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Integrating Image Data Fusion and ResNet Method for Accurate Fish Freshness Classification

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ORIGINAL STUDY

Integrating Image Data Fusion and ResNet Method for Accurate Fish Freshness Classification

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ABSTRACT

Fish freshness classification is critical for protecting public health and ensuring efficient economic, regulatory and environmental sustainability. Classifying accurately reduces the risk of foodborne illness, protects product quality, builds consumer trust and supports sustainable resource conservation through waste minimization. However, the traditional methods for determining fish freshness are variable, time consuming and subjective, precluding practical use. This research presents an improved framework that integrates image data fusion and a deep learning ResNet model to differentiate fresh and nonfresh fish. From multiple sources, a comprehensive dataset including 16,640 samples was curated, and data fusion was used to increase the diversity and reliability of the extracted features. The classification model was developed via ResNet, which is well known for its extraordinary feature extraction features. High performance was shown by the proposed approach, with 92% precision, 94% recall and an F1 score of 0.93 for fresh fish. For nonfresh fish, the precision was 95%, the recall was 93%, and the F1 score was 0.94. Overall accuracy of classification. This suggests that the model proposed in this work is a feasible and reliable solution for real-time fish freshness classification that outperforms traditional methods. This is followed by the use of image data fusion along with ResNet to further state deep learning in food quality assessment, maintain environmental sustainability, contribute to public health, and improve economic value. This research illuminates the value of data fusion for enhancing model performance while offering a novel means to address central problems in the seafood industry.

Keywords: Machine learning, Deep learning, Data fusion, ResNet, Classification, Food quality, Fish freshness

1. Introduction

Peculiarities of the current world concern the abilities and preferences of people in terms of selecting food products that would be safe and healthy for further consumption [1–3]. Consequently, factors such as the quantity and quality of food have become vital to any identity that embraces healthy living [4–6]. These elements are critical predictors of the safety of the food that we consume [7]. Among these factors, freshness is deemed most relevant because it not only identifies the time within which foods taste the best but also actively contributes to the regulation of the production of pathogenic compounds that come from spoiled foods [8, 9]. It is important, as it protects us from some health hazards that may result from the consumption of badly produced foods [10].

Because fish dishes are tasty and contain more nutritional value, consumers across the globe favor these dishes [11]. However, fish and other marine products are often fresh, easily perishable foods [12, 13]. This poses a serious challenge in regard to monitoring time and establishing the freshness of fish [14]. The factors that cause the freshness of fish are immense [15]. These include the molecular makeup [16], the biological hierarchy [17], the cell architecture, temperature variations, different types of preservation methods, and alterations in the physical

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characteristics within time and storage conditions [18–20]. All of these factors contribute to the evaluation of the freshness of the fish, as well as its quality and safety.

Considering the need for tools to evaluate fish freshness, it is crucial to allocate more attention to the development of approaches and technologies for the evaluation of fish freshness as soon as possible [21]. In this way, consumers are in a position to relish fish foods while still being safe and meeting the quality standards that are set in the market [22]. Thus, solving this critical problem will ensure that every consumer, depending on fish meal as part of his or her daily diet, will be guaranteed a healthy meal in compliance with the principles of food quality and safety.

To solve this problem, sophisticated and accurate methods for distinguishing fresh and nonfresh fish are needed, which traditional methods may find difficult. Thus, the current paper is designed to offer a new and revolutionary approach to the classification of fresh fish through integration and date fusion (which is the act of taking multiple sources of data and putting them together in a way that is more consistent, more accurate, and more useful) of the significant number of images taken from various sources combined with the highly effective residual neural network (ResNet) model [23]. The processes of image acquisition and data collection require careful and intensive work to develop a sample with great variety and a large quantity of sources. This particular dataset has since been well used to train the ResNet model, which is globally acclaimed for its ability to identify highly complex features and differentiate many images.

A machine learning approach is proposed, which shows considerable improvement in both accuracy and precision in discriminating fresh and nonfresh fish. This method combines both diverse image data and the ResNet model, forming a powerful and effective method to improve fish freshness classification. This study has important implications, and its findings are valuable to researchers and stakeholders in the fisheries sector. With the incorporation of image data into the ResNet deep learning model, a novel approach for freshness classification is proposed, bringing a state-of-the-art technology to reduce the time spent in the seafood industry. These advancements show how advanced computing can be applied to resolve practical and real-world problems and enhance decision making in food quality control. Finally, this research demonstrates the value of academics across disciplines and the potential of applying the newest technology to increase both human welfare and economic efficiency beyond determining only the freshness of fish.

Paper Organization: The remainder of this paper is structured as follows. Section 2 reviews current advances in fish freshness classification and presents related work. In Section 3, we describe how we proceeded with the data collection and preprocessing, as well as model development. The results are presented in Section 4 to examine the model performance and key driving metrics. In Section 5, the findings, implications, and future research directions are discussed.

1.1. Background and motivation

The application of image data fusion is considered to be highly beneficial in the food industry, especially for the evaluation of food [24, 25]. In this way, a fresh quality assessment of fish products allows for the early determination of spoiled items for the exclusion of their distribution to consumers, hence minimizing cases of food wastage [26]. Additionally, it is important to mention that, in achieved results, consumer safety and satisfaction are provided. The other possible implementation can be used in the identification of food spoilage, where the fusion of image data can help in identifying various types of spoilage, such as enzymatic and nonenzymatic spoilage [27]. The information can thus be helpful in developing improved ways of conserving original identifiers and the appropriate storage environment for the identifiers. Additionally, image data fusion can improve object recognition accuracy in vision systems when applied to fish products that may have different colors and skin textures [28]. In addition, integrating image data fusion with other sensors can provide a comprehensive and better approach to fish freshness to create a far better quality control system [29]. In general, the use of image data fusion has numerous applications in increasing the efficiency of food spoilage detection, as well as seafood quality in the food industry.

For analysis of the fused dataset, the ResNet model, a deep convolutional neural network that is commonly used in image classification tasks all around the globe because of its feature extraction efficacy, is utilized [30]. The ResNet model eliminates the vanishing gradient problem through residual learning, as the experiments indicate this, especially in very deep networks [31]. This particular characteristic is very useful for enhancing the capacity of distinguishing levels of fish freshness because this is quite impossible otherwise. The proposed method is more efficient for classification when data obtained from different sources and multiple features are used.

The integration of image data fusion with the ResNet method produces a highly accurate approach for classifying the freshness of fish, which is a long way from meeting the challenge of attaining accurate and efficient classification [32]. This integration enables the superimposition of data from various sources of the image, thus leading to the provision of a more comprehensive analysis of the freshness of the fish. Furthermore, the ResNet method is a strong model from which features from the fused image data can be copied [33].

1.2. Research objectives

An accurate determination of the freshness of fish is important to avoid diseases related to food, the quality of the fish, and customer satisfaction. It is economically important since it eliminates wastage and improves the quality of fish products, hence their market value economically; it is physically important in reducing labor and costs involved in fishing; and it is a legally auspicious tax basis since it avoids legal consequences or fines that the law may prescribe. As with these other elements, it is admirable to adopt environmentally responsible behavior by reducing waste and conserving the bounty of seas or rivers. Additionally, this application combines data fusion and deep learning to facilitate the development of food technology, further improving overall operations.

This study aims to improve the methods of fish freshness classification and the reliability of fish freshness assessment decision making on the basis of these state-of-the-art AI technologies and to provide a reference and guideline for future investigations of food quality evaluation. The novelty of this work is the multiple sources and attributes used to perform the classification. In this method of classification, all the different aspects of fish are taken, whereas it does not fully depend on the separate attributes of a fish. With the aid of a wider field of application, the conclusions of this research are expected to be useful and helpful; they will provide producers, suppliers, regulators and consumers with further insights and educational tools about standards of food safety and product quality, which is expected to improve the mentioned standards. As a proof of how AI acts as a tool through which traditional procedures can be improved and how this works in tackling current problems in the food sector, we apply AI in fish freshness classification.

2. Related works

Artificial intelligence (AI) is a field of computer science focused on developing machines with human-like intelligence, such as learning, reasoning, and problem solving [34–37]. Machine learning (ML) is a key component of AI [37–39], allowing systems to learn and improve from data without explicit programming by using techniques such as supervised, unsupervised, and reinforcement learning [40–43]. Deep learning (DL), a specialized subset of ML [44, 45], employs multilayered neural networks to model complex patterns in large datasets, which excels in areas such as image and speech recognition, natural language processing [46–49], and autonomous systems [50, 51]. ML and DL drive advancements in AI, leading to more sophisticated intelligent systems [52–55]. Image data processing of objects for food monitoring has become a significant area within image processing and communication [56–59]. Precise object recognition is crucial in computer vision when various forms of image data are used [60, 61]. Recently, artificial intelligence has been widely studied for object identification, particularly via transfer learning techniques [62]. In the current technological era, computer vision has become increasingly essential and advantageous. Food fault diagnosis, a highly relevant domain for research in information farming, has garnered considerable attention in recent years [63].

Correct identification of the freshness of fish is an important factor of concern in the food processing industry; hence, several techniques have been developed over the past decade to meet this need [64]. Qualitative tests are traditionally applied to evaluate the freshness of fish via methods such as sensory analysis [65], chemical methods [66], and microbiological examination [67]. Sensory analysis, which is based on one's ability to identify some characteristics, such as smell or texture, is qualitative and thus may involve significant variations in measures and results [68]. Chemical procedures that quantify gaseous substances or the acidity/alkalinity of the air also provide more factual information, but these procedures are slightly more precise and call for equipment [69]. Basic analysis for bacteria includes counting colonies or identifying specific pathogenic agents, which is tedious and requires extensive personnel [70].

Recently, in the fields of AI and ML, there have been new opportunities to enhance methods for classifying fish freshness yield and accuracy [71, 72]. In the area of image classification, deep learning, which is a branch of artificial intelligence, has been enormously successful because it uses neural networks to learn and obtain features by itself from a large dataset [73]. CNNs such as ResNet (residual network) and similar CNNs have been quite effective because of their ability to handle enormously large volumes of data patterns [74]. The ResNet model with the help of residual learning bypasses this problem and enables the training of networks so deep that they are able to capture fine details in the images they process [75].

Scientific research on the detection and identification of underwater fish species and their classification in aquaculture has revealed relative progress and future difficulties. This was established in [76] with the use of a convolutional neural network (CNN)-based method to address the challenges of light scattering and absorption in underwater images. When transfer learning initialized with the ResNet-50 network was used, the authors observed higher classification performance despite the limited annotated datasets. Thus, the proposed model of fine-tuning the ResNet-50 model with only the last layer produced high precision, recall, and F1 score values of 0.94, 0.85, and 0.89, respectively, which proves that it is very effective, especially under difficult conditions in the water area.

The introduction of deep learning applications [77] and updates on aquaculture, reviewing the use of DL for live fish identification, species classification, and water quality prediction, continue. While the review praised DL for its ability to automatically set and extract the features it requires, it also noted that such network operations depend on large labeled datasets and, at the moment, could be considered rather weak forms of AI.

When the conditions are noisy and the number of variations is high, [78] suggested a two-part deep learning method to detect fish via YOLO and classify species via a convolutional neural network with a squeeze-and-excitation architecture. The implementations of this method incorporated ImageNet and Fish4Knowledge pretrained models to optimize the accuracy of fish identification to 99.27% for the pretraining phase, and the posttraining accuracies for the proposed method reached 83.68% and 87.74%, respectively, to provide a clear indication of its performance, especially under water conditions.

With respect to high-density aquaculture systems, [79] presented a two-phase deep learning method based on a CNN pretrained on ImageNet to identify abnormalities in groupers. The average accuracy of the InceptionV3 model was 98.94% for identifying three types of abnormally looking grouper, indicating that the model can be used for disease detection in aquaculture.

Finally, [80] proposed a new technique to minimize the deaths of small fish that occur due to trawling in commercial fishing. Compared with the original Mask R-CNN structure for fish localization and segmentation, the method was able to address stereo images and handle images with multiple fish that overlapped in the image. The proposed approach, which was evaluated on a dataset with over 2600 manually annotated fish images, proves the effectiveness of the developed methods for the segmentation of individual fish and could help to decrease overfishing.

The related works highlight the achievements in fish freshness classification based on traditional methods (sensory and chemical analyses) and the most recent AI-based solutions. Although extensively given, traditional methods are usually subjective and labor intensive and prone to human error, rendering them unfit for consistent and scalable industry applications. Over the past few years, machine learning and deep learning have offered automated solutions capable of handling larger datasets and generating more stable results. However, these methods are limited by small datasets, making generalization to new species, conditions, and imaging variations difficult.

Convolutional neural networks (CNNs) have been shown to be promising AI-based methods for image-based classification tasks. However, few studies use advanced models such as ResNet, which are intended to map complex image features important for the task of fish freshness classification. Additionally, to our knowledge, fish classification has not previously been performed via data fusion (combining multiple datasets to increase dataset diversity). Since data fusion is not used, the variability of training data is limited, and models do not generalize, as they are extremely dependent on training data.

Therefore, the existing methods lack comprehensive, diverse datasets; use of advanced feature extraction models such as ResNet; and data fusion techniques for fish classification. To address these gaps, this study fills an innovation gap by pioneering the use of image data fusion with the ResNet model for scalable, accurate, and robust fish freshness classification.

3. Methodology

By following the methodology in Fig. 1, these steps can be effectively utilized for fish freshness classification.

3.1. Dataset collection

In the field of machine learning, the results often depend heavily on the datasets used for training/validating. In this study on the identification of fish freshness, we collected eight different datasets from different sources. These datasets are collections of images that are annotated according to their freshness level, and they are highly important in formulating a proper and accurate classification model.

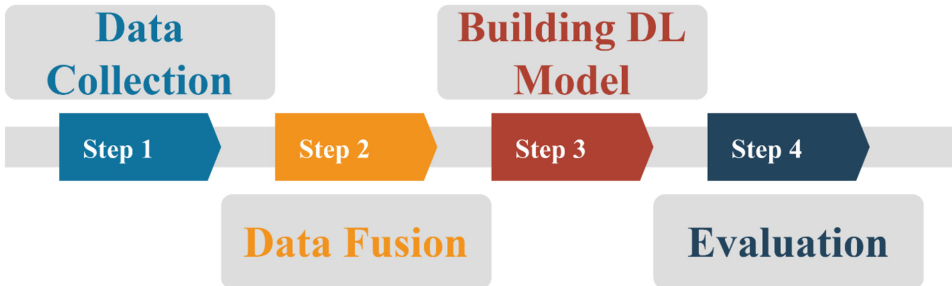


Fig. 1. Steps of the methodology.

- **Dataset 1:** Fish Freshness 4 by Roboflow [81]

Description: This dataset is made up of pictures of fish with the corresponding freshness level of each fish in the image. The images are labeled to enhance the training of machine learning algorithms useful for the classification of fresh fish from those that are not. The given dataset is described with numerous metadata as well as annotations required to achieve the correct model training and testing.

- **Dataset 2:** Fish Freshness 3 by Roboflow [82]

Description: As in Dataset 1, a variety of fresh fish images are offered, which are helpful for training the classification models. The dataset contains clear images, so the model can discern the freshness degree.

- **Dataset 3:** Fish Eye Freshness by Roboflow [83]

Description: This dataset contains images of fish eyes with annotations that can help determine the freshness of a fish through the condition of its eye. Importantly, the images are taken under the same lightning to draw attention to the characteristics employed during freshness determination.

- **Dataset 4:** Fish Freshness Detection on Kaggle [84]

Description: This dataset is represented by images of different types of fish and corresponding metadata containing annotations of fish freshness optimized for quality control of seafood products. The images are of various types, involving various species and ailments, which can be used to develop a strong classification model.

- **Dataset 5:** Fresh and Non-Fresh Fish Dataset on Kaggle [85]

Description: This compiled set of images is specifically divided into fresh and nonfresh data types, which are perfect for binary classification of data for machine learning models. In this way, the scope of the conditions and settings presented in the dataset is vast, making training of the model rather thorough.

- **Dataset 6:** Fish Classification Dataset on Kaggle [86]

Description: This dataset provides various images of fish of various species and, with/without freshness information, can be used for species and freshness prediction. The added advantage of having many species means that this dataset is quite useful when creating models that are required to classify various types of fish.

- **Dataset 7:** Fresh and nonfresh tilapia fish species on Kaggle [87]

Description: This dataset involves tilapia, and it provides samples accompanied by labels to distinguish fresh fish from the remaining fish. The images are collected from various sources, meaning that different conditions and settings are available for the model.

- **Dataset 8:** Fish freshness dataset from Mendeley [88]

Description: This dataset consists of various types of fish images whose labels are fresher or not for enhancing the ability to classify fish freshness via artificial intelligence (AI). The dataset is rich and includes multiple species of fish and multiple freshness conditions; this is important when developing the classification model.

In so doing, the integration of a broad range of such datasets is expected to yield a large-scale comprehensive dataset capable of increasing the reliability of the presented fish freshness classification model (see Fig. 2). Thus, a comprehensive approach would help our model be prepared for different scenarios and conditions and enhance the generally low quality of seafood on the market. While achieving this, the process entails data gathering, formatting, scrubbing, labeling, mashing-up, and preprocessing the data to obtain a good dataset for research.

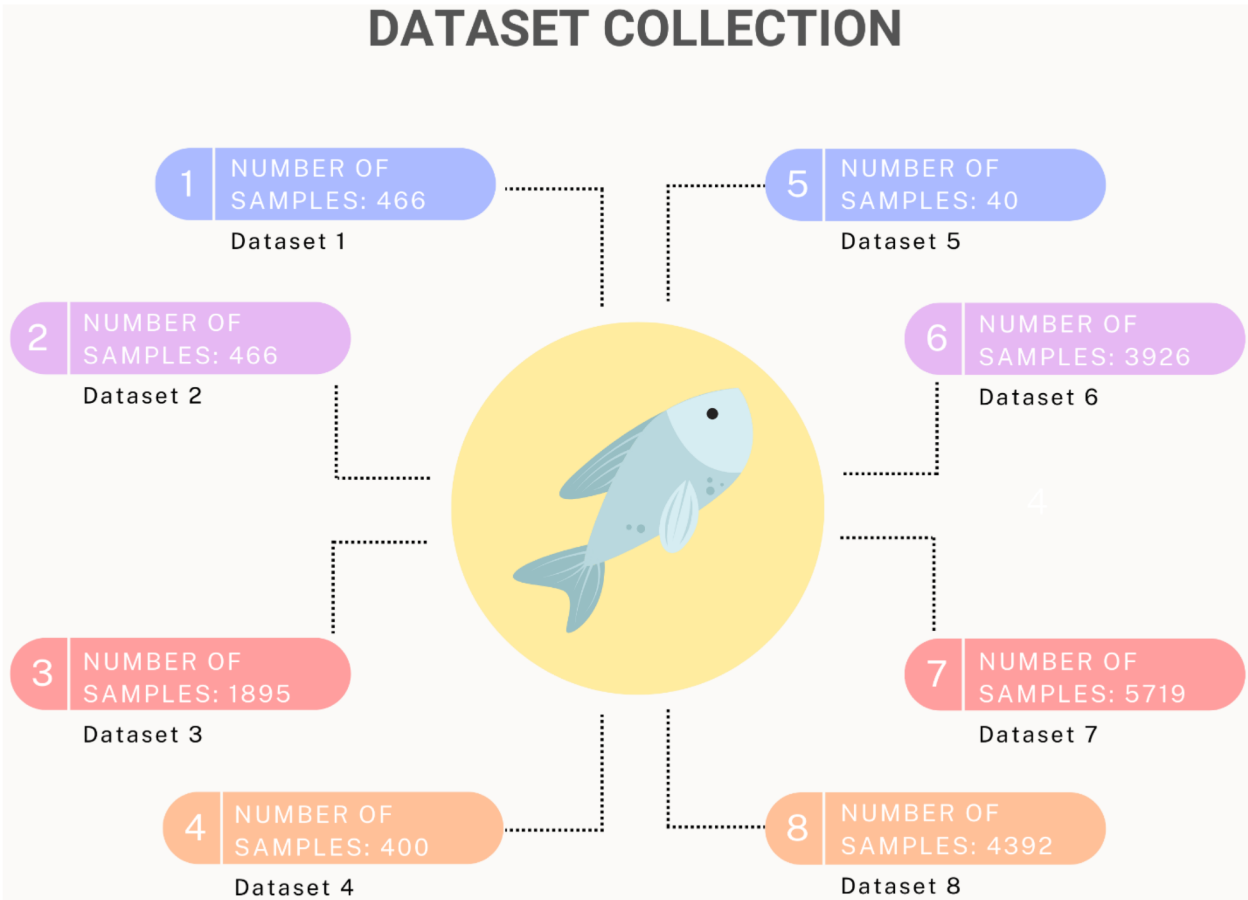


Fig. 2. Number of samples for the collected datasets.

3.2. Data fusion

After the fusion of 8 datasets for fish, the following steps are required to ensure that the data are fit for use in ML applications. All these steps aim at standardizing the images, cleaning them, annotating them, preprocessing them, integrating them and better managing them to arrive at a highly sound dataset for training (see Fig. 3):

1. **Data standardization:**

To ensure that the format and size of the image are standardized throughout the entire dataset, they are no different. Since '. jpg' can easily be processed various image processing tools, all the images can be converted to '. jpg format to be compatible with the different image processing tools.

2. **Data Cleaning:**

To filter out all the images that could be irrelevant or of low quality for training the models. This step involves the removal of duplicate images from the dataset, as having duplicate images in the dataset will enhance overfitting and bias the model. It also requires elimination of images that could be blurry, overexposed, underexposed or of generally poor quality to ensure that only quality images that are able to offer good features for the model and that will enable the models to perform well are used.

3. **Data Annotation**:

Each picture should be tagged correctly, and the tags should be consistent, which is important in supervised learning. This entails giving all images a uniform labeling convention, for example, 'fresh' and 'non fresh', and this helps the classes to be differentiated by the model.

4. **Data Preprocessing**:

This means that the images are in the right format related to model training and enhancements. This step normalizes the pixel values of the images, for example, to the range between 0 and 1 or between −1 and 1, to ensure that the training process takes less time and enhances model performance. Additionally, data preprocessing techniques such as rotation,

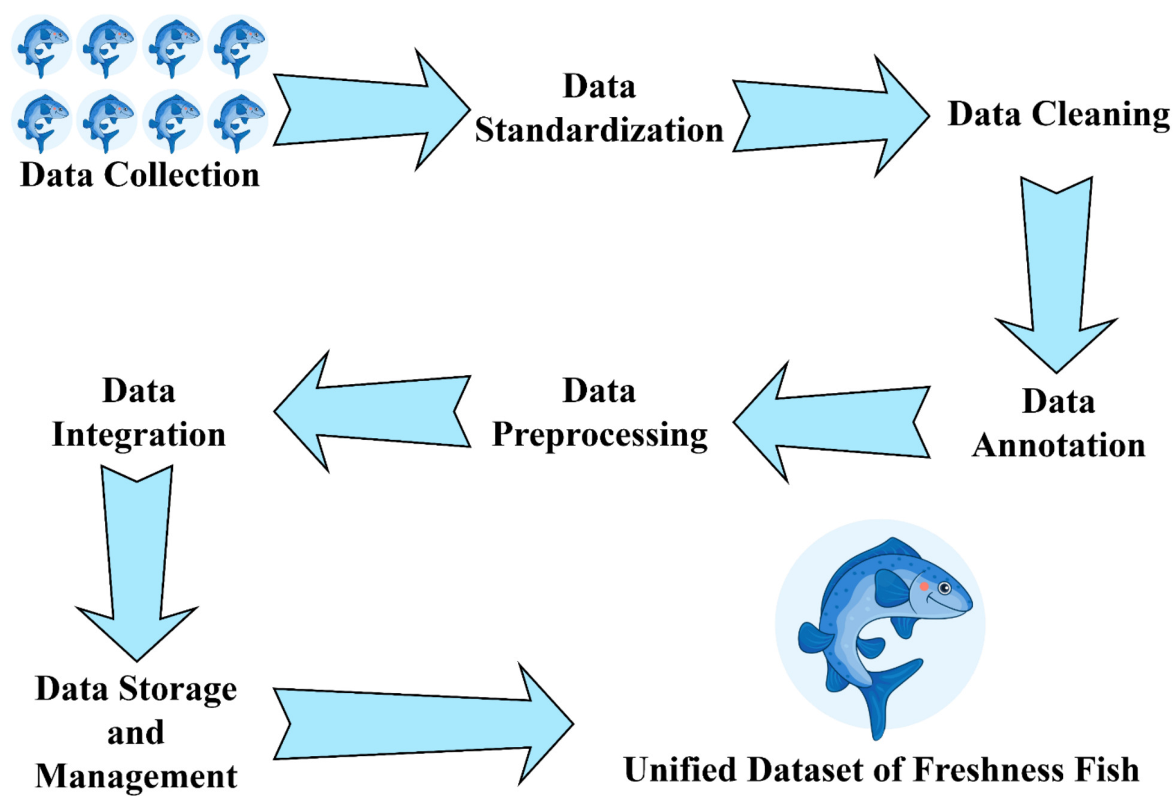


Fig. 3. Steps of data fusion.

flipping, cropping and color editing are applied to increase the diversity of the training set. Augmentation techniques here artificially enlarge the dataset such that new images are created by varying the original images [89, 90]. Consequently, the model is more robust to different fish orientation variations, lighting conditions and the ability to position fish during testing. This diversity in the training set has increased, which in turn enables the model to learn more generalized features; the risk of overfitting is reduced, and a better ability to classify unseen data accurately is achieved.

5. **Data Integration:**

To bring together several datasets into a single set, which has a single directory tree. This is the process through which different datasets are combined to make one, by replicating the files into one folder through copying. It also ensures that no clashes in file naming and labeling occur while merging and maintaining the integrity of the dataset for use.

6. **Data Storage and Management**:

To ensure that after the two datasets are merged, the new dataset is organized in a logical and consistent order that enhances efficient access to the data and provides an efficient way of managing the data. By placing the dataset into a logical structure where it can easily be retrieved, the directory of labels such as ‘fresh’ and ‘nonfresh’ can be managed. Source files in more formal tabular rather than picture record formats are preserved; metadata files themselves (for instance, CSVs) are kept to describe the sources, annotations, and other information concerning the images necessary to trace their nature and origin. Moreover, the utilization of the backup and version control measures is applied to protect the dataset and keep records of the changes made, which can be very useful in the case of loss of data, as well as managing the versions of the data.

Thus, by performing these steps, the given eight datasets for fish are preprocessed and normalized into a clean set with a correct and uniform format that can be used for effectively training a high-quality accurate image classification model.

The dataset for this study (Unified Freshness Fish Dataset) consists of a total of 16,640 images collected from various sources to capture a comprehensive range of fish freshness states. The images were divided into two categories: “Fresh” and “Non-Fresh.” The key details are as follows:

- Fresh images: 8723 images
- Non-Fresh Images: 7917 images

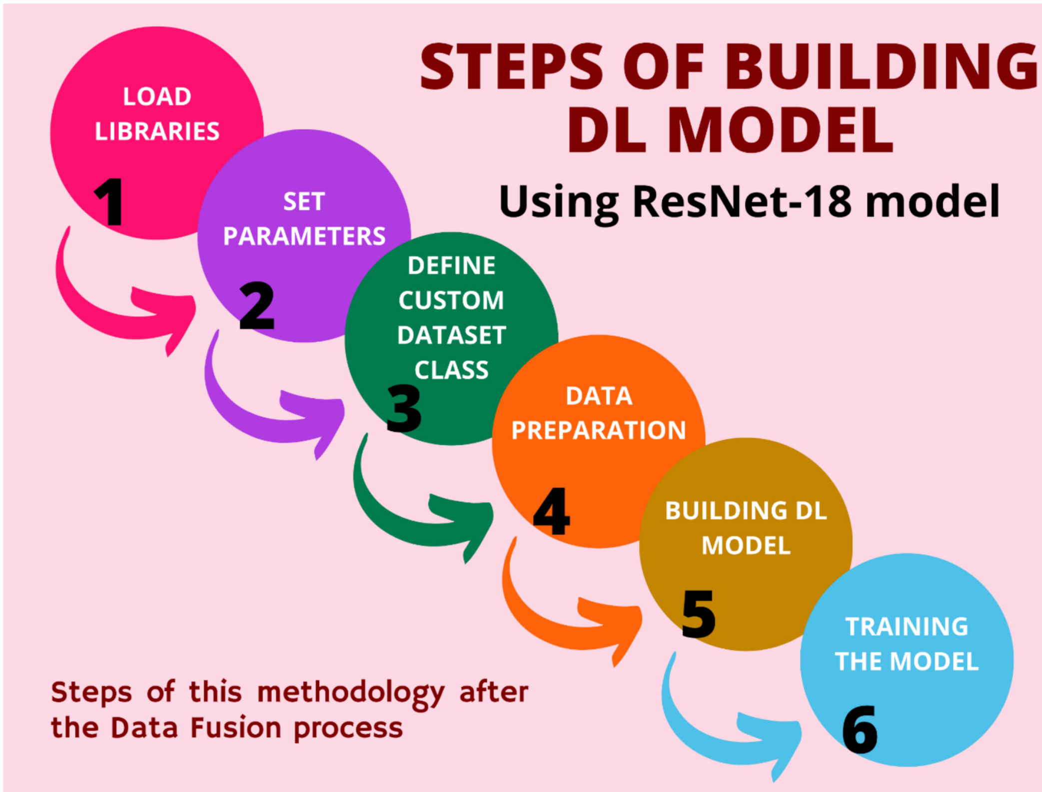


Fig. 4. Methodology steps for building the DL model.

3.3. Building the DL model

This methodology outlines how to identify fish freshness via a deep learning procedure. The proposed fish freshness classification algorithm was developed and executed via Python programming on Google Colab (https://colab.research.google.com). Using Google Colab with GPUs for provision is an accessible platform that helps shell out large datasets and deep learning models for training. Python's library lists were used for data preprocessing, machine learning, and deep learning, and tools such as TensorFlow and PyTorch were used for development and training of the model. This setup allowed us to build, train, and evaluate the ResNet-based model in a scalable and flexible environment.

The methods used in this study are grouped into data gathering, data preparation, model development, and model assessment. This approach applies the classification mechanism by using the ResNet-18 model to categorize fresh and nonfresh fish images (see Fig. 4).

1. Load Libraries:

The first part of the process encompasses the importing of relevant libraries such as data handling, visualization, preprocessing, training, and assessment. The main libraries used are dataframes, numerical operations, images, and deep learning frameworks libraries. These libraries help in efficient data handling and data visualization for building and evaluating the models.

2. Set parameters:

The parameters, which include the batch size, mode of the device, and category of the label, are stated. These constants assist in enabling and the way that the model is trained. The device configuration guarantees that the model takes advantage of the GPU if available, which greatly decreases the training time.

3. Define custom dataset class:

For the image data and annotations, a custom dataset class is defined. This class consists of precursors for loading or otherwise preparing images and functions for acquiring images with labels. It orders the loading of the data and aligns each image with its appropriate label, making it easy to train the deeper learning model.

4. Data Preparation:

The dataset is prepared into training and validation sets for better measurement of the model's efficiency.

In addition to resizing, normalization and augmentation are also performed on the data to improve the model's accuracy/generalization. Resizing normalizes the input size and can be used as a data generator, normalization scales the pixel values of the images and augments the number of available pictures by flipping them, rotating, changing their color balance, and applying random distortions.

5. Building the Deep Learning Model:

The structure of the deep learning model is based on ResNet-18, which is a convolutional neural network considered to demonstrate excellent feature extraction performance. This means that the model is refined according to the task of classification of the two classes, namely, 'fresh' and 'nonfresh' fish.

Furthermore, ResNet-18 is trained using the pretrained weights, as it helps in utilizing the features learned from a large dataset. This transfer learning approach enhances the performance of a model and simultaneously decreases the time taken to train the model. The last layer is consequently altered depending on the number of output classes in the fish freshness classification task.

The final layer configuration is as follows:

- Fully connected layer with 256 units and ReLU activation
- Dropout layer with a rate of 0.5 for regularization
- Output layer with units matching the number of classes (2)

Hyperparameters:

- Batch size: 128 (GPU memory constraints)
- Learning rate: 0.001, optimized with the Adam optimizer
- Epochs: 10
- Loss Function: Cross-entropy loss, which is suitable for multiclass classification
- Data Augmentation: Resizing to 224×224, along with transformations such as random rotation, flipping, and cropping

6. Model training:

During model training, categories include the loss function, the optimizer, and the learning rate schedule. The loss function quantifies the difference between the predicted and actual labels or the extent of the error, which drives the search process. The optimizer fine tunes the model's parameters by reducing the loss function, and on the other hand, the learning rate scheduler increases the stability of the training phase.

In the training phase, the specifics of the model being fitted are adjusted via the training data. An epoch is multiple passes of the image through the model when the model receives the image batch, computes its loss, and updates the parameters. The continuous training loop also includes validation steps and thus the fit of the model to the trained data.

3.4. Model evaluation

Once the training is complete, the model is tested on the validator operation to check for possible performance. The evaluation of the results involves the use of measures such as accuracy, a confusion matrix, and a classification report. Oversampling techniques help address the problem of class imbalance, and the confusion matrix offers a way of presenting true and false predictions of classes. The two primary metrics used in the classification report are precision and recall, whereas the F1 score provides a measure of the model's classification capability.

In this way, the evaluation metrics serve to determine the peculiarities of the model and the areas requiring further enhancement. The confusion matrix is presented in the form of a heatmap to make it easier to analyze the results in the next section.

4. Results

The experiments for the framework using the deep learning model for fish freshness detection were performed for ten successive epochs. The entire dataset included 16,640 images and was split into a training set and a validation (70%, 15%, 15%) set to obtain a good estimate of the model performance.

Fig. 5 shows that in the first epoch, the training accuracy reached 82.74%, whereas the validation accuracy of the same model was 89.60%. Training was completed with a loss equal to 0.3586, and the validation loss was 0.2444. This means that, from the beginning, the model was able to obtain meaningful information from the dataset. The relatively high validation accuracy indicates that the model performed well in generalizing to new unseen data even in the early epochs of training.

The training accuracy at the end of the third epoch was 91.05% for the training data and approximately 90% for the validation data. The training loss decreased to 0.1964, and the validation loss decreased to 0.1923. The results of the model increased gradually, which demonstrated that learning and generalization are feasible. The fact that the accuracy increases and the loss values decrease shows that the weights of the model are being properly updated and that the model is learning more complex patterns of the images.

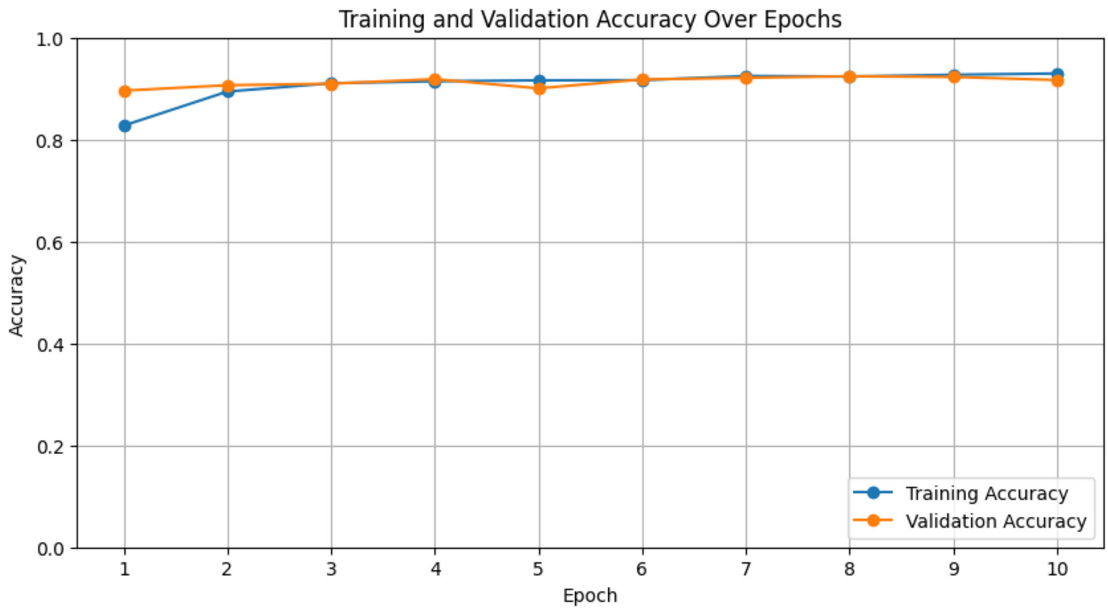


Fig. 5. Training and validation over epochs.

The training accuracy reached 92.96% by the ninth epoch, and the validation accuracy of the model was 91.68%. Similarly, the corresponding losses were 0.1517 for training and 0.1748 for validation. Although there was a slight increase in the validation loss toward the last epoch, overfitting was minimal, whereas the validation accuracy was high during the best epoch. The values of the training loss also decrease, which indicates that the model can fit the training data well, as evidenced by the high training accuracy (see Figs. 6 and 7).

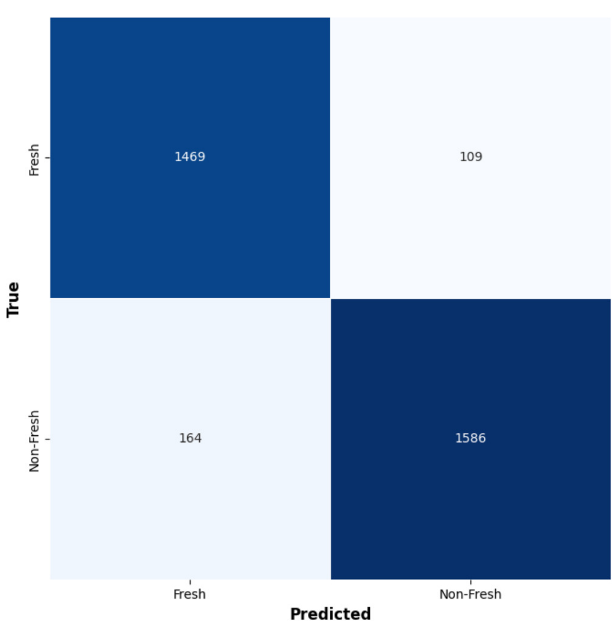


Fig. 6. Confusion matrix for test validation.

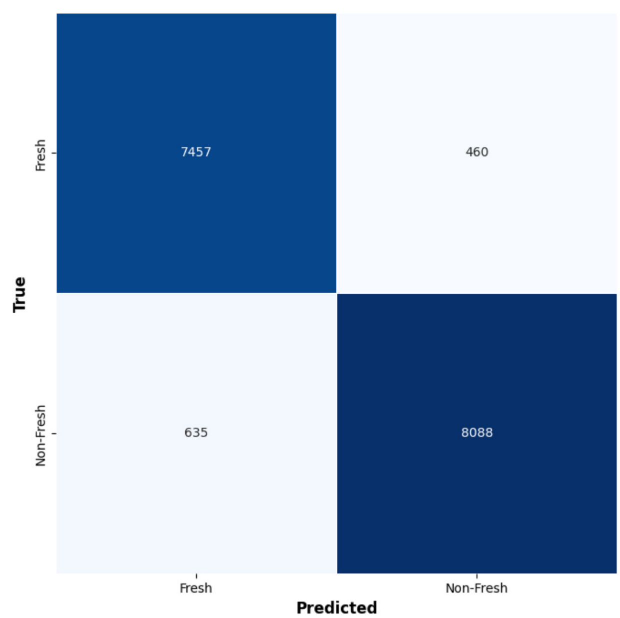
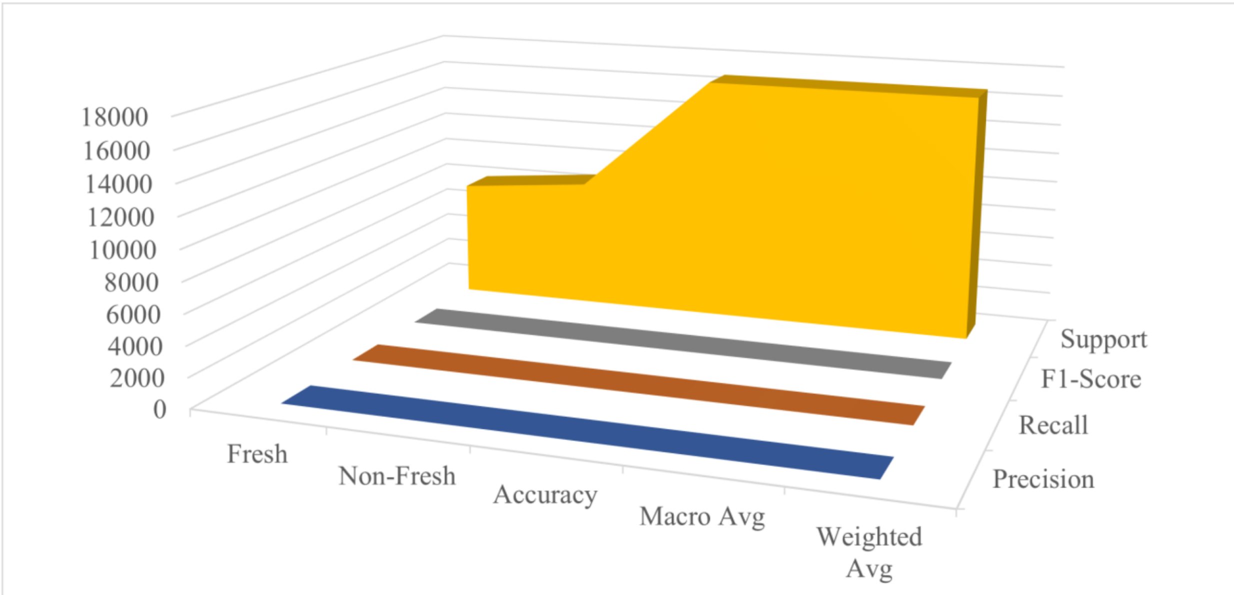


Fig. 7. Overall confusion matrix.

The final balanced accuracy on the validation set was 91. 86, which shows that the model considered in this work has a high level of effectiveness in working with imbalanced classes. This is especially true in cases where the dataset has class imbalance problems; the system should show a fair level of accuracy for all the classes. For the test set, the balanced accuracy level was 93.46%, which reflects the position that has been found to be proficient in unseen data in the model. This high balanced accuracy shows that the



	Fresh	Non-Fresh	Accuracy	Macro Avg	Weighted Avg
Precision	0.92	0.95		0.93	0.93
Recall	0.94	0.93		0.93	0.93
F1-Score	0.93	0.94	0.93	0.93	0.93
Support	7917	8723	16640	16640	16640

Precision Recall F1-Score Support

Fig. 8. Results of classification report.

model has the ability to generalize accurately to the test set as well as to other different sets of data.

For the classification report, the precision and recall rates of the 'Fresh' class were 90%, 93%, and 91%, respectively, and those of the 'Non-Fresh' class were 94%, 91%, and 92%, respectively (see Fig. 8).

The general accuracy obtained was 93%, with a macro- and weighted average F1 score of 93%, confirming that the performance of the two classes was equally good.

The values for the precision, recall and F1 score of the 'Fresh' class were 92%, 94%, and 93%, respectively, whereas those for the 'Non-Fresh' class were 95%, 93%, and 94%, respectively.

The overall accuracy was calculated to be 93%, and the macro- and weighted average F1-scores were also 93%, indicating that the model does not lose its efficiency during other evaluation procedures, as the values of all the metrics are high.

The high level of precision and therefore the recall values for the two classes indicate that the model worked well in discriminating "Fresh" from "Non Fresh' fish images. Precision values above 0. 90 shows that the specificity level is high, hence suggesting that the model rarely misclassified images as being 'Non-Fresh' when, in the actual sense, it is 'Fresh'. A high recall value means that false-negative errors are low, which ensures that a model correctly distinguishes most of the 'Fresh' or 'Non-Fresh' images.

To further illustrate, Fig. 9 shows examples of correctly classified images and misclassified images to provide further examples of what the model was able to do. These visual examples of some of the issues with the model, as well as in general, provide insight into the model's strengths and weaknesses. The model is able to identify freshness or non freshness associated with features such as texture, color and shape. The misclassified images, however, may show edge cases, that is, cases where the fish images are ambiguous or where external factors, such as lighting or background variations, influence the classification.

The fact that the values of the three performance metrics do not deteriorate when moving to the test set shows that the model performs well on the data. This is especially important for the growth of the model for actual real-life use in the seafood industry, where the model is presented with a number of images. The slight differences between the training accuracy

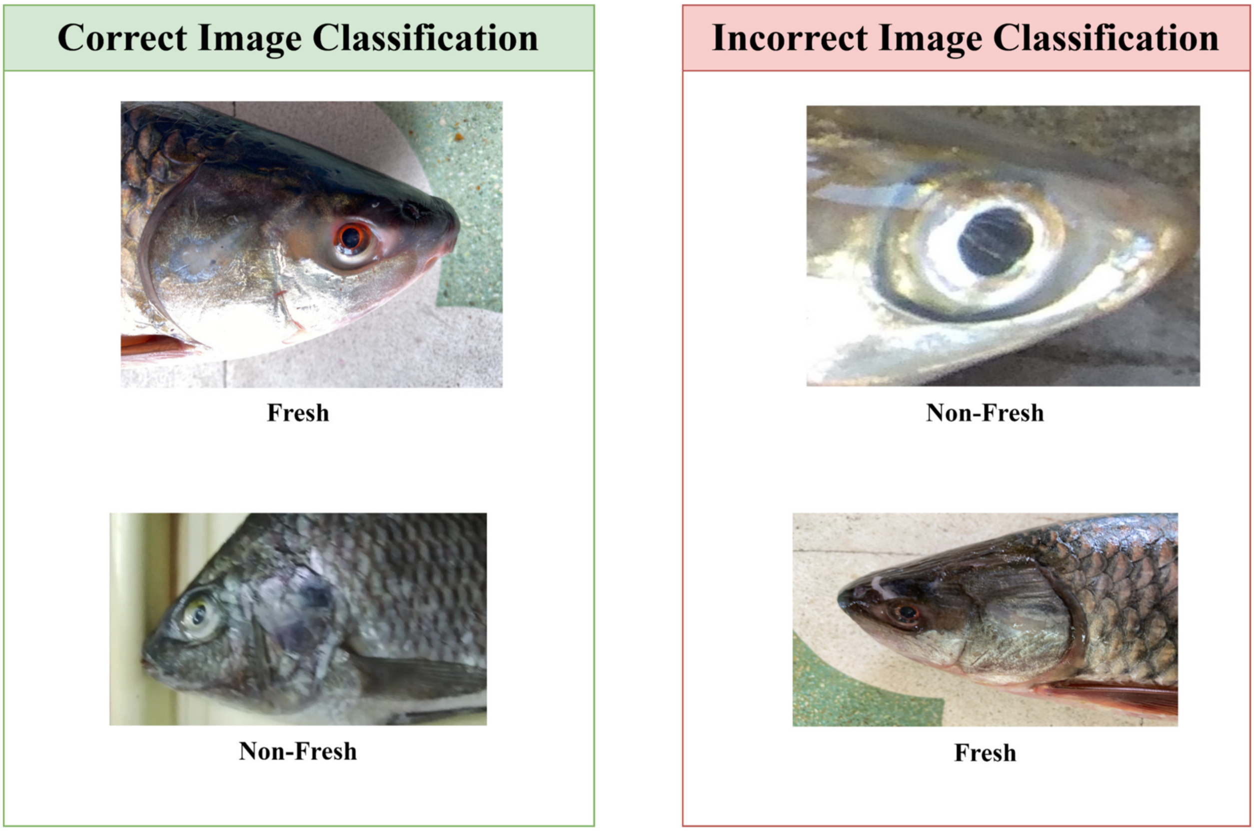


Fig. 9. Examples of classification.

and validation accuracy as well as training loss and validation loss show that the model does not overfit and is capable of good generalization.

On the basis of the analysis of the findings, the proposed ResNet-18-based deep learning model performs well in predicting the freshness level of fish. High accuracy, precision, recall, and F1-scores were obtained across the training, validation and testing datasets, which test the reliability of the model. In this way, this approach can significantly improve the classification of fish freshness and create a useful tool for the fish industry to maximize the quality of products and protect consumers.

By achieving almost equal accuracy, having consistent classification report metrics and through the detailed performance analysis, it can be concluded that the proposed model should be suitable for real-life use. The approach of performing transfer learning from a pretrained network, specifically ResNet-18, in addition to the data preprocessing and augmentation strategies explained above, guarantees that the model has reasonably good accuracy and reasonable inference time complexity. For this reason, it is a practical tool for implementation on a large scale in the seafood sector, as it may revolutionize quality assurance and consumer protection.

5. Conclusion and future work

In this study, we present an innovative method for classifying fish freshness on the basis of the combination of image data fusion and the ResNet deep learning model. Traditional methods of evaluating fish freshness usually rely on subjectiveness, time consumption and difficulty in interference by human factors. This research addresses these limitations by leveraging the robust feature extraction capabilities of the ResNet model. The model is trained to predict complex features indicative of freshness with precision, recall and F1 scores very high on the training set, validation set and test set (both are derived from two independent sources). These high-performance metrics show that the proposed model generates reliable results in discriminating fresh from nonfresh fish, with much lower rates of false positives and false negatives, demonstrating its suitability for real-world usage.

An added value of this study is its unique data fusion with a deep learning approach for improving classification accuracy and generalizability. Through aggregation of diverged image data, the approach ensures maximal model robustness against variations in lighting, orientation and fish species, which are required in dynamic real-world settings. This integration represents a major jump from data that only use a single source of data, which can work well for some contexts but cannot generalize well in other environments. The proposed method, therefore, not only improves food safety and consumer confidence but also minimizes product waste and is linked to economic efficiency and environmental sustainability in the seafood supply chain.

Future work in this area will explore further data modalities, such as spectroscopic or sensor-based data, for additional information to further improve classification accuracy. Field testing within seafood processing facilities would also enable simulation of model performance under operational conditions and identification of improvements to enable real-time use. This framework could be expanded to classify other perishable food products ranging from other perishable food products and could be used as a broader and comprehensive tool for the food industry. In addition, this research not only establishes a foundation for the improved classification of fish freshness but also shows the potential of AI-based solutions to contribute to industry efforts to improve food quality and safety standards.

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Conflicts of interest

The authors declare no conflict of interest.

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