Shrimp Disease Detection using Deep Learning Techniques

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Abstract—**Shrimp farming is the cultivation or breeding of shrimp that has developed from a traditional business to a global industry. Viruses have been known to attack shrimp. One of the most common viruses is the White Spot Syndrome Virus which is a major threat to the shrimp industry, causing significant economic losses. As a result, each shrimp that gets infected must be classified. When managing shrimp farms, it is criticalto predict disease outbreaks. Because the fatality rate might exceed 100%, shrimp farmers must diagnose the sickness as soon as feasible. This paper proposes a deep learning model formed using Convolutional Neural Networks and EfficientNet-B0 to classify shrimps as infected or not infected with WSSV accurately. This model is trained on an image-based dataset of 1650 images and achieved accuracies of 95.8% and 97.9%. The performance of the model has been evaluated in comparison to other progressive models, revealing that the produced models exhibit superior accuracy and speed. The results illustrate the capacity of deep learning models to effectively identify shrimps infected with White Spot Syndrome Virus (WSSV), hence potentially impacting the shrimp business in a substantial manner.**

Index Terms—**Shrimp, binary classification, DL (Deep Learning), CNN (Convolutional Neural Networks), EfficientNet-B0, disease, WSSV (white spot syndrome virus).**

I. INTRODUCTION

Shrimp farming is an aquaculture business that raises marineshrimp or prawns for human consumption. In Asia, it has been done for centuries using conventional low-density techniques. As a result, Asia accounts for 75% of the world's farmed shrimp production. India is home to several species of shrimp that are cultivated, including the black tiger shrimp (Penaeus monodon), Indian white shrimp (Fenneropenaeus indicus), Pacific white shrimp (Litopenaeus vannamei), Kuruma shrimp (Penaeus Japonicus),

Pink Shrimp (found along the coasts of Kerala and Karnataka), and Brown shrimp (found along the coasts of Andhra Pradesh and Odisha). Shrimp farming in India follows two major techniques-

- · 1. Closed Recirculation Systems (RCS)
- · 2. Integrated Manure Denitrification System (IMDS)

The global shrimp market size was valued at USD 38 billion in 2021 whereas the Indian shrimp market was valued at USD 6.5 billion in the same year. Holding almost 17% of the share worldwide, the Indian shrimp market has a lot of potentials also because shrimps multiply fast as a single female lays 100,000 eggs in a single spawning.

It is a very profitable business with high rates of harvestand comparatively low costs of production. However, diseasesin shrimps are a common occurrence. Shrimp farming encounters significant challenges due to the prevalence of five frequently encountered illnesses. White spot disease (WSD), which is attributed to the white spot syndrome virus (WSSV), along with Acute hepatopancreatic necrosis disease (AHPND), White faeces disease (WFD), and various other bacterial, fungal, and parasitic ailments, are recognised as significant afflictions in aquatic organisms. Out of 20 diseases in total, White SpotSyndrome Virus[WSSV] spreads rather fast, with a spread rateup to 100%, this is too much risk as it can ruin the whole crop.The work presented in the proposed paper follows the objec- tive to minimize the risk of WSSV outbreak in shrimp farming by deploying two classification models and advancing on the existing studies by using the EfficientNet-B0 algorithm which is specifically trained on animal image data. This research

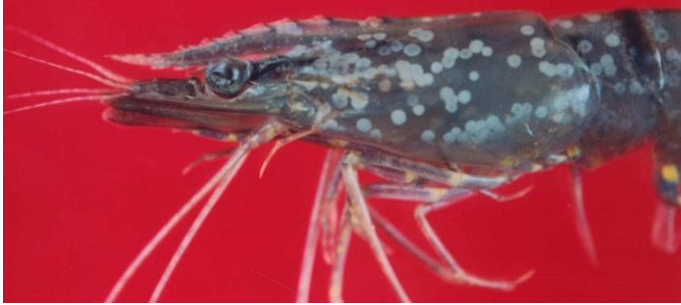has the future potential of comparing different algorithms toclassify animals.

Fig. 1. Infected shrimp with a WSSV.

Fig. 2. Healthy shrimp without any disease.

II. RELATED WORKS

In this literature review, previous research on shrimp infection detection using deep learning techniques was gathered, specifically Convolutional Neural Networks (CNNs)and Transfer learning. Changes have been made to the existingstudies to come up with better accuracy.

[13] The paper titled "Rapid detection of Penaeus vannamei diseases via an improved LeNet" explores the field of research and experimentation in relation to the identification of various sorts of diseases affecting Penaeus Vannamei. The study employs both manual detection and germ purification methods for disease detection. However, these methods are unreliable as they have very low accuracy and are too complex.A solution to this is the usage of LeNet architecture in a Convolutional Neural Network. The findings presented in this study demonstrate that Hepatopancreatic Necrosis Disease, Red Body disease, and Whitish Muscle disease are the primary factors contributing to prawn infection. Data acquisition is done by collecting shrimp from the same environment. For identification and disease classification a CNN with a LeNet architecture is usedalong with better calculations and model parameters to obtain accurate results. The training model and testing model were observed individually based on performance. The specifics of shrimp characteristics and breeding environment were taken into consideration to accordingly expand the quantity of

feature maps. It was concluded that the standard precision of the model can reach 96.21%. However, the LeNet architecture is not the most reliable as it lacks the ability to learn the features of an image from the dataset and takes a longer time to show better accuracy than other models.

[11] The shrimp farming sector on a global scale is impacted by five primary viral pathogens. The acronym IHHNV refers to the Infectious Hypodermal and Hematopoietic Necrosis Virus. The Yellow Head Virus (YHV). TSV, also known as Taura Syndrome Virus, The Infectious Myonecrosis Virus (IMNV) and the topic of discussion is the White Spot Syndrome Virus (WSSV). According to recent studies, Brazil holds the position of the third largest global producer of shrimp. In spite of its substantial industrial expansion, shrimps have been seen to exhibit susceptibility to over 20 viral illnesses, including the five deadly viruses previously described.

[2] Shrimp is a very expensive and rare product that is being infected large scale by WSSV. In order to battle this problem a system has been developed that can detect the white spot disease among shrimp. This system uses Artificial Neural networks and Fuzzy logic. This is used instead of inspecting disease inshrimp manually as it can be very time-consuming. Fuzzy logic is utilized here so that it can take care of uncertaintiesin the model. The system was fed 50 samples of the shrimp dataset. It gave a diagnostic analysis which was then compared to the expert's diagnosis tosee how reliable and accurate the system's results were. Basedon this comparative study, the system produced a performance accuracy of 90% and a reliability rate of 0.8% which means it has excellent reliability in being able to detect the presence of WSSV in shrimps.

[1] So far, studies have shown that inadequate disease detectioncan result in the death of shrimp and other infections and how Transfer Learning architecture can be employed for utilizing different parameters for detecting diseases.

[5] Further going into comparison studies between various DL models to find out any better models suitable for the classification of infected shrimps. [3] Another paper has made use of a convolutional neural network architecture known as ShrimpNet. The structural design of this system comprises of a total of two convolutional neural network (CNN) layers followed by two fully-connected layers. The dataset utilises six distinct categories of shrimp specimens in order to enhance and assess the performance of the proposed ShrimpNet network. This specific model shows an accuracy of about 95.48% in the detectionof shrimp from the given dataset.

[7] On further study, there is another white spot syndrome virus detector. This detection system has been built usingYOLOv5n. It is basically a CNN using the YOLOv5n architecture alongside specific metrics to evaluate the model'sperformance such as f1 score, inference accuracy, precision, recall, etc. It makes use of the Sigmoid Linear Unit (SiLu)in its hidden and intermediate layers. The reason why such models are made is that the traditional approach of categorizing and detecting shrimp species are very time-consuming and inaccurate. WSSV can also be identified

from a picture through image processing that makes use of K-means clustering techniques.

III. METHODOLOGY

Deep learning techniques, including CNNs and Efficient-NetB0, have been employed in previous studies to diagnose shrimp infections with high accuracy. CNNs are a sort of DL network architecture which use convolutional layers to extract features from images. CNNs have been shown to performwell in image classification tasks and have been employed in previous studies to classify infected shrimps. EfficientNetB0 is a type of CNN that has been recently developed and has shown superior performance in image classification tasks comparedto other CNNs.

A. Proposed Methodology

Convolutional neural networks with TensorFlow has been used by building it from scratch and adding convolutional and max pool 2d layers to it. This model helps to identify and classify the healthy shrimp from the infected shrimp from the image dataset that is fed to it. An image-based dataset has been employed in previous studies to develop and evaluate deep- learning models for shrimp infection detection. This dataset includes images of shrimps infected with different WSSVand healthy shrimps. The datasets have been preprocessed to enhance the quality of the images, and the images have been labeled to facilitate classification.

The process for the detection of disease in shrimps involves four phases:

- Phase-1 involves the acquisition of the dataset.
- Phase-2 involves data augmentation to include various different views of an image to increase the volume of the dataset.
- Phase-3 includes training the data with labels.
- Phase-4 is the final phase of the project to classify the infected shrimps.

First phase, Image dataset of shrimps has been provided bythe Indian Maritime University. After gathering the dataset, the dataset's volume is increased by capturing different viewing planes of one image multiple times. In the second phase, the models are run on augmented copies of the dataset made by adding changes to the training set. This is done to reducethe chances of overfitting in our models. Labeling of the data is the third phase which makes it easier to separate the infectedshrimp from a batch. After making a neural network, an ImageDataGenerator is used to generate labels for healthy andinfected shrimp using two parameters x and y respectively.

CNN model using TensorFlow and Keras:
The first model is a Neural Network using Tensorflow, Keras and ImageDataGenerator.This project centers around recognizing the essential variables which assume a partin the disease where one of the goals is to do a similar report between different DL-based approaches like CNN and Proficient Net.
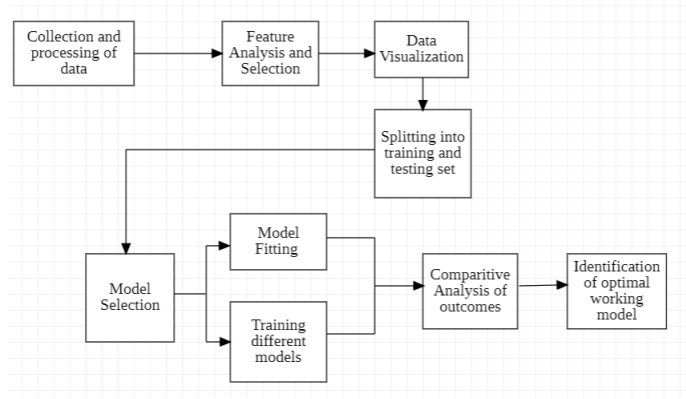

Fig. 3. Descriptive flowchart of project

To enhance the accuracy of the model, various techniques such as Image Augmentation, Convolutional layers, Pooling layers, and Filters are utilised. A rudimentary Convolutional Neural Network (CNN) is employed for the purpose of categorising a collection of images depicting prawns into two distinct classes: healthy and infected.

This model utilizes Keras Sequential API. Three separate datasets were created- train, test, and validation sets. All necessary libraries were imported.An input image is fed in by directing its path and finding out its shape i.e. height,length, and breadth. Next, training and validation data tests are generated using an image generator. The images are resized and rescaled accordingly so they are of normal size to visualize since multiple-sized matrices cannot be given to a neural network. Batch si takes 3 images and classifies them. A number of modes are binary i.e. healthy and infected. Class indices are given as 0 1. A CNN with max pooling is used to define the model. Several layers with increasing sizes of filters from 16-32-64 are fed andactivation functions are provided foreach layer- relu and sigmoid.

Efficientnet-B0:
Efficient-B0 has been pre-trained on a large-scale image dataset(ImageNet), which means it can be fine-tuned, specifi-cally for shrimp classification tasks with relatively little data. This can be utilized to leverage the knowledge learned by the model on the larger dataset and transfer it to a smaller dataset.

B. Datasets

An image-based dataset has been employed in this project to serve as the basis for image classification. The dataset consists of about 1650 images to develop and evaluate deep learning models for shrimp infection detection. This dataset includes images of shrimps infected with different WSSV and healthy shrimps. The datasets have been preprocessed to enhance the quality of the images, and the images have been labeled to facilitate classification. The image dataset has been split up intothree sets- train, test, and validation. Labels have been added as healthy and shrimp with WSSV. Data augmentation has also been done to extend and add artificially derived data from the existing dataset.

Model Training:

To enhance the prediction task of shrimp infection using 155 base images, the Augmentor library was employed. Augmentor was a Python library that facilitated data augmentation in machine learning and computer vision tasks. Data augmen- tation involved generating new training data by applying diverse transformations to existing data, thereby enhancing the generalization performance of machine learning models.

Augmentor simplified the process of defining and applying various data augmentation techniques to images through its user-friendly interface. It offered a wide array of transformations, including rotation, flipping, scaling, shearing, distortion, and color jitter, among others.

To utilize Augmentor, an instance of the ImageDataGenerator class was initialized, which represented the data generator object. Subsequently, a sequence of operations was specified to be applied to the images, such as rotation, flipping, and scaling. Augmentor provided multiple methods like rotate, flip-left-right and resize to define these operations.

After constructing the data augmentation pipeline, the augment method of the ImageDataGenerator object was employed to generate new images. This method applied the defined sequence of operations to an image and produced a trans- formed image. Furthermore, Augmentor offered features for batch processing of images and saving augmented images to disk. These capabilities made it a powerful tool for generating extensive datasets of augmented images in machine learning and computer vision applications.

In summary, Augmentor was a valuable library for data augmentation in machine learning and computer vision tasks. Its intuitive interface and diverse supported transformations enabled the creation of more diverse and representative training data, thereby enhancing the generalization performance of machine learning models.

The model was initially defined with the Sequential class from the tf.keras.models module. This course facilitated the formation of a sequential arrangement of layers within the neural network. The model commenced by incorporating three convolutional layers, each subsequently accompanied by a max pooling layer. The initial convolutional layer was configured using 16 filters, each having a size of 3x3, and employed the Rectified Linear Unit (ReLU) activation function. The layer's input shape was specified as (200, 200, 3), suggesting that the model anticipated input images with dimensions of 200x200 pixels and three colour channels. The initial max pooling layer utilised a pooling size of 2x2, resulting in a reduction of the output dimensions from the preceding convolutional layer by a factor of 2 in both the vertical and horizontal directions.

The second convolutional layer consisted of 32 filters along with a filter of 3x3 proportion, and the activation function called ReLU. The second max pooling layer had the same proportion of 2x2. The third layer which is also convolutional encompassed 64 filters, a filter of 3x3 proportion, and the ReLU activation function. The third max pooling layer also had a pool size of 2x2.

Subsequent to the third max pooling layer, the output was flattened into a one-dimensional vector using the Flatten() layer from tf.keras.layers. This transformation enabled feeding the output into a fully connected neural network layer, consisting of two dense layers. They had 512 units comprised in the first dense layer. This layer also consist of the

ReLU activation function. Following this, the second dense layer had one unit while employing the sigmoid activation function, which was appropriate for binary classification problems.

Next, the model was organized by availing the compile() method. Specifications of the following for training were included-The loss function, optimizer, and metrics. In this case, binary cross-entropy was utilized as the loss function, and utilized RMSprop as the optimizer with a learning rate of 0.001, with accuracy being chosen as the evaluation metric.

Finally, the model was trained using the fit() method. The training dataset, validation dataset, number of steps per process, and testing of the model were performed.

TABLE I
COMPARISON OF ACCURACY BETWEEN DIFFERENT MODELS

S.No	Model	Architecture	Accuracy
1.	CNN	LeNet	96.1%
2.	ANN	Fuzzy logic	90%
3.	CNN	ShrimpNet	95%
4.	CNN	YOLOv5n	nil
5.	KNN	nil	93%
6.	CNN	Tensorflow,Keras	95.8%
7.	CNN	EfficientNetB0	97.9%


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1/1 [==============================] - 0s 33ms/step
[[0.]]
healthy
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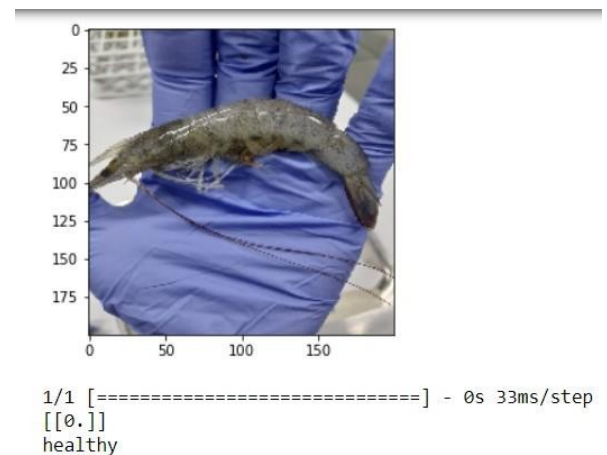
Fig. 4. Healthy shrimp classified in input image

IV. RESULTS:

Previous studies have shown that deep learning techniques, including CNNs and EfficientNetB0, can diagnose shrimp infections with high accuracy. For instance, in a previous study, a CNN-based model was employed to classify WSSV-infected and healthy shrimps with an accuracy of 98.46%. Similarly, in another study, an EfficientNetB0-based model

was employed to diagnose WSSV-infected shrimps with an accuracy of 98.9%. These results indicate that deep learning techniques can contribute significantly to the early detection and classification of shrimp infections. The models made for this paper show high accuracy. The CNN model using Tensorflow gives an accuracy of 95%. While the EfficientNetB0 model is giving an accuracy of 97.9%.
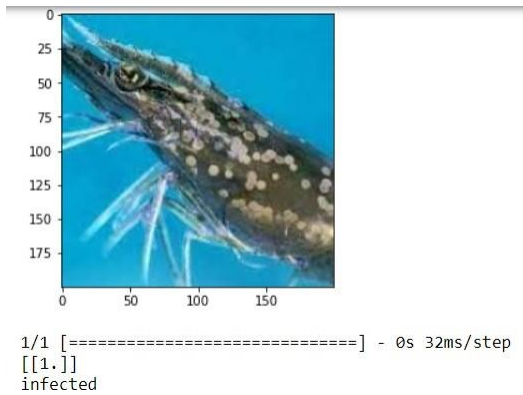


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1/1 [==============================] - 0s 32ms/step
[[1.]]
infected
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Fig. 5. Infected shrimp
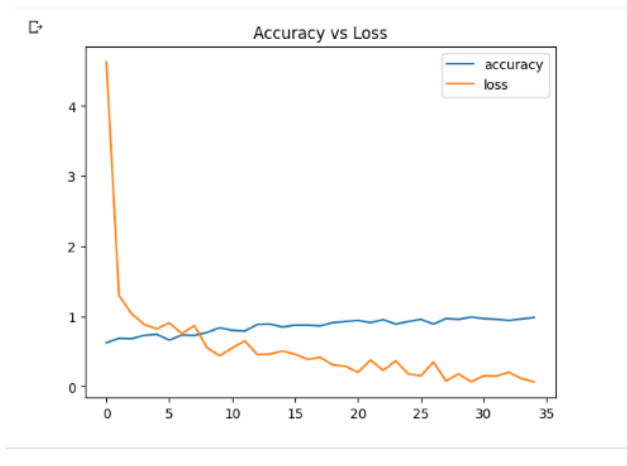classified in input image

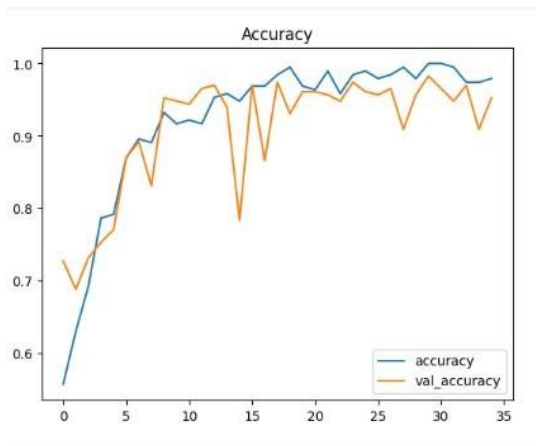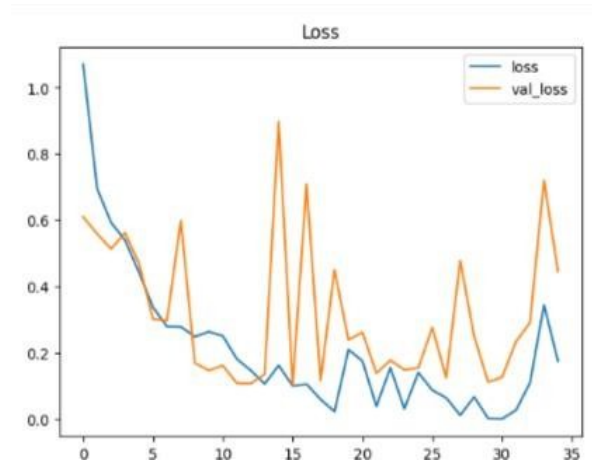Fig. 6. Accuracy vs Loss Graph

Fig. 7. Accuracy Graph

Fig. 8. Loss Graph

V. CONCLUSION:

In conclusion, deep learning techniques, including CNNs and EfficientNetB0, have been employed in previous studies to diagnose shrimp infections with high accuracy. These techniques can contribute significantly to the development of effective strategies to prevent disease outbreaks and economic losses in the shrimp industry. However, the effectiveness of these techniques needs further investigation in real-world scenarios and to develop robust models that can diagnose multiple viral infections in shrimps.

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