervised classification algorithms. Real-Time detection and Classification of Fish in Underwater Environment using YOLOV5 was presented in [22]. The authors utilize a deep neural network model, to detect fish images, after which the model was trained with a properly annotated fish dataset. Evaluation was carried out with the use of metrics such as Precision, Recall, and F1-Score, which demonstrated satisfactory fish detection and classification capabilities enabling model optimization to achieve a balance between accuracy and detection completeness. However, the model requires a high-speed.

The research gap created by these limitations justifies the need to develop a fish classification based on deep learning techniques.

III. METHODOLOGY

Figure 5 presented the CNN model architecture designed for the work. The design combined VGG16 and RestNet for the classification of fish species. The architecture comprises of acquisition of fish image dataset, image enhancement, model training, evaluation and classification. The enhancement stage prepares the fish images for training and testing by reducing the dimensionality of the images to a uniform size by scaling the images to a specified width and height for data consistency, convert the resized fish images to grayscale for easier to process computationally, this is significant for machine learning models that require a large amount of data as grayscale images can reduce the size of the dataset and accelerate the training process. The fish image is then normalized by applying color normalization.

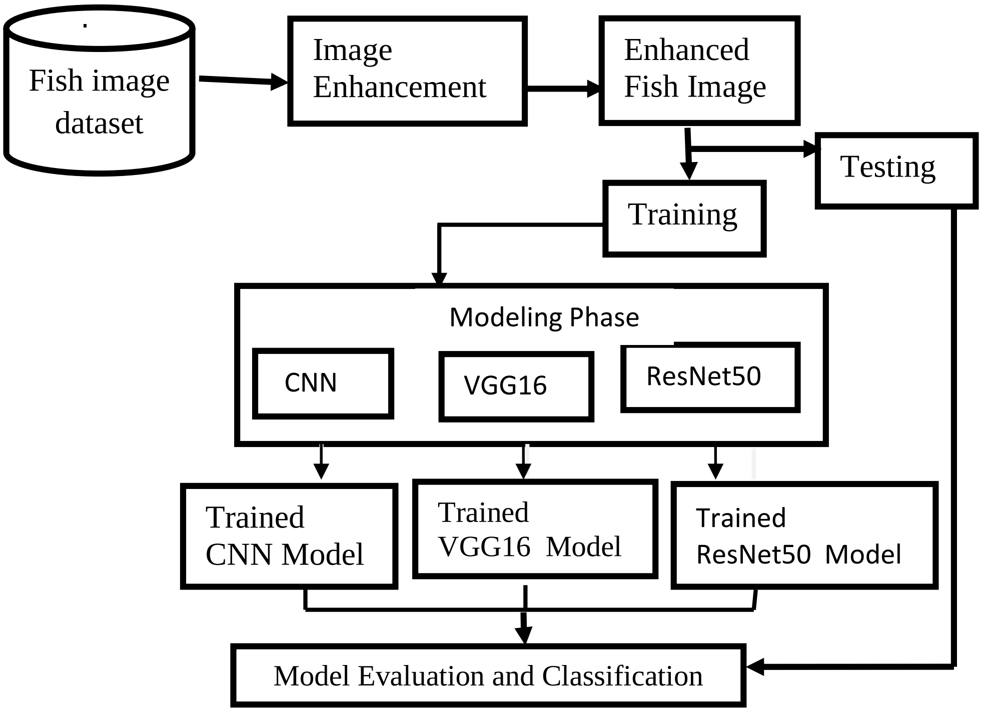

Fig. 5: Model Architecture

Data augmentation is used to increase the size of the dataset and prevent over-fitting which normally occurs when the machine learning model performs well on the training data but perform badly on new data. Data augmentation involves generating new artificial images from the existing dataset by applying transformations such as rotation, zooming, flipping or adding noise to the original images.

3.1 Image Acquisition and Processing

The benchmarked fish dataset used for model evaluation was acquired from an open-source repository, Kaggle.com was considered for this research work. The dataset comprises of 9 different fish species, namely, Striped Red Mullet, Red Sea Bream, Horse Mackerel, Black sea Sprat, Gilt-head Bream, Shrimpfish, Trout, Sea Bass, and Herring. The dataset contains a total of 9000 (1,000 images per species) images of different types of fish species. 70% (6.300) of the dataset was splitted for training the model, 15% (1,350) for testing while 15% (1,350) of the images for validation. The training set is used for training the CNN, VGG16 and ResNet50 models, while the validation set enhances smooth monitoring of the model's performance and the tuning of the hyper-parameters. During training stage, the fish images are subjected to the CNN operation for the extraction of relevant features. This involves the multiple convolutional layers designed for the use of filters to capture the extracted features. Next is the use of the pooling layers to reduce spatial dimensions. The output from the convolutional layers is subsequently compressed and directed into fully connected layers for the classification operation. For testing stage, the images were also subjected into enhancement steps as the training data. Each model then make classification on the testing images.

3.2 Image Enhancement

The process of fish image enhancement is very crucial stage which allows the input fish images to be preprocessed in order to enhance their quality and make the fish species suitable and fit for classification.

3.2 Dimensionality reduction

Most of the fish images are high-dimensional and need to be resized to a lower dimension so as to reduce the computational complexity and improve the classification. This process is done by applying a fixed width and height to the images or by maintaining the aspect ratio while adjusting the longer dimension.

3.3 Normalization

Image normalization is performed to ensure that the input image is standardized the intensity value in an image by rescaling them within the desired range of values of 0 and 1. It is used to reduce the impact of varying pixel values and enhances the convergence of the training process.

3.4 Feature extraction

After image resizing and normalized, the salient features are extracted from an enhanced image using a deep convolutional neural network (CNN). The CNN is pre-trained on a dataset of fish images. The extracted features from the CNN are the quality attributes that form the meaningful representation that could be utilized for classification.

IV. THE EXPERIMENTAL SETUP AND RESULT

The experimental study was carried out on a personal computer core i5 with 4GB RAM, 250GB HDD 205 GHz processor with 64-bit Operating System. The software requirements include Python libraries, TensorFlow/Keras, Google Colab Jupyter Notebook, Matplotlib, Numpy and Python Image Library (PIL). For the dataset's size expansion, data augmentation involving various random transformations was used. The augmentation was used to reduce the risk of over-fitting while enhancing the model's generalization ability. A rotation range of 15 degrees, brightness adjustments within a range of 0.5 to 1.5, and horizontal as well as vertical flips were used for the augmentation. Since each image come with different sizes and dimension, there is need for images uniformity in order to reduce the computational time, the tf.image.resize() function was used for image dimension specification and resizing to 128x128 pixels, followed by image normalization to the desired range of 0 and 1 pixel.

4.1 Hyperparameters of CNN

The influence of hyperparameters on CNN model performance is necessary for optimal performance of the algorithm implementation [7]. The following hyperparameters of the CNN model as shown in Table 1 were adjusted and used.

TABLE 1: Hyperparameters used in CNN training process

Hyperparameters	Parameter values
Optimizer	Adam
Learning rate	0.00001
Batch size	32
Epochs	50
Loss function	Categorical cross-entropy

4.2 Performance Evaluation Metrics

The performance evaluation metrics is based on accuracy, precision, recall and F1 score as expressed in equations 9-12.

i. Precision is defined by True Positive (TP) divided by the summation of True Positive (TP) and False Positive (FP) is expressed as follows:

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

ii. Recall is True Positive divided by the summation of True Positive and False Negative is expressed as follows:

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

iii. F1-score is defined by 2 times precision times recall divided by the summation of Precision and Recall is expressed as follows:

$$F! - score = 2 * \frac{Precision \times Recall}{Precision \times Recall} \quad (11)$$

iv. Accuracy is the summation of true Negative and True Positive divided by the summation of True Negative, True Positive, False Positive and False Negative

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FN} \quad (12)$$

4.3 Performance of the fish classification models

Table 2, Figure 6 and Figure 7 show the plot of the performance of the models in terms of the accuracy and loss respectively. The models were subjected to training for multiple epochs with each epoch contained 32 samples, which are complete passes through the entire training dataset. The training loss experiencing decreased from 0.24 for CNN, 0.08 for VGG16 to 0.05 for ResNet50. This indicates that, the built model is learning and working fine. Also, the model's prediction and classification improved over time, becoming more accurate. The training accuracy increased from 92.5% for CNN to 98.5% for ResNet50 indicating a considerable increased in correct classification of the fish species in the training set. Figure 6 and Figure 7 show the plot of the performance of the models used in terms of accuracy and loss respectively.

TABLE 2: Training performance of the models

Model	Training accuracy	Validation accuracy	Training loss	Validation loss
CNN	92.5%	88.3%	0.24	0.35
VGG16	97.8%	95.1%	0.08	0.12
ResNet50	98.5%	96.7%	0.05	0.10

The models performance on the validation dataset in which the validation loss consistently decreased implied that the models' prediction on unseen data improved consistently during training while the validation accuracy also improved considerably to 96.7% for ResNet.

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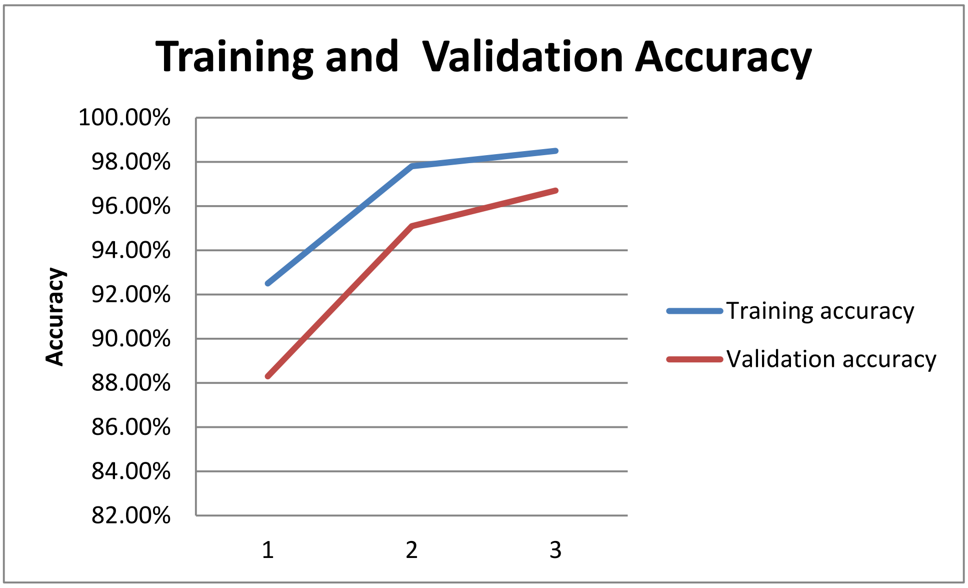

Fig. 6: Training and Validation Graph

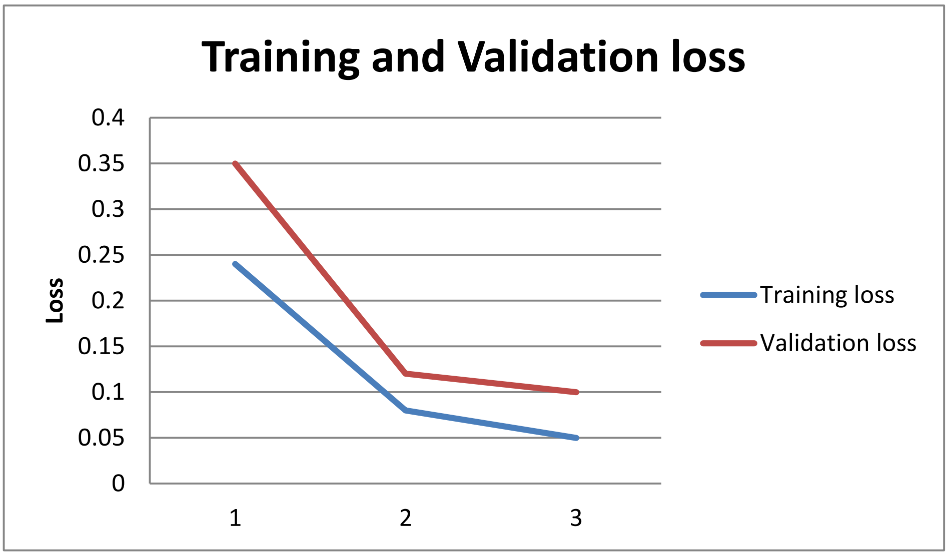

Fig. 7: Training and Validation Loss Graph

Furthermore, the evaluation of the models was performed on a separate test dataset with data not encountered during training. A test accuracy of 87.6% was achieved for CNN, 94.5% for VGG16 while test accuracy of 96.2% was achieved for ResNet50, indicating a correct classification and very strong generalization of most of the samples in the test dataset. From the available results shown in Table 3, the ResNet50 model achieved highest precision and accuracy, proving that deep residual networks are effective for fish classification tasks. While the VGG16 model also achieved high precision with slightly lower accuracy of 94.5%. The CNN model had a lower precision and accuracy compared to the VGG16 and ResNet models with the correct classification of 87.6%.

TABLE 3: Test performance of the models

Model	Test accuracy	Precision	Recall	F1-score
CNN	87.6%	0.89	0.88	0.88
VGG16	94.5%	0.95	0.94	0.94
ResNet50	96.2%	0.97	0.96	0.96

Figure 8 and Figure 9 present the plot comparative analysis of these results. The classification accuracy of the fish species as shown in Table 4 indicate that, CNN model classified Striped Red Mullet species with the accuracy of 94.4% while Sea Bass species obtained the lowest accuracy of 88.4%. VGG16 model classified Striped Red Mullet species with the accuracy

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of 97.0% while Sea Bass species obtained the lowest accuracy of 93.6%, while ResNet50 model classified Striped Red Mullet species with the highest accuracy of 98.1% while Sea Bass species obtained the lowest accuracy of 93.8%. The ResNet50 model correctly classified most species, with slight misclassifications between Sea Bass and Trout due to similar body shape and color.

TABLE 4: Comparative Analysis Table

Species	Accuracy (%)		
	CNN	VGG16	ResNet50
Striped Red Mullet	94.4	97.0	98.1
Red Sea Bream	88.6	96.4	97.5
Horse Mackerel	87.9	95.8	95.3
Black Sea Sprat	90.2	96.7	94.7
Gilt-Head Bream	92.1	94.3	96.8
Shrimpfish	91.3	93.8	97.1
Trout	90.8	94.1	94.2
Sea Bass	88.4	93.6	93.8
Herring	91.7	94.7	96.5

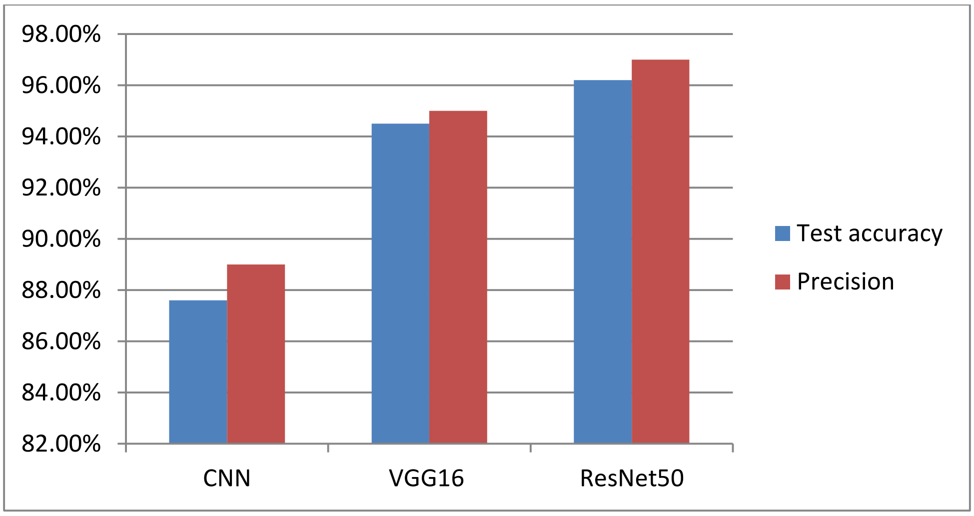

Fig. 8: Comparative Analysis of the Model Result

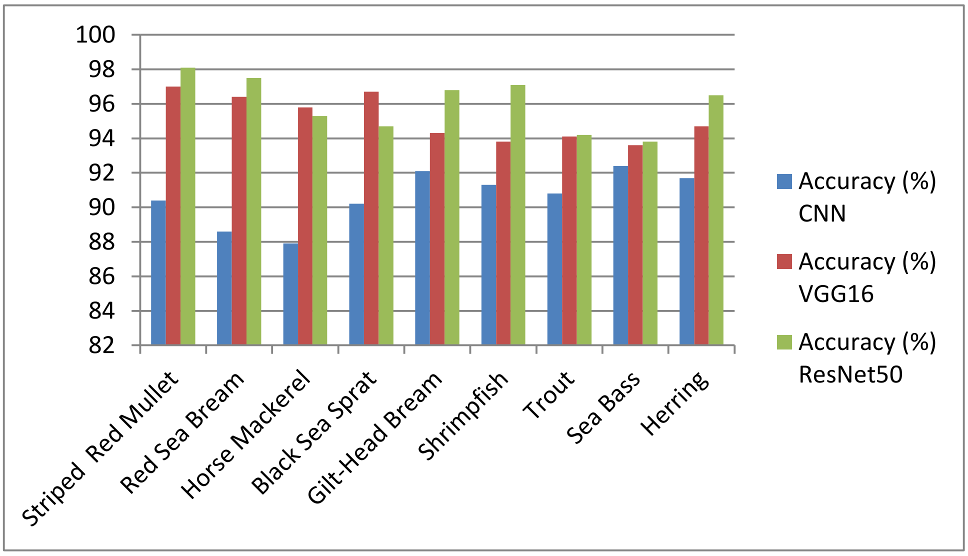

Fig. 9: Comparative analysis of the model based on Fish Species

V. CONCLUSION

The study focused on using deep leaning technique for fish species classification. A detailed of fish classification related literature, deep learning and other topics in the research domain were extensively discussed. A benchmarked fish image dataset of nine (9) different types of fish species from Kaggle source was used to investigate the performance of the proposed models. A deep learning framework was used achieve an improved and efficient classification of various fish species beyond what is obtainable in existing techniques. Data augmentation was carried out using augmentation functions such as image rotation, scaling, flipping to improve model generalization and reduce over-fitting. The experimental dataset was divided into 3 sets of 70% training, 15% validation and 15% testing. The ResNet50 and VGG16 models achieved the best performance and outperformed the CNN, proving that deep residual networks are effective for fish classification tasks. Misclassification mostly occurred between visually similar species such as Troutand Sea Bass, Mackrel and Herring. Analysis of the results showed the model effectively and efficient in handling any classification of fish species. The model therefore is suitable for automated fishery monitoring, biodiversity conservation, and smart aquaculture applications.

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