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Research Article

Fish freshness detection from eye images using feature-based fusion and support vector machine (SVM) classification

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Abstract

Fish is a staple food for people, and ensuring its freshness is crucial for the industry. Various parameters, including fish eye characteristics, gill features, and fish fins, are commonly used to distinguish fish quality. In this study, we propose a novel method to assess fish freshness using fish eye images. Initially, data augmentation is employed to increase the effective size of the training dataset, enhancing robustness to variations, balancing class distributions, and reducing overfitting. In the proposed method, we utilized three convolutional neural networks: Inception-v3, VGG16, and MobileNetV3, to detect fish spoilage. We made slight structural modifications to each of these networks to enhance their performance in detecting fish freshness. In addition, we extracted feature vectors from the global average pooling layer of each network. We then used a Support Vector Machine (SVM) to classify the freshness of the fish. This study utilized the Freshness of Fish Eyes (FFE) dataset, which includes 8 species of fish at 3 levels of freshness. The proposed method, using Inception-v3 and the SVM classifier, achieved an accuracy of 81.21%, which is 4% better than the existing method on this dataset. This method provides a significant advancement in fish freshness assessment, offering a more accurate and reliable means of determining fish quality. This can greatly benefit the food industry by ensuring higher standards of freshness, reducing waste, and improving consumer satisfaction. The demonstrated improvement in accuracy highlights the potential of this method to set new benchmarks in fish quality assessment.

Introduction

The global demand for fish has markedly increased due to its outstanding nutritional advantages. This rise is predominantly linked to the recognition of fish as a primary source of omega-3 fatty acids, which are effective in reducing the risk of stroke and cardiovascular diseases (Karimian *et al*., 2024, Suhaimi *et al*., 2024). Furthermore, research demonstrates that these fatty acids play a vital role in brain growth and development. Since the human body cannot synthesize omega-3 fatty acids, health professionals recommend the inclusion of fish in the diet at least twice weekly (Kesbiç *et al*., 2024). Consequently, many individuals are replacing chicken and beef with fish to fulfill their daily protein requirements while benefiting from its low unsaturated fat content (Pastoral *et al*., 2000). As a result, the appetite for fish consumption is consistently on the rise. Nevertheless, the inclination of consumers towards freshly caught fish presents obstacles for the food sector in terms of guaranteeing high-quality offerings and fulfilling consumer demands on time. Insufficient storage environments and inadequate transportation techniques can result in the formation of dangerous toxins and bacteria in fish, which can jeopardize human health. Thus, mitigating fish spoilage has become essential for satisfying consumer expectations and preventing related financial losses (Banwari et al., 2022, Sharma *et al*., 2023). To achieve this, it is imperative to assess the quality indicators based on the freshness of the fish to ensure consumer safety. Numerous traditional techniques exist for assessing the freshness and deterioration of fish samples in laboratory settings, yet these methods tend to be both time-intensive and laborious. Moreover, many of these approaches carry a risk of errors in evaluating the fish's freshness (Murdika *et al*., 2023). For instance, while the condition of the fish eye can be visually assessed, it is often challenging for an average consumer or even a specialist to accurately determine the fish's freshness in certain instances. Consequently, the creation of an efficient, objective, and dependable system is essential to tackle the challenges associated with fish freshness and spoilage, ultimately reducing the financial strain on vendors. This research concentrates on classifying fish freshness based on the appearance of the eye (Saeed *et al*., 2022, Akgül *et al*., 2023).

In recent years, various methods have emerged in the literature for assessing and automatically identifying the freshness of fish through images (Zhang *et al*., 2023). Typically, the suggested models for computer-assisted analysis and diagnosis are structured around four key stages: 1) image acquisition, 2) image preprocessing, 3) feature extraction, and 4) classification (Xu *et al*., 2021). It is essential to highlight that within the diagnostic model workflow, the classification phase is regarded as a crucial component, as its effectiveness directly influences the model's accuracy (Nasrolahzadeh *et al*., 2020). In this context, classification methods are categorized into two groups: conventional machine learning and deep learning. Conventional machine learning approaches, including Artificial Neural Networks (ANN) (Nasrolahzadeh *et al*., 2015), PCA (Wold *et al*., 1987), and

Support Vector Machines (SVM) (Nasrolahzadeh *et al*., 2018), depend significantly on manually developed feature engineering for effective execution. Most current research has concentrated on classification and feature engineering, presuming that fish images are taken under ideal circumstances. Nevertheless, fish images may not consistently showcase the complete feature set, or only a minor section of the image may exhibit notable characteristics. Consequently, many of the prevailing techniques are founded on laborious and complex processes, resulting in restricted practical use and general applicability. Conversely, deep learning models represent a novel research paradigm within the field of machine learning, garnering considerable attention for fish classification (Banan *et al*., 2020). A key benefit of the deep learning methodology lies in its capacity to autonomously acquire effective feature representations from unprocessed data, thereby greatly minimizing the need for manual feature engineering. Additionally, deep learning integrates the processes of feature extraction and classification during the early phases of image processing (Nasiri *et al*., 2019). Given that deep learning models require substantial computational power and extensive datasets for training, several of these models employ transfer learning techniques to mitigate these challenges (Nasrolahzadeh *et al*., 2024).

Recently, fish eyes have garnered significant interest as a robust characteristic for assessing and categorizing the freshness of fish. This is primarily due to research indicating that the visual characteristics of fresh versus stale fish eyes differ, making them a valuable metric for freshness evaluation (Murakoshi *et al*., 2013). In this regard, numerous investigations have been conducted to establish classifications of fish freshness based on its eye, including techniques for locating and counting fish in the ocean amidst considerable background fluctuations, as well as creating a system that utilizes eye and gill features throughout a 10-day ice-storage period (Jalal *et al*., 2020). Jarmin *et al*. presented RGB color indices as a method for evaluating the freshness of fish. Their approach employed a sensor known as the Torrymeter to assess the freshness of three distinct fish species. The results of the study indicated that features based on the RGB color space effectively identified fish spoilage within a three-day period (Jarmin *et al*., 2012). Lalabadi *et al.* employed a supervised learning methodology to derive multiple color space features from the gills and eyes of fish in RGB, HSV, and L*a*b* color spaces. These features were subsequently categorized to evaluate the fish's freshness. The research attained classification accuracies of 96% and 84% through the use of ANN and SVM for assessing fish freshness, respectively (Lalabadi *et al*., 2020). Cengizler introduced a method for unsupervised clustering aimed at attribute extraction from fish eye images. This approach divided each image into three segments according to color distribution, with freshness assessed through the variation in intensity within the clusters. The research attained an accuracy level of 95% during this procedure (Cengizler, 2023). Prasetyo *et al*. introduced the Cosine K-Nearest Neighbors classification method for assessing fish freshness. Their research included the extraction of ocular features from 71 fish images, achieving a classification accuracy of 96.79% (Prasetyo *et al*., 2020). Tolentino *et al*. developed a method for evaluating the freshness of fish by examining the characteristics of their eyes and gills. Their research employed SVM to classify the freshness levels of fish, attaining a remarkable accuracy of 98% (Tolentino *et al*., 2017). Issac *et al*. devised an automated method for segmenting fish gills using images of fish. Their approach included the development of an evaluation model that leveraged the statistical relationship of the segmented gill area to assess the freshness of the fish. The research, which encompassed 8 fish and 144 data examples, indicated that merely two data examples yielded a negative classification result (Issac *et al*., 2017).

Different from conventional techniques that depend on extraction and feature engineering, deep learning approaches, particularly convolutional neural networks (CNNs), have gained significant attention in assessing fish freshness through image analysis. For instance, Taheri-Garavand *et al*. utilized the VGG-16 framework to autonomously derive features from fish eye photographs. The research attained a classification accuracy reaching 98.21% (Taheri-Garavand *et al*., 2020). Prasetyo *et al*. introduced a MobileNetV1 Bottleneck algorithm for fish eye classification, utilizing a CNN model to assess fish freshness. The study reported a classification accuracy of 63.21% (Prasetyo *et al*., 2022b). Asadi Amiri *et al*. utilized an Inception-ResNet-v2 CNN architecture to identify significant features that differentiate fresh fish from stale fish by analyzing images of fish eyes. They implemented the mRMR technique to select relevant features. The suggested method attained a classification accuracy of 97% (Asadi Amiri *et al*., 2024). Lanjewar and Panchbhai combined NasNet and LSTM models to extract features from fish eye images. This method achieved a Matthew's correlation coefficient and Cohen's kappa coefficient of 91%. Furthermore, utilizing the 5-fold cross-validation technique, the two coefficients together attained a value of 97% for identifying fresh fish (Lanjewar and Panchbhai, 2024).

In this study, we propose a novel method to assess fish freshness using fish eye images, employing data augmentation to enhance the training dataset. We utilized three convolutional neural networks—Inception-v3, VGG16, and MobileNetV3—with slight structural modifications to improve performance. Feature vectors were extracted from the global average pooling layer of each network. Finally, we classified fish freshness using the Support Vector Machine (SVM) classifier. By extracting feature vectors and feeding them into this classifier, we significantly improved the accuracy and reliability of fish freshness detection. This approach leverages the strengths of both deep learning and traditional machine learning techniques, resulting in a more robust assessment method.

The remainder of this study is structured as follows: Section material and methods provide a comprehensive explanation of the proposed algorithm. Section results, details the experimental findings. Lastly, Section discussions present insights and suggestions for future research.

Materials and methods

FFE dataset

The Freshness of the Fish Eyes (FFE) dataset consists of 4390 fish eye images, each with a resolution of 767×1022 pixels (Prasetyo *et al*., 2022a). These images are organized into 24 distinct classes based on both species and freshness levels. Specifically, this dataset comprises images of eight distinct fish species, each categorized into three freshness levels: highly fresh (days 1 and 2), fresh (days 3 and 4), and not fresh (days 5 and 6). The images for this study were collected by storing fish in a styrofoam box for six days, mimicking a real-world ice storage process. The amount of ice used throughout the storing process was equal to the weight of the fish, maintaining a 1:1 ratio of ice to fish weight. A mobile phone camera was used to take daily photographs of fish conditions. These images were captured under varying lights and with different backgrounds, creating a range of environmental factors (Prasetyo *et al*., 2022b). Table 1 provides an overview of the dataset by displaying the names of the eight fish species alongside the corresponding number of images available for each freshness level. This information is crucial for understanding the composition and distribution of fish eye images within the FFE dataset.

Table 1: Freshness levels and corresponding image counts for eight fish species.

SL#	Fish Species	Highly Fresh	Fresh	Not Fresh	Total Species Images
01	*Chanos chanos*	168	162	170	500
02	*Eleutheronema tetradactylum*	80	80	80	240
03	*Johnius trachycephalus*	80	80	80	240
04	*Nibea albiflora*	173	125	121	419
05	*Oreochromis mossambicus*	174	289	162	625
06	*Oreochromis niloticus*	328	231	246	805
07	*Rastrelliger faughni*	336	216	217	769
08	*Upeneus moluccensis*	310	252	230	792
	Total freshness images	**1649**	**1435**	**1306**	**4390**

Figure 1 presents one fish species with three different freshness levels. The FFE dataset is a valuable resource for advancing research in fish freshness assessment and classification.

Proposed method

In this paper, a novel method for fish freshness image classification is proposed by analyzing their eye images. Initially, in the pre-processing stage, the number of training images is increased using operations such as reflection, rotation, and zooming to enhance diversity. This augmentation improves the robustness of the model by exposing it to a wider variety of scenarios, thereby reducing overfitting and improving generalization.

Subsequently, three learning models, Inception-v3, VGG16, and MobileNetV3, are employed to train the classification of fish freshness. In the proposed method, two fully connected layers with 2560 and 1200 neurons, respectively, are added after the global average pooling layer. This addition enhances the model's capacity to learn complex features and improves its classification accuracy. In the proposed method, after using the three models (Inception-v3, VGG16, and MobileNetV3) for classifying fish freshness, the method goes a step further by extracting features from each of these models. Feature extraction involves taking the learned features from the models, which are essentially patterns or characteristics that the models have identified as important for determining fish freshness.

Figureure 1: Eye images of the *Oreochromis mossambicus* fish species depicting three freshness levels. a) Highly fresh, b) Fresh and c) Not fresh.

Once these features are extracted, they are used as input for the SVM classifier. SVM can further analyze the features to make more accurate predictions about the freshness of the fish. By combining the strengths of the deep learning models with the SVM classifier, the proposed method aims to improve the overall accuracy and reliability of the fish freshness detection process. This hybrid approach leverages the powerful feature extraction capabilities of deep learning models and the robust classification abilities of SVM. Figure 2 presents the flowchart of the proposed method, which integrates deep learning and machine learning techniques for assessing fish freshness.

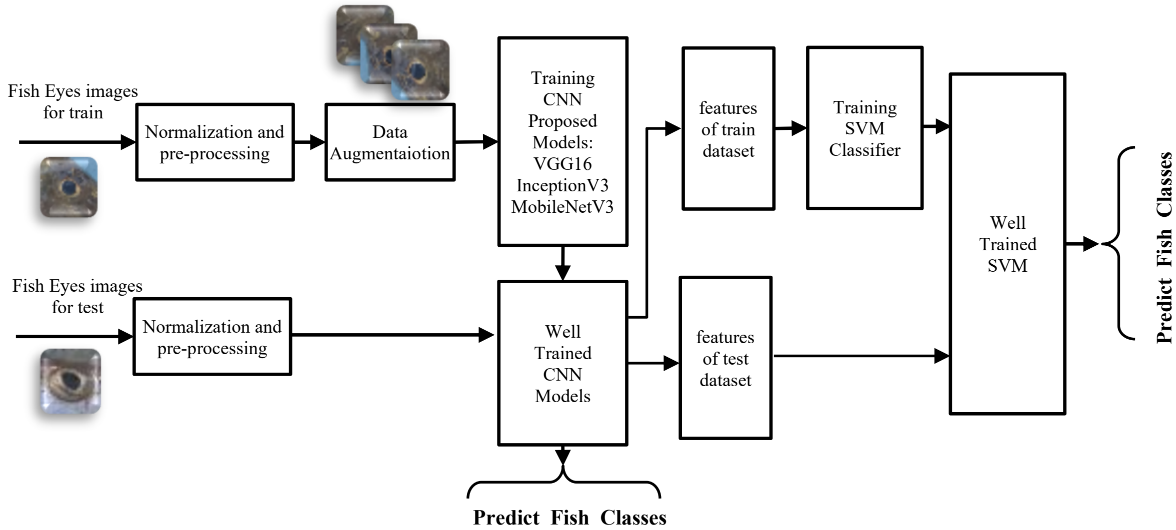
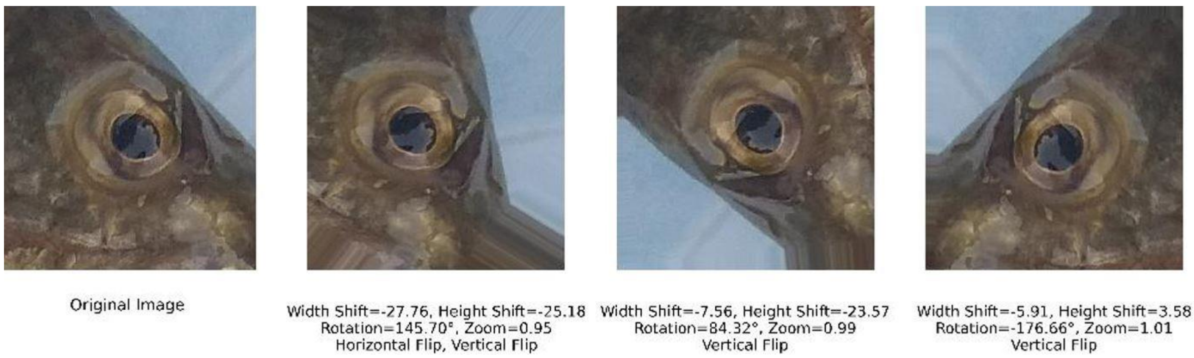


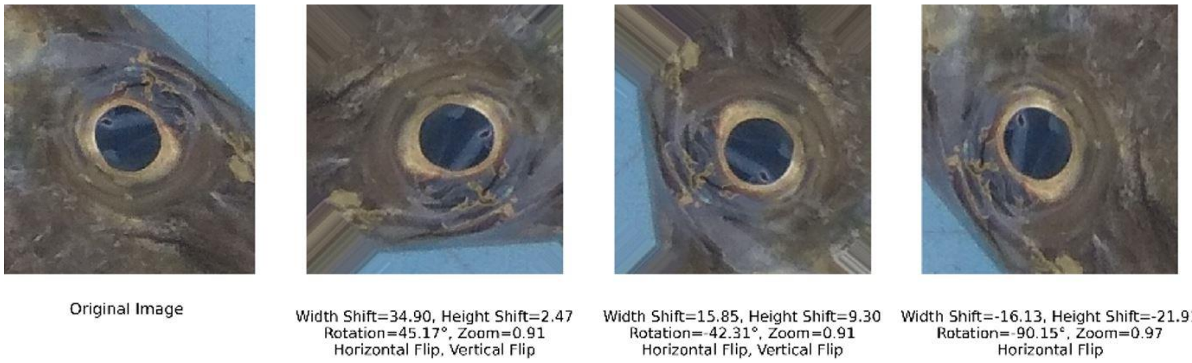
Figure 2: Flowchart of the proposed method integrating deep learning and machine learning for assessing fish freshness.

Preprocessing

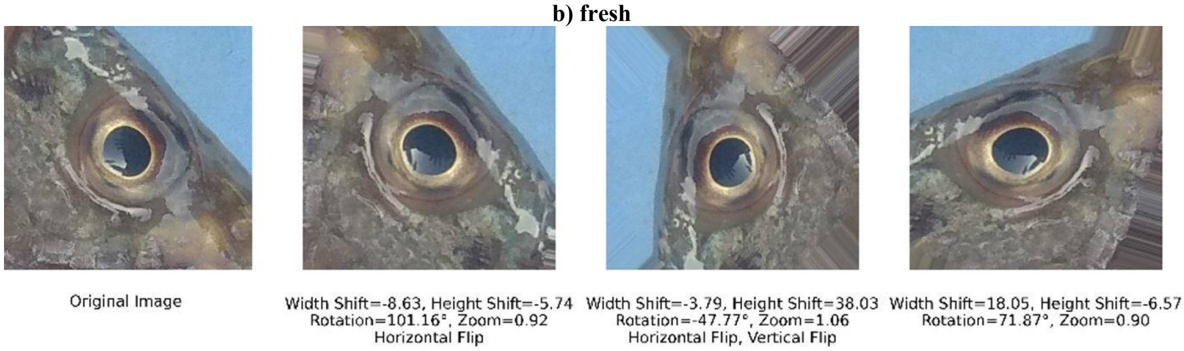
Preprocessing is a crucial step in any machine-learning pipeline, especially for image classification tasks. It helps in enhancing the quality of the dataset, ensuring that the models are trained on diverse and representative samples. By employing techniques such as data augmentation, we can significantly increase the robustness of the model, reduce overfitting, and balance class distributions. During the preprocessing phase, we initially allocated 60% of the images for training, 20% for validation, and the remaining 20% for testing. To enhance the training data, we employed augmentation techniques, which increased the number of training samples for each class to approximately 1000. Figure 3 illustrates examples of augmented images for one species of fish, *Oreochromis Niloticus*, at three levels of freshness: highly fresh, fresh, and not fresh. This visualization demonstrates the effectiveness of our augmentation techniques in creating a diverse and comprehensive training dataset.



a) highly fresh



b) fresh



c) not fresh

Figure 3: Augmented images of *Oreochromis niloticus* fish species at three levels of freshness.

Table 2 provides a comprehensive overview of the number of images for each of the 24 classes in the present study, detailing the distribution across training, validation, and test datasets. The augmentation process significantly increased the number of training samples for each class in the training set, ensuring a more balanced and robust dataset for model training. This augmentation helped enhance the model's ability to generalize and perform accurately on unseen data.

Table 2: A comprehensive overview of the number of images in the present study.

Class Name	Total Images	Train		Validation	Test
		Before Augmentation	After Augmentation		
Chanos chanos - Fresh	162	97	1020	32	33
Chanos chanos -Highly Fresh	168	101	707	33	34
Chanos chanos - Not Fresh	170	102	714	34	34
Eleutheronema tetradactylum - Fresh	80	48	1008	16	16
Eleutheronema tetradactylum - Highly Fresh	80	48	1008	16	16
Eleutheronema tetradactylum - Not Fresh	80	48	1008	16	16
Johnius trachycephalus - Fresh	80	48	1008	16	16
Johnius trachycephalus - Highly Fresh	80	48	1008	16	16
Johnius trachycephalus - Not Fresh	80	48	1008	16	16
Nibea albiflora - Highly Fresh	173	104	728	34	35
Nibea albiflora - Fresh	125	75	800	25	25
Nibea albiflora - Not Fresh	121	73	780	24	24
Oreochromis mossambicus - Fresh	174	104	728	35	35
Oreochromis mossambicus - Highly Fresh	289	173	915	58	58
Oreochromis mossambicus - Not Fresh	162	97	1020	33	32
Oreochromis niloticus - Fresh	231	139	973	46	46

Table 2 continued:

Oreochromis niloticus - Highly Fresh	328	197	1035	66	65
Oreochromis niloticus - Not Fresh	246	148	1036	49	49
Rastrelliger faughni - Fresh	216	129	903	44	43
Rastrelliger faughni - Highly Fresh	336	202	858	67	67
Rastrelliger faughni - Not Fresh	217	130	910	43	44
Upeneus moluccensis - Fresh	252	151	805	51	50
Upeneus moluccensis - Highly Fresh	310	186	980	62	62
Upeneus moluccensis - Not Fresh	230	138	966	46	46

Modified inception-v3

Inception-v3 has been trained on the ImageNet dataset. This is an important dataset in the classification and image recognition field. It contains 1.4 million images over 1000 object classes (Russakovsky *et al*., 2015). The Inception-v3 architecture consists of three components: the basic convolutional block, the Inception module, and the classification layer. The basic convolutional block, which alternates between convolutional and max-pooling layers, is used for feature extraction. The architecture of the Inception module is based on the Network In-Network model introduced by Lin *et al*. (Lin *et al*., 2013). This design has improved efficiency and performance compared to the previous versions. Inception-v3 uses the 1 × 1 convolutional kernel to reduce feature channels and speed up training. In the classification layer, using auxiliary classifiers results in accuracy improvement (Szegedy *et al*., 2016, Amiri *et al*., 2025). The architecture of the modified Inception-v3 model is presented in Figure 4. In this modification, two fully connected layers with 2560 neurons and 1200 neurons, respectively, were added after the global average pooling layer. Both layers use a ReLU activation function to expand the feature representation. These additions help in expanding the feature representation, enhancing the model's ability to accurately classify the data. Finally, a fully connected layer with softmax activation is added. The final output layer includes 24 neurons, which indicate the three levels of fish freshness based on eight different species.

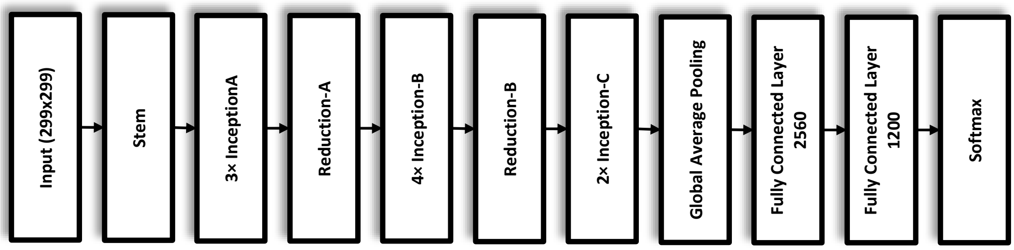


Figure 4: Schematic representation of our modified Inception-v3 architecture.

Modified VGG16

The VGG16 convolutional neural network architecture was developed to enhance image recognition capabilities. It has been trained on the ImageNet dataset. The model accepts images of size 224×224×3, which first pass through two convolutional layers. Subsequently, these images are processed by a max-pooling layer. This pattern repeats, adding another two convolutional layers and a max-pooling layer. The architecture then includes three sets of convolutional layers, each followed by a max-pooling layer. Following the convolutional and max-pooling layers, the architecture includes fully connected layers with ReLU activation functions. The number of filters varies across layers. Convolutional layers utilize a 3×3 filter size with a stride of 1, while max-pooling layers employ a 2×2 filter size with a stride of 2 (Simonyan and Zisserman, 2014). The architecture of the modified VGG16 model is presented in Figure 5.

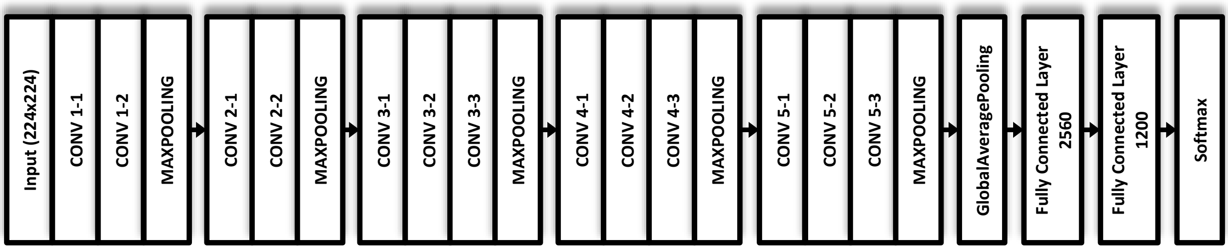


Figure 5: Schematic representation of our modified VGG16 architecture.

As shown, we added a global average pooling layer following the last max pooling layer. This adjustment reduces the model's complexity and mitigates overfitting. Similar to the modified Inception-v3, the performance of VGG16 is improved by adding two fully connected layers with 2560 and 1200 neurons, respectively, following the global average pooling layer. Both layers use a ReLU activation function to expand the feature representation. Finally, a fully connected layer is added, employing a softmax activation function to produce class probabilities for multi-class classification tasks.

Modified mobileNetV3

MobileNetV3 is a lightweight model, based on MobileNetV1 and MobileNetV2 network. The model accepts an input image with dimensions of 224×224×3. It integrates deep separable convolution and an inverse residual structure with a linear bottleneck to boost computational efficiency and enhance feature extraction. To optimize network structure and parameters, platform-aware Neural Architecture Search (Zoph and Le, 2016) and Neural Network Adaptation (Yang *et al*., 2018) are employed. Additionally, the Squeeze-and-Excite (SE) (Cui *et al*., 2021) channel attention module enhances network performance and operational efficiency. MobileNetV3 has two versions: MobileNetV3-Small and MobileNetV3-Large both have a similar architecture but different complexity. MobileNetV3-Small is ideal for low-performance mobile and embedded devices, offering a balance between computational cost and model efficiency. The architecture of the modified MobileNetV3-Small model is presented in Figure 6.

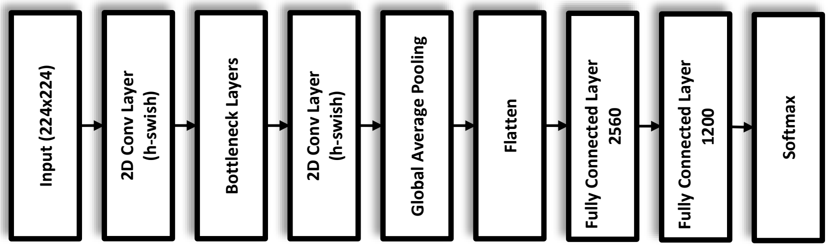


Figure 6: Schematic representation of our modified MobileNetV3-Small architecture.

Similar to the preceding models, the performance of MobileNetV3-Small is enhanced by incorporating two fully connected layers with 2560 and 1200 neurons, respectively, after the global average pooling layer. Both layers utilize a ReLU activation function to enrich the feature representation. Finally, the output layer uses a softmax activation function to produce probability distributions for classification.

Feature extraction

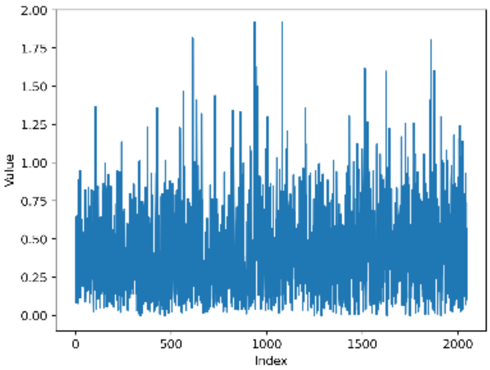
In the proposed method, we utilize three models— Inception-v3, VGG16, and MobileNet—to classify the freshness of fish. Additionally, we leverage a combination of deep neural networks and machine learning to enhance the accuracy of fish freshness classification. After training the models with the training samples, we use the global average pooling layer for feature extraction.

For Inception-v3, the output of this layer is a feature vector of length 2048. VGG16 provides a feature vector of length 512, while MobileNet yields a feature vector of length 576. These feature vectors represent the essential characteristics and patterns identified by the models as important for determining fish freshness. Each feature vector encapsulates various attributes such as texture, color, and structural details of the fish eye images, which are crucial indicators of freshness. By applying each image from the database to the respective models, we extract these feature vectors, which serve as a compact and informative representation of the input images.

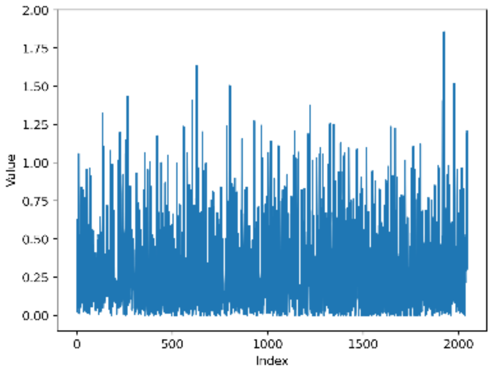
Figure 7 illustrates the feature vectors obtained from three models: Inception-v3, VGG16, and MobileNetV3, for two different classes in the dataset. The feature vectors for each of the three models are shown below their respective images. These feature vectors demonstrate a high capability for distinguishing the freshness of fish, enhancing the robustness of the model, and improving its generalization across various scenarios. This approach provides a reliable method for fish freshness classification. The extracted features enable the models to make accurate predictions by focusing on the most relevant aspects of the images, ensuring that the classification is both precise and consistent.

a) Highly Fresh

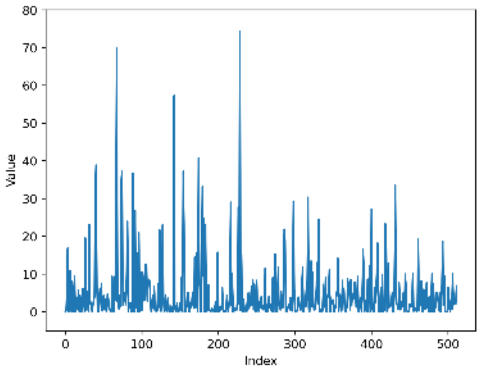
b) Not Fresh



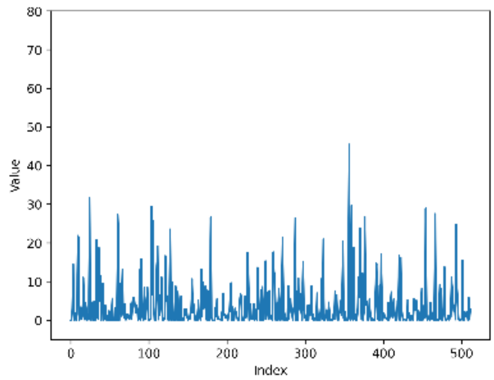
c) Feature extracted from Inception-v3 for image a



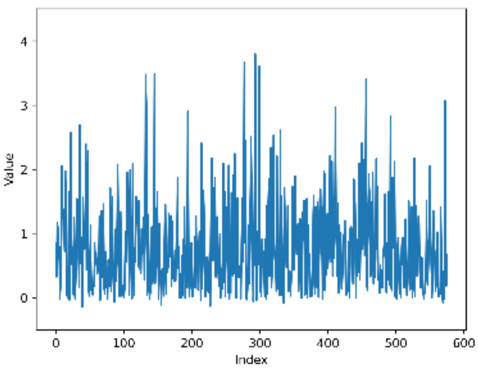
d) Feature extracted from Inception-v3 for image b



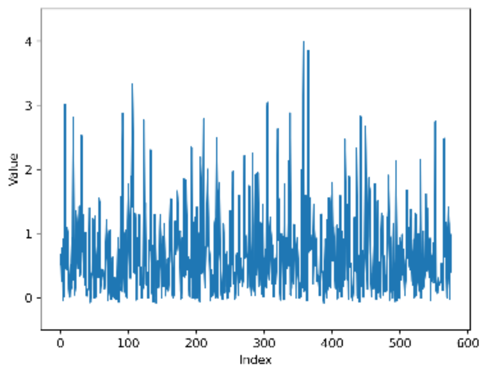
e) Feature extracted from VGG16 for Image a



f) Feature extracted from VGG16 for image b



g) Feature extracted from MobileNetV3 for image a



h) Feature extracted from MobileNetV3 for image b

Figure 7: Feature vectors from Inception, VGG16, and MobileNetV3 models for two different classes, highlighting effectiveness in distinguishing fish freshness.

SVM

SVM, a robust computational model for classification tasks, excels in both classification and regression. As a supervised learning method, it's highly effective with a strong statistical foundation (Hassanpour and ASADI, 2011). SVM performs classification by creating a hyperplane in higher-dimensional space. It identifies vector points that define the decision boundary, ensuring a significant margin separates the classes (Guyon *et al*., 2002). In the decision plane, SVM separates classes by maximizing the marginal distance between them (Prajapati and Patle, 2010, Kuo *et al*., 2013).

Results

This section presents a comprehensive analysis of our experimental setup and findings. We also compare our proposed method with other existing approaches. All three proposed models were trained on the FFE dataset to classify fish freshness using fisheye images. The implementation details, evaluation metrics, and results of our method are presented. Additionally, we provide a comparative analysis with other methods to highlight the effectiveness of our approach. The results demonstrate that our method significantly improves the accuracy and robustness of fish freshness classification.

Evaluation metrics

The confusion matrix is a statistical tool to assess the performance of a method. This matrix holds information regarding classification results for measuring a model's ability to differentiate data across different classes. The values on the main diagonal of this matrix show the number of correct predictions made by the model. The off-diagonal values, on the other hand, represent the misclassifications, indicating where the model has failed to accurately predict the class of certain instances. By analyzing these values, the performance of the proposed models in classifying 24 classes of the FFE dataset has been evaluated using metrics such as accuracy, precision, recall, and F1-score, which provide deeper insights into the model's strengths and weaknesses (Asadi Amiri *et al*., 2022). The equations associated with these evaluation metrics are as follows:

$$Accuracy = \frac{(TP+TN)}{total\ examples} \quad (1)$$

$$Precision = \frac{(TP)}{(TP+FP)} \quad (2)$$

$$Recall = \frac{(TP)}{(TP+FN)} \quad (3)$$

$$F1-score = \frac{2*(precision*recall)}{(precision+recall)} \quad (4)$$

In these equations, 'TP' denotes true positives, representing the correct predictions of the actual positive class; 'TN' denotes true negatives, reflecting the correct predictions of the actual negative class; 'FP' indicates false positives, representing the incorrect predictions of the actual positive class; and 'FN' denotes false negatives, indicating the incorrect predictions of the actual negative class.

Detail of simulation

The proposed method was implemented using Python, leveraging a variety of frameworks and libraries. TensorFlow and Keras were utilized for building and training deep learning models. Pandas and

NumPy were used for data processing, particularly for handling and processing the extracted features from the fish images. For data visualization, we employed Matplotlib and Seaborn to create graphs and plots. Additionally, CUDA was utilized for enhanced computational efficiency. Experiments were conducted in the Kaggle environment using a 16GB NVIDIA Tesla T4 GPU. We utilized three models: Inception-v3, VGG16, and MobileNetV3. The models employed the Adam optimizer with a learning rate of 0.001 and an epsilon value of 0.1 to ensure stability during optimization. Transfer learning was used to leverage pre-trained models on the ImageNet dataset. Each model was trained for 20 epochs with a batch size of 32, allowing efficient data processing while minimizing memory usage. Table 3 provides a comprehensive list of the hyperparameters for these three models.

Table 3: Hyperparameter values for the three models Inception, VGG16, and MobileNet.

Parameters	Value
Batch-size	32
Epochs	20
Optimizer	Adam
Learning rate	0.001
Epsilon	0.1
Loss Function	Categorical Crossentropy
Activation Function	Softmax

FFE classification performance evaluation

Tables 4, 5, and 6 present the classification performance of the modified Inception-v3, VGG16, and MobileNetV3-Small models, respectively, along with the features extracted using SVM for the 24-class FFE dataset. The results in Table 4 show that the combination of Inception-v3 with SVM generally improves the precision, recall, and F1-score across most classes compared to using Inception-v3 alone. For instance, the precision for "*Eleutheronema Tetradactylum* - Fresh" increased from 56.25 to 76.47, and the F1-score for "*Chanos Chanos* - Fresh" improved from 69.57 to 73.53. This indicates that the SVM classifier effectively enhances the performance of the features extracted by Inception-v3.

Table 4: Classification performance of modified Inception-v3 and the features extracted using the SVM.

Class name	Inception-v3			Inception-v3 + SVM		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Chanos chanos - Fresh	66.67	72.73	69.57	71.43	75.76	73.53
Chanos chanos -Highly Fresh	96.55	82.35	88.89	96.55	82.35	88.89
Chanos chanos - Not Fresh	77.78	82.35	80	81.08	88.24	84.51
Eleutheronema tetradactylum - Fresh	56.25	56.25	56.25	76.47	81.25	78.79
Eleutheronema tetradactylum - Highly Fresh	81.25	81.25	81.25	100	87.50	93.33
Eleutheronema tetradactylum - Not Fresh	66.67	75	70.59	82.35	87.50	84.85
Johnius trachycephalus - Fresh	62.50	62.5	62.5	66.67	62.50	64.52

Table 4 continued:

Johnius trachycephalus - Highly Fresh	93.33	87.5	90.32	93.33	87.50	90.32
Johnius trachycephalus - Not Fresh	64.71	68.75	66.67	66.67	75	70.59
Nibea albiflora - Highly Fresh	87.50	80	83.58	93.33	80	86.15
Nibea albiflora - Fresh	72.41	84	77.78	70.97	88	78.57
Nibea albiflora - Not Fresh	90.91	83.33	86.96	95.24	83.33	88.89
Oreochromis mossambicus - Fresh	64.71	94.29	76.74	70.45	88.57	78.48
Oreochromis mossambicus - Highly Fresh	96	82.76	88.89	89.29	86.21	87.72
Oreochromis mossambicus - Not Fresh	92.59	78.13	84.75	93.10	84.38	88.52
Oreochromis niloticus - Fresh	89.66	56.52	69.33	87.5	60.87	71.79
Oreochromis niloticus - Highly Fresh	81.08	92.31	86.33	83.1	90.77	86.76
Oreochromis niloticus - Not Fresh	83.02	89.8	86.27	83.02	89.80	86.27
Rastrelliger faughni - Fresh	76.19	74.42	75.29	70.21	76.74	73.33
Rastrelliger faughni - Highly Fresh	93.44	85.07	89.06	95.08	86.57	90.62
Rastrelliger faughni - Not Fresh	75	81.82	78.26	76.09	79.55	77.78
Upeneus moluccensis - Fresh	70.83	68	69.39	70	56	62.22
Upeneus moluccensis - Highly Fresh	75.71	85.48	80.30	74.65	85.48	79.70
Upeneus moluccensis - Not Fresh	81.4	76.09	78.65	75.51	80.43	77.89

In Table 5, the VGG16 model combined with SVM also demonstrates improved performance metrics. For example, the precision for "*Chanos Chanos* - Fresh" increased from 78.12 to 77.14, and the recall for "*Eleutheronema Tetradactylum* - Highly Fresh" remained high at 93.75. These results suggest that the SVM classifier can leverage the features extracted by VGG16 to achieve better classification results. Table 6 highlights the performance of the MobileNetV3-Small model with and without SVM. The combination with SVM shows notable improvements in several classes. For instance, the F1-score for "*Oreochromis Mossambicus* - Fresh" increased from 83.54 to 86.84, and the precision for "*Chanos Chanos* - Highly Fresh" remained high at 96.88. These findings indicate that the SVM classifier can effectively utilize the features extracted by MobileNetV3-Small to enhance classification performance.

Table 5: Classification performance of modified VGG16 and the features extracted using the SVM.

Class name	VGG16			VGG16 + SVM		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Chanos chanos - Fresh	78.12	75.76	76.92	77.14	81.82	79.41
Chanos chanos -Highly Fresh	100.00	94.12	96.97	96.88	91.18	93.94
Chanos chanos - Not Fresh	77.78	82.35	80.00	84.85	82.35	83.58
Eleutheronema tetradactylum - Fresh	57.89	68.75	62.86	75.00	75.00	75.00
Eleutheronema tetradactylum - Highly Fresh	83.33	93.75	88.24	100.00	93.75	96.77
Eleutheronema tetradactylum - Not Fresh	90.00	56.25	69.23	76.47	81.25	78.79
Johnius trachycephalus - Fresh	56.25	56.25	56.25	57.89	68.75	62.86
Johnius trachycephalus - Highly Fresh	77.78	87.50	82.35	83.33	93.75	88.24
Johnius trachycephalus - Not Fresh	52.94	56.25	54.55	71.43	62.50	66.67
Nibea albiflora - Highly Fresh	81.25	74.29	77.61	76.47	74.29	75.36

Table 5 continued:

Nibea albiflora - Fresh	60.00	84.00	70.00	60.61	80.00	68.97
Nibea albiflora - Not Fresh	88.89	66.67	76.19	84.21	66.67	74.42
Oreochromis mossambicus - Fresh	68.89	88.57	77.50	76.32	82.86	79.45
Oreochromis mossambicus - Highly Fresh	96.23	87.93	91.89	91.23	89.66	90.43
Oreochromis mossambicus - Not Fresh	92.86	81.25	86.67	92.86	81.25	86.67
Oreochromis niloticus - Fresh	80.95	73.91	77.27	82.61	82.61	82.61
Oreochromis niloticus - Highly Fresh	81.94	90.77	86.13	87.88	89.23	88.55
Oreochromis niloticus - Not Fresh	86.96	81.63	84.21	89.36	85.71	87.50
Rastrelliger faughni - Fresh	62.26	76.74	68.75	63.27	72.09	67.39
Rastrelliger faughni - Highly Fresh	93.55	86.57	89.92	89.06	85.07	87.02
Rastrelliger faughni - Not Fresh	83.78	70.45	76.54	80.49	75.00	77.65
Upeneus moluccensis - Fresh	64.41	76.00	69.72	67.27	74.00	70.48
Upeneus moluccensis - Highly Fresh	90.57	77.42	83.48	83.33	72.58	77.59
Upeneus moluccensis - Not Fresh	77.78	76.09	76.92	75.00	78.26	76.60

Overall, the results demonstrate that combining deep learning models with SVM classifiers can significantly improve the classification performance for the 24-class FFE dataset, particularly in terms of precision, recall, and F1-score. While deep learning models typically require substantial training time, the SVM classifier provides a considerable advantage in terms of training speed. The training process for the SVM is much faster than deep learning models, making it a highly efficient component in our hybrid approach. Notably, this hybrid approach not only avoids significant computational overhead compared to an end-to-end deep learning model but also substantially improves classification performance.

Figure 8 presents the graphical results of Tables 4, 5, and 6 using box plots. These box plots provide a clearer and more concise visualization of the data compared to the large tables. The six methods shown include three deep learning models (Inception-v3, VGG16, and MobileNetV3-Small) both with and without SVM. Specifically, Figure 8 a) shows the precision for the six methods, Figure 8 b) illustrates the recall for the six methods, and Figure 8 c) displays the F1-score for the six methods. Each box plot graphically represents the results for the 24 classes, making the data more readable and easier to interpret.

Table 6: Classification performance of modified MobileNetV3-Small and the features extracted using the SVM.

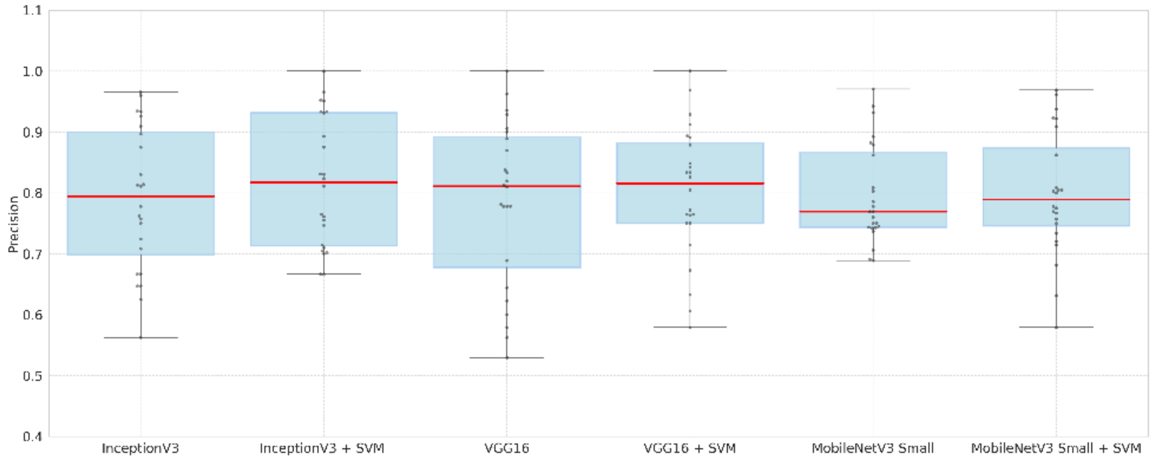
Class name	MobileNetV3-Small			MobileNetV3-Small + SVM		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Chanos chanos - Fresh	74.19	69.7	71.88	76.67	69.7	73.02
Chanos chanos -Highly Fresh	97.06	97.06	97.06	96.88	91.18	93.94
Chanos chanos - Not Fresh	74.29	76.47	75.36	75.68	82.35	78.87
Eleutheronema tetradactylum - Fresh	76.92	62.5	68.97	57.89	68.75	62.86
Eleutheronema tetradactylum - Highly Fresh	88.24	93.75	90.91	92.31	75	82.76
Eleutheronema tetradactylum - Not Fresh	77.78	87.5	82.35	75	75	75
Johnius trachycephalus - Fresh	70.59	75	72.73	63.16	75	68.57
Johnius trachycephalus - Highly Fresh	73.68	87.5	80	77.78	87.5	82.35

Table 6 continued:

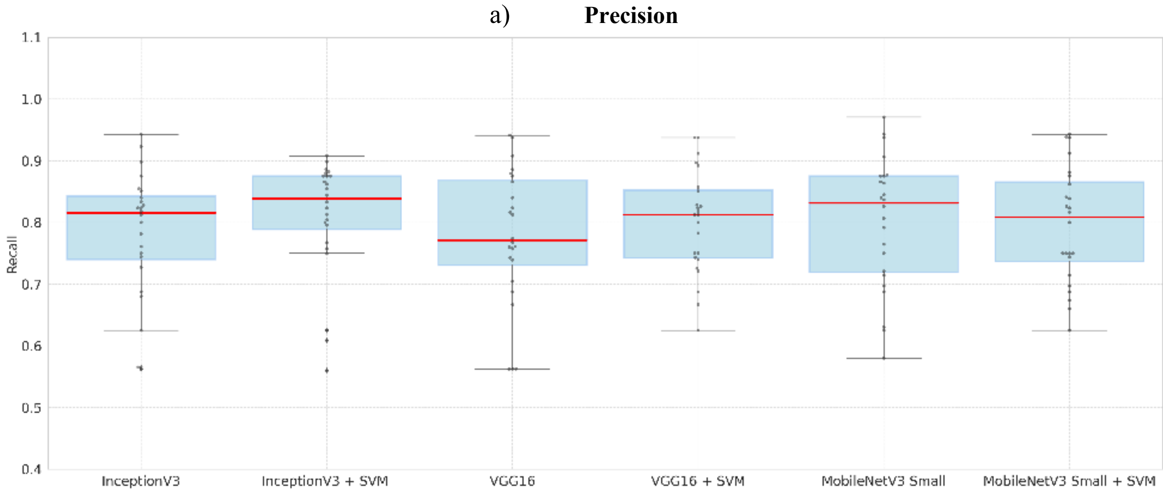
Johnius trachycephalus - Not Fresh	78.57	68.75	73.33	76.92	62.5	68.97
Nibea albiflora - Highly Fresh	86.21	71.43	78.13	86.21	71.43	78.13
Nibea albiflora - Fresh	75	84	79.25	71.43	80	75.47
Nibea albiflora - Not Fresh	76	79.17	77.55	72	75	73.47
Oreochromis mossambicus - Fresh	75	94.29	83.54	80.49	94.29	86.84
Oreochromis mossambicus - Highly Fresh	94.23	84.48	89.09	96.15	86.21	90.91
Oreochromis mossambicus - Not Fresh	87.88	90.62	89.23	93.75	93.75	93.75
Oreochromis niloticus - Fresh	74.36	63.04	68.24	77.5	67.39	72.09
Oreochromis niloticus - Highly Fresh	80.28	87.69	83.82	80.26	93.85	86.52
Oreochromis niloticus - Not Fresh	93.18	83.67	88.17	90.91	81.63	86.02
Rastrelliger faughni - Fresh	68.89	72.09	70.45	68.09	74.42	71.11
Rastrelliger faughni - Highly Fresh	89.23	86.57	87.88	92.19	88.06	90.08
Rastrelliger faughni - Not Fresh	80.85	86.36	83.52	80.43	84.09	82.22
Upeneus moluccensis - Fresh	69.05	58	63.04	73.33	66	69.47
Upeneus moluccensis - Highly Fresh	76.92	80.65	78.74	80	83.87	81.89
Upeneus moluccensis - Not Fresh	74.51	82.61	78.35	80.85	82.61	81.72

Figure 9 shows the confusion matrices for the three deep learning methods combined with SVM across the 24 classes. This visualization helps in understanding the misclassification patterns and identifying which classes are often confused with each other, thereby providing insights for further model improvement. Figure 10 presents the ROC curves for these methods, illustrating the trade-off between true positive rates and false positive rates. The ROC curves are beneficial for evaluating the overall performance of the classifiers and comparing their effectiveness in distinguishing between classes.

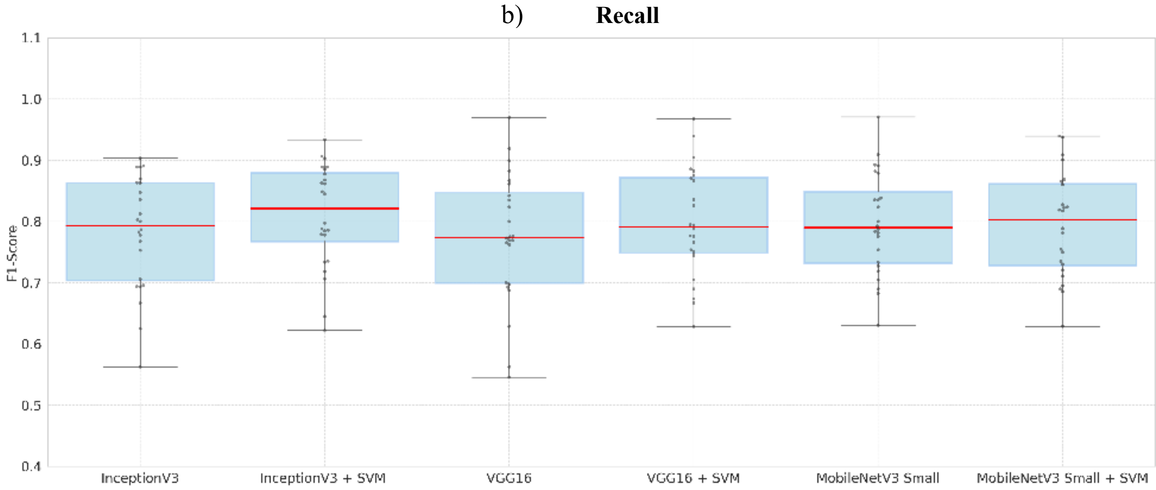
Table 7 compares the results of the proposed methods with previous methods on the FFE dataset. The table includes accuracy, precision, recall, and F1-score metrics for each method. The proposed methods, which include Inception-v3, VGG16, and MobileNetV3-Small, both with and without SVM, show significant improvements over previous methods such as MobileNetV1, MB-BE (1 1 1), and ResNet50.



a) **Precision**

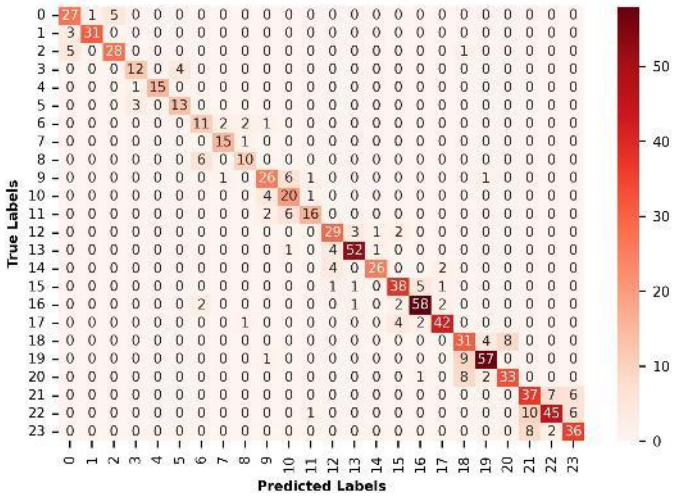


b) **Recall**

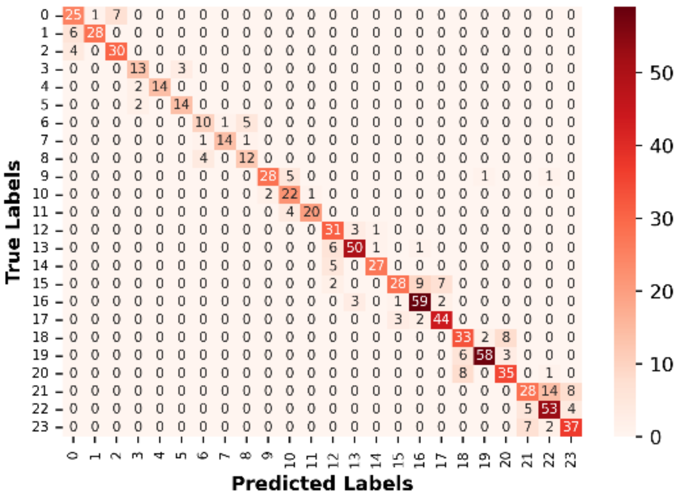


c) **F1-score**

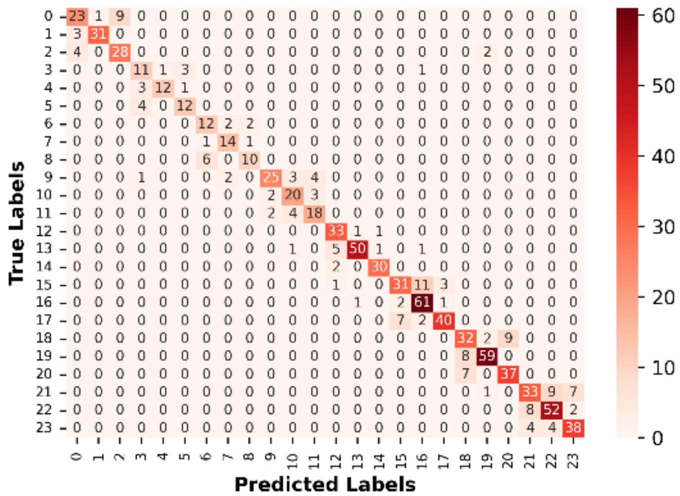
Figure 8: Box plots showing precision, recall, and F1-score for three deep learning models (Inception-v3, VGG16, and MobileNetV3-Small) with and without SVM across 24 classes.



a) Proposed VGG16 + SVM

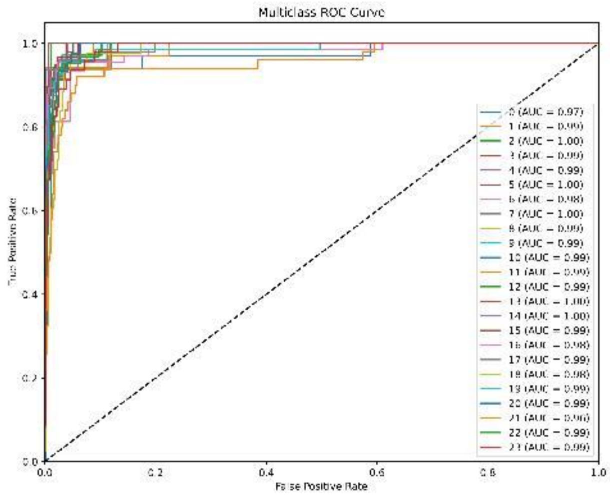


b) Proposed Inception-v3 + SVM

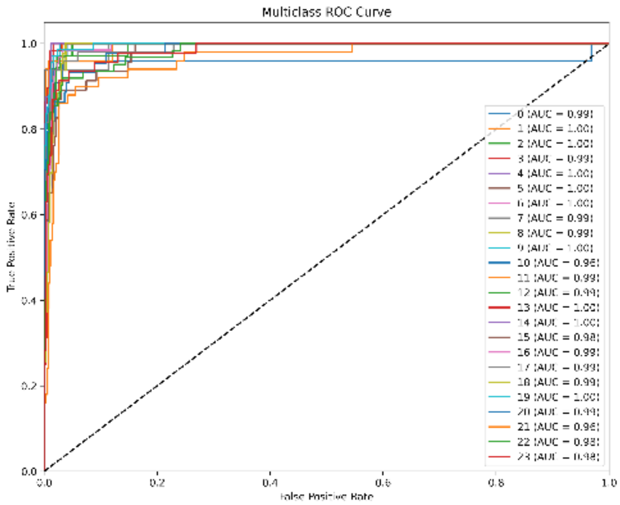


c) Proposed MobileNetV3-Small + SVM

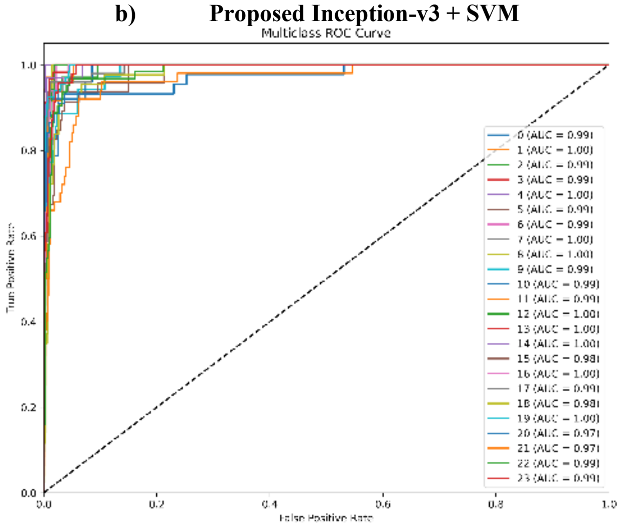
Figure 9: Confusion matrices for three deep learning methods (Inception-v3, VGG16, and MobileNetV3-Small) combined with SVM across 24 classes.



a) Proposed VGG16 + SVM



b) Proposed Inception-v3 + SVM



c) Proposed MobileNetV3-Small + SVM

Figure 10: ROC curves for three deep learning methods (Inception-v3, VGG16, and MobileNetV3-Small) combined with SVM across 24 classes.

Table 7: Comparison of the proposed methods with previous methods on the FFE dataset.

Method	Accuracy	Precision	Recall	F1-Score
MobileNetV1 [28]	59.11	59.74	57.98	58.85
MB-BE (1 1 1) [28]	60.02	58.41	58.06	58.24
ResNet50 [28]	78.82	79.14	77.70	78.41
Inception-v3 [Proposed Method]	79.84	80.92	79.84	79.88
Inception-v3 + SVM [Proposed Method]	81.21	81.95	81.21	81.18
VGG16 [Proposed Method]	79.61	80.99	79.61	79.85
VGG16 + SVM [Proposed Method]	80.64	81.32	80.64	80.80
MobileNetV3 Small [Proposed Method]	80.30	80.52	80.30	80.17
MobileNetV3 Small + SVM [Proposed Method]	81.09	81.59	81.09	81.10

The results indicate that the combination of deep learning models with SVM generally enhances performance across all metrics. For instance, the Inception-v3 + SVM method achieved the highest accuracy of 81.21%, precision of 81.95%, recall of 81.21%, and F1-score of 81.18%. The best results are highlighted in bold. Similarly, the VGG16 + SVM and MobileNetV3-Small + SVM methods also demonstrated superior performance compared to their standalone counterparts and previous methods. These findings highlight the effectiveness of integrating SVM with deep learning models for improved classification performance on the FFE dataset.

Discussion

This paper presents a novel methodology for evaluating fish freshness by analyzing ocular images, employing features extracted from the proposed models in conjunction with established classifiers. The dataset comprises eight distinct fish species, each having three potential quality states, thereby transforming the classification challenge into a 24-class problem. Using the proposed method, we achieved significant accuracy in classifying these images, surpassing the accuracy of previous works. The proposed method combines deep learning models with SVM classifiers, enhancing the precision, recall, and F1-score across all classes. For future work, it would be beneficial to explore other deep models for this task. It also considers focusing on the freshness of fish without any attention to its species. Implementing these methods in real-time quality assessment systems in commercial settings could also enhance the sustainability of fish supply chains by reducing waste and ensuring that only the freshest products reach consumers.

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Conflict of interest

The authors declare no conflict of interest.

Ethics approval

The study was conducted in accordance with ethical guidelines, and approval was obtained from the relevant ethics committee.

Data/Code availability

The datasets and code used in this research are available upon request.

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