Identification And Detection of Freshness In Edible Fishes Using Iot And Machine Learning Techniques

Bharath Gowda R[1], J.V Alamelu[2*], Varsha K[3], Shantala[4], Anjan Shetty R[5], Manjappa N[6]

[1]Electronics and Instrumentation Engineering, Ramaiah Institute of Technology, Bengaluru, India
bharath89601@gmail.com
[2*]Electronics and Instrumentation Engineering, Ramaiah Institute of Technology, Bengaluru, India
jvalamelu@msrit.edu
[3]Electronics and Instrumentation Engineering, Ramaiah Institute of Technology, Bengaluru, India
varshalathakumar@gmail.com
[4]Electronics and Instrumentation Engineering, Ramaiah Institute of Technology, Bengaluru, India
shan27patil@gmail.com
[5]Electronics and Instrumentation Engineering, Ramaiah Institute of Technology, Bengaluru, India
anjushetty86@gmail.com
[6]Fisheries Research and Information Centre (I), Karnataka Veterinary, Animal and Fisheries Sciences University
Bengaluru, India
manjappan701@gmail.com

***Corresponding Author:** J.V Alamelu
*Electronics and Instrumentation Engineering, Ramaiah Institute of Technology, Bengaluru, India
jvalamelu@msrit.edu

Abstract**—** The identification and detection of freshness and chemical contaminants in edible fish are significant aspects of food safety and quality control. The current work is proposed to detect freshness and chemical contamination in fish using IoT and machine learning approaches. The proposed system consists of a formaldehyde sensor that can detect volatile organic compounds of formaldehyde coated on fish surfaces by the sellers to increase its shelf life. Further, a machine learning model is implemented that can classify the fish samples based on the fish's iris image of the eye. The real-time dataset is collected from the live fish market. Machine learning models such as Dense Net Algorithm and Efficient Net Algorithm have been used to classify fresh and non-fresh fish from the dataset considered by evaluating the model. The EfficientNet and DenseNet algorithms used have an accuracy of 0.085 and 0.075, respectively, for the datasets collected in real time. The model's accuracy is evaluated and tabulated. Based on these results, it can be stated that the EfficientNet algorithm has better accuracy than DenseNet. The formaldehyde sensor used has an accuracy of 1-50 ppm. The coating of formaldehyde varies according to the type, variety, and size of the fish. Based on the online references, the edible range of formaldehyde content coated on the fish varies from 0-4 ppm. If the sensor's output is less than 4 ppm, it is considered edible, or else it is regarded as unsuitable for consumption. Experimental results show that the proposed system seems to be accurate in identifying fresh fish samples and also in detecting formaldehyde content. The proposed work aids the consumers to identify suitable fish for consumption.

Index terms—Algorithm, contaminants, consumption, model.

I. INTRODUCTION

Assuring the safety and quality of seafood items for human consumption is a crucial concern in the food industry [1]. Highly nutritious fish is an essential component of a healthy diet [1]. However, the presence of chemical contamination and poor storage conditions can significantly impact the quality and safety of fish [1]. One of the major concerns in the seafood industry is the use of formaldehyde as a toxic chemical coating on edible fish to enhance their appearance and extend their shelf life [2]. Consumption of formaldehyde-coated fish can lead to severe health consequences, including cancer and other long-term health problems [2]. Hence, there is a need to identify and detect freshness [11][12] and chemical compounds in edible fish to ensure consumer safety and maintain the quality of seafood products.

To ensure the freshness of fish, various parameters such as odour, texture, eye appearance, gill colour, and mucous on the skin can be measured [3]. These parameters serve as indicators of the fish's quality and can determine whether the fish has been preserved for too long or exposed to unfavourable storage conditions [3]. Furthermore, the presence of chemical compounds, such as chemical coatings, pesticides, and antibiotics, poses a significant health risk to consumers [4]. Therefore, detecting and quantifying these chemical compounds in fish is crucial to guarantee the safety and quality of seafood products [4].

In recent years, the utilization of Internet of Things (IoT) technology has shown promise in the identification and detection of formaldehyde coating in edible fishes [6][10]. IoT technology involves interconnected devices and sensors that collect and transmit data, which can be analysed for detection purposes [6]. Machine learning techniques, particularly convolutional neural networks (CNN), have been successfully employed to detect the freshness of edible fishes by considering iris images of the fish [5]. These innovative approaches leverage the capabilities of IoT and machine learning to develop efficient and accurate methods for assessing fish freshness and identifying chemical substances in edible fishes. The significance of these methods and techniques for ensuring the safety and quality of seafood products is emphasized in several research papers [1][2]. These papers discuss the various methodologies, including the use of sensors, spectrometers, physical recognition, and chemical detection techniques, employed to monitor and evaluate fish freshness [7]. The development of machine learning-based computer vision technology, specifically using supervised learning algorithms such as k-nearest neighbour (k-NN) and naive Bayes (NB), has also been explored to assess fish freshness [8], Also freshness of the fish can be determined by using near-infrared hyperspectral imaging [16] and efficient BP neural networks [14]. These innovative methods offer accurate and reliable approaches for identifying the freshness of fish and can potentially revolutionize the fish management process.

In this study, the aim is to provide a comprehensive analysis of the methods and techniques used for the identification and detection of freshness and chemical substances in edible fishes [9][10]. These methods are significant and relevant in ensuring the safety and quality of seafood products for human consumption [1][13]. Furthermore, we investigate the potential application of IoT technology and machine learning algorithms, such as CNN [15], in the detection of formaldehyde coating and assessment of fish freshness [5][6][10]. By combining these innovative approaches, we strive to offer practical solutions for the seafood industry, enabling improved monitoring and control of fish quality and enhancing consumer confidence in the safety and freshness of seafood products.

II. MATERIALS AND METHODS

The proposed workflow shown in figure 1 provides the overall process of detection and identification of freshness and chemical substances in edible fishes. This study includes the detection of the freshness of edible fishes through image processing and the identification of formaldehyde coating on fishes for food safety.

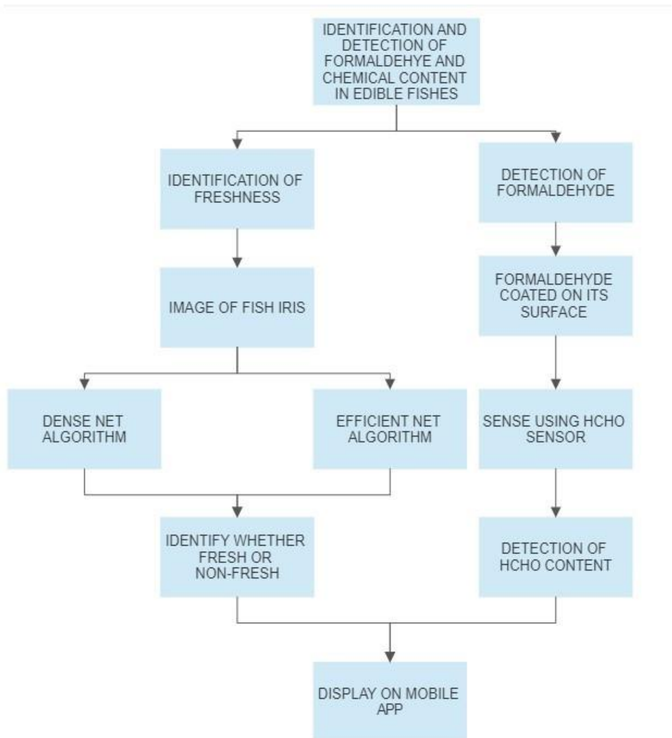

Fig. 1. Flow diagram

A. Identification of freshness

There are many ways in which the freshness of harvested fishes are achieved, such as through its gills, colour, eyes, texture of the skin, etc. In this study, we are considering the iris of the edible fish as a parameter to detect its freshness through image processing, where we have used EfficientNet and DenseNet algorithms to train the model. The differences in the accuracy of both models are compared, and the EfficientNet model is found to be the appropriate model based on its training results on a real-time dataset. The model is then deployed into the mobile app for testing.

B. Detection of Formaldehyde:

Formaldehyde content is applied to edible fish to improve their shelf life. HCHO Sensor relates to the microcontroller to detect the formaldehyde presence coated on edible fish. If the formaldehyde content of the coating goes above 4 ppm, then the LCD displays "No, it's not edible" and if the range of ppm is below 4 ppm, then the LCD displays "Yes, it's edible".

C. Software Implementation

1) ***Data Sets:*** The dataset used in this project is collected from the online website and in real-time which are shown in Figures 2,3,4 and 5 respectively. The real-time datasets collected from the Yeshwantpur and Mangalore fish market shown in Figures 4 and 5. These datasets are split into two subsets. These subsets are labeled as training and testing datasets. Further, each dataset is classified as Fresh and NonFresh subsets.

Fig. 2. Fresh fish dataset collected online from the Kaggle website

Fig. 3. Non-Fresh fish dataset collected online from the Kaggle website

Fig. 4. Non-fresh dataset collected in real-time from the Yeshwantpur fish market

Fig. 5. Fresh dataset collected in real-time from Mangalore fish market

Online collected dataset figure 2 and 4 has fresh and nonfresh images collected from online websites. The machine learning model is trained using the data set to compare different machine learning algorithms to find the appropriate algorithm that gives higher accuracy

2) ***Data Pre-Processing****:* Figure 6 shows the overall Image processing flow diagram.

The collected dataset is split, in which 80–90% of the data is used for training the model while 20–10% is used for testing the model. After splitting the dataset, image processing plays a crucial role in analysing and manipulating the individual image samples. This process involves a series of operations aimed at extracting meaningful information and enhancing the visual quality of the images. Segmentation allows for the identification and separation of different objects or regions within an image, enabling subsequent analysis on a localised level.

Feature extraction involves extracting relevant characteristics from the images. The EfficientNet and DenseNet Algorithm are used to train the model. To determine which algorithm appropriately suits the dataset collected. Their accuracy is then found to choose the appropriate classifier. The trained model is deployed into the Android App. The fish iris image is captured using the Android App. It combines image preprocessing, feature extraction, and machine learning inference, and gives the results as Fresh or Non-Fresh.

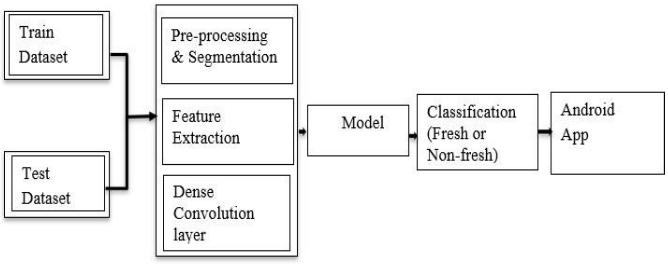

Fig. 6. Image Processing Flow Diagram

3) ***EfficientNet and DenseNet Algorithm**:* The EfficientNet and DenseNet Algorithm are used to train the model. To determine which algorithm appropriately suits the dataset collected.

The EfficientNet algorithm was originally introduced by offering an incredible method for scaling neural network models by enhancing depths, breadth, and precision. It is a convolutional neural network (CNN) design and scaling technique that applies a com- pounded coefficient to scale up all depth, width, and resolution dimensions evenly. The EfficientNet scaling method consistently increases network breadth, depth, and resolution with a set of preset scaling parameters, contrasting standard practice, which ad- just these factors randomly. It is scaled up the base network to create the EfficientNet class of deep learning methods. There are a total of 18 convolution layers, each having a k(3,3) or k(3,3) kernel (5,5). The size of the input image is 224 by 224 pixels. The next layers are reduced in resolution to lower the size of the feature map but increased in width to improve accuracy. The second convolution layer, for example, has W = 16 filters, whereas the next convolution layer has W = 24 filters. For the last layer, which is sent to the fully connected layer, the maximum number of filters is D = 1, 280.

Dense Net is a neural network architecture that is a variation of the convolutional neural network (CNN) that is designed to improve the flow of information through the network and alleviate the vanishing gradient problem. The key idea behind Dense Net is to connect each layer to every other layer in a feed-forward fashion, which creates a dense block. In this method, the pixels are arranged in layers. The dropout layer ignores a set of pixels randomly. This is used to prevent the over-fitting of pixels. After the loading and training of the datasets for the alphabet are done, the Layer activation function is used. The main objective of using an activation function that is added to a neural network is to help the network learn complex patterns in the data. Among the various types of activation functions available in Keras, we use two types of Activation Functions, which are relu function and softmax function.

Their accuracy is then found to choose the appropriate classifier. The trained model is deployed into the Android App. The fish iris image is captured using the Android App. It combines image preprocessing, feature extraction, and machine learning inference, and gives the results as Fresh or Non-Fresh.

TABLE I COMPARISON OF MODELS USING ONLINE DATASET

Algorithms	Accuracy	Cross Validation	Validation accuracy
1.EfficientNet	0.100	0.040,0.050,0.090,0.090,0.095	0.100
2.DenseNet	0.100	0.042,0.086,0.0100,0.086,0.0100	0.095

TABLE II COMPARISON OF MODELS USING REAL-TIME DATASET

Algorithms	Accuracy	Cross Validation	Validation accuracy
1.EfficientNet	0.086	0.083,0.075,0.067,0.075,0.075	0.085
2.DenseNet	0.098	0.080,0.085,0.085,0.085,0.085	0.075

4) ***Confusion Matrix***It is a table that is used to describe the performance of a classification model which is shown in the table III. The machine-learning algorithm's accuracy, recall, and precision can be determined using a confusion matrix. Accuracy is the measure of how correctly the algorithm will classify the data.

Accuracy = TP + TN/TP + TN + FP + FN

TABLE III CONFUSION MATRIX

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

Precision is the ratio of correct positive predictions to the total predicted positives. Precision tells the percentage of predictions that is truly positive, out of all the positive predicted values.

Precision = TP/TP + FP

Recall is the ratio of correct positive predictions to the total positives. The recall is the percentage that is predicted positive, out of the total positive.

Recall = TP/TP + FN

- TP stands for True Positive-the algorithm correctly predicts positive value.

- TN stands for True Negative- the algorithm correctly predicts a negative value.
- FP stands for False Positive- the algorithm incorrectly predicts data as positive when actually the data is negative.
- FN stands for false Negative- the algorithm incorrectly predicts data as negative when actually the data is positive.

D. Hardware Implementation

The hardware components include ARDUINO UNO, Arduino UNO is a microcontroller board based on the ATmega328P, and The Grove - HCHO Sensor, which is a semiconductor VOC gas sensor. It uses the VOC sensor WSP2110 whose conductivity changes with the concentration of VOC gas in the air. This sensor has a very high sensitivity and stability, it can detect the gas whose concentration is up to 1ppm-50ppm, and an LCD display, in order to display the values.

The Grove formaldehyde sensor is connected to Arduino Uno. The signal pin of the Arduino Uno is connected to the A1 pin of the Arduino Uno board. when the HCHO sensor senses the outside Formaldehyde, then the change in the signal triggers the micro-controller to display the value of formaldehyde content on the Android application display. The data received from the sensor is first sent to the cloud storage and then to the Android app through the WIFI module. The Hardware implementation block diagram is shown in Figure7.

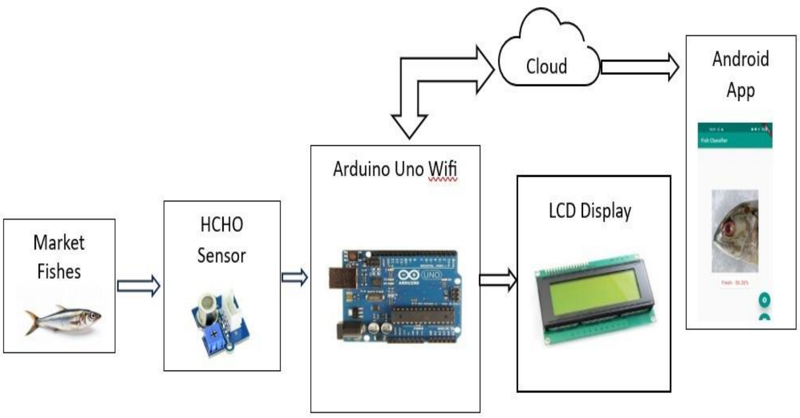

Fig. 7. Hardware Implementation block diagram

If the Android app indication is more than 4ppm, it displays “No, it is not edible” Similarly, if the coated formaldehyde is less than 4ppm, then it displays “Yes, it’s edible”.

III. RESULTS AND DISCUSSION

The main objective of this project is to find the formaldehyde coating and freshness of edible fishes.The results shown here are a simple comparison of EfficientNet and DenseNet models and the freshness results are displayed on the mobile application, also based on coated Formaldehyde content on edible fishes, its edibleness is notified to the users using LCD display.

A. Comparison of Machine learning algorithms

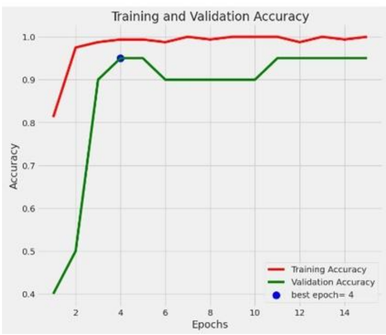

Fig. 8. Accuracy responses for online dataset trained using EfficientNet algorithm

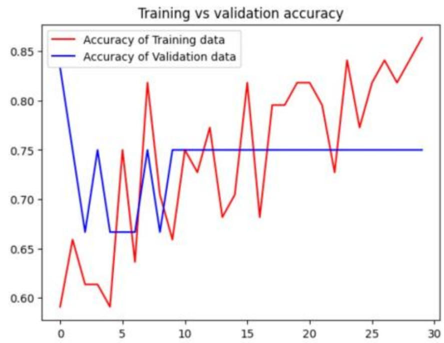

Fig. 9. Accuracy responses for self dataset trained using DenseNet algorithm

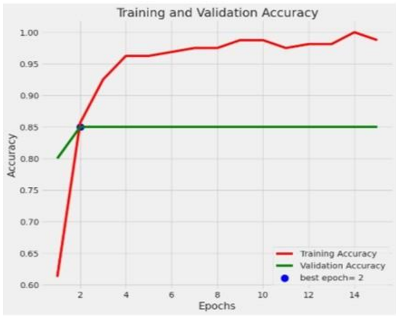

Fig. 10. Accuracy responses for self dataset trained using EfficientNet algorithm

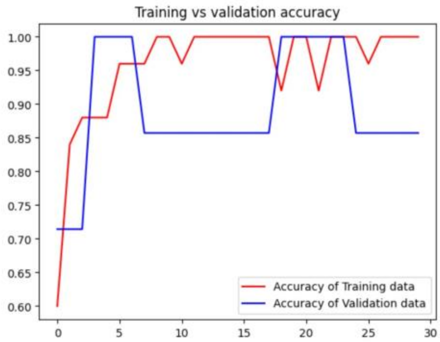

Fig. 11. Accuracy responses for online dataset using DenseNet algorithm.

Figure 8 and 9 shows the graph of training vs validation accuracy for the online dataset using DenseNet and EfficientNet algorithms respectively. In contrast, Figure 10 and Figure 11 show the graph of training vs validation accuracy for a self-dataset using DenseNet and EfficientNet algorithms respectively. Table 4 shows the accuracy of algorithms for both online and real-time datasets.

We have compared EfficientNet and DenseNet algorithms using K-Fold Cross-Validation. EfficientNet gave us 86% as total average accuracy and 85% as cross-validation accuracy.

The Densenet algorithm gave us 98% as total average accuracy and 75% as cross-validation accuracy. Thus, Efficientnet is the most suitable classification algorithm

TABLE IV ACCURACY OF ALGORITHMS FOR ONLINE AND REAL-TIME DATASET

Algorithms	Total average accuracy	Cross Validation accuracy
EfficientNet(online)	0.100	0.095
DenseNet(online)	0.100	0.100
EfficientNet(self)	0.086	0.085
DenseNet(self)	0.098	0.075

B. Hardware Results

The hardware setup of the study is shown in figure 12 which shows the overall setup of hardware. The value of formaldehyde content is shown on the LCD Crystal with comments showing the fish's edibleness.

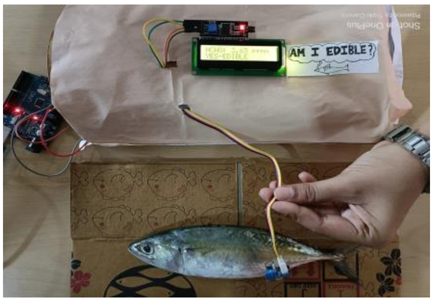

Fig. 12. Hardware setup

The plot of sensitivity vs parts per million(ppm) for the HCHO sensor is shown in Figure 13. sensitivity is the ratio of the sensor resistance value when kept in open air to the resistance value of the sensor when kept in formaldehyde gas. The plot obtained is linear, which indicates that the results obtained are highly sensitive.

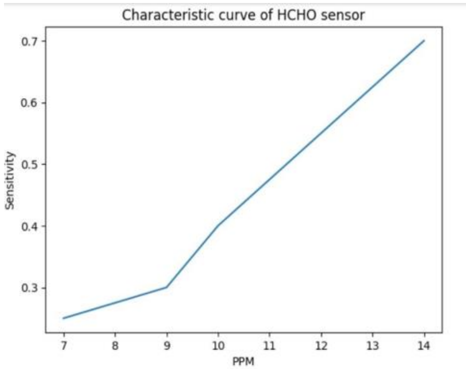

Fig. 13. Characteristic curve of HCHO sensor

C. Testing using Mobile application

The results of the machine learning model and formaldehyde sensor have been obtained on the mobile app. The clicked or picked fish eyes image is fed into the model, and the image is classified as fresh or non-fresh, as shown in Figures 14 and 15.

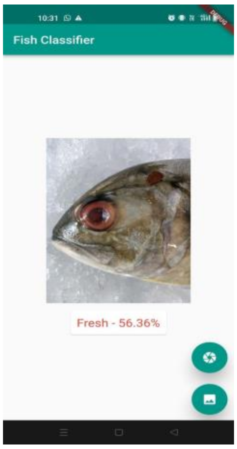

Fig. 14. Predicted fresh fish eyes

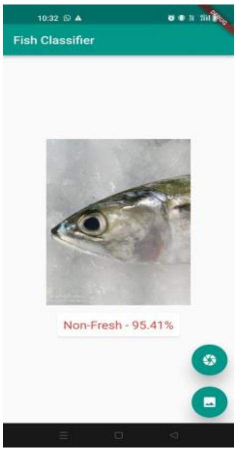

Fig. 15. Predicted non-fresh fish eyes

IV. CONCLUSION

The main objective of this project is to determine the formaldehyde coating and freshness of edible fish. By developing a GUI-based deep learning mobile app to identify fish freshness. It is operated in a simple manner to show the freshness of the fish through its iris image and the formaldehyde content on the fish's surface. Thereby reducing the misjudgment of freshness by buying fish in the market, avoiding eating stale and adulterated fish by mistake, and protecting consumers' health. The accuracy of training and verification data is as high as 85%. It is learned from deep learning that the establishment of the database is very important.

In the future, the collection of fish data will be improved, and more fish species will be collected to make the database more complete and improve the test accuracy.

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