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Deep Learning Based Fish Species and Freshness Detection Using Convolutional Neural Networks

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Abstract: Maintaining fish freshness is essential in the seafood industry to ensure product safety, quality, and consumer satisfaction. Conventional assessment techniques primarily depend on manual inspection or laboratory-based analysis, which may be subjective, time-intensive, and unsuitable for rapid evaluation. This study introduces a deep learning–driven method for identifying fish species and determining freshness levels using Convolutional Neural Networks (CNN). The framework categorizes fish images into defined freshness classes, including Fresh, Medium, and Spoiled. A MobileNet-based model is adopted due to its lightweight architecture and efficient computational performance. The dataset comprises annotated fish images collected under different storage conditions. Model training and evaluation are conducted using standard classification metrics. Experimental findings indicate strong predictive accuracy and demonstrate the feasibility of deploying the system for real-time applications in seafood markets and processing facilities.

Keywords: Fish Freshness Detection, Fish Species Classification, Deep Learning, Convolutional Neural Network, MobileNet, Image Processing.

I. INTRODUCTION

Fish is one of the most widely consumed sources of animal protein worldwide, playing a vital role in nutrition, food security, and economic development. However, fish is highly perishable, and its freshness deteriorates rapidly due to microbial activity and biochemical reactions after harvest. Maintaining seafood quality is therefore essential to prevent foodborne illnesses and minimize economic losses within the supply chain. Traditional freshness assessment methods primarily depend on sensory evaluation techniques such as visual inspection, odor assessment, and texture examination. Although commonly practiced, these approaches are subjective, require experienced personnel, and may produce inconsistent results under varying environmental conditions.

With advancements in intelligent sensing and machine learning technologies, automated freshness detection systems have attracted increasing research interest. Several studies have investigated Internet of Things (IoT)–based monitoring combined with deep learning algorithms for meat and seafood quality evaluation. IoTenabled meat freshness classification frameworks have demonstrated promising accuracy within smart monitoring environments [1]. Similarly, IoT-integrated fish freshness detection systems have been developed to improve quality control in seafood markets [2]. Deep convolutional neural networks have also been applied for fish detection and species recognition under challenging underwater conditions, illustrating the robustness of computer vision techniques [3].

In addition to image-based approaches, alternative sensing technologies such as electronic noses and gas sensor arrays have been explored for freshness classification [4], [9]. Hardwareoriented spoilage detection methods, including CMOS-based sensing systems and impedance spectroscopy techniques, have shown effectiveness in controlled settings [5], [7]. Furthermore, self-powered freshness monitoring systems integrated with ensemble learning models have been proposed to enhance sustainability and predictive performance [6]. Computer vision has also been utilized for automated fish monitoring and behavioral analysis in aquatic environments, demonstrating the versatility of visual intelligence applications [8]. Despite these advancements, many existing solutions rely on specialized sensors, laboratorygrade setups, or high-cost hardware components, which restrict accessibility for small-scale vendors oo

portable, and user-friendly system capable of delivering real-time freshness assessment using readily available computing platforms. To address this requirement, an intelligent fish species and freshness detection framework based on a lightweight MobileNetV2 deep learning architecture is introduced. The system performs image acquisition, preprocessing, and classification to identify fish species and categorize freshness levels as Fresh, Medium, or Spoiled. To improve accessibility for regional users, prediction results are converted into Tamil speech using text-tospeech technology and transmitted through a Bluetooth speaker. The integration of edge computing, computer vision, and regional language audio feedback enables practical deployment in fish markets, seafood processing facilities, and food safety monitoring environments

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II. METHODOLOGY

The proposed system is designed as a deep learning-based multiclass image classification framework for automatic fish species identification and freshness assessment. The complete methodology consists of dataset preparation, image preprocessing, transfer learning-based feature extraction, classification model design, training optimization, performance validation, and realtime deployment. The overall workflow is illustrated through sequential processing stages: image acquisition, preprocessing, feature extraction, classification, and output generation.

A. *Problem Formulation*

The objective is to classify an input fish image into one of sixteen predefined categories representing a combination of species and freshness level. Instead of performing two separate tasks (species detection and freshness detection), the problem is formulated as a single 16-class multi-class classification task.

Let:

- X = Input fish image
- $Y \in \{1,2,...,16\}$= Class label

The goal is to learn a mapping function:

$$f(X) \rightarrow Y$$

where each class corresponds to a specific species–freshness combination such as:

Fresh – Mathi
Medium – Parai
Spoiled – Shankara , etc..

This formulation enables simultaneous prediction of both species and freshness in a single inference step.

B. *Dataset Description*

The dataset consists of real fish images categorized into freshness levels:

Fresh, Medium, Spoiled The species included are:
Kola, Mathi, Nagarai, Nei, Parai, Shankara

The dataset statistics are:

The dataset used in this work consists of fish images categorized based on species and freshness level. A total of 1,959 images were used, divided into:

- 1572 training images
- 387 validation images
- 16 total classes
- 1959 total images

C. *System architecture*

The system integrates image acquisition hardware, embedded deep learning inference, and multimodal output feedback within a

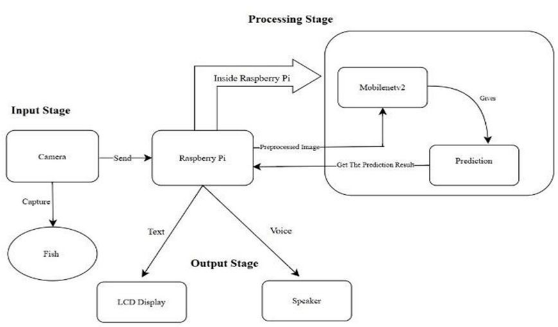

FIG 1 System Architecture

compact edge device. A camera module captures fish images, which are processed locally using a fine-tuned MobileNetV2 convolutional neural network. The final classification output includes both fish species and freshness category.

1) Input Stage - Image Acquisition

A high-resolution RGB camera module is interfaced with the Raspberry Pi. Fish specimens are placed within a predefined capture region to maintain consistent framing conditions.

The captured images contain key visual freshness indicators such as:

- Eye transparency and brightness
- Gill coloration
- Skin reflectance and discoloration
- Surface texture integrity
- Structural firmness appearance

These visual cues form the basis for computational feature extraction.

Each captured image is directly stored in Raspberry Pi memory for preprocessing and inference.

2) Processing Stage (Embedded Deep Learning Framework)

The processing stage performs three major operations:

- Image Preprocessing
- Deep Feature Extraction
- Multi-Class Classification

All computations are performed locally on the Raspberry Pi.

a) Image Preprocessing

To standardize input data, the following operations are applied:

- Image Resizing

All input images are resized to:

$$224 \times 224 \times 3$$

This dimension matches the required input specification of the MobileNetV2 architecture.

- Pixel Normalization

Pixel intensity values are scaled from the range [0,255] to [0,1] using:

$$X_{normalized} = \frac{X}{255}$$

Normalization stabilizes gradient propagation and ensures consistent inference behaviour.

- Data Formatting

Images are converted into NumPy array format and reshaped into batch tensors before being passed to the neural network.

b) Deep Feature Extraction Using MobileNetV2

The backbone of the proposed system is the MobileNetV2 convolutional neural network due to its lightweight design and reduced computational complexity.

c) Depthwise Separable Convolution

MobileNetV2 replaces traditional convolution with depthwise separable convolution.

Traditional convolution computational complexity:

$$D_k \times D_k \times M \times N \times D_f \times D_f$$

Depthwise separable convolution complexity:

$$D_k \times D_k \times M \times D_f \times D_f + M \times N \times D_f \times D_f$$

Where:

- D_k = Kernel dimension
- M = Number of input channels

- N = Number of output channels
- D_f = Feature map dimension

This architectural modification significantly reduces parameter count and enables efficient embedded deployment.

3) Transfer Learning Strategy

Instead of training the model from scratch, pre-trained weights from the ImageNet dataset were used for initialization. The final classification layer was modified to accommodate:

$$K = 16$$

output classes representing different fish species and freshness categories.

Fine-tuning was performed on the custom fish dataset to adapt general visual features to domain-specific freshness patterns.

4) Multi-Class Classification

The final output layer applies the Softmax activation function:

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Where:

- $K = 16$ output classes
- z_i = Logit value for class i

The class with the highest probability score is selected as the final prediction.

5) Model Training Configuration

The model was trained using the following configuration:

- Optimizer: Adam
- Learning Rate: 0.001
- Loss Function: Categorical Cross-Entropy
- Batch Size: 32
- Epochs: 20

The categorical cross-entropy loss is defined as:

$$L = -\sum_{i=1}^{K} y_i \log(\hat{y}_i)$$

Where:

- y_i = True label
- $\hat{y}_i$ = Predicted probability The model achieved:
- Training Accuracy: 99.01%
- Validation Accuracy: 95.86%

The high validation accuracy indicates strong generalization capability.

D. Output Stage

The output stage enhances usability and accessibility for end users.

1) LCD Display Interface

The predicted output is displayed on an LCD screen connected to the Raspberry Pi. The display includes:

- Fish species
- Freshness level

This provides immediate visual confirmation.

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2) Tamil Text-to-Speech Module

To improve accessibility for regional users, the predicted label is converted into Tamil speech using a text-to-speech engine.
The workflow includes:

- Convert predicted label to Tamil text
- Generate audio waveform
- Output audio via speaker

This feature ensures usability in noisy fish market environments and supports non-technical users.

III. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the proposed fish freshness detection system using a deep learning model. The system was trained using a labeled dataset of fish images categorized into different freshness levels such as Fresh, Medium, and Spoiled. The performance of the model was evaluated using training and validation accuracy and loss metrics.

A. Output

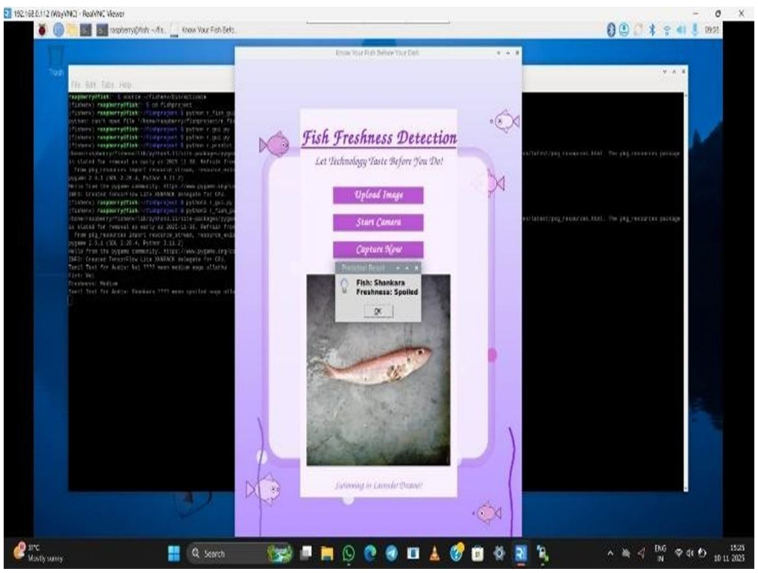

Fig 2. Prediction Result Display

B. Model Training Performance

The MobileNet CNN model was trained using the TensorFlow deep learning framework. During training, the model learned features such as color changes, texture differences, and visual degradation patterns in fish images. The training process was monitored using training accuracy and validation accuracy.

C. Training Results

Metric	Value
Training Accuracy	95%
Validation Accuracy	92%
Training Loss	Low
Validation Loss	Stable

Table 1. Training Results

D. Training and Validation Loss

Fig 3. Training and Validation Loss of the Proposed Model

The loss curve shows how the model error decreases during the training process. Initially, the loss value is high because the model has not yet learned meaningful features from the dataset. As training continues, the loss gradually decreases, indicating that the model is learning relevant patterns from the fish images. The validation loss also reduces and stabilizes around 0.25, showing that the model performs well on unseen data.

E. Training and Validation Accuracy

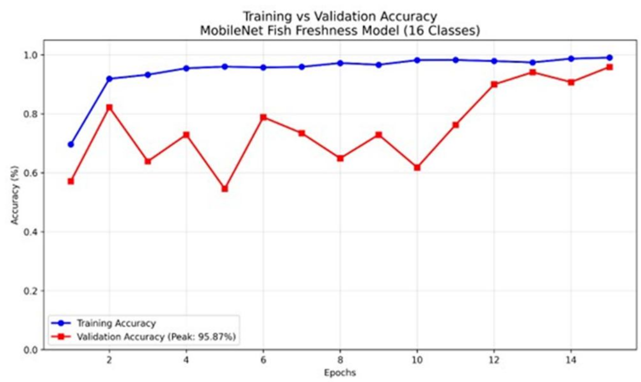

Fig 4. Training and Validation Accuracy of the Proposed Model

Accuracy measures how many samples are correctly classified by the model. The training accuracy increases steadily across epochs and reaches nearly 99%, while the validation accuracy achieves approximately 95.87%. The small difference between the two values indicates that the model generalizes well and does not suffer from significant overfitting.

F. Comparison with Existing Methods

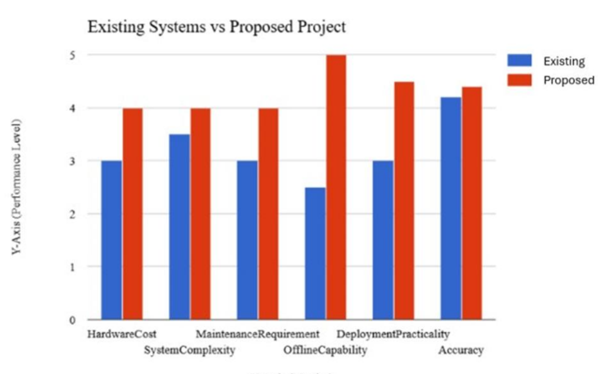

Fig 5. Comparison between Existing Systems and Proposed System

A comparison was performed between traditional fish freshness assessment methods and the proposed deep learning-based approach. Existing systems usually involve manual inspection or complex hardware setups. In contrast, the proposed system provides higher accuracy, lower system complexity, reduced maintenance, and better deployment flexibility. These advantages make the proposed approach more suitable for real-time applications.

Overall, the experimental results demonstrate that the proposed MobileNet-based model can effectively classify fish freshness levels with high accuracy and reliability.

IV. CONCLUSION

This study presented a deep learning-based system for fish freshness detection using the MobileNet convolutional neural network. The model was trained on a dataset of fish images and successfully classified them into different freshness categories. Experimental results showed that the proposed system achieved high classification accuracy, with training accuracy close to 99% and validation accuracy around 95.87%. The lightweight structure of MobileNet makes the model efficient and suitable for real-time applications.

The proposed approach provides a practical and automated solution for fish freshness assessment, which can support food quality monitoring in fish markets and seafood industries.

V. FUTURE ENHANCEMENT

Future work can focus on expanding the dataset with more fish species and images captured under different conditions. The system can also be improved by integrating IoT sensors to monitor storage conditions such as temperature and humidity. In addition, developing a mobile or embedded application can make the system more accessible for realtime freshness detection in fish markets

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