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The Safe Catch: AI Protects Your Health from Formalin-Laced Fish

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ABSTRACT

In Bangladesh, where fish is a staple food, ensuring its safety from formalin contamination poses a critical challenge due to its perishable nature. This study introduces an intelligent application employing digital image processing for the rapid and non-intrusive detection of formalin in fish. Leveraging image analysis of fish eyes, the system distinguishes between formalin and non-formalin treated fish. The proposed architecture, utilizing EfficientNet-B3 and VGG-16 models, achieved a 98.05% and 98% accuracy rate in training and validation on the dataset. This method offers a swift and accurate means of examination without damaging sample preparation, particularly beneficial in large-scale operations where manual inspection is impractical. Unlike human senses, digital image processing algorithms remain impartial, overcoming human biases and subjective judgments. Challenges persist, such as the diverse appearance of fish and external factors like varying illumination, which may impact the reliability and effectiveness of image processing programs for formalin detection. Nonetheless, this technology holds promise in addressing the pressing need for dependable and automated formalin detection in the fish supply chain, ensuring food safety and public health.

1. INTRODUCTION

Fish is a major part of Bangladeshi diets and a key source of protein. It's also a driving force in the country's economy, contributing significantly to exports, job creation, poverty reduction, and economic growth [1]. Bangladesh stands as one of the world's top inland fishing nations, earning considerable foreign revenue from fish and related exports. Between 1998 and 2009, inland water capture in Bangladesh doubled, but it has since declined to about 1.0 million metric tonnes. This decline contrasts with Bangladesh's strategic location in the Ganges-Brahmaputra-Meghna delta, covering 14.4 million square kilometers. Fishing employs 1.2 million people in inland water and 0.3 million in sea fishing. The sector contributes 3.8% to the GDP, with fish supplying 55% of Bangladesh's protein intake [2]. Bangladesh's fisheries sector contributes 25.30% to the agricultural GDP and 1.5% from fish exports. Recent data shows a significant rise in fish production: 47.59 lakh metric tons in 2021–2022, up from 30.62 lakh in 2010–2011 and 7.54 lakh in 1983–84. Fish now represents 1.24% of export revenue, with over 50 countries involved in fish trade [3]. The freshness of commercially accessed fish greatly influences its quality. Maintaining freshness post-harvest, often conducted near lakes, is crucial [1] . While ice is conventionally used for cooling, its effectiveness is limited, leading to additional expenses like purchasing stones. Consequently, harmful substances, notably formalin, are employed for fish preservers [21]. Formalin is a solution of 40% formaldehyde in water, is clear and colorless but hazardous to human health. Despite its risks, formalin is utilized to improve appearance and prolong shelf life, albeit at the expense of safety [4].

Detection of formalin in fish through image processing remains challenging despite successful fish safety evaluations

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via spectral imaging [5]. Formalin, widely used in various industries, is highly detrimental to human health, capable of causing severe gastrointestinal damage, respiratory distress, and even cancer with as little as 30mL ingestion. Research in Bangladesh reports formalin contamination in domestic fish markets ranging from 0.5 to 1% [6]. While solutions like chemical-based tests exist, their accessibility and costs pose challenges. Various studies employ diverse methods like Naïve Bayes, CNNs, and deep learning, achieving accuracies ranging from 86% to 100% in detecting formalin-treated fish [7], yet limitations persist in real-world application and methodology weaknesses, necessitating further refinement and accessibility enhancement of detection techniques [8].

Further, formaldehyde, a naturally occurring compound composed of carbon, hydrogen, and oxygen (CH2O), found utility in tissue preservation and embalming since its discovery in 1893 by Ferdinand Blum [2]. Globally, around 46 billion pounds of formaldehyde are produced annually, with significant contributions from the US, Asia, and the European Union, the latter producing over 3.6 million tons yearly, constituting 30% of the world's production[10]. Detecting formalin in fish through image processing remains a challenging yet a crucial task, necessitating accuracy and robustness. This research aims to tackle this challenge using EfficientNet B3 and VGG-16 classifiers within conventional neural networks (CNN), chosen for their efficiency and adaptability across diverse data. While various methods exist, some are costly or demand fixed infrastructure, hindering practical implementation. Recent strides have been made in identifying formalin-treated fish, yet cost-effectiveness alongside accuracy and robustness remains a priority. Our approach focuses on a cost-effective, deep-learning solution devoid of external GPUs, aiming to identify necessary features with minimal computational resources.

In this situation, detecting formalin in fish is vital for health. Recent methods explore behavior monitoring and image datasets, focusing on features like gills and eyes. However, limited dataset diversity hampers accuracy. Concentrating on eye datasets, this study highlights color "variation" but acknowledges the need for more diverse images to improve accuracy. With limited computational resources, the study aims to establish standardized benchmarks for fair comparisons with future advancements.The objects of this research are:

- An in-depth examination of two pre-trained models, including a detailed explanation of their operating approaches as well as an explanation of their inherent advantages and useful method for identifying formalin fish.
- Developing method can be efficient for further work that will provide a low computational power.
- Understanding a fish quality from an image and through this image people can undrstand fresh or non fresh fish.
- Utilization the performance of two models and compare them with the other exsiting models.

The remainder of the paper is organised as follows: Section 2 goes over the technique we utilised to conduct this systematic review or lierature review, Section 3 goes over the methodology, and some of the most commonly used datasets, pre-processing. Section 4 then examines the result analysis of this paper. Finally, the conclusion finishes in section 5.

2. Literature Review

The application of deep learning, especially using the EfficintNetB3, VGG16 architecture and analysing fish eye images to detect formalin presence is pivotal, especially in places like Bangladesh where fish is a staple [9]. Deep learning's adeptness with unstructured data, especially images, is crucial across many fields. It enhances images, ex-tracts vital information, and ensures food safety by identifying fresh fish. However, formalin, a form of formaldehyde, is highly toxic, causing severe harm even in small amounts when ingested. It poses risks like organ damage, breathing issues, and heightened risks for vulnerable groups such as pregnant women and children [11]. Simply washing fruits doesn't eliminate formalin, highlighting the need for stringent measures to prevent its presence in food. Already there are many solutions available for detecting formalin fish. Recently, researchers in Bangladesh developed a brand-new technique to find formalin in fish. This method uses a chemical-based test that can identify formalin within 30 seconds [7]. However, using this kit is a little difficult, and many people are unable to use it. Also, formalin detection equipment costs roughly $259 in Bangladesh [9].

Nag et al. presented a platinum-based electrode that was used to detect formaldehyde levels in formalin, a food preservative, through voltammetry techniques. The sensor showed a broad linear working range from 100 μM to 1000μM, with the lowest detection limit of 5 μM. Principal component analysis (PCA) and machine learning algorithms achieved a 100% classification accuracy for different formalin concentrations [12]. Roikhanah et al. proposed a mobile application utilizing digital image processing and deep learning, specifically a Convolutional Neural Network (CNN) algorithm with MobileNet architecture, which was developed. It focused on assessing fish quality based on the appearance of the eyes and gills. Training accuracy for the eye dataset reached 100%, while for the gill dataset, it reached 98%. Testing on the mobile application showed high accuracy, with eye dataset accuracy at 100% and gill dataset accuracy at 95% [14]. Yang et al. introduced FishSeg, an improved open-source fish tracking code designed to address challenges in video-based fish tracking. FishSeg utilized a modified Mask R-CNN for multi-fish tracking and 3D conversion to flume coordinates. The model was trained and validated using datasets from live-fish tests, with brown trout and European eel as target species. Results showed that FishSeg generates more continuous and accurate tracks compared to previous methods, with mean Average Precisions (mAPs) of 0.837 and 0.876 for trout and eel, respectively [15]. Anandhu et al. presented a novel approach for identifying fish freshness using VGG-16 CNN using transfer learning, leveraging eye, gill, and skin features from a dataset of 6000+ real fish samples collected around Kerala, resulting in extremely accurate findings when compared to ground truth [13]. Mathur et al. proposed a transfer learning-based approach using ResNet-50 to address the limited dataset issue. By training only, the last few layers of ResNet-50, the method achieves high classification accuracy without data augmentation. Experimental results on large and small datasets show validation accuracies of 98.44% and 84.92% respectively. The approach also yields high precision, recall, and F1 score values, demonstrating its effectiveness in fish formalin detection classification [16].

Rafafi et al. addressed the challenge of differentiating between fresh and non-fresh fish, crucial for maintaining quality in fish delivery to consumers. Self-organizing maps (SOM) are employed as the primary methodology, focusing on identifying fresh and non-fresh tilapia using eye image data. The process involved obtaining, pre-processing, and feature extraction of the data, followed by classification using SOM. The system achieved a good accuracy of 85.71% in identifying fresh and non-fresh fish based on eye images [17]. Tsai et al. introduced a fish freshness identification system using deep learning. It proposes an App allowing consumers to upload fish images to a cloud database for freshness analysis. The system employs a model to provide freshness indicators, aiding consumers in assessing the quality of purchased fish accurately [18]. Mahata et al. presented a method for identifying fish adulteration and assessing quality using a chemo-resistive gas sensor and machine learning (ML) techniques. Sensing behaviour was examined over time to estimate spoilage level, and ML tools achieved 100% accuracy in classifying fresh and adulterated fish samples. Regression models quantified storage duration and spoilage level. The study highlights the potential of nanomaterials combined with ML for accurate food adulteration detection [25]. Zhang et al. addressed the challenge of detecting adulterated salmon, particularly when frozen-thawed flesh is sold as fresh. A flexible bioimpedance-based non-destructive detection system was designed to monitor changes in bioimpedance signals, ambient temperature, and relative humidity in real time. An improved machine learning classification model, PCA-BOA-SVM, was developed to effectively identify frozen-thawed adulterated salmon with a high accuracy of 0.9683, precision of 0.9708, recall of 0.9683, and F1 score of 0.9679. This work offered a solution to improve the authentication of food adulteration in the perishable food supply chain, enhancing traceability and sustainability in the food industry [26].

In the study, it is seen that existing methods for formalin detection on fish vary in efficiency and usability. While Formalin Detection Kits offer accurate results, they aren't practical for customers during purchase. CNN and VGG-16, although effective, demand extensive data and memory, making them time-consuming. To address these limitations, more efficient and user-friendly EfficientNetB3 architecture is proposed for formalin detection on fish. While various methods like CNN and VGG-16 are effective, they demand substantial resources and time, highlighting the need for further research to develop efficient, user-friendly systems for safe and secure use in detecting formalin in fish.

3. MATERIALS AND METHODS

In this section, we present an overview of our implemented methodology. Initially, we collected the dataset and proceeded to pre-process it, segmenting it into three folders: train, validate, and test. After careful consideration, we selected three deep learning-based models suitable for our task. Notably, pre-trained deep learning models, are widely favoured for transfer learning due to their structural efficiency and speed. For our study, we opted to utilize VGG16 as the first model for training and testing and finallyEfficientNetB3. These models were chosen for their proficiency in image categorization and efficiency compared to others. The schematic representation of the system architecture for formalin detection on fish is visually depicted in the accompanying figure 1. It commences with data collection, followed by partitioning the dataset into two segments, typically allocating 70% for training and 20% and 10% for validation. Subsequently, the selected DL models are trained either from scratch or through transfer learning techniques. The training and validation plots are scrutinized to gauge the significance of the models. Performance metrics are then employed to evaluate image classification, specifically in identifying crop diseases and pests. Finally, visualization techniques are applied to aid in image classification. This structured approach ensures a systematic progression from data pre-processing to model evaluation, ultimately aiming for effective classification outcomes.

3.1 EfficientNetB3

EfficientNet is a neural network architecture created in 2019 by Tan and Quoc V. Le of Google AI [23]. It's designed to deliver cutting-edge performance while remaining computationally efficient. It boosts performance and efficiency by increasing depth, width, and resolution on a regular basis. This balanced scaling the method enhances accuracy while decreasing processing demands, yielding a robust but resource-efficient neural network architecture. Figure 2 described the architecture of EfficirntNet-B3.

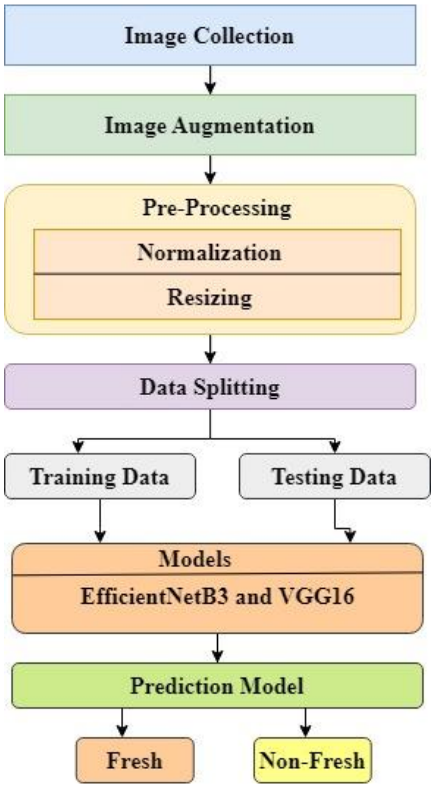

Fig. 1. The image presents the workflow of our proposed method.

The convolutional network, EfficientNetB3, introduces a revolutionary scaling technique that alters network depth, breadth, and resolution parameters uniformly. To determine how several basic aspects of network scalability relate to one another, this model uses a fixed resource restriction. This process might be used to determine the proper scaling coefficients for each dimension that has to be adjusted. Using these established criteria as a basis, the basic network dimensions were scaled accordingly to the necessary size [22]. With improved accuracy achieved through parameter tuning, EfficientNet-B3 stands out. EfficientNet-B3 accommodates devices with limited resources by maintaining a sophisticated equilibrium between precision and effectiveness. Its smaller form reduces the need for processing and storage. It provides adaptability across a range of applications on simple integration, guaranteeing efficient multitasking and superior transferability.

3.2 VGG-16

VGG16 is a CNN architecture created by the Visual Graphics Group (VGG) at the University of Oxford. It is a VGG family model and is named after the "VGG" group. VGG16 stands out for its depth and simplicity, with 16 weight layers, 13 convolutional layers, and 3 fully linked layers. The internal structure of VGG16 is depicted in the figure. It excelled in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014.VGG has several versions, including VGG11, VGG13, VGG16, and VGG19 [24]. It is a popular picture 3 categorization model due to its simplicity and efficacy. Figure 3 described the architecture of VGG-16.

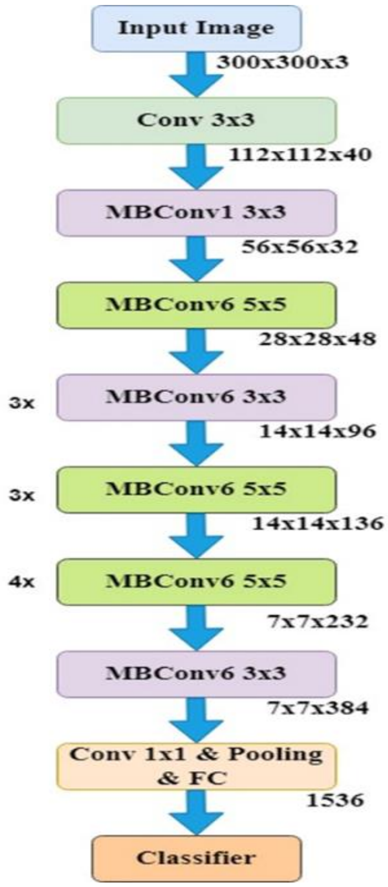

Fig. 2. The image presents the architecture of EfficientNetB3

VGG-16, often known as VGGNet, is a convolutional neural network (CNN) model with 16 layers that is essential for object recognition and classification. Prominent for having all of the necessary convolutional neural network properties included in one complete package, VGG16 has 138 million parameters in its network. With an impressive 92.7% accuracy rate in classifying 1000 photos in various categories, it has become a widely used image classification technology that may be easily implemented using transfer learning. Utilizing pre-existing, usable VGG-16 models increase the viability of using transfer learning. This is particularly useful in scenarios when there is a dearth of labelled data since the model may leverage knowledge gained from training on large datasets. VGG-16's simple architecture makes it easier to deploy and integrate into image-processing workflows and frameworks. Furthermore, VGG-16 is now a widely accepted standard in the field of image processing, providing a generally accepted framework for evaluating and analysing new approaches. In light of the aforementioned advantages, the decision to employ the EfficientNetB3 model and VGG-16 has been made for the purposes of this paper.

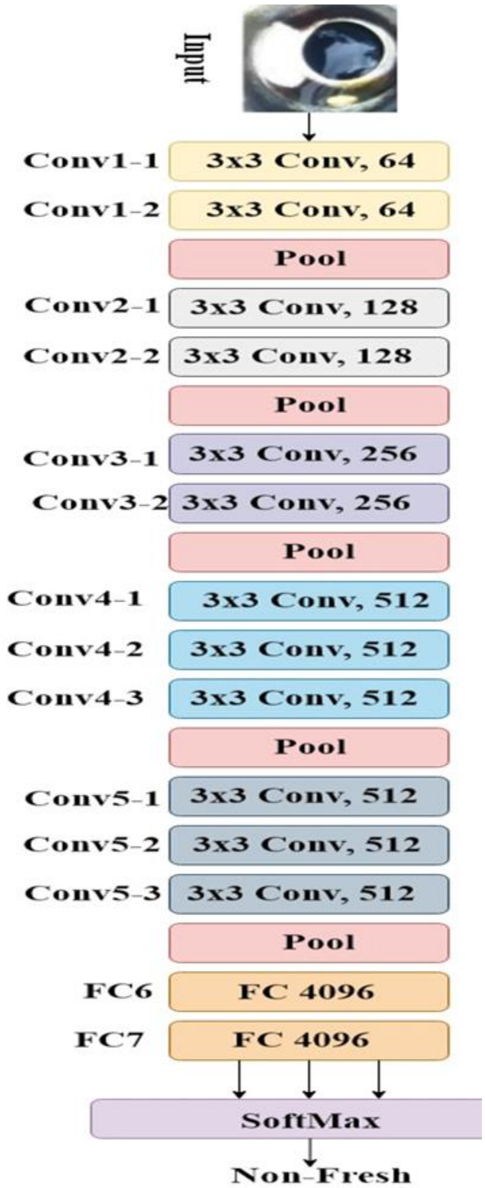

Fig. 3. The image presents the architecture of VGG-16

3.3 Dataset

The Fish Eye dataset from Kaggle was the source of the dataset used in this paper's experiments. Using this dataset, these two models were trained to enable the prediction of fish samples classified into formalin-free and formalin-based classifications, and its method was thoroughly evaluated and improved.

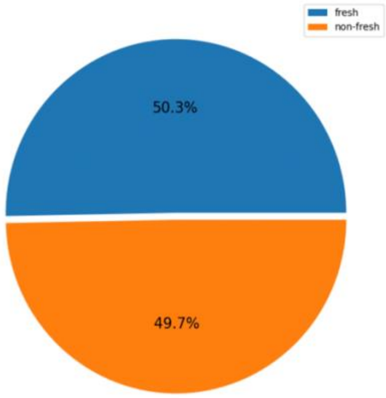

Fig. 4. Data distribution of fresh non-fresh fishes

The distribution of fresh samples (50.3%) and non-fresh samples (49.7%) was observed in the dataset used for algorithm assessment and training figure 4 can illustrate it. A thorough evaluation of these two algorithms' performance over a variety of dataset categories is guaranteed by this well-balanced composition. Figure 5 described few examples of our dataset. In this dataset we can see fresh and non-fresh fish's eyes. Fresh fish can be distinguished by certain characteristics. Their pupils are black, contrasting with clear corneas. The gills of fresh fish appear dark red and lack the secretion of mucus. When touched, the flesh feels elastic and dense. Additionally, the mucus on the skin's surface is clear and colourless. On the other hand, non-fresh fish exhibits noticeable signs. The pupils of their eyes appear cloudy, while the gills turn brown. The texture of the meat becomes soft, and a bad starts to emanate from the fish. Non-fresh fish's eyes colour is fade than actual fish. Sometimes in their eye sight the colour is yellow and fade white and grey. There'll be some sport in the fish's eye.

Fig. 5. Image sample of fresh and non-fresh fish

4. RESULTS AND ANALYSIS

The implementation of EfficientNetB3 and VGG-16 was conducted on a Windows 10 x64 platform featuring an Intel Core i7 CPU operating at 2.5GHz, 8GB of RAM, and no external graphics processing unit. This hardware configuration served as the experimental environment for our dataset evaluations. The datasets were systematically partitioned into three subsets: training (70%), testing (20%), and validation (10%). A detailed breakdown of the data split is showed in Table 1.

Table 1. A comprehensive description of Training, Testing, and Validation.

Dataset	Training	Testing	Validation
Kaggle	70%	20%	10%

Finding the accuracy, precision, recall, f-measure, and error rate on each difficult dataset was done in order to assess the performance of our suggested method. The simplest way to express accuracy, which is the natural way to gauge performance, is as a ratio between correctly predicted discoveries and all finds. Precision described the ratio of accurately predicted positive finds to all predicted positive findings. The error rate is the ratio of incorrectly anticipated finds to all findings. False positive predictions are abbreviated as FP and True positive predictions as TP. True positive predictions and false positive predictions are denoted by the letters TN and FN, respectively. Table 2 and 3 contains the precision, recall, and f-score for both models.

Table 2. Precision, recall, f1-score for EfficientNetB3

Precision	Recall	F1-Score
97.6%	98.02%	98.60%

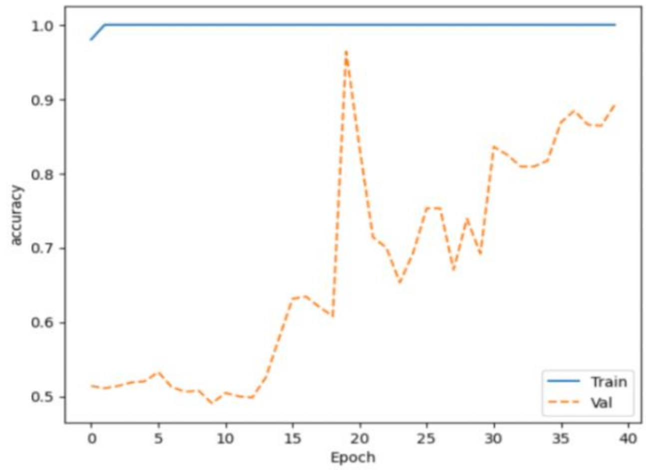

Fig. 6. The accuracy rate of the training dataset (EfficientNet-B3)

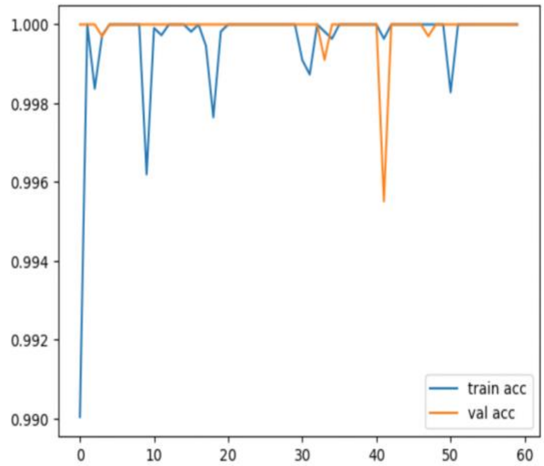

Fig. 7. The accuracy rate of the training dataset (VGG-16)

Table 3. Precision, recall, f1-score for VGG16

Precision	Recall	F1-Score
98.56%	98.92%	99.20%

The result of training curve accuracy at 1.0 validation accuracy reached 0.9 based on this figure. The validation accuracy approached one in the most recent period. The more epochs that are added, the closer the value of the training and validation process is to 1.0. If the training and validation accuracy values decrease, the trained algorithm cannot execute the classification correctly.

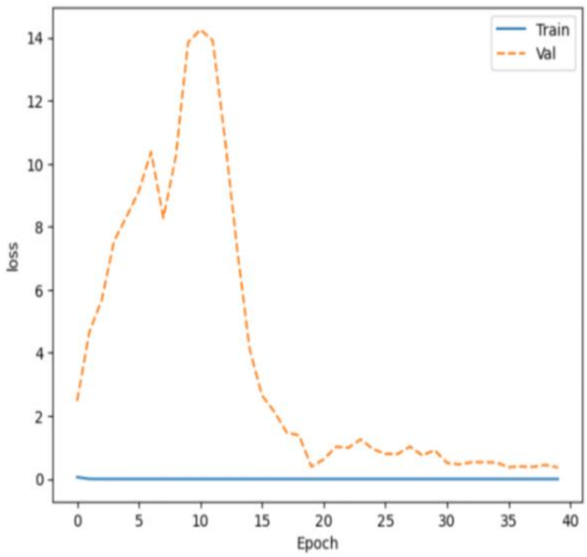

Fig. 8. The error rate of the training dataset (EfficientNet-B3)

Table 4. Accuracy for EfficientNetB3 and VGG16

EfficientNetB3	VGG16
99.05%	99.9%

According to Figure, the training accuracy and validation training curves are close to 0.0 as epoch 40 increases. The training error value hit 0 and the validation accuracy value reached 0.1 in the most recent epoch.

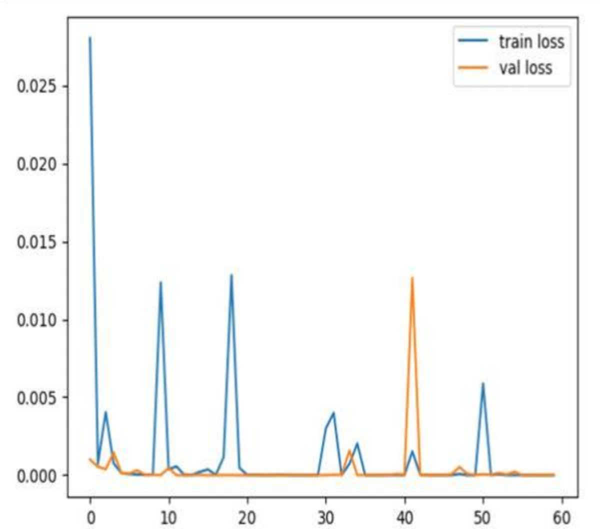

Fig. 9. The Error rate of the training dataset (VGG-16)

The confusion matrix contains information on the comparison of the system's classification results with the actual classification results. According to the figure, the confusion matrix from the fish eye dataset test result and the formalin eye dataset result showed that the predictions were accurate 138 and incorrect 0. The confusion matrix result for formalin-added fish is accurate 122 and incorrect 8. The confusion matrix of our result contains in figure 10.

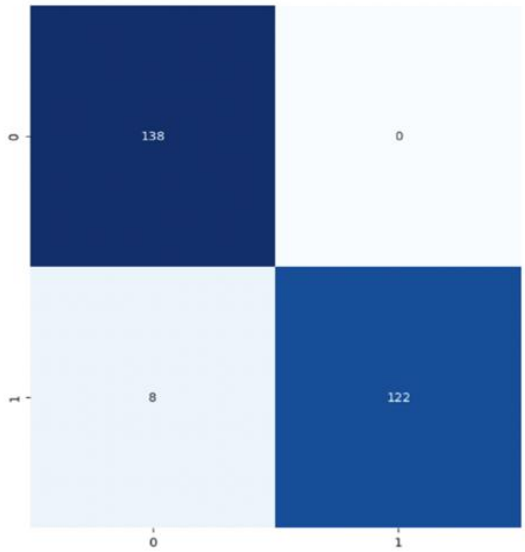

Fig. 10. Confusion Matrix of our results

On the Kaggle dataset with less computational capacity, our model performed well. To identify formalin in fish both EfficientNetB3 and VGG-16 performed well and reached the best accuracy. Figure 6,7 describe the accuracy rate of both models and 7,8 describe the error rate of both models. Both architecture EfficientNetB3 and VGG-16 predict very nicely with an accuracy of 99.05% and 99.9% The error rate for both an architecture EfficientNetB3 and VGG-16 is 0.95% and .10%. Table 4 contains the accuracy results of both models.

5. CONCLUSION

Fish is a staple food for many Bangladeshis, but the presence of formalin in fish poses a significant health risk. Identifying formalin-free fish is crucial for consumer safety, yet distinguishing it during purchase is challenging. To address this issue, we have proposed a Deep Learning model, a subset of Machine Learning, aimed at detecting formalin in fish. This innovative approach utilizes eye images of fish to determine the presence of formalin with remarkable accuracy. Our model, particularly designed with the VGG-16 architecture, achieves an outstanding accuracy rate of 99.9%. This surpasses existing models which often struggle with errors and inaccuracies in identifying formalin in fish. By leveraging advanced computational techniques, our model not only enhances the accuracy of detection but also provides a reliable tool for consumers to ensure the safety of their fish purchases. The implementation of our proposed model holds great promise in alleviating the concerns surrounding formalin-contaminated fish. Empowering consumers with the ability to discern formalin-free fish will not only safeguard public health but also foster trust and confidence in the seafood market. Ultimately, our model contributes to reducing human suffering by mitigating the risks associated with formalin consumption.

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