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Fish Freshness Detection Through Artificial Intelligence Approaches: A Comprehensive Study

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ABSTRACT

Fish is regarded as an important protein source in human nutrition due to its high concentration of omega-3 fatty acids In traditional global cuisine, fish holds a prominent position, with seafood restaurants, fish markets, and eateries serving as popular venues for fish consumption. However, it is imperative to preserve fish freshness as improper storage can lead to rapid spoilage, posing risks of potential foodborne illnesses. To address this concern, artificial intelligence techniques have been utilized to evaluate fish freshness, introducing a deep learning and machine learning approach. Leveraging a dataset of 4476 fish images, this study conducted feature extraction using three transfer learning models (MobileNetV2, Xception, VGG16) and applied four machine learning algorithms (SVM, LR, ANN, RF) for classification. The synergy of Xception and MobileNetV2 with SVM and LR algorithms achieved a 100% success rate, highlighting the effectiveness of machine learning in preventing foodborne illness and preserving the taste and quality of fish products, especially in mass production facilities.

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Introduction

Fish and other seafood are the most important basic component of a balanced and healthy diet and provide numerous nutritional benefits It is a rich source of vitamins and minerals, which makes it an important part of a healthy lifestyle. Fish is known for its easy digestibility and lower fat content compared to other high-protein foods. It is indicated that omega-3 fatty acids are beneficial in preventing and treating various diseases, including heart diseases, cancer, diabetes, and high blood pressure. Seafood is the only proven source of the healthful n-3s, eicosapentaenoic acid and docosahexaenoic acid, which are crucial for mental and cardiovascular health (Dighriri et al., 2022; Innes & Calder, 2020; Sweeney et al., 2023). Therefore, consuming fish is recommended as an essential component of a healthy lifestyle.

When consuming fish, it is important to prioritise fresh and quality products to ensure food safety (Jennings et al., 2016). Consumers should obtain fish from reliable sources, check for freshness when making purchases, and store them appropriately. Similarly, individuals working in the fish processing and distribution sector must adhere to hygienic standards and ensure proper storage conditions. Moreover, improper storage of fish can cause rapid loss of freshness, leading to the growth of microorganisms. Consuming contaminated food can lead to digestive system disorders, food poisoning, and serious health issues. To ensure the safety and quality of perishable food products, technology and machine learning advancements are being utilized for more reliable results.

The identification of the body parts of the fish, especially the gills and eyes of the fish, is important in species identification, and the observation of colour changes in various colour spaces is important in determining the freshness of the fish as well as species identification (Dutta et al., 2016; Zhang et al., 2003). The classification of fish has become a pivotal focus with the advancement of machine learning. In the literature, Kristian Muri Knausgard and his team used the “YOLO” object detection technique on a public dataset called Fish4Knowledge

For temperate fish detection, using a pre-training model, they achieved a successful result with an accuracy of 99.27%. (Knausgård et al., 2022). Chhabra et al. (2020) developed a two-stage system to detect eight different fish species. In the first stage, morphological images were obtained from the images using the VGG16 model. Experimental evaluations were made with machine learning algorithms such as kNN (k-Nearest Neighbors), SVM (Support Vector Machines), and RF (Random Forest) and Tree. As a result, they reported that they achieved a high performance of 93.8% in the classification of fish species (Chhabra et al., 2020). Kaya et al. (2017) performed machine learning based classification by extracting features based on shape, colour and texture from Fish4Knowledge dataset to detect three different fish species. In experimental evaluations, they reported that they achieved a high performance of 98.8% with ANN (Kaya et al., 2017). Ou et al. (2023) proposed a two-stage study to identify the species of tuna caught in the high seas of China. In the first stage, morphological expressions were obtained from images using VGG16 and GLCM model. Afterwards experimental evaluations were made with the SVM machine learning algorithm and as a result, they reported that they achieved a high performance of 95% in classifying the species of tuna (Ou et al., 2023). Lanjewar and Panchbhai (2023) balanced two merged but highly imbalanced datasets from Kaggle using SMOTEENN and Random Under Sampler methods. They then used NasNet (Neural Architecture Search Network)and LSTM (Long Short-Term Memory) models to extract features from the images and reported that they applied a feature selection technique to determine the most appropriate features. As a result, they reported that the proposed NasNet-LSTM approach achieved impressive Matthew correlation coefficient (MCC) and Cohen's kappa coefficient (KC) scores of 99.1% (Lanjewar & Panchbhai, 2023).Yasin et al. (2023) using a dataset consisting of 4476 fish body images classified as fresh and stale, SVM (Support Vector Machines), ANN (Artificial Neural Networks), and LR (Logistic Regression) models from deep learning algorithms to classify fish according to their freshness resulted in 100% accuracy for each deep learning method (Yasin et al., 2023).

Fish eyes and gills can be distinguished by evaluating the colour degradation in different spectrums. Fish gills can also be grouped for segmentation purposes. Various image processing techniques are available for segmenting fish gills based on colour degradation or clustering (Alkaff & Prasetiyo, 2022; Jany Arman et al., 2022; Kunjulakshmi et al., 2020; Lalabadi et al., 2020). The freshness of fish can be determined through sensory, chemical, microbiological, and physical methods. Image-based analysis tools can accurately assess fish freshness well before the onset of microbiological and chemical spoilage, as well as food spoilage or cold chain breakage. Fresh fish have transparent, bright, almost protruding eyes, whereas the eyes of stale fish collapse and the colour fades. As well as the eyes, the gills are also important in determining the freshness of the fish. Fresh fish gills are bright red or pink and free of mucus. Stale fish is indicated by pale colours such as grey, brown, or green and gills with a mucus layer (Parkes et al., 2010). The objective of this study is to identify distortions in various structures, such as gills and eyes, in fish images as an indicator of fish deterioration. This will be achieved by using different artificial intelligence-based methods that are efficient and accurate.

In our study, we aimed demonstrating the effectiveness of a feature descriptor derived from data generated by pre-trained models, specifically using the VGG16 with a transfer learning strategy and MobileNetV2, Xception and AlexNet. Then, the classification of fish freshness status based on morphological features extracted by SVM, LR, ANN and RF machine learning algorithms was performed.

The contributions of the proposed system can be listed as follows:

- A high-performance and efficient system for classifying fish freshness images.
- Feature extraction from the images was conducted using MobileNetV2, Xception, and VGG16 algorithms.
- Four different algorithms, Support Vector Machine (SVM), Logistic Regression (LR), Artificial Neural Network (ANN) and RandomForest (RF), were used for classification.
- Proposed is an intelligent system that categorizes fish freshness by considering specific image features.
- The proposed system has done the classification of fish freshness with less equipment instead of using special and costly imaging devices.
- Fast, reliable and robust classification of fish freshness has been achieved.

Material and Method

The "Fish Freshness Classification" dataset, available on the public "Kaggle" platform (Rayan et al., 2021), comprises 4476 images capturing fresh and stale fish from various angles. The fish images have a resolution of 224x224 pixels. Distinguishing features include bright skin and pupils for fresh fish, whereas stale fish exhibit pale skin and pupils. Images of the data set are presented in Figure 1.

The dataset has been split using three different methods. The first one involves a 70% training and 30% testing data split, the second one uses an 80% training and 20% testing split. Additionally, the data has been divided using k-fold cross-validation with k=10. Model training was performed using pre-trained architectures, specifically employing three different transfer learning architectures: MobileNetV2, Xception, and VGG16.

MobileNetV2 represents the second iteration of MobileNet, a lightweight and fast deep learning model developed by Google's research team and introduced in 2018 (Sandler et al., 2018). MobileNetV2 aims to improve the performance of deep neural networks that can be used on mobile devices and other resource-constrained environments. The primary goal of the model is to make deep network architectures lighter and faster to achieve high accuracy. MobileNetV2 is designed to address certain weaknesses of its predecessor MobileNet and further improve its performance. One of the key features of MobileNetV2 is the use of "inverted residue" blocks. These blocks enable the construction of deeper models with lower computational costs compared to traditional residual blocks. In addition, another notable feature is the inclusion of "linear bottlenecks" that allow the model to carry more information with less computation (Sandler et al., 2018). MobileNetV2 architecture is presented in Figure 2.

Fresh Fish Stale Fish

Figure 1. Fish Freshness Classification Datasets

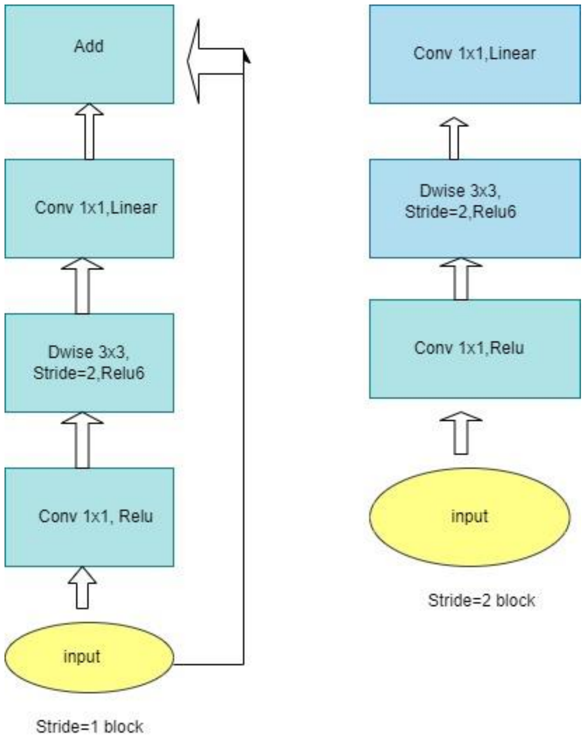

Figure 2. MobileNetV2 Architecture.

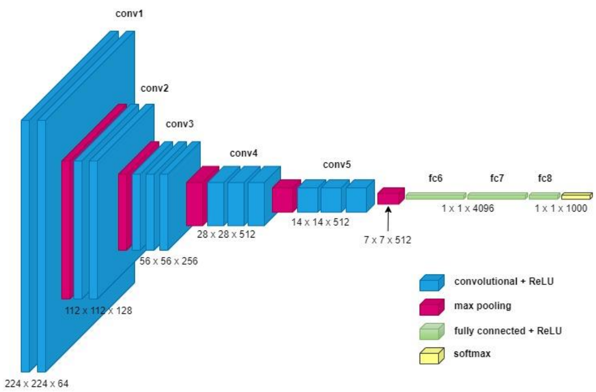

Figure 3. VGG16 Architecture

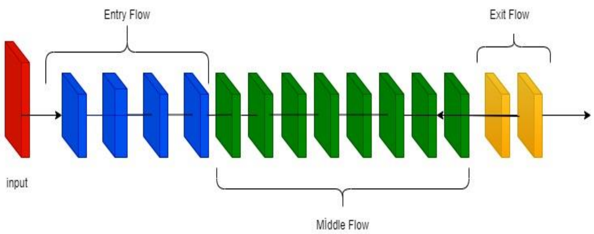

Figure 4. Xception Architecture

VGG16 is a deep learning model developed by Oxford University's Visual Geometry Group (VGG) and launched in 2014 (Simonyan & Zisserman, 2014). It is used for image classification tasks and consists of numerous convolutional and fully connected layers. The model's architecture is inspired by earlier works and predominantly utilizes small-sized filters with a dimension of 3x3. The model's architecture is inspired by earlier works and predominantly utilizes small-sized filters with a dimension of 3×3. The main objective of VGG16 is to investigate deeper and more intricate network architectures in order to attain superior performance.

To improve performance, the VGG team designed VGG16 with a more complex structure consisting of 16 layers, surpassing previous deep neural network models. This increased number of layers has resulted in higher representational power (Simonyan & Zisserman, 2014). The input image is rescaled to 224x224 pixels and then passed through a feature extraction network that consists of consecutive convolutional and pooling layers. Afterward, it connects to a classification network composed of fully connected layers. The VGG16 architecture is shown in Figure 3.

In 2016, Google's research team developed Xception, a deep learning model that combines the concepts of 'Extreme Inception' with the Inception architecture of the GoogLeNet deep neural network to enhance architectural design concepts. Employing "depthwise separable convolutions," it addresses computational costs in deep neural networks through a two-stage process: depthwise convolution applied separately to each input channel, reducing computational expenses, and pointwise convolution combining outputs with 1x1-sized filters to learn relationships between channels. This structure enables Xception to present a more streamlined model with reduced parameters and computational costs, showcasing proficiency in understanding deeper and more complex features. Demonstrating excellence in ImageNet classification tasks, Xception has become a foundational model applicable to various tasks, contributing significantly to the evolution of effective and efficient model designs in deep learning (Chollet, 2017). Figure 4 presents the Xception architecture.

Before initiating the model training, feature extraction was implemented using transfer learning models, a crucial process in image recognition aimed at representing and distinguishing objects within images. This step is pivotal for achieving accurate image classification. Feature extraction has three primary purposes: enhancing classifier performance by reducing classification time, improving efficiency by minimizing the amount of processed data, and bolstering the reliability of the recognition system. The goal is to ensure that the extracted features remain stable and unaffected by uncontrollable parameters of the system, enabling generalizability and enhancing the system's ability to make precise decisions (Türkoğlu & Arslan, 2002).

Feature extraction, a crucial step in image processing, involves two main approaches: manual design or automatic learning of features. Manual methods rely on heuristic techniques, using specific visual attributes like edges or color histograms, benefiting from expert knowledge for effective representation. However, manual design may struggle with complex visual structures. In contrast, automatic machine learning, often implemented with deep learning models such as CNNs, aims to automatically learn features from the dataset, demonstrating the capability to represent intricate and high-level features. This approach is preferred for superior classification performance. During feature extraction, selected features must effectively represent objects for the classification task, capturing diverse aspects like shapes and colors. Following this stage, the model is trained using various machine learning algorithms, such as Random Forest, Logistic Regression, Support Vector Machine, and Artificial Neural Networks, each with specific parameters (Barreiro et al., 2018).

Experimental Evaluations

The experimental evaluation involved classifying fish freshness through feature extraction using three transfer learning methods. Table 1 displays the results of the features extracted using the transfer learning methods MobileNetV2, Xception, and VGG16, and the machine learning methods SVM, LR, ANN, and RF. All experiments were conducted using K-fold:10, split 70:30 and 80:20. The experimental performances were evaluated based on the accuracy, precision, recall, and F-score criteria.

Table 1. Results obtained using k-fold=10 and MobileNetV2.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9993	0.9989	0.9995	0.9992
Logistic Regression	0.9989	0.9995	0.9978	0.9987
SVM+Lineer	0.9949	0.9989	0.9989	0.9939
ANN	0.9986	0.9990	0.9979	0.9984

Table 2. Results obtained using 70% Training, 30% Test and MobileNetV2.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9978	1.00	0.9945	0.9972
Logistic Regression	0.9978	1.00	0.9945	0.9972
SVM+Lineer	0.9933	0.9891	0.9945	0.9918
ANN	0.9989	1.00	0.9973	0.9986

Table 3. Results obtained using 80% Training, 20% Test and MobileNetV2.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9978	1.00	0.9945	0.9973
Logistic Regression	0.9978	0.9945	0.9945	0.9973
SVM+Lineer	0.9933	0.9891	0.9945	0.9918
ANN	0.9989	1.00	0.9973	0.9986

Table 4. Results obtained using 70% Training, 30% Test and Xception.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9985	0.9982	0.9982	0.9982
Logistic Regression	1.00	1.00	1.00	1.00
SVM+Lineer	1.00	1.00	1.00	1.00
ANN	0.9985	0.9982	0.9982	0.9982

Table 5. Results obtained using 80% Training, 20% Test and Xception.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9989	1.0	0.9973	0.9986
Logistic Regression	0.9989	0.9973	1.00	0.9986
SVM+Lineer	1.00	1.00	1.00	1.00
ANN	0.9245	0.9317	0.9441	0.9374

Table 6. Results obtained using 70% Training, 30% Test and VGG16.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9963	0.9927	0.9982	0.9954
Logistic Regression	0.9985	0.9963	1.00	0.9981
SVM+Lineer	0.9784	0.9981	0.9486	0.9727
ANN	0.9926	0.9855	0.9963	0.9909

Table 7. Results obtained using 80% Training, 20% Test and VGG16.

Algoritma	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9933	0.9891	0.9945	0.9918
Logistic Regression	0.9989	0.9973	1.00	0.9986
SVM+Lineer	0.9787	0.9971	0.9508	0.9734
ANN	0.9923	0.9812	1.00	0.9905

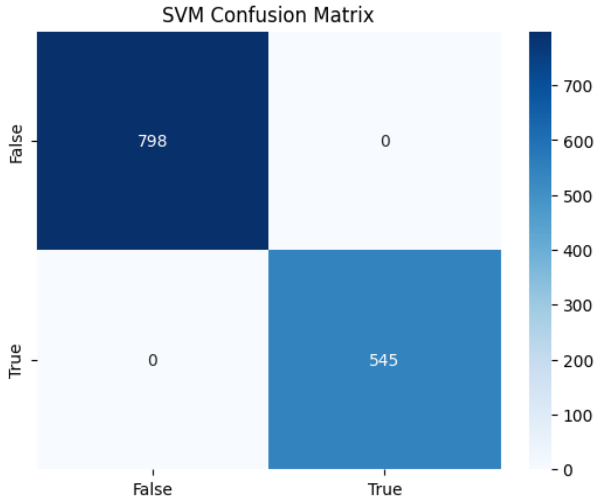

Figure 5. Confusion Matrix of the Most Successful Application (SVM) 70% Training, 30% Test with Xception algorithm

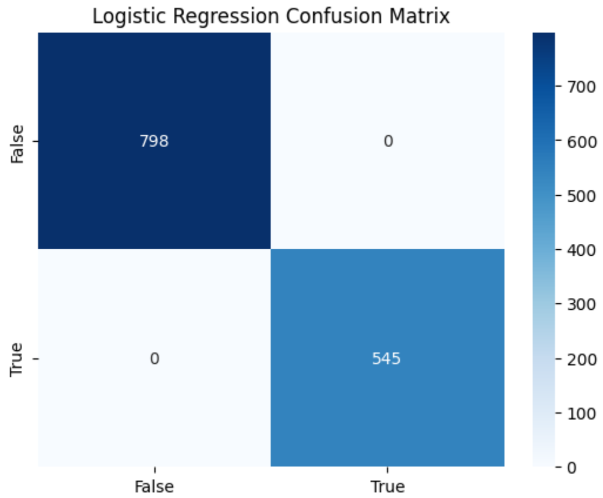

Figure 6. Confusion Matrix of the Most Successful Application (LR) 70% Training, 30% Test with Xception algorithm

The tables display the performance metrics of several machine learning algorithms, such as Random Forest, Logistic Regression, SVM with a linear kernel, and ANN, using different training and test datasets and two deep learning models (MobileNetV2, Xception, and VGG16) for image classification.

In Table 1, where k-fold cross-validation with k=10 is employed using MobileNetV2, all algorithms demonstrate high accuracy, precision, recall, and F1-score, with Random Forest achieving particularly 99.93% results. Tables 2 and 3 show results with 70% and 80% training data, respectively, using MobileNetV2. The algorithms consistently perform well, with only slight metric variations between the two configurations. Tables 4 and 5 show the results obtained using Xception. Logistic Regression, SVM and ANN achieved perfect scores in various metrics and showed excellent performance with 100%.

However, ANN shows a noticeable decrease in F1-score in Table 5. In Tables 6 and 7, results using VGG16 show that Random Forest and Logistic Regression consistently perform well across various metrics, while SVM shows a drop in performance in terms of recall. The different split parameters were compared to each other. ANN shows a decrease in accuracy, precision, recall, and F1-score in second training group (80% Training, 20% Test) when compared to first training group(70% Training, 30% Test). The highest accuracy value is achieved in Table 4, using the Xception architecture with 70% training and 30% test data. Logistic Regression, SVM+Linear, and ANN models achieved 100% accuracy in this table. In summary, the performance of machine learning algorithms is impacted by the choice of model (MobileNetV2, Xception, VGG16) and the distribution of training and test data. The presented models and configurations demonstrate high classification accuracy and robustness across different metrics. The confusion matrices according to the Xception method with the best success are given in Figures 5 and 6.

The Figure 5 and 6 provided confusion matrix corresponds to the evaluation of an SVM an LR models trained with a 70% dataset and tested on a 30% dataset using the Xception algorithm. The matrix exhibits exceptional performance, with 798 true negatives and 545 true positives, indicating accurate predictions of both negative and positive instances. Overall, the high true positive and true negative counts reflect the robustness and effectiveness of the SVM and LR models in its classification task, showcasing a successful application of the Xception algorithm in conjunction with a 70/30 training-testing split.

Conclusion

As machine learning and image processing technologies continue to advance, the field of object classification has gained significant importance. Feature extraction plays a crucial role in representing objects and can be accomplished through both automated learning methods and manually crafted features. Machine learning algorithms and deep learning models have emerged as the preferred approaches to achieve superior performance in object classification. The Xception architecture and multiple algorithms (Logistic Regression, SVM+Linear and ANN) with 70% training and 30% testing separation achieved 100% accuracy. Thus, in the context of the data provided, this particular combination of algorithm and architecture appears to produce the highest overall performance for object classification. The utilization of these algorithms proves effective in preventing the distribution of spoiled fish, particularly in high-production factories where the risk of defective products is elevated. Consequently, these technologies contribute to ensuring the quality and reliability of products reaching the customers.

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