

# Fish Disease Detection using Deep Learning and Machine Learning

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## ABSTRACT

Fish farming is the practice of rearing fish in cages for human consumption. It is the area of animal food production that is expanding most rapidly. It thus is vital for higher fish production. However, it is deteriorating as a result of several diseases. Numerous ailments and conditions known to harm fish have documented causes, including concern, overcrowding, poor water quality, and failure to quarantine any recently arrived or ill fish to prevent disease transmission. Untrained farmers have a difficult time spotting fish disease. This issue can be resolved with low-cost fish disease detection equipment. Since we're going in the era of data science, we want to compare which deep learning or machine learning method is better suited for this area of study. To build an accurate model, we gather a total of 1382 images for the four classes of White Spot, Black Spot, Red Spot, and Fresh Fish. When it comes to image classification, deep learning outperforms machine learning. In this study, we used a segmentation technique to locate the afflicted area. With the aid of performance evaluation matrices, nine popular classification algorithms as well as two ensemble methods are also used to measure performance. The highest accuracy, 99.64%, is achieved by the VGG16 and VGG19 ensemble models, while ResNet-50, a pre-trained model, achieved 99.28% accuracy, outperforming Random Forest's 90.25% accuracy.

## Keywords

Fish Disease, Segmentation, Machine Learning, Deep Learning, Evaluation Matrices. CNN, Ensemble model.

## 1. INTRODUCTION

Among the most important groups of vertebrates that provide sustenance for humans are fish. On fish farms, diseases can lead to significant issues. They might obliterate fish populations or render a farmer's products unsellable. Fish eradication and state and federal quarantines can result in significant financial losses if exotic diseases are found on fish farms. There are currently 25,000 species of fish that can be identified by scientists, and another 15,000 species may or may not be recognized. Fish demand continues to rise as the world's population grows and the benefits of fish as a source of animal protein become more widely recognized [1]. Fish

production is harmed by infectious illnesses, which also reduce fish quality and quantity.

Approximately 15% of fish productivity is reduced annually due to infectious illnesses [2]. As of 2020, 97% of all seaweed production and about 53% of all fish and invertebrate production worldwide were produced by aquaculture. This makes it one of the fastest expanding food production sectors [3]. When every gadget equally provides useful data and everything is automated, smart fish farming is effective. Despite being expensive, this approach yields better results. Customers and regulators, who value a safer product, will provide farmers who can prove the health of their fish a competitive advantage.

After all, we decided to apply deep learning model. Because deep learning models are data hungry and find the pattern easily from large dataset as well as provide a better result.

## 2. BACKGROUND

Compared to other meat from terrestrial animals, and eating fish offer a number of benefits for your health, nutrition, environment, and social life. According to the Food and Agriculture Organization (FAO), fish consumption is raising significantly, which has improved diets around the world by introducing more varied and nutrient-dense foods. Approximately 17% of the animal protein ingested by the world's population and 6.7 percent of all protein consumed in 2013 came from fish. In many LIFDCs and least-developed nations, little amounts of fish can significantly improve the nutritional quality of plant-based diets. Unsaturated fats found in fish are typically high and offer protection against cardiovascular illnesses. (FAO 2016). According to one assessment, the world's appetite for fish is predicted to nearly double by 2050 as a result of rising wealth and population. The demand is likely to be satisfied by a notable increase in farmed seafood. Modeling based on World Bank and International Monetary Fund projections of future economic and population growth

and data from the UN Food and Agriculture Organization (FAO) on the types of fish consumed in 10 countries that account for 55% of global fish consumption allowed the researchers to arrive at their conclusions.

## 2.1 Contribution

In this research, we employed several preprocessing methods, including resizing, color conversion, and image segmentation, to detect fish diseases. Furthermore, we used deep learning and machine learning models to detect this disease. The ensemble model that achieved the highest accuracy was merely a CNN-pretrained model.

## 3. LITERATURE REVIEW

Fish disease detection has been studied extensively as it is an attractive subject for research. The authors of [1] gathered a total of 90 images for the three classes of white spot (30), red spot (30), and healthy (30). They only used the CNN model, which had a 94.44% accuracy rate. In [2], the authors ensemble data in real time. They build an automated system for classifying EUS, Fin and Tail Rot, and Healthy. They were using machine learning models, and Random Forest obtained the highest accuracy of 88.87%. The authors of [3] collected a total of 266 images that were used to train and validate our model. After the augmentation, they perceived that the total number of training and testing images was 1,105 and 221, respectively for two classes: fresh fish and infected fish. With and without augmentation, SVM performs admirably, with 91.42% and 94.12% percent accuracy, respectively, for this research. In [4], the authors worked on an automated system for real-time EUS fish disease identification. They worked in the MATLAB environment. They also employed FAST-PCA-NN and PCAs-HOG-NN. However, they were able to achieve 86.0% accuracy using FAST-PCA-NN. The authors of [5] worked on multiclass fish diseases and collected 1120 data. The outcomes demonstrate that the C4.5 algorithm performs admirably to detect fish diseases for the lowest class and highest class accuracy at 55.3% and 88.4%, respectively.

In our research, we used a variety of machine learning, deep learning, and ensemble models to accurately detect fish diseases.

## 4. METHODOLOGY

The research's primary area of interest is the system architecture. It makes it possible for every researcher to comprehend the work being done in this study. It is decided to simplify and make more sense of the system architecture shown in Fig. 1. As a result, we follow each step in the proper order.

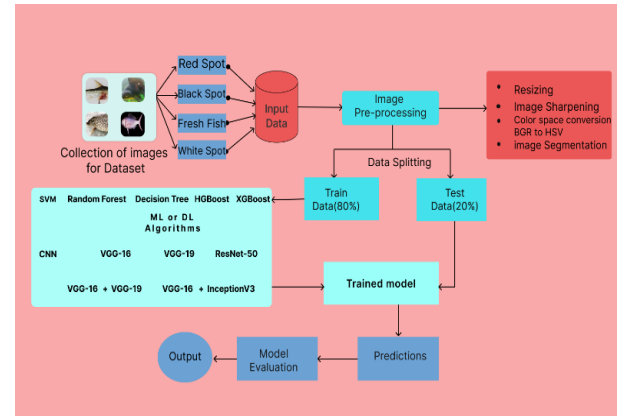


Fig. 1: System Architecture

### 4.1 Dataset Collection

We acquired 1382 images of fish with red spots, black spots, white spots, and fresh fish after gathering image data from multiple publicly accessible locations including Kaggle. We have not discovered any datasets in any of the resources because image-based disease identification of fish is not yet the subject of extensive research. There is no precise dataset on this topic. Therefore, we had to create a brand-new, authentic dataset of fish disease images for this study. In this collection of data, we used some Kaggle datasets [17] [18]. Though that dataset has few images, according to our class, we decided that we have to collect some data to increase our dataset. We also collect data from renowned social media sites, websites, and free stock photos.

### 4.2 Description of Classes

• **Red spot disease:** A typical fish disease is red spot disease. It is primarily recognized as an epizootic ulcerative syndrome (EUS) and is brought on by oomycete fungi. Fish with sickness from EUS develop horrifying lesions. Most typically, lesions are visible on the nearby surface; however, they can also be located in any area of the sick fish's body. It quickly spread throughout the water [2].

• **White spot disease:** The "white spot" fish parasite disease is contagious. The parasite, which is caused by Ichthyophthirius multifiliis, enters the fish after traveling from the pond's bottom. Once attached to the fish, the parasite burrows beneath the skin to feed on the fish's cells and bodily fluids.

• **Black spot disease:** Fluke disease or diplopstomiasis are other names for black spot disease. This flatworm disease in freshwater fish is brought on by Neascus flatworm larvae. On the flesh, fins, and skin of the fish, it appears as minute black patches.

• **Fresh fish:** Fresh fish is defined as fish that has only been chilled and has not been preserved, cured, frozen, or otherwise processed. The body ought to be immaculate.

### 4.3 Image Preprocessing

Pre-processing takes place to raise the image's quality so that we can examine it more effectively. Through pre-processing, we can remove unwanted distortions and enhance specific properties that are essential for the application we are developing. Those qualities might alter based on the application.

#### 4.3.1 Resizing image

Resizing an image entail altering its dimensions, whether by adjusting the width, the height, or both. Additionally, the enlarged image may retain the original image's aspect ratio. OpenCV includes the cv2.resize() method to resize an image. We used 224 X 224 resizing for easier to apply any deep learning algorithm which is shown in Fig. 2.

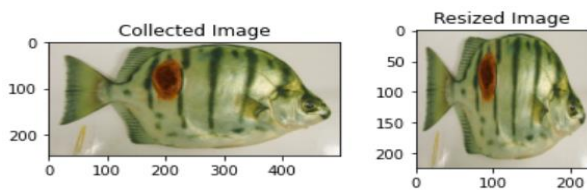


Fig. 2: Image Resizing

#### 4.3.2 Image Sharpen

In Python, we need to use the filter2D() method to sharpen an image. This technique takes in a few contentions, 3 of are vital.

**src:** The picture that is sharpened.

**ddepth:** ddepth=-1, that means the output image's depth match that of the input image, we informed the compiler.

**Kernel:** We use the kernel that is depicted in Table 1 to sharpen an image.

Finally, we get a sharp image which is shown in Fig. 3.

Table 1 Kernel for image Sharpening

<b>Sharpen</b>	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$
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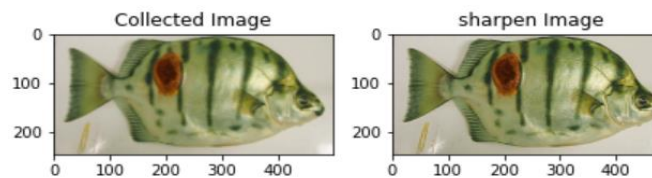


Fig. 3: Image sharpening

#### 4.3.3 BGR color space to HSV color space

The function cv.cvtColor(input image, flag), where flag specifies the type of conversion, is used to convert colors. HSV has a color space of [0,179], a saturation space of [0,255], and a value space of [0,255]. Scales used by different software vary. Therefore, you must normalize these ranges if you plan to compare OpenCV values with them.

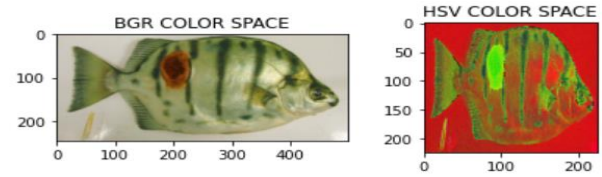


Fig. 4: Convert color space

#### 4.3.4 Image segmentation

Segmenting images is a technique for breaking up a digital image into smaller groupings called image segments, which reduces the complexity of the image and makes each segment more easily processed or analyzed [9] [1].

**inRange():** mainly contains three parameter. Parameter are given below

- src
- lowerb
- upperb

**single-channel input array:**

$$dst(I)=lowerb(I)0 \leq src(I)0 \leq upperb(I)0$$

**two-channel input arrays:**

$$dst(I)=lowerb(I)0 \leq src(I)0 \leq upperb(I)0 / Alowerb(I)1 \leq src(I)1 \leq upperb(I)1$$

and so on.

In other words, if src (I) is outside of the given 1D, 2D, 3D, etc. box, dst (I) is set to 0 and otherwise to 255 (all 1-bits).

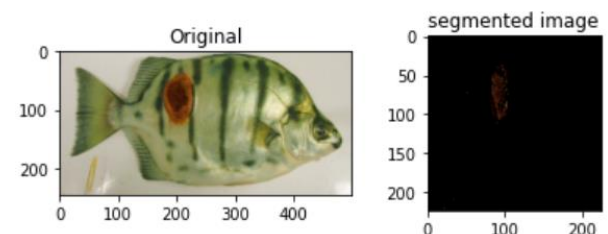


Fig. 5: Segmented Image

In order to apply our mask for segmenting the image, we employ the bitwise AND operation. In Fig. 5, a segmented image is displayed.

### 4.4 Dataset Splitting

After utilizing parameter tuning, we chose to split the dataset into train and test data at 80% and 20%, respectively. For our acquisition dataset, this splitting dataset provides the best accuracy. In total, our dataset contains 1382 images.

### 4.5 Classifiers

The researchers utilize the action research methodology as the foundation for their study. A technique called action research greatly emphasizes social interaction [1]. CNN is the most renowned technique for computer

vision research. The most common base algorithm used by researchers conducting deep learning-based research is CNN. In this case, we used CNN and pre-trained models such as VGG16, VGG19, and ResNet-50, as well as two combinational models, VGG16+VGG19 and VGG16+Inception v3. Most of the researchers applied SVM[3], C4.5[5], and other techniques in their earlier work. In contrast, we used the most updated variation on bagging and boosting techniques to gain higher accuracy.

#### 4.5.1 Convolutional Neural Network

Fig. 6 displays our CNN model. The goal of this model is to predict whether a disease would be categorized as "white spot," "red spot," "black spot," or "fresh fish". CNN has building blocks, which are also called layers [1]. Images have to be normalized before being input into the CNN model. The image height and weight will also be a concern, as we prefer 224 X 224 for CNN and the rest of the pre-train model. The Softmax function is also used as an activation function.

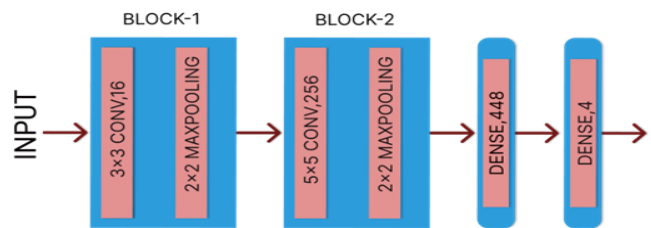


Fig.6:CNN model

#### 4.5.2 Pooling layer

Pooling, a type of non-linear down-sampling, is another crucial idea in CNNs. Pooling can be implemented using a variety of non-linear functions, the most popular of which being max pooling. The size of the pooling operation or filter, which is typically 2x2 pixels applied with a stride of 2 pixels, is smaller than the size of the feature map. This means that each feature map will always be compressed by a factor of 2.

#### 4.5.3 Fully Connected Layer

The neural network uses fully connected layers after a number of convolutional and max pooling layers to carry out the high-level reasoning. In conventional (non-convolutional) artificial neural networks, neurons in a fully connected layer have connections to all activations in the preceding layer. The loss was calculated using the SoftMax activation function, which allocates each input to one of the mutually exclusive classes [1][12].

#### 4.5.4 Activation Function

Applying a mathematical formula called Softmax, a vector of numerals can be shifted into a vector of probabilities. Sigmoid used for binary classification while, Softmax used for multiclass classification.

#### 4.5.5 Optimizers

Optimizers are techniques that modify neural network's weights and learning rates to minimize losses. Although there are various optimizers, the Adam optimizer

performs well in the case of multiclass classification. By parameter tuning, we also prove it in this research.

#### 4.5.6 Batch size and Number of Epochs

The batch size of a neural network during training is the number of training images used in one forward or backward pass. On the other hand, the number of epochs indicates that an epoch has occurred when a full dataset has been processed by the neural network exactly once, both forward and backward.

#### 4.5.7 Parameter Tuning

Finding hyperparameter values for an algorithm to learn more quickly and deliver correct results is a process known as parameter tuning. Random search, gridsearchcv, and Bayesian optimization are the three most widely used methods for parameter tuning.

#### 4.5.8 Overfitting prevention

Overfitting is avoided by employing the dropout layer, Regularization L1 or L2, and early stopping. Overfitting occurs when a model performs well on the training dataset but poorly on the testing dataset. Therefore, we employ this technique to prevent this discrepancy.

#### 4.5.9 Pretrained Model

**VGG-16:** The well-known benchmark architecture for computer vision tasks encompasses 16 layers [14]. It is a pre-trained model that was trained on the ImageNet database. The layers that had to be frozen in this study to attain the best level of accuracy are represented in Fig. 7.

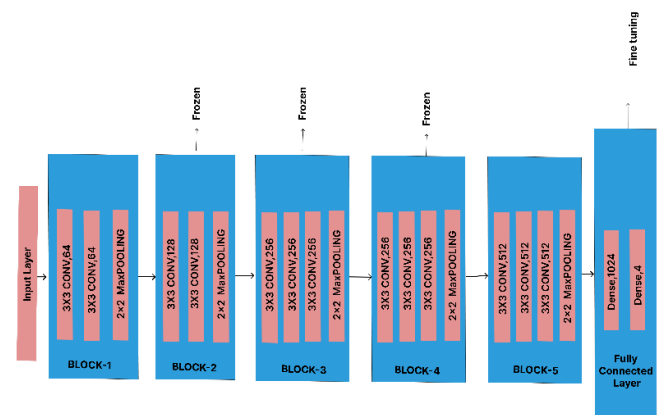


Fig.7:VGG16 model

**VGG-19:** VGG19 consists of a total of 19 layers. It is an expansion of the VGG16 model [15]. Moreover, it is a pre-trained model based on the ImageNet database. To improve the accuracy of this study, we froze a few layers, as shown in Fig. 8.

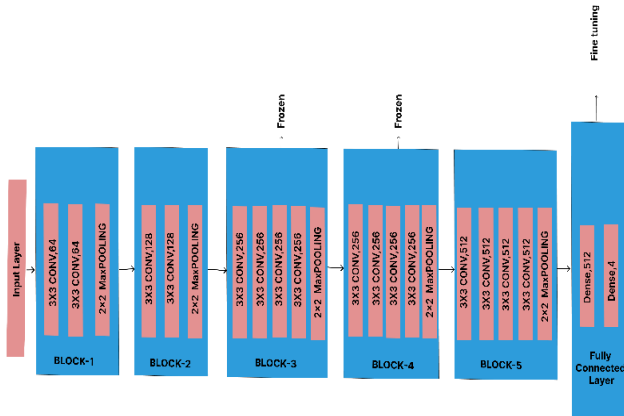


Fig.8:VGG19 model

**ResNet-50:**ResNet-50, one of the best image-based classification models, was released by Microsoft in 2015 [16]. Furthermore, it was trained on the ImageNet dataset, which outperforms VGG16 and VGG19 in terms of performance. Additionally, it is achieving the highest accuracy within our dataset.

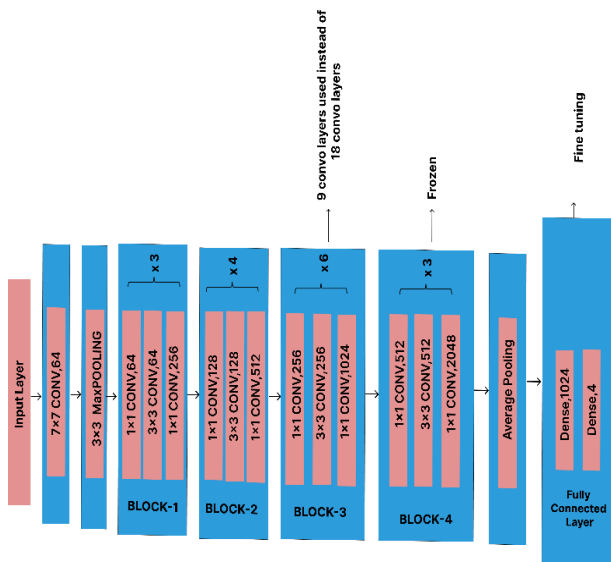


Fig.9: ResNet-50 model

In this model, which is shown in Fig. 9, all of the 9 layers of Block-4 had frozen, and we also used 9 layers instead of the 18 layers from Block-3. Furthermore, we tuned the dense layer by using 1024 fully connected layers and 4 dense layers, which predicted the output.

**Ensemble Model:**Ensemble learning refers to a machine learning strategy in which predictions from various models are combined to improve the accuracy and robustness of the final forecasting. Basically, we try out two ensemble models in this study: VGG16+VGG19 as well as VGG16+InceptionV3. In our case VGG16 + VGG19 outperforms than VGG16+InceptionV3.

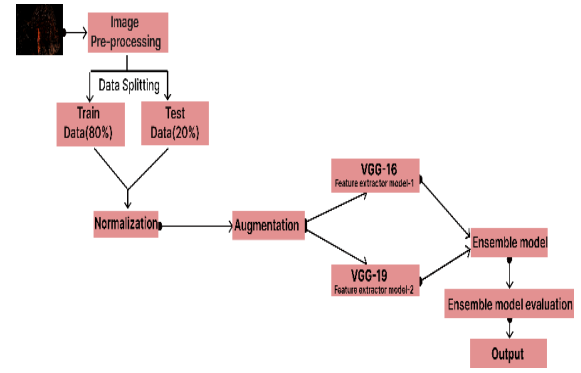


Fig. 10: Ensemble model

In the ensemble model demonstrated in Fig. 10, the VGG16 model is first trained using Blocks 1 and 5 as feature extractors, 1024 fully connected layers, and 4 dense layers as classifiers. It uses a variable to store the model's output. In a similar manner, we trained the VGG19 model, which had frozen Blocks 3 and 4, and then applied the classifier model, which consists of 512 completely connected layers and 4 dense layers. The output of this model is stored in a different variable. We integrate the two models and trained them both. The output of the ensemble model is then generated by averaging the outputs of the VGG16 and VGG19 models.

#### 4.5.10 Performance Evaluation

We split the dataset into an 80:20 ratio where the training set contains 80%, and the testing set contains 20%. A confusion matrix was used to demonstrate the results of the research. The classification accuracy, precision, and recall rates for each fish disease were calculated by using the following equations.

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad 1$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad 2$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\% \quad 3$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \quad 4$$

		Confusion Matrix			
		Black Spot	Fresh Fish	Red Spot	White Spot
Actual	Black Spot	59	1	0	0
	Fresh Fish	1	84	0	0
	Red Spot	0	0	76	0
	White Spot	0	0	0	56
		Predicted			
		Black Spot	Fresh Fish	Red Spot	White Spot

Fig. 11: Summary of confusion matrix on ResNet-50 model



A confusion matrix is shown in Fig. 11 for ResNet50 model. True positive value 59, 84, 76 and 56 for black spot, fresh fish, red spot and white spot respectively. True negative value 216, 191, 201, 221 for black spot, fresh fish, red spot and white spot respectively. False Positive values 1, 1, 0, 0 for black spot, fresh fish, red spot and white spot respectively. Finally True negative value 1, 1, 0, 0 for black spot, fresh fish, red spot and white spot respectively. To sum up, True positive values are considered remaining diagonal values, while True negative value considered remaining all values without particular class of rows and column value. False positive denote as particular class of columns value, on the other hand False negative denote as particular class of rows value.

The accuracy of a model is measured by the proportion of its total predictions that were correct. Recall evaluates the precision of positive predictions.

F1-score is a harmonic mean of precision and recall. The number of times a model correctly predicted the entire dataset is measured by the accuracy statistic.

F1 score usually get higher priority than accuracy when data are not equally distributed.

## 5. EXPERIMENTAL RESULTS

For fresh fish, there are a total of 277 images of fish diseases, and the other three types of images have also been examined. This section examines the performance of machine learning and deep learning model using results from the datasets. In this section, we present the actual findings and comparisons using a few visual illustrations and tables.

### 5.1 Parameter Tuning with keras tuner

We frequently used keras tuner to find the best parameter for our deep learning model. The keras tuner is simple to use and produces results as quickly as possible. To quickly create search space and locate the best hyperparameter values for models, utilize one of the search algorithms that are available.

Table 2 Parameter Tuning Result

Activation Function	Name	Accuracy
	<b>relu</b>	<b>95.56%</b>
	tanh	94.94%
Optimizers	<b>Adam</b>	<b>97.11%</b>
	RMSprop	95.31%
	SGD	83.75%
Learning Rate	0.01	91.44%
	0.001	94.38%
	<b>0.0001</b>	<b>96.55%</b>
	0.00001	91.69%
Loss Function	<b>categorical_crossentropy</b>	<b>96.38%</b>
	binary_crossentropy	93.14%
Epochs	10	92.14%

	20	94.94%
	<b>30</b>	<b>95.66%</b>
	40	94.58%
	50	93.86%
Batch Size	64	94.95%
	32	93.38%
	<b>20</b>	<b>95.44%</b>
	16	90.97%
	12	94.39%

The outcome of parameter tuning is presented in Table 2. We construct each deep learning model and achieve the highest accuracy by using this parameter. We use relu in the case of the hidden layer's activation function. We apply Adam optimizers as optimizers. The highest accuracy is produced at a learning rate of 0.0001. For multiclass classification, categorical cross entropy is always preferred. The number of epochs and batch size are 30 and 20, respectively.

### 5.2 Comparative Analysis

Deep learning models are always preferred over machine learning models for image-based studies. The machine learning model cannot produce up-to-the-mark results. Performance is measured by the system using five machine learning models, four deep learning models, and two ensemble models.

Table 3 Comparison of Performance for Machine learning models

Models	Class Name	Precision	Recall	F1-Score	Accuracy
Random Forest	Black Spot	0.9157	0.9383	0.9268	90.25%
	Fresh Fish	0.9294	0.9875	0.9576	
	Red Spot	0.8065	0.9091	0.8547	
	White Spot	0.9574	0.7377	0.8333	
SVM	Black Spot	0.9322	0.9483	0.9402	87.00%
	Fresh Fish	0.9367	0.9250	0.9308	
	Red Spot	0.7125	0.9344	0.8085	
	White Spot	0.9322	0.7051	0.8029	
Decision Tree	Black Spot	0.8684	0.9041	0.8859	82.31%
	Fresh Fish	0.8421	0.8101	0.8258	
	Red Spot	0.7714	0.8438	0.8060	
	White Spot	0.8000	0.7213	0.7586	
HistGradient Boosting	Black Spot	0.9296	0.9706	0.9496	88.09%
	Fresh Fish	0.9277	0.9277	0.9277	
	Red Spot	0.7500	0.9836	0.8511	
	White Spot	0.9535	0.6308	0.7593	
XGBoost	Black Spot	0.9571	0.9437	0.9504	89.17%
	Fresh Fish	0.9437	0.9178	0.9306	
	Red Spot	0.7857	0.9429	0.8571	
	White Spot	0.9038	0.7460	0.8174	

Table 3 compares the five different machine learning models performance. It is obvious that Random Forest outperforms every other machine learning model in

terms of performance. Random Forest is usually a bagging method, which is a better performer in the case of classification. In the boosting technique, XGBoost performs better than HistGradient Boosting. Despite the fact that HistGradient boosting is a unique boosting method for multiclass classification.

**Table -4: Comparison of Performance for Deep Learning models**

Models	Class Name	Precision	Recall	F1-Score	Accuracy
CNN	Black Spot	1.0000	0.9722	0.9859	95.67%
	Fresh Fish	0.9714	0.9855	0.9784	
	Red Spot	1.0000	0.8676	0.9291	
	White Spot	0.8718	1.0000	0.9315	
VGG-16	Black Spot	1.0000	0.9577	0.9784	97.83%
	Fresh Fish	0.9605	1.0000	0.9799	
	Red Spot	1.0000	0.9571	0.9781	
	White Spot	0.9545	1.0000	0.9767	
VGG-19	Black Spot	0.9859	0.9859	0.9859	98.56%
	Fresh Fish	0.9865	1.0000	0.9932	
	Red Spot	0.9861	0.9726	0.9793	
	White Spot	0.9833	0.9833	0.9833	
RESNET-50	Black Spot	0.9833	0.9833	0.9833	99.28%
	Fresh Fish	0.9882	0.9882	0.9882	
	Red Spot	1.0000	1.0000	1.0000	
	White Spot	1.0000	1.0000	1.0000	

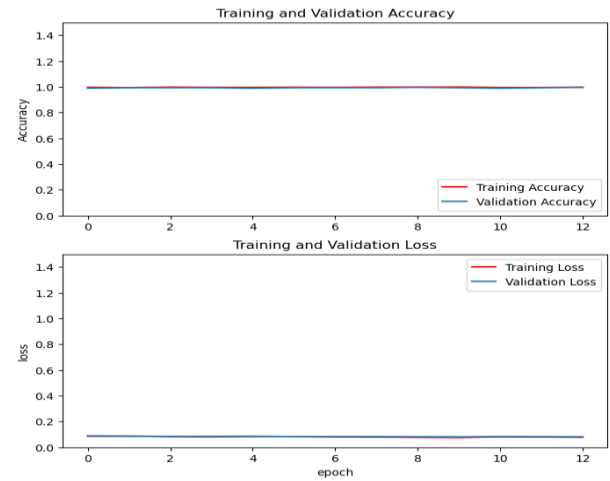
ResNet-50 performs better than all other models, according to Table-4, which compares the performances of four different deep learning models. We are aware that the ResNet-50 typically outperforms other multiclass classification algorithms in the ImageNet dataset. As a result, ResNet-50 has once again proven to be the best performer in multiclass classification.

**Table -5: Comparison of Performance for Ensemble models**

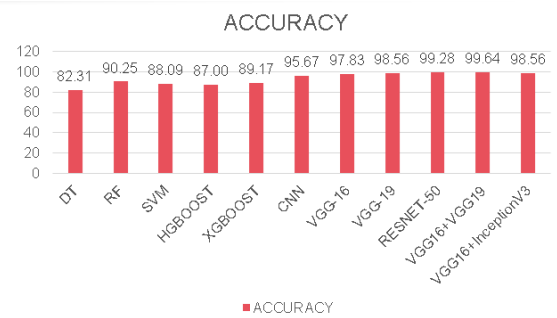
Models	Class Name	Precision	Recall	F1-Score	Accuracy
VGG16 and Inception v3	Black Spot	0.9706	0.9851	0.9778	98.56%
	Fresh Fish	0.9881	0.9881	0.9881	
	Red Spot	0.9825	0.9825	0.9825	
	White Spot	1.0000	0.9855	0.9927	
VGG16 and VGG19	Black Spot	1.0000	1.0000	1.0000	99.64%
	Fresh Fish	1.0000	1.0000	1.0000	
	Red Spot	0.9851	1.0000	0.9925	
	White Spot	1.0000	0.9859	0.9929	

The performance of the ensemble model is displayed in Table 5. The ensemble model outperforms the isolation model in terms of results. In our research, the ensemble models VGG16 and VGG19 perform better than VGG16 and InceptionV3. We can also see that the ensemble model of VGG16+VGG19 is superior to VGG16+InceptionV3 in the context of the F1-score.

Graphical representations of the model's efficacy are provided. In our model, various accuracy and loss graphs are examined. We've included the best one in Fig. 12 to support our prediction.



**Fig. 12: Ensemble model accuracy and loss graph**



**Fig. 13: Comparison accuracy between machine learning and deep learning**

Fig. 13 displays an analysis of accuracy comparison. Among all the machine learning models, Random Forest and XGBoost provide the best results. VGG19 and VGG16+InceptionV3 provide the similar outcomes. However, CNN outperforms all of the machine learning models. Random Forest outperforms the research paper [2] in terms of accuracy, with 90.25%. In our research work, decision Tree provides the lowest accuracy, while the VGG16+VGG19 ensemble model produces the highest accuracy.

### 5.3 Augmentation

By making modified copies of a dataset using previously collected data, data augmentation is a technique for artificially expanding the training set. The dataset may be slightly modified, or new data points may be produced using deep learning.

	precision	recall	f1-score	support
Black Spot	0.9538	0.9538	0.9538	65
Fresh Fish	0.9485	0.9485	0.9485	97
Red Spot	0.9149	1.0000	0.9556	43
White Spot	0.9706	0.9167	0.9429	72
accuracy			0.9495	277
macro avg	0.9469	0.9547	0.9502	277
weighted avg	0.9503	0.9495	0.9494	277

**Fig. 14: Classification report before augmentation in CNN model**

	precision	recall	f1-score	support
Black Spot	1.0000	0.9722	0.9859	72
Fresh Fish	0.9714	0.9855	0.9784	69
Red Spot	1.0000	0.8676	0.9291	68
White Spot	0.8718	1.0000	0.9315	68
accuracy			0.9567	277
macro avg	0.9608	0.9563	0.9562	277
weighted avg	0.9614	0.9567	0.9568	277

Fig. 15: Classification report after augmentation in CNN model

By using data augmentation, we can achieve better results because the data is created from several angles. While in some cases, this would produce superior results than a data collector, is actually time-consuming in real life.

Classification report of after and before augmentation in CNN model is presented in Fig. 14 and Fig. 15, respectively.

## 6. CONCLUSION & FUTURE WORK

Throughout this study, we made a variety of attempts to determine which models produce the best results, and on 1382 images from four different categories, our application was successful. Machine learning and Deep learning technique was used in a study to identify fish illnesses. Four categories of fish disorders were investigated in this study.

From this research, we can infer that deep learning is the best technique for classifying images. In comparison to all machine learning models, deep learning performed better. For Resnet50, we acquired a better result. We used two ensemble models, and VGG16+VGG19 performed the best. Additionally, VGG16+VGG19 outperforms Resnet50 in terms of results. As a result, it is possible to draw the conclusion that the suggested deep learning fish disease detection method works well.

The dataset represents among the most significant knowledge gaps in the field of fish disease detection. Despite the fact that one dataset with a modest amount of data was uploaded to Kaggle. Consequently, the next stage of our research will be to gather a sizable dataset from all available sources. Additionally, a comparison of the various segmentation techniques we used to create our dataset. Moreover, we wish to apply more deep learning models as well as we think web-based application or mobile based application would be great beneficial.

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