Computer Vision-Based Intelligent Non-Destructive Testing for Fish Meat Quality Assessment: A Hybrid Convolutional Neural Network and Support Vector Machine Approach

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ABSTRACT

Ensuring food safety has historically been one of humanity's most significant challenges, often accompanied by considerable costs, time, and potential for errors. The verification and classification of fish meat traditionally rely on destructive testing methods, such as physical and chemical tools, which present various problems and challenges. Today, with the expanding application of artificial intelligence, it is possible to classify fish meat with high speed and accuracy. Therefore, the aim of this research was to present a non-destructive intelligent model for the classification and identification of fish meat into three classes: healthy, normal, and spoiled. The dataset for modeling and analysis was collected from the Kaggle database, with each class containing 400 images. This study analyzes and implements two deep learning-based approaches for detecting fish freshness from images. The first method involves training a Convolutional Neural Network (CNN) model using the MobileNetV2 architecture with added dense layers. In the second approach, MobileNetV2 is utilized as a feature extractor, and then a Support Vector Machine (SVM) classifier is trained on the extracted features. The results indicate that both approaches achieve acceptable accuracy, but the hybrid MobileNetV2 + SVM model demonstrates significantly superior performance in classifying fish freshness categories. This study emphasizes the effectiveness of transfer learning and the advantage of using SVM for final classification in practical applications.

Keywords: *Fish Freshness Detection, Computer Vision, Deep Neural Network, Transfer Learning, MobileNetV2, Support Vector Machine (SVM).*

1.INTRODUCTION

Food shelf-life is a complex subject with significant gaps still remaining in its understanding. In fact, the deterioration of certain quality characteristics may lead to a product not being sold, but it does not necessarily indicate a loss of hygienic, sensory, or nutritional quality. Furthermore, the shelf-life of perishable items can only be related to specific environmental and production conditions. Therefore, when discussing food shelf-life, it is essential to consider all influential factors. Consequently, a prominent book defines shelf-life as: "the period of time which – under specified conditions (such as packaging, transport, storage practices, and climate) – corresponds to an acceptable reduction in product quality." In 2015, global human consumption of fishery products reached 149 million tonnes, accounting for 88% of total fishery production. The average worldwide fish consumption per capita was estimated at 20.3 kg [1].

The main factors contributing to the increased consumption of aquatic products among people today are their high nutritional value and appealing taste [2]. Due to its unique characteristics, including being rich in protein, vitamins, and minerals, low in fat, having a pleasant taste, and being easily digestible and absorbable, fish serves as a crucial food source for daily human consumption [3].

Fish freshness is a fundamental aspect of fish product quality and is highly dependent on appropriate storage conditions, especially time and temperature after catching. The ideal storage temperature for fresh fish ranges from -1 to 0 degrees Celsius, while a 5-degree Celsius increase can significantly reduce shelf-life

by more than half. Generally, biochemical changes occurring in fish tissues after catching are strongly influenced by storage temperature, catching method, and the fish's prior living conditions, which are the main factors contributing to the loss of freshness, with microbial spoilage occurring at a later stage. The aquaculture sector requires fish quality assessment because fish products can spoil rapidly due to biochemical and microbial decomposition processes. Given the strong correlation between fish freshness and its safety and taste, freshness is considered a significant factor for consumers. Therefore, there is a strong need for new methods to ensure food security in the fisheries sector [4].

As a problem statement, it can be asserted that fish freshness is a key factor in the quality of seafood products, dependent on storage conditions (time and temperature), and traditional freshness assessment methods (chemical, sensory, and microbial) are time-consuming, destructive, and sometimes inefficient. The need for developing non-destructive, rapid, and objective methods for fish freshness assessment, especially for valuable fish species, is strongly felt. The lack of sufficient research in the application of Computer Vision Systems (CVS) and Artificial Intelligence (AI), and the absence of a suitable framework for evaluating parameters related to fish freshness and health (such as eye color, gill mucus, skin color, etc.) without destructive testing, have been identified as research gaps. Therefore, the main objectives of this research are to present an intelligent system based on Artificial Neural Networks (ANN) for assessing the freshness of valuable fish during storage, and also to combine image processing and machine learning algorithms (SVM, K-NN, ANN) for fish freshness classification as specific objectives.

2. Literature Review and Research Background

Tapi et al. (2017) conducted research on the application of a Computer Vision System (CVS) as a powerful non-destructive technique for evaluating the freshness of red mullet fish (Mullus barbatus). In this study, red mullet fish samples were stored at temperatures between 0 and 4 degrees Celsius for 10 days. The samples were assessed based on chemical evaluation using trimethylamine as a spoilage indicator and sensory evaluation employing the Quality Index Method (QIM) to assess apparent characteristics such as skin appearance, gills, and Eye Color Index (ECI). The research utilized a Computer Vision System for image analysis to measure three parameters for identifying changes: Epidermal Pigmentation Loss (EPL), gill mucus formation, and eye deformation. Statistical analyses were then used to examine the correlation between chemical, sensory, and ultimately, computer vision data. Based on the results, temperatures above 4 degrees Celsius accelerated fish spoilage. The eye indentation and pigmentation loss indices showed a high correlation with QIM and TMA-N results, while gill mucus did not have a significant correlation with other parameters. Therefore, it can be stated that CVS, especially the ECI and EPL indices, is an effective, non-destructive, and rapid method for assessing the freshness of red mullet, consistent with traditional (chemical and sensory) methods [5].

In 2019, researchers in China, led by Wu et al., conducted a study titled "Novel Techniques for Freshness Quality Evaluation of Fish: A Review of Recent Advances." This research focused on evaluating new, non-destructive methods for assessing fish freshness and safety. Wu and colleagues investigated the use of biosensors, biosensing techniques, and spectroscopy as alternatives to traditional, time-consuming, and destructive methods. They recommended the application of biosensors for examining and measuring chemical parameters, bionic techniques for rapid and qualitative detection of spoilage, and hyperspectral imaging for spatial visualization of food spoilage. However, their review also highlighted significant challenges, including standardization, cost, and the development and generalization of models for other fish species [6].

In 2019, Taheri Garavand et al. published a study titled "Non-destructive and Real-time Monitoring of Common Carp Freshness Using Robust Vision-Based Intelligent Modeling Approaches." This research aimed to provide an intelligent, non-destructive, and rapid method for assessing the freshness of common carp (Cyprinus carpio) during ice storage. Their proposed method leveraged image processing and machine learning techniques, starting with capturing images of fish stored on ice for two weeks. These images underwent preprocessing, including noise removal, background elimination, and conversion to various color spaces. Six textural features (mean, standard deviation, uniformity, skewness, energy, and entropy) were then extracted from nine color channels. An ABC-ANN hybrid algorithm was used for feature selection, optimizing 54 extracted features down to 22. Finally, the images were classified into four freshness classes (freshest, fresh, relatively fresh, and spoiled) using Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), and Artificial Neural Network (ANN). The ANN model achieved the highest accuracy at 93.01%, while SVM and

K-NN showed 91.52% and 90.48% accuracy, respectively. This research successfully proposed a non-destructive, rapid, and accurate solution for fish freshness evaluation in the aquaculture industry [7].

In 2021, Medeiros et al. conducted research titled "Computer Vision and Machine Learning for Classification of Tuna and Salmon Meat Freshness," presenting a non-destructive approach to assess the quality and freshness of tuna and salmon using computer vision and machine learning. Their primary goal was to create an automated, objective system to replace less accurate, traditional human sensory evaluations. The study used quantitative methods and machine learning algorithms, processing labeled tuna and salmon images captured by a CVS sensor with white light. Image preprocessing involved resizing, Gaussian filtering, thresholding, and defining regions of interest, followed by extracting color parameters from RGB, HSV, HSI, and Lab color spaces. Automated machine learning then classified the meat as healthy or unhealthy. Model evaluation using metrics like accuracy, ROC curves, Precision, Recall, F1-Score, and confusion matrices showed high capability and accuracy, outperforming previous methods. However, the research was limited by a small sample size, and future studies were advised to explore deep learning with more extensive datasets [8].

In 2022, Zhixin Jia et al.'s research, "Determination of Salmon Freshness by Exploiting Computer Vision Based on Eye Color," presented a rapid, highly accurate, and non-destructive testing process for salmon. This study demonstrated a direct relationship between changes in fish eye color during storage and established freshness indicators like TBA, TVB-N, TVC, and K-Value. The researchers utilized Multiple Linear Regression (MLR) and Support Vector Regression (SVR) models for prediction, with MLR proving notably more accurate (R2> 0.9989) in predicting salmon's health and freshness compared to SVR. This research offers a promising and efficient new method for quality control in the fish industry [9].

In 2023, Grassi et al. reviewed Electronic Sensing (E-sensing) systems, encompassing e-eye, e-nose, and e-tongue technologies, for assessing the shelf-life of fresh animal-derived foods. These systems evaluate visual characteristics, volatile compounds, and taste, respectively, offering advantages like speed, simplicity, non-destructiveness, and inline applicability. The review, spanning 10 years of literature, highlighted their use in meat, fish, dairy, and egg evaluation, emphasizing multivariate data analysis (PCA, PLS, SVM, ANN) for sensor data. Findings showed e-eye achieved up to 94% accuracy with SVM for color/texture changes; e-nose rapidly detected spoilage via volatile compounds (e.g., TVB-N); and e-tongue measured freshness using chemical compounds. Notably, integrating e-nose and e-tongue boosted fish spoilage detection accuracy to 91%. While these systems are fast, non-destructive, and cost-effective for real-time quality control, challenges include the need for precise calibration and environmental control, and a lack of global standardization. Future directions suggest developing low-cost AI-based sensors and integrating with IoT for smart supply chain monitoring to enhance spoilage detection [10].

In 2024, Gao et al. published research from China titled "Intelligent Method for Fish Freshness Classification and Identification Based on the DWG-YOLOv8 Network Model," which introduced a non-destructive and automated approach to assess Conger fish freshness using computer vision and deep learning. The study aimed to fill research gaps by providing a precise and efficient system that bypasses traditional sensory and chemical evaluations. They utilized 243 spoiled and 241 healthy labeled samples, developing a DWG-YOLOv8 model incorporating Ghost and DW-GhostConv modules to reduce computational load while maintaining high accuracy. The results demonstrated the proposed model's superior accuracy and efficiency compared to models like ResNet18 and MobileNetV3, with heat map analysis highlighting the effectiveness of abdominal region features for freshness assessment. This fast and accurate model represents a significant advance in fish freshness evaluation, capable of deployment on resource-limited devices and in industrial production lines due to its high accuracy and compact size [11].

Table 1 offers a comprehensive review of prior research in this field by various active researchers, spanning from 1991 to 2023. For each entry, the table provides the author(s)' names, the publication year of their article, the objective of their research, the method or system used for analysis and evaluation, and the key results obtained from their studies.

Table 1; Other Research Conducted in the Field of Meat and Fish Spoilage Identification (1991-2023)

Authors	Year	Method/System Used	Research Objective	Results
Nielsen et al.[12]	1991	Computer Vision System (CVS)	Investigating fish quality with imaging techniques	Feasibility of using CVS for fish quality control.
Huss [13]	1995	Chemical and Sensory Methods	Examining quality changes in fresh fish	Impact of temperature and time on fish spoilage.
Lapa-Guinaraes et al. [14]	2002	Sensory and Chemical Methods	Evaluating squid freshness	Color and texture changes associated with spoilage.
Di Natale [15]	2003	Multi-sensor Data Analysis	Determining an artificial quality index for fish	Correlation between sensory and instrumental data.
Schubring [16]	2003	Skin Color Measurement	Investigating changes in fish skin color	Relationship between color changes and fish quality.
Ozyurt et al. [17]	2009	QIM and Chemical Methods	Evaluating the freshness of red mullet and other species	Determination of shelf-life based on QIM.
Muhamad et al. [18]	2009	Fuzzy Logic	Classifying fish freshness	Use of visual features for classification.
Hong et al. [19]	2012	E-nose (PEN2)	Evaluating beef freshness	High-accuracy prediction of TVB-N and microbial count.
Dowlati et al. [20]	2013	Image Processing and ANN	Evaluating fish freshness by analyzing eye and gill color	Eye color changes are suitable for freshness evaluation.
Feng et al. [21]	2013	Regression-based Image Processing	Evaluating fish freshness using eye images	Development of a model based on eye color changes.
Dowlati et al. [22]	2013	Image Processing	Evaluating fish freshness by analyzing eye and gill	High-accuracy freshness detection.
Han et al. [23]	2014	E-nose + E-tongue	Evaluating the freshness of *Pseudosciaena Crocea* fish	Data fusion increased detection accuracy.
Kishore Dutta et al.[24]	2016	Automated Image Processing	Estimating fish freshness by analyzing gill texture	Proposed a non-destructive and rapid method.

Ghasemi-Varnamkhasti et al. [25]	2016	Image Processing	Evaluating shrimp freshness	90% accuracy in freshness classification.
Apetrei & Apetrei [26]	2016	Voltammetric E-tongue	Detecting ammonia and putrescine in beef	Modified electrodes showed high sensitivity.
Fatahi et al. [27]	2017	Image Processing and ANN	Classifying chicken meat freshness	92% accuracy using selected features.
Rocculi et al. [28]	2018	Image Processing and 3D Scanner	Evaluating hake freshness by eye analysis	Identification of color and morphological changes.
Arsalane et al. [29]	2018	E-eye	Predicting beef freshness	SVM model developed for high-accuracy freshness classification.
Grassi et al.	2019	E-nose (Mastersense)	Evaluating meat and fish freshness	Portable system detected freshness with 83.3% accuracy.
Jia et al. [30]	2020	E-nose (FOX4000)	Evaluating salmon fillet freshness	High correlation with chemical and microbial indicators.
Ehsan et al. [31]	2021	E-nose (Cyranose320)	Evaluating pasteurized milk spoilage	Detection of aromatic changes associated with microbial spoilage.
Bassey et al. [32]	2022	E-nose (PEN3) + GC-IMS	Investigating volatile compounds in pork	Identification of aromatic spectrum changes during storage.
Li et al. [33]	2023	E-nose + E-tongue + E-eye	Evaluating the freshness of *Trachurus japonicus* fish	Data integration improved the prediction accuracy of biochemical indicators.

Table 2 offers a technical and specialized look at livestock, poultry, and aquatic meats, detailing how they're categorized as healthy or spoiled using AI and machine vision models. This classification relies on their external characteristics and visual features. The table includes the author(s)' names, the type and number of samples (livestock, poultry, or aquatic), the color space (color characteristics) analyzed, the machine learning classification models used, and the computational accuracy of each model.

Table 2: Application of Classification Models and Machine Vision in Food Safety and Spoilage Classification for Various Meats

Authors	Sample Type	Number of Samples	Color Spaces / Features	Classification Models	Accuracy
Trientin et al. (2015)	Beef	Undetermined	RGB, HSV	KNN, ANN	75%, 71.4%
Jang et al. (2015) [34]	Beef	Undetermined	Ultrasound Images	ANN	83.33%
Adi et al. (2015) [35]	Beef	Undetermined	RGB, HSV	KNN	Method suitability
Winiarti et al. (2018) [36]	Beef	40	RGB, HSI	K-means	Freshness level clustering
Arsalane et al. (2018)	Beef	81	HSI	SVM	100%
Sun et al. (2018)	Pork	100	RGB, HSI, L*a*b*	Linear Regression	83%
Hosseinpour et al. (2019) [37]	Beef	167	RGB, Grayscale	ANN	99%
Taheri-Garavand et al. (2019)	Chicken	3000	RGB, HSI, L*a*b*	ANN	98%
Taheri-Garavand et al. (2019)	Carp Fish	1344	RGB, HSI, L*a*b*	SVM, KNN, ANN	93.01%
Lugatiman et al. (2019) [38]	Tuna Fish	60	RGB	KNN	86.60%
Moon et al. (2020) [39]	Salmon, Tuna, Beef	3202-5042	VIS/NIR Spectroscopy	CNN	84-92%
Tan et al. (2020) [40]	Beef Steak	400	Color Scoring	DL	90%

3. Methodology

Researchers in this study developed an intelligent and non-destructive method for detecting the freshness of fish meat (Barbonymus gonionotus) during ice storage. This was achieved using an Artificial Neural Network (ANN) and Machine Vision. The primary objective was to provide an automated, accurate, and real-time system for evaluating fish freshness.

For this research, an RGB CCD camera was used to capture color images in a controlled lighting environment (a light chamber with halogen light sources at a color temperature of 6500K). The captured images were saved in JPEG format.

Image processing and segmentation were performed using Python software. This involved background removal using the B-filter from the RGB color space and thresholding. Subsequently, morphological operations (opening and closing) were applied through Python coding to remove noise and enhance edges. Finally,

supervised machine learning algorithms were utilized to classify fresh and spoiled fish meat. The research methodology is illustrated in Figure 1.

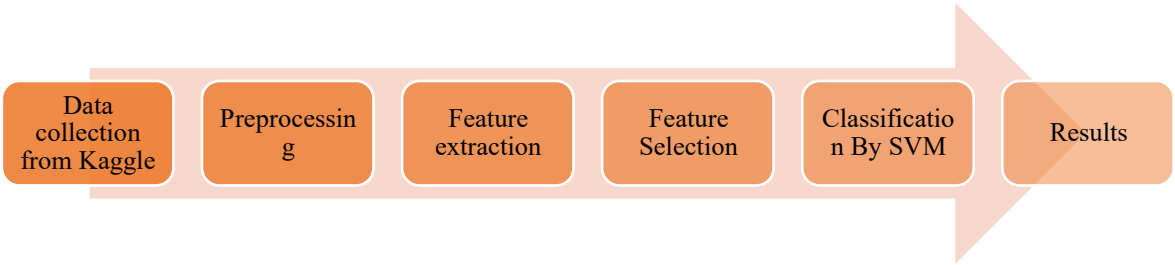


Fig 1: *Research Methodology for Identifying Fish Meat Freshness*

The fish samples used in this study were sourced from a Kaggle dataset [41], which contains high-resolution images of Silver Barb (Barbonymus gonionotus) collected from Lam Pao Dam, Thailand. These images are classified into three distinct categories based on freshness: C1 for fresh fish (1-2 days post-capture), C2 for moderately fresh fish (3-4 days post-capture), and C3 for spoiled fish (5-6 days post-capture), totaling 1200 images across these classifications. Table 3 further details these defined fish freshness classes.

Table 3: Classification of Captured Fish

Class Type	Class Description	Fish Condition
C_1	1-2 days post-capture	Fresh
C_2	3-4 days post-capture	Normal
C_3	5-6 days post-capture	Spoiled

This research, implemented through Python programming, develops a fish freshness classification system using a Kaggle dataset and leverages PyTorch and TorchVision for data processing. The system incorporates a Visualization class for image data analysis and display, facilitating dataset partitioning into training, validation, and test sets. Following this, Support Vector Machine (SVM) analysis is employed to distinguish between healthy and unhealthy fish across three classes. A Plot Learning Curves class is also included to visualize model learning trends and diagnose issues like overfitting or underfitting. The core of the image classification relies on MobileNetV2, a lightweight and efficient deep learning convolutional neural network architecture introduced by Google in 2018, which utilizes inverted residual blocks and linear bottlenecks for improved computational efficiency and parameter reduction, making it highly suitable for mobile and embedded applications [42]. In addition to MobileNetV2, an SVM classifier was trained and evaluated. The processed dataset consists of 960 images for training and 240 for validation, representing an 80% to 20% data split, respectively.

4.Results

4.1 - Model Classification

In this study, 960 fish images were designated for training and another 240 images for validation. Figure 2 illustrates the classification of fish into three classes: C1 (Fresh), C2 (Normal/Intermediate), and C3 (Spoiled). Based on this distribution, it can be stated that 80% of the data was allocated for training and the remaining 20% for model validation and testing.

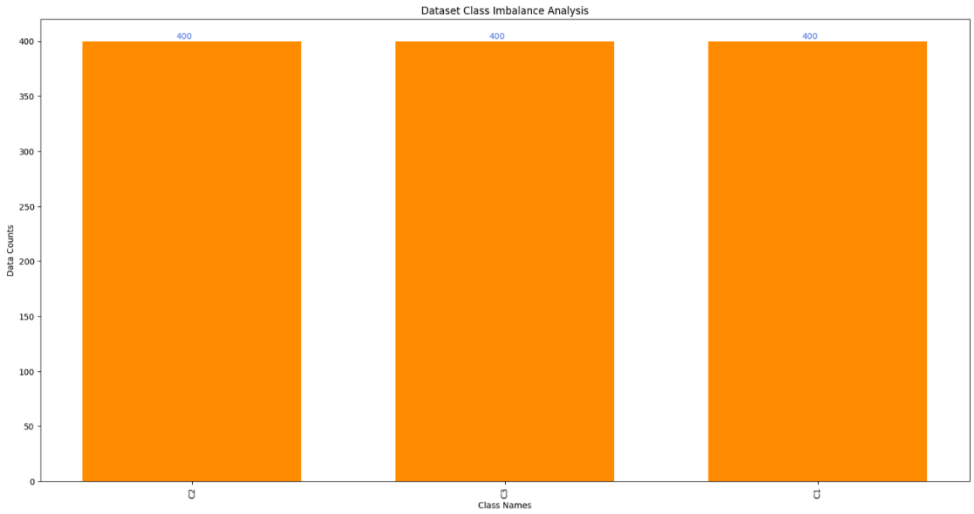


Fig 2: Classification of Fish Data into Three Classes

In the image processing settings, ImageDataGenerator with Rescale=1/255 was used for normalization, ensuring that the fish images' pixel values fall within the range of 0 to 1. Additionally, the TargetSize was set to (224, 224) pixels, which is the standard input size for MobileNetV2 [42,43].

4.2. Data and Image Visualization

Figure 3 is dedicated to visualizing the training data for the fish classes. This involves displaying the current status of each fish within its respective class, based on the processed data found in each of the different class folders. Furthermore, Figure 4 addresses the visualization of the validation data.

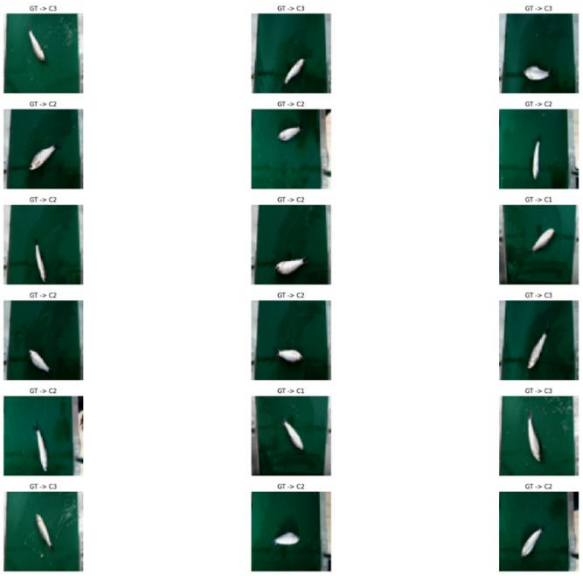


Fig.3. Visualization of Training Data

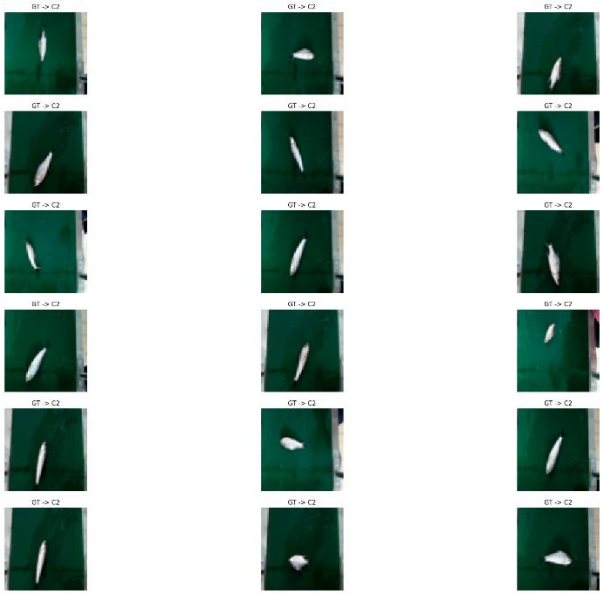


Fig.4. Visualization of Validation Data

4.3. Modeling with Transfer Learning (MobileNetV2)

As explained in Section 3 regarding MobileNetV2, this model offers a balance between speed and accuracy due to its efficiency and high processing speed for images. Therefore, in this research, a deep learning model based on MobileNetV2 was constructed using a Transfer Learning approach. This model served as the base model and was loaded with pre-trained weights from the ImageNet dataset (weights='imagenet'). Its final classification layer (include_top=False) was removed to adapt the model for the task of detecting fish freshness and spoilage. The model was compiled with the 'adam' optimizer, categorical_crossentropy as the loss function (suitable for one-hot encoded labels), and 'accuracy' as the metric. The model output is as follows:

The MobileNetV2 model, with deep layers (Dense), achieved an accuracy of 99.07% on the training set and 79.17% on the validation set over 10 epochs of training. The accuracy and loss curves (Figure 5) indicated good convergence on the training data. The classification report for the deep model (on the entire dataset) is as follows:

Overall Accuracy: 0.96 (96%).

Per-Class Performance Analysis (Precision, Recall, F1-score):

C1 (Class 0): Precision: 0.99, Recall: 1.00, F1-score: 1.00.

The model performed exceptionally well in detecting C1.

C2 (Class 1): Precision: 0.89, Recall: 1.00, F1-score: 0.94.

The model detected C2 with perfect Recall, but a slightly lower Precision indicates that some samples (especially from C3) were incorrectly classified as C2.

C3 (Class 2): Precision: 1.00, Recall: 0.88, F1-score: 0.93.

The model was highly precise in predicting C3 (Precision 1.00), but lower Recall indicates that a significant number of actual C3 samples (46 out of 400 samples) were misclassified as C2, according to the Confusion Matrix.

Sample Prediction: An image from class C1 was correctly predicted as C1 with a probability of 99.9%.

4.4. Model Training

In this research, the model underwent 10 epochs of training. Training accuracy significantly improved from 60.84% in the first epoch to 99.07% in the tenth, alongside a continuous reduction in training loss from 0.9966 to 0.0398, demonstrating effective learning on the training dataset. However, validation accuracy, while starting at 80.42% and peaking at 81.67% in epoch 9, fluctuated thereafter, concluding at 79.17% in the final

epoch, with validation loss showing similar instability. These inconsistencies in validation performance suggest potential overfitting, where the model excels on training data but struggles with generalization, indicating a need for strategies like increased dropout or reduced training epochs to enhance robustness.

4.5. Plotting Accuracy and Loss Graphs

Figure 5 displays the accuracy and loss graphs, illustrating the model's training progression over 10 epochs. The left side of Figure 5 evaluates the model's accuracy with two curves: blue representing Train Accuracy and orange representing Validation Accuracy. Based on the research findings in this section, the training accuracy, i.e., accuracy on the training set, consistently increased, reaching up to 99%, indicating high model precision. Regarding the orange curve within Figure 5, which examines the model's validation accuracy, it can be inferred from the model's output that validation accuracy initially increased but then fluctuated, showing less stability after epoch 5 compared to earlier epochs.
On the right side of Figure 5, the model's cost (loss) is evaluated. In that figure, two curves are presented: Train Loss in blue and Validation Loss in orange. Based on the figure's output, it can be stated that the loss on the training set is rapidly and continuously decreasing significantly. The Validation Loss, which represents the validation loss, initially decreased but then became accompanied by fluctuations after a few epochs. However, the presence of a gap between training and validation accuracy strengthens the likelihood of the Overfitting phenomenon.

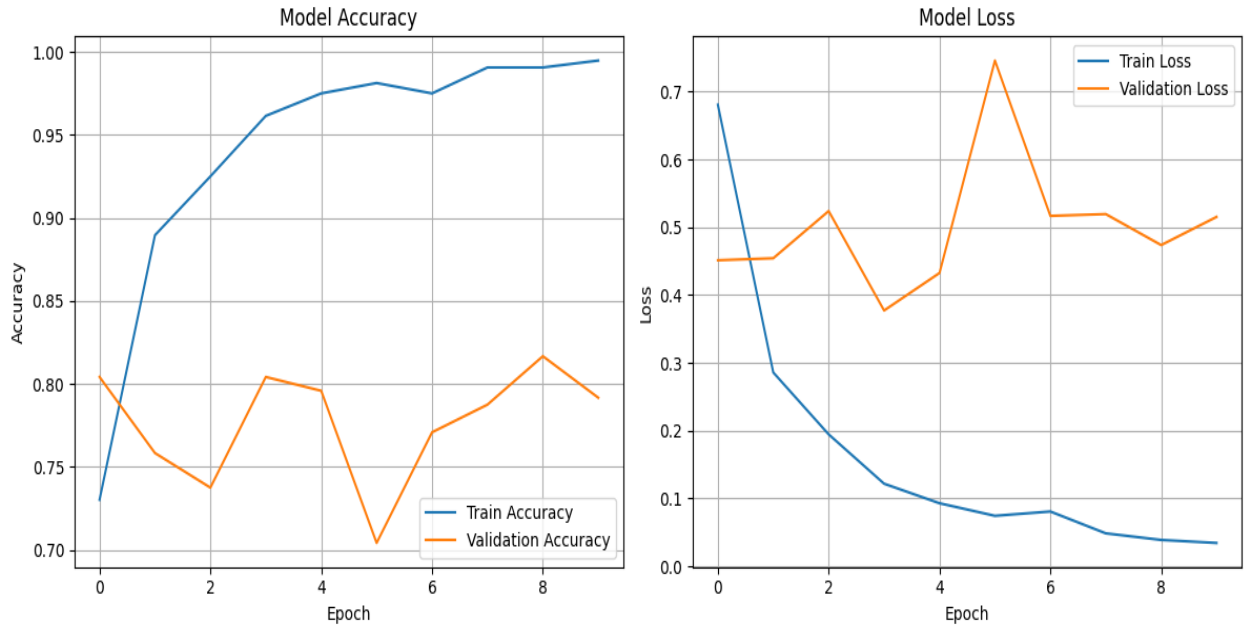


Fig.5. Model Accuracy and Loss Graphs

4.6. Prediction of a Sample Image and Its Assignment to One of the Classes

In this section of the research, a randomly chosen or desired fish image is provided as input to the developed model. After processing, the model determines which class the input fish image belongs to: fresh fish, normal/intermediate fish, or spoiled fish. The model's processing results are presented in the following steps:

I. Step 1: Selecting an Image File for Testing

Prediction for image: /root/.cache/kagglehub/datasets/atcharachol/freshness-fish-dataset/versions/1/Freshness Fish Dataset/C1/WIN_20241126_12_13_59_Pro.jpg

II. Step 2: Output of Predicted Information

Model Output: [[9.9917251e-01 5.9663877e-04 2.3081858e-04]] Class Names: ['C1', 'C2', 'C3'] Predicted: C1 – meaning the selected input image, after model processing and analysis, was classified as fresh fish with a probability of 0.99917251.

4.7. MobileNetV2 + SVM Classification Model

To prevent premature convergence and potentially mitigate overfitting, a hybrid model combining SVM and MobileNetV2 was employed. This composite model, utilizing MobileNetV2 as a Feature Extractor and SVM as the classifier, demonstrated significantly superior performance. In this section, PCA [2] (Principal Component Analysis) was applied to reduce the dimensionality of features extracted by MobileNetV2 to two principal components. Subsequently, a new SVM classifier was trained on these two-dimensional features, enabling the visualization of its decision boundaries. This approach leverages features extracted by the (frozen) MobileNetV2 model to train a Support Vector Machine classifier, representing a common and effective Transfer Learning strategy where a deep network extracts robust features, and a simpler classifier (like SVM) is then trained on these features. Figure 6 illustrates the plotting of the SVM along with the influence of MobileNetV2 and its deep layers. Table 4 presents the model's findings, comprising Precision, Recall, and F1-Score.

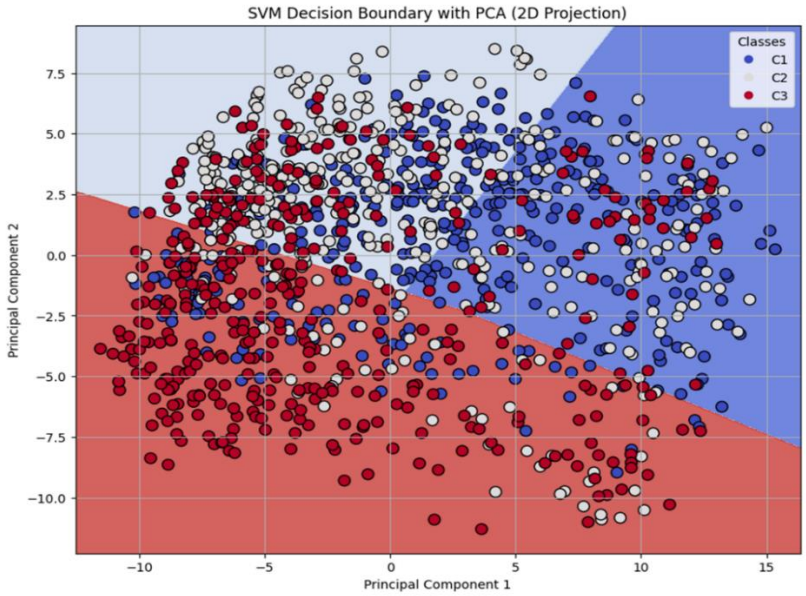


Fig.6. Classification of the Three Fish Classes in the Dataset

Table 4: SVM Classification Report

Class Type	Precision	Recall	F1-score	Support
C1	1.00	1.00	1.00	80
C2	0.99	0.99	0.99	80
C3	0.99	0.99	0.99	80

accuracy			*0.99*	*240*
macro avg	*0.99*	*0.99*	*0.99*	*240*
weighted avg	*0.99*	*0.99*	*0.99*	*240*

SVM Accuracy on Test Set: 0.9917

In Table 4, the analysis begins with the model's accuracy, calculated by Precision for the three classes:

- *C1: 0.99 - Of all predictions made by the model for C1, 99% were actually C1.*

- *C2: 0.89 - Of all predictions made by the model for C2, 89% were actually C2. This indicates that the model performed with slightly less precision in predicting C2 and might have incorrectly identified other classes as C2 (as observed in the Confusion Matrix, C3 was mistakenly classified as C2).*
- *C3: 1.00 - Of all predictions made by the model for C3, 100% were entirely C3.*

Next, the analysis addresses the Recall (sensitivity):

- *C1: 1.00 - The model correctly identified 100% of the actual C1 images.*
- *C2: 1.00 - The model correctly identified 100% of the actual C2 images.*
- *C3: 0.88 - The model only identified 88% of the actual C3 images. This means that 12% of the C3 images were incorrectly classified as another class (which, as specified in the Confusion Matrix, were classified as C2).*

The harmonic mean of Recall and Precision, represented by F1-Score, was calculated as follows:

- *C1: 1.00*
- *C2: 0.94*
- *C3: 0.93*

Finally, the Overall Accuracy for the model was 0.96, meaning the model correctly classified 96% of the images overall. Macro Avg and Weighted Avg represent the averaging of the above metrics across all classes. Macro Avg gives equal weight to all classes, while Weighted Avg weighs based on the number of samples in each class.

Figure 7 examines the Confusion Matrix [1]. In this section, the model performed final predictions on the entire dataset (including training and validation data) for evaluation. Based on the model's findings, it can be stated that:

- *C1: 398 out of 400 C1 images were correctly classified as C1 (True Positives). 2 images were mistakenly classified as C2 (True Positive here seems to be a typo and should be False Positive or a different class).*
- *C2: 399 out of 400 C2 images were correctly classified as C2. 1 image was mistakenly classified as C1.*
- *C3: 354 out of 400 C3 images were correctly classified as C3. 46 images were mistakenly classified as C2.*

The accuracy on the test set [2] is 0.9917. The classification report for SVM on the test set shows an overall accuracy [3] of 0.99 or 99%, and the performance for each class is as follows:

- *C1: Precision: 1.00, Recall: 1.00, F1-score: 1.00.*
- *C2: Precision: 0.99, Recall: 0.99, F1-score: 0.99.*
- *C3: Precision: 0.99, Recall: 0.99, F1-score: 0.99.*

The analysis of the Confusion Matrix for SVM (Image 3 in the original code) also confirms that the number of misclassifications has been minimized (only one classification error among a total of 240 test samples).

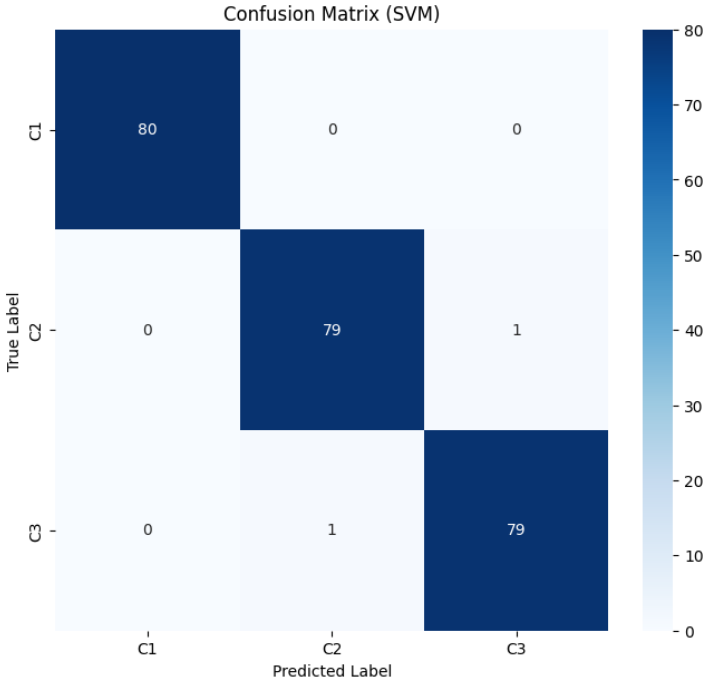


Fig. 7. Confusion Matrix

5. Discussion and Conclusion

In this research, the objective was to classify fish into three categories: fresh, normal/intermediate, and spoiled, and to predict the class of a given fish image by leveraging machine vision tools combined with deep neural networks and machine learning. Based on the obtained results, the model demonstrated excellent performance and exceptional efficiency in detecting Class C1. For Class C2, the performance was also strong. However, for C3, the model exhibited lower Recall or sensitivity, indicating a challenge in identifying all C3 samples, with some being mistakenly classified as C2. This could stem from visual similarities between C3 and C2 or insufficient diversity in the C3 training data.

The overall accuracy of 96% indicates a highly effective and efficient model. The findings of this study highlight the significant potential of deep learning and transfer learning in image classification tasks, particularly in the domain of fish freshness detection. While the MobileNetV2 model with deep layers achieved 96% accuracy, the phenomenon of overfitting was evident, leading to a relatively weaker performance in fully detecting Class C3. In contrast, the hybrid approach, utilizing MobileNetV2 as a feature extractor and SVM as the final classifier, demonstrated significantly higher accuracy (99.17%). This result emphasizes that features extracted by deep networks are highly powerful and can be effectively discriminated by a simpler, more efficient classifier like SVM. This approach not only leads to higher accuracy but may also be more computationally efficient in the final classification stage. Although the SVM decision boundary plot with PCA is useful for visualization, it suggests that reducing dimensions to 2D results in a loss of important information and reduces model performance. Therefore, for real-world applications, using full-dimensional features (1280-dimensional in this case) for SVM is essential. The analysis and conclusion from the confusion matrix also confirm that the number of misclassifications has been minimized. For future work, other CNN architectures could be explored, and their outputs compared with the findings of this research.

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