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ORIGINAL PAPER

Detection of fish freshness using artificial intelligence methods

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Abstract
Fish is commonly acknowledged as a highly nutritious food in many regions worldwide, and humans have been consuming fish for centuries to meet their protein and nutritional requirements. The consumption of fresh fish offers numerous benefits, as they contain essential proteins and materials that may be challenging to obtain from alternative sources. However, the freshness of fish decreases after a few days. Humans can determine the freshness of fish by looking at its eyes, smelling it, and checking its gills. But, can machines do the same? This study proposes a novel approach to evaluate the freshness of fish using deep learning techniques. Despite the long-standing tradition of humans determining fish freshness by sensory analysis, the objective evaluation of fish freshness has been challenging. By employing deep learning algorithms (SqueezeNet and InceptionV3) to classify fish based on their freshness using a dataset of 4476 images of fish bodies categorized as fresh and stale, this study provides a new method to address this challenge. Analyzing the results of the study revealed that the SVM, ANN, and LR models result in an accuracy rate of 100% for each deep learning method. This outcome indicates a greater percentage than the previous research, which was 98.0%. This research's novelty lies in its application of deep learning techniques to determine fish freshness objectively, providing a reliable and cost-effective method to evaluate fish freshness. The significance of this study lies in its potential applications in the food industry, offering a reliable method for quality control and food safety.

Keywords Deep learning · Machine learning · Fish freshness · Transfer learning · Classification · Skin coloration · Fish body

Introduction

The main reasons behind the consumption of fish are its freshness, quality, and taste (Tomic et al. 2016). The consumer market has developed a preference for high-quality seafood products that are immune to diseases in recent years. In terms of safety, nutritional value, availability, freshness, storage, and processing methods play an important role in determining fish quality parameters. During the production, transportation, sale, and food preparation of fish, there are a number of factors that may affect the quality and freshness of the fish [1, 2]. Fish is a nutritious meal [3], Human wellness depends on its nutrients, vitamins, and proteins [4, 5]. Protein, omega-3 fatty acids, and vitamins (health benefits) are all found in this multi-nutrient food [6]. Since fish is economical and fresh, people tend to prefer it as a meal [7]. When fish is fresh, its nutritional quality increases. The result is that when consumers are shopping for fish, it is difficult for them to determine whether it is fresh or not. The flexibility of the fish's body can be determined by touching and squeezing it, and quickly decide the freshness of it. Normally fresh fish has higher elasticity. Unfortunately, utilizing this approach can result in the contamination of food with microorganisms, which can be harmful to fish and result in food-borne illnesses [8, 9]. A fish's quality can vary greatly depending on how it is handled, processed, and stored from the moment it is caught until it is eaten. For fish to maintain its highest quality after harvest, it must be kept at a specific temperature for a specific period of time [1]. Furthermore,

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with greater technical advancements, there have been attempts to create a way of measuring and assessing seafood freshness that is more dependable. The criteria used to determine freshness include sensory, physical, chemical, and microbiological. Rapid protein liquid chromatography and hyperspectral imaging techniques are also considered [5]. It is thought that fish's eye region has a strong relationship between its coloration and the period during which they are stored. As a result of these characteristics, the degree of freshness of the fish sample can be determined by observing how they deteriorate over time [10].

There are two primary sources of decomposition once it starts: biological spoilage and chemical spoiling [11]. As bacteria enter the fish's body through its gills, they degrade its tissues and organs. Due to chemical interactions, a chemical spoilage causes a disagreeable odor and also affects the flavor [12]. Fish spoilage refers to the process whereby the quality of fish is degraded, resulting in changes to its color, odor, taste, and texture of flesh. When pH and nitrogen substances are increased, microorganisms multiply, changing eyeballs, body surfaces, abdomens, and muscles after an initial spoilage stage [6, 13].

The changeover from fresh to stale is indicated by coloration in gills from brilliant pink to dark red or yellowish red. Generally speaking, freshness is determined by the changing color of the skin from a bright, shiny color to a faded color when it has lost its freshness. When compared to fish that is not fresh, fresh fish will have a shiny and bright skin, while fish that is not fresh will have a dull color and less shine. The freshness of fish is influenced by multiple factors, including the hue of its flesh. As the fish ages, the flesh's color shifts from cream to yellowish, brown, and ultimately blue, indicating the degree of freshness. This color variation is a key determinant of fish freshness [14].

The evaluation of fish freshness and quality is the paper's key objective. This is achieved by utilizing deep learning models. Training and testing of freshness are performed with images. The study utilized a dataset to determine how fish body color can be used as an indicator of freshness. The skin slime is initially clear and fluid, but as bacterial growth increases, it progressively turns murky and discolored [15]. AI subfields of deep learning method as well as a machine learning method have been used in this study in combination. Multiple pre-built models exist, and each has its own strengths and limitations that must be evaluated. Important considerations include the size of the model, its accuracy before retraining, and the rate at which it can predict new inputs. The significance of these aspects varies based on how the model is planned to be deployed. If you want to start with transfer learning, it is suggested that you opt for a faster network such as SqueezeNet or GoogLeNet and test out various options for data preprocessing and training. After finding the most effective settings, you can attempt using a more precise network like Inception-v3 or a ResNet to enhance your outcomes.

Our research employs SqueezeNet and InceptionV3 for conducting feature extraction on the images in our dataset. In the subsequent stage of the study, five machine learning algorithms are utilized to make predictions.

Related works

Following the development of machine learning, classification of fish becomes crucial [16]. Numerous studies have concentrated on identifying fish body parts, and one technique for segmenting fish gills and eyes is to observe the alteration in their color in various color spaces. This color shift of fish gills and eyes has been studied as a means of detecting these body parts [17], fish eyes and gills can be segmented based on the degradation of color in different colors [2], fish gills can be clustered to be segmented [1], and there are several image processing techniques that can be used to segment fish gills based on their color degradation or clustering [9, 18].

It was Muri Knausg˚ard et al. who applied the YOLO or You Only Look Once method to detect objects in their study. They employed a Convolutional Neural Network (CNN) within a Squeeze-and-Excitation (SE) architecture to grasp the characteristics of each fish in the image by implementing a Convolutional Neural Network (CNN) as part of the second phase of this process for the purpose of categorizing each fish without the need for pre-filtering of any kind. Due of the small number of temperate fish training data, transfer learning is used to increase classification accuracy [19]. They obtained the 99.27% of pre-training model accuracy and 83.68% and 87.74% in post-training model without augmentation of images in Fish4Knowledge public dataset.

Three squid species were identified using a deep learning model known as the "Improved faster recurrent convolutional neural network" by Hu et al. The three metrics that were utilized to evaluate the categorization were Accuracy, Intersection-over-Union, and Average Running Time. 600 pictures of the squid were taken on a uniform black background. The test samples' average values for Average Running Time, which is used to assess the categorization, are 85.7%, 80.1%, and 0.144 s, accordingly [20].

Prasetyo et al. proposed “You Only Look Once version 4 tiny (Yolov4-tiny)” which can recognize fish body sections with a fair amount of detection accuracy. Fish and Fish Parts Detection (FFPD) is a dataset consisting of 600 photos and 4486 annotations, from which it was determined that different models could perform better than Yolo-based research model when compared with it. The model's updated version is called WCL-Yolov4-tiny. According to experimental findings, Precision, Recall, AP, and mAP are, accordingly, 97.48%, 93.3%, 94.07%, and 92.38%. Using this model, it is possible to detect fishes in their entirety, their eyes, and their tails with more precision [9].

Wu et al. used a novel methodology called CNN_LSTM (convolutional neural network_ long short-term memory) that was able to determine freshness throughout a range of temperature changes. Since under specific constant temperature settings, there has previously been an attempt to forecast freshness for foods using microbial kinetic equations, but they stopped working when the temperature was changed [21].

The current work is the first to demonstrate the effectiveness of a feature descriptor that is based on data generated from pre-trained models, such as the VGG16, applying a transfer learning strategy and AlexNet [22–24]. Several deep learning methods, such as the Artificial Neural Network (ANN), are employed to categorize the characteristics after extraction [25–27], Convolution Neural Network (CNN) [28–32], Deep Learning Network (DLN) [23]. Numerous recent articles proposed employing support vector machines (SVM) and in addition to other machine learning approaches [33].

In this paper, Abu Rayan et al. suggested a mixed deep learning model-based technique for classifying fish freshness using image processing and Nile Tilapia as a model fish. This model for machine learning (ML) was constructed by extracting features based on the VGG-16 neural network architecture and bi-directional long short-term memory (LSTM) in addition to the suggested language set. When tested against the testing dataset, the suggested model has achieved 98% accuracy [34]. Fresh fish can be identified by their bright, black eyes, white skin, and undamaged fins, whereas stale fish have gray eyes, red skin, and a swollen belly, among other signs [34].

Dutta et al. proposed a method of image processing that does not cause damage to determine the level of freshness of the fish. To extract the characteristics of the fish's gill tissues in the wavelet transformation domain, the autosegmentation method is used to segment the gill tissues using a clustering-based method, and the Haar filter is then used to extract the tissue characteristics of the sample [1].

In their study by Atasoy et al., a fish freshness system was built using an electronic nose that was set up and had eight metal oxide gas sensors. In this study, Artificial Neural Networks (ANN) were utilized to accomplish the classification procedure. There are 7 classes to be classified. The highest success rate recorded was 98.94% [35].

To address the background variant problems on FC, Jany Arman et al. presented a fish classification method incorporating salient object recognition. SVM, K-NN, Logistic Regression, and Decision Tree ensemble layers significantly contribute to the classification of fishes. On model 1, the test result was 99.77%, while on model 2, it was 100% [16]

Issac et al. gave an automated and effective approach to perform segmentation of the gills in an image of a fish sample. The developed algorithm's greatest correlation with the expert-sourced ground truth findings was 92.4%. Imaging was performed over the next 13 days, with a two-day interval between each image taken after the sample had died. In total, four various species of fish were used in the experiment [36].

Kaladevi et al. proposed a deep learning methodology to improve the sardine fish's freshness detection precision. The dataset contains 1049 fresh by 1078 stale sardine fish images. DCNN was implemented and the performance metrics yielded the following results: The performance metrics for the model are as follows: precision of 99.5%, true positive rate of 96.2%, true negative rate of 92.3%, positive predictive value of 92.6%, negative predictive value of 96%, and F1 score of 94% [37].

The study presented Table 1, which compiles previously performed methods for detecting the freshness of fish. The table includes details such as the number of images used, the method of categorization, the techniques applied, and the resulting accuracy ratio, all of which were mentioned in the articles. Image number varies in each study with the class of images that have been used. In their study Abu Rayan et al. mentioned that other methods can be used an tried for the classification, this lets a new study objective and performing different AI methods for better results [38].

Table 1 Summary of fish freshness detection

No.	Images	Class	Method	ACC (%)	References
1	27,230	4	YOLO, CNN-SENet with SE	99.27	[19]
2	600	3	Improved Faster R-CNN	85.7	[20]
3	4486	3	Yolov4-tiny, WCL	94.07	[9]
4	102	-	CNN_LSTM, TVC	95.0	[21]
5	4000	2	VGG-16, Bi-directional LSTM	98.0	[38]
6	110	7	ANN	98.94	[35]
7	2678	5	U^2-net	99.77	[16]
8	2127	2	DCNN	99.5	[37]

Materials and methods

This study utilized algorithms of deep learning and machine learning to categorize a dataset of fish bodies based on their freshness. Figure 1 illustrates the workflow of the study, and the subsequent sections provide further details. The deep learning models used in this study were SqueezeNet, and InceptionV3. The freshness classification of fish was achieved by integrating machine learning techniques such as K-NN, SVM, ANN, LR, and RF with the models.

Fish body dataset

This study used a dataset from Kaggle consisting of images of fish [38]. Even though the previous study did not utilize all the images in the dataset, we opted to utilize the dataset in its original form, without any modifications. The dataset was separated into two categories, fresh and stale, and included a total of 4476 images. 2581 images were of fresh fish, while 1895 were of stale fish. The images were taken from 50 Nile Tilapia fish using a Sony Alpha A6000 camera with a 3.5–5.6/PZ 16-50 mm lens and APS-C sensors with 24.3 megapixels. Sample of images in the dataset presented in Fig. 2.

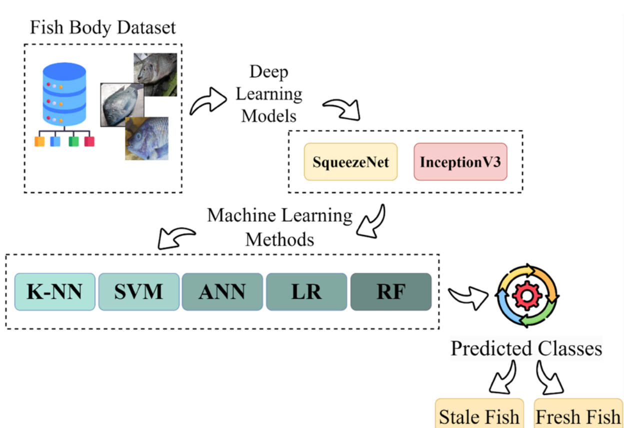

Fig. 1 Flow diagram of classification Models

Deep learning models

Convolutional Neural Networks (CNNs) are an artificial neural network architecture which is primarily designed for analyzing images. In an image, each pixel is represented by a numerical value that forms a matrix. When an image is input into the CNN, It is crucial to maintain the correlation between pixel values [39]. To transform the input into an output, the network applies multiple layers of mathematical operations. A CNN consists of three main operations: convolution, pooling, and classification [40–42]. The convolution operation is used in CNNs to detect features within the input images. The 2 models we are going to apply in this study are mentioned: SqueezeNet and InceptionV3 were utilized for feature extraction to determine the freshness of fish. Both models are pre-trained convolutional neural networks (CNNs) that have been widely used in image recognition tasks. The SqueezeNet model is a lightweight CNN that uses small filters to reduce the number of parameters while maintaining accuracy. The InceptionV3 model is a deeper CNN that employs multiple filters with different sizes and is capable of capturing features at different scales [43]. During feature extraction, each fish image was passed through the network, and the resulting features were extracted from the last pooling layer. InceptionV3 extracted 2048 features, while SqueezeNet extracted 1000 features. These features represent different characteristics of the image, such as color, texture, and shape, and can be used as input to train the machine learning models [44].

InceptionV3 has been pre-trained on a large dataset, making it an effective feature extraction method. It is designed to extract features from images at multiple scales, which makes it suitable for a variety of image recognition tasks [45]. The use of InceptionV3 for feature extraction in this study offers several benefits [46].

- Firstly, InceptionV3 has a large number of parameters, allowing it to extract a wide range of features from the input image. It is capable of capturing high-level features such as edges, corners, and curves, as well as more complex features such as textures and patterns. This makes

Fig. 2 Sample of Fish Body Dataset

it a powerful feature extraction method that can identify subtle differences between fresh and stale fish.

- Secondly, InceptionV3 is designed to be computationally efficient. It uses a combination of convolutional layers, pooling layers, and 1×1 convolutions to reduce the number of parameters and increase the efficiency of the network. This makes it suitable for use in applications with limited computational resources.
- Lastly, InceptionV3 has been extensively tested and used in various image recognition tasks, making it a well-established feature extraction method. This ensures that the extracted features are reliable and accurate, and that the resulting machine learning models are robust and effective.

The use of InceptionV3 as a feature extraction method in this study offers several benefits, including its ability to extract a wide range of features, computational efficiency, and reliability [45].

In this study, SqueezeNet was also used as a feature extraction method to determine the freshness of fish [47]. There are several benefits of using SqueezeNet as a feature extraction method:

- Firstly, SqueezeNet has a small number of parameters compared to other deep learning models. This makes it a lightweight network that can be easily deployed on resource-constrained devices, such as smartphones or embedded systems.
- Secondly, SqueezeNet uses a combination of 1×1 convolutions, which reduce the number of parameters, and fire modules, which capture features at different scales. This enables SqueezeNet to extract meaningful features from images while maintaining high accuracy.
- Thirdly, SqueezeNet was designed to be trained on small datasets, making it suitable for use in applications where only a limited number of training samples are available. In this study, SqueezeNet was able to extract 1000 features from the fish images, which were then used as input for machine learning models to classify fresh and stale fish.
- Finally, SqueezeNet has been widely used in various image recognition tasks, demonstrating its effectiveness as a feature extraction method. It has achieved state-of-the-art results on several image recognition benchmarks, including the ImageNet Large Scale Visual Recognition Challenge.

The use of SqueezeNet as a feature extraction method offers several benefits, including its lightweight architecture, ability to extract meaningful features, suitability for small datasets, and demonstrated effectiveness in image recognition tasks [46, 47].

After the feature extraction process, the extracted features from SqueezeNet and InceptionV3 were used to train five different machine learning (ML) models, including support vector machines (SVM), artificial neural networks (ANN), k-nearest neighbors (K-NN), logistic regression (LR), and random forest (RF) models. These ML models were trained to identify patterns in the extracted features that differentiate fresh fish from stale fish [48].

Machine learning algorithms

A type of algorithm that can perform particular tasks without explicit coding instructions from a human, and it is a branch of science that explores algorithms and statistical models in the context of computer programs is machine learning algorithm. These algorithms have various applications such as data mining, image processing, and predictive analytics. One of the significant benefits of machine learning is that once the algorithms learn how to handle data, they can perform their work automatically. In this research, five different algorithms were selected and employed for the classification process, and each algorithm's details are presented in the study.

(a) **K-NN:** In machine learning, this model is among the frequently used models. That is used for performing classification tasks, since it does not learn from training data, but memorizes them instead. To classify a new data point, the model looks for the closest neighbors of that data point. The value of k, representing neighbor's number, is computed during the algorithm's execution. The model then assigns the incoming test data point to the appropriate class based on its proximity to the k nearest neighbors [49–51].

(b) **SVM:** Support Vector Machines (SVMs) were initially developed for solving binary classification problems. The classification is achieved by applying a hyperplane that separates the data into two classes. However, when dealing with datasets that have multiple classes, more than one hyperplane is needed to perform the classification. In such cases, multi-class SVMs are used, which consist of SVM classifiers with multiple hyperplanes [40, 42].

(c) **ANN:** Typically, neural networks have three layers: an input layer that accepts the input data, a hidden layer that lies between the input and output layers, and an output layer that contains neurons equal to the number of classes in the problem. The model utilizes the input data to learn and generate predictions based on the interconnections between these layers [52]. The neural network model's architecture is based on the connections between its input, hidden, and output layers, which are improved through learning from data [51].

(d) **Logistic Regression:** Logic Regression, also known as Logistic Regression is a machine learning technique that allows for numerical or categorical classification of data. The process involves using the sigmoid function, also known as the logistic function, to describe the process. A normal distribution is not necessary for the LR algorithm if the objective can be inferred from one or more variables. Instead of predicting outcomes, LR predicts the probability of a given data point belonging to a certain category [40, 42, 53].

(e) **Random Forest:** There are a variety of classification algorithms, but the Random Forest (RF) algorithm is one that is made up of multiple Decision Trees, where each decision tree provides a classification for the input data. Based on these classifications, the RF algorithm determines which one is the most popular and creates a new classification. RF is able to handle large datasets with a high number of variables, and it is also highly effective at predicting missing data [54].

In this workout, these specific algorithms based on their popularity and effectiveness in similar image recognition tasks. Support Vector Machines (SVMs) and k-nearest neighbors (K-NN) are well-known and widely used classification algorithms that are often used in image recognition tasks. Artificial neural networks (ANNs) are also popular and effective for image recognition, while logistic regression (LR) is a simple and efficient classification algorithm that is often used as a baseline in machine learning tasks. Random forest (RF) is a powerful and versatile ensemble learning algorithm that has been used in a variety of image recognition tasks. The selection of these algorithms chosen based on their potential to provide accurate and reliable classification results for the task of fish freshness evaluation, as well as their effectiveness in similar tasks.

Cross-validation

Cross-validation is a technique that involves dividing data into subsets or "folds" for training and validation purposes. A common way to evaluate learning models is to use this method. During model training, to train a model, a set of datasets is split into a training set and a testing set, in which the training set is used for training, and the testing set is used for testing the model. Cross-validation, also known as K-fold, allows for the rotation of training and validation across multiple folds of the data. K-fold refers to the number of folds the dataset is divided into. Using cross-validation, it's possible to estimate model performance using unseen data that was not used during training. In this study, the dataset was partitioned into ten folds, as illustrated in Fig. 3.

The tenfold cross-validation used to evaluate the performance of the machine learning models used to determine fish freshness. This means that the available data were divided into 10 subsets, and the models were trained and evaluated 10 times, with each fold serving as the validation set once. The use of tenfold cross-validation provides several benefits. Firstly, it helps to reduce overfitting, which occurs when the model is too complex and fits the training data too closely, leading to poor performance on new data. Cross-validation allows the model to be evaluated on different subsets of the data, reducing the risk of overfitting. Secondly, tenfold cross-validation provides a more reliable

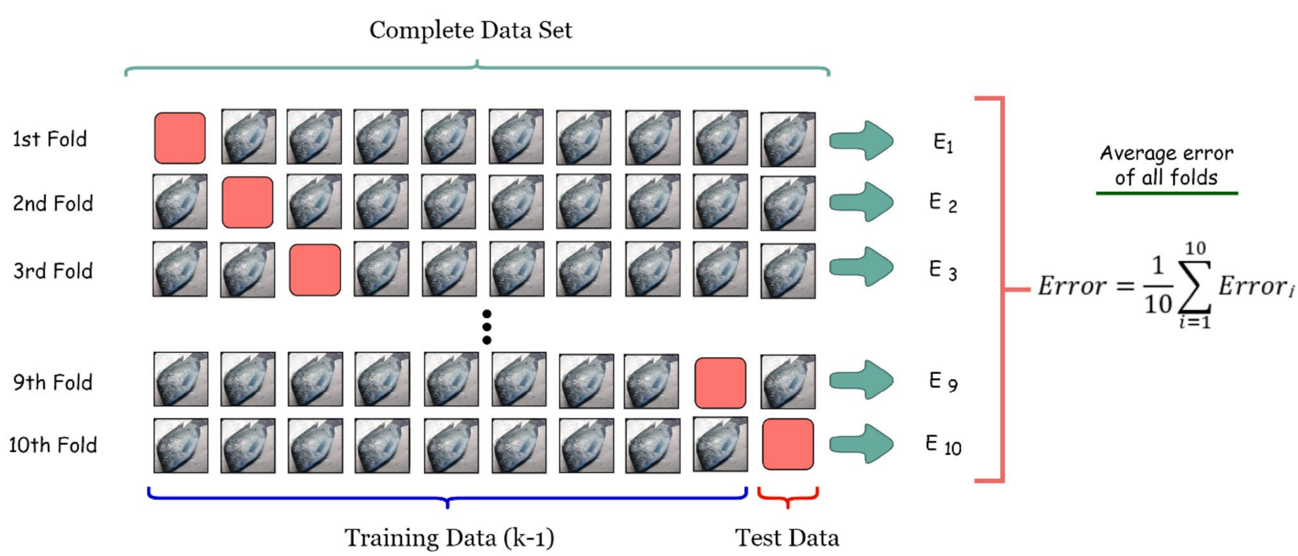

Fig. 3 The performance Fish body dataset cross validation

estimate of the model's performance than a single split of the data into training and testing sets. By averaging the results over multiple splits, the estimate of the model's performance is less affected by the specific choice of the training and testing sets [55].

The number of folds used in cross-validation can be adjusted based on the size of the dataset and the computational resources available. In general, a larger number of folds (such as tenfold or fivefold cross-validation) can provide a more reliable estimate of the model's performance, but it also requires more computational resources and longer training time. On the other hand, a smaller number of folds (such as twofold or threefold cross-validation) can be used when the dataset is large, or the computational resources are limited. However, a smaller number of folds may not provide a reliable estimate of the model's performance, especially when the dataset is small.

The choice of the number of folds should be based on the size and complexity of the dataset, as well as the computational resources available. The use of tenfold cross-validation in this study helps to ensure that the machine learning models used to determine fish freshness are reliable and accurate, by reducing the risk of overfitting and providing a more robust estimate of the models' performance [48].

Confusion matrix

Confusion matrices show how well a classification model performs by comparing predicted and actual values [56]. The following expressions can be used to derive the values present in a confusion matrix: Confusion matrices are a valuable resource for storing data related to the actual and expected classifications of a classification model. Typically, a matrix is employed to assess the model's performance, by providing the necessary data to calculate various performance metrics, including accuracy, precision, recall, and F-1 score, this can be computed from the measurements found in the confusion matrix. In Table 2, TP represents is correctly identified as Fresh fish and it was fresh actually, TN is correctly identified as not fresh fish and truly it was not fresh, FN is misidentified actually it was fresh but predicted as not fresh, and FP is misidentified as fresh fish but it was stale fish [49].

The accuracy measures the percentage of accurate predictions out of the total number of predictions. It is a widely used performance metric, but it may not always be the most appropriate measure of model performance, especially when the data are imbalanced or when the cost of misclassification is not equal for all classes [56–58].

Table 2 Confusion matrix for fresh fish classification

	Predicted	
	Fresh	Stale
Actual		
Fresh	TP	FN
Stale	FP	TN

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{TN} + \text{FN}) \times 100 \quad (1)$$

Precision measures the proportion of true positive predictions in relation to all the positive predictions produced by the model. It measures the ability of the model to correctly identify the positive class [56–58]. Formula for Precision:

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

An analysis of the recall of a dataset is also referred to as the sensitivity or the true positive rate, which is the percentage of true positive predictions in comparison to all the actual positive examples in the dataset. It measures the ability of the model to correctly identify the positive class [56–58].

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

F1 score is a statistical measure that combines precision and recall in a balanced way, utilizing the harmonic mean. It is frequently used as a sole performance metric to evaluate the efficacy of classification models [56–58]. Formula for F1 score:

$$F1 - \text{score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \quad (4)$$

Experimental results and discussions

Here's a summary of the outcomes obtained from employing deep learning methodologies to train convolutional neural network structures, including SqueezeNet, and InceptionV3. Orange data mining was utilized for creating the AI model designs in the suggested study. The research employed a computer running Windows 11 Enterprise version 22H2 equipped with an Intel® Core™ i7-870H processor clocked at 2.20 GHz and 16 GB of RAM. The computer's storage capacity included a 2 TB HDD and a 250 GB SSD, and it featured an NVIDIA GeForce GTX 1050 Ti graphics card. Table 3 displays the learning parameters utilized in the present study. The Orange data mining desktop software was utilized to develop a classification model. Different parameters were utilized for each machine learning algorithm and these values can be found in the table. The parameters for machine learning used in the study were chosen from the default parameters [59, 60] that are offered in the Orange Data Mining tool.

The dataset was extracted at first step and the features that were extracted and selected. After selecting and preparing

Table 3 Machine learning parameters in Orange

Models	k-NN	SVM	ANN	LR	RF
Parameters	Number of neighbors: 5	Cost(C): 1.00	Neurons in hidden layers: 100	Regularization type: Ridge (L2)	Number of trees: 10
	Metric: Euclidean	Regression loss epsilon(Ɛ): 0.10	Activation: ReLu	Strength C = 1	Do not split subsets smaller than: 5
	Weight: Uniform	Kernel: RBF g: auto	Solver: Adam Regularization, $\alpha = 0.0001$		
		Numerical tolerance: 0.0010	Maximal number of iterations: 200		
		Iteration limit: 100			

the data, the Training-Test data distribution phase was executed. This phase involved implementing a 10-layer cross-validation methodology to classify the data. The classification process was completed during this stage. Five different categorization techniques were used to evaluate the effectiveness of neural networks. These techniques included Random Forest, artificial neural networks, support vector machines, k-nearest neighbors, and logistic regression.

According to Table 4, The SqueezeNet model had the most successful results when used with SVM and LR models. All the images were accurately classified as either fresh or stale, with no misclassified images. However, the results differed when k-NN, ANN, and RF models were used, as they did not perform as well as the SVM and LR models with the SqueezeNet. In k-NN 2 predictions were misclassified they were stale but predicted as fresh, and 1 fresh image was predicted as stale. While in ANN algorithm 1 stale and 1 fresh image were predicted wrongly. So far in RF 9 stale images were predicted as fresh and 3 were fresh but predicted incorrectly.

Depending on Table 5, the InceptionV3 model was utilized with 5 distinct machine learning models. The best results were achieved with SVM and LR models, as they accurately classified 2581 images as fresh, and predicted them as fresh, while also correctly identifying 1895 images as stale. While the k-NN model misclassified 5 images from stale fish and 1 from fresh once. However, the RF model produced different results, with 2575 images being correctly classified, while 1881 images that were actually stale were mistakenly classified as stale. So far for ANN model the misclassified image was for a fresh fish that was predicted as stale.

In accordance with the Tables 6 and 7, the results obtained from each model were almost identical to the other algorithms. SVM, ANN, and LR produced accurate results for the SqueezeNet algorithm, and this was also the

Table 4 Confusion matrix with SqueezeNet

k-NN		Predicted	
		Fresh	Stale
Actual	Fresh	**2580**	1
	Stale	2	**1893**

SVM		Predicted	
		Fresh	Stale
Actual	Fresh	**2581**	0
	Stale	0	**1895**

ANN		Predicted	
		Fresh	Stale
Actual	Fresh	**2580**	1
	Stale	1	**1894**

LR		Predicted	
		Fresh	Stale
Actual	Fresh	**2581**	0
	Stale	0	**1895**

RF		Predicted	
		Fresh	Stale
Actual	Fresh	**2578**	3
	Stale	9	**1886**

Table 5 Confusion matrix with InceptionV3

k-NN		Predicted: Fresh	Predicted: Stale
Actual	Fresh	**2580**	1
Actual	Stale	5	**1890**

SVM		Predicted: Fresh	Predicted: Stale
Actual	Fresh	**2581**	0
Actual	Stale	0	**1895**

ANN		Predicted: Fresh	Predicted: Stale
Actual	Fresh	**2580**	1
Actual	Stale	0	**1895**

LR		Predicted: Fresh	Predicted: Stale
Actual	Fresh	**2581**	0
Actual	Stale	0	**1895**

RF		Predicted: Fresh	Predicted: Stale
Actual	Fresh	**2575**	6
Actual	Stale	14	**1881**

Table 6 Evaluation of SqueezeNet-based metrics for ML models

Algorithms	Accuracy (%)	Precision	Recall	F1 score
k-NN	99.9	0.999	0.999	0.999
SVM	100	1.000	1.000	1.000
Random Forest	99.7	0.997	0.997	0.997
ANN	100	1.000	1.000	1.000
Logistic Regression	100	1.000	1.000	1.000

Table 7 Evaluation of InceptionV3-based metrics for ML models

Algorithms	Accuracy (%)	Precision	Recall	F1 score
k-NN	99.9	0.999	0.999	0.999
SVM	100	1.000	1.000	1.000
Random Forest	99.6	0.996	0.996	0.996
ANN	100	1.000	1.000	1.000
Logistic Regression	100	1.000	1.000	1.000

case for the InceptionV3 algorithm. The two tables present data on the performance measurements of machine learning models, including accuracy, precision, recall, and F1 score. The accuracy results are presented as percentages for each model, while precision, recall, and F1 score are given as decimal values. The results obtained from the models show accuracy rates ranging from 99 to 100%, with the exception of the RF model which has a slightly lower accuracy rate of 99.7%. The results indicate that there is minimal difference between the performance of the machine learning models when using the features extracted by SqueezeNet and InceptionV3. Both feature extraction methods yielded comparable results when paired with the chosen machine learning algorithms.

Our study produced better results when compared to a previous study that used the same data set of 4000 images with an equal number of fresh and stale images. The related findings showed that a combination of VGG-16 and Bi-directional LSTM methods achieved a success rate of 98.0% [34].

The study's findings suggest that other machine learning algorithms, which were not employed in this research, could potentially yield similar accuracy results to those reported in the study. However, given the reported high accuracy rates of 100% achieved by the selected machine learning algorithms and their performance superiority compared to the previous study, it is recommended that future research endeavors should focus on exploring the potential of these other algorithms.

The prediction results presented. In terms of the ANN model, the outcomes were 100%, and 100% for each of the deep learning methods. On the other hand, the k-NN results were 99.9%. For SqueezeNet 99.7% and 99.6% for RF was obtained by InceptionV3 extraction. Results for SVM were 100% and 100% for both SqueezeNet and InceptionV3 models. So far the results don't change in LR and they were both 100%. The results gained in RF were lower according to the other model and it was 99.7% in SqueezeNet and 99.6% in InceptionV3.

Since the freshness of fish is not detected easily, especially in the areas where they are far from sea or fish is not the major food. Detecting the freshness of fish is not a problem for cities that consume fish or for local fishermen. However, it will be difficult to find fresh fish if we include other areas. For this reason, the study was conducted to address this issue.

Machines that learn from experience and perform tasks autonomously are the ultimate goal of artificial intelligence. By adapting to various situations, making decisions based on data analysis, and communicating with humans naturally, these machines will be able to make better decisions. While the artificial intelligence is used and the methods among this science were applied to human's daily life and utilizing the deep learning with machine learning. The ultimate goal of feature classification in deep learning is to enable machines to learn and generalize from complex, unstructured data, through the automated extraction of features, deep learning models have the potential to achieve higher levels of accuracy and performance compared to traditional machine learning models that heavily rely on manually crafted features. This is the reason, DL models performed on the available dataset and then prediction taken place. The ultimate goal of prediction in machine learning is to build models that can make accurate and reliable predictions on new, unseen data, which can be used to inform decision making and improve outcomes.

This research presents a hybrid method of using deep learning and machine learning models to evaluate the freshness of fish. While previous studies have tested different algorithms through various methods and models of AI, this study employs a unique approach that demonstrates the potential of using these techniques for objective fish freshness evaluation. It is recommended that future research endeavors should focus on exploring the potential of other algorithms. As noted in the introduction, the freshness of a fish can also be determined by examining its gills. Therefore, this study's approach of using deep learning techniques to evaluate fish freshness could be applied to a dataset containing images of fish gills. Such a dataset could potentially allow for the development of a model that is specifically tailored to detecting fish freshness through gill images. The use of SqueezeNet and InceptionV3 for feature extraction in combination with the five different ML models proves to be a promising and effective method for determining fish freshness. This approach has the potential for future applications in the food industry, offering a reliable and objective method for evaluating the freshness of fish.

Conclusion

Humans can assess the freshness of fish by examining its eyes, smelling it, and inspecting its gills, but for machines accomplishing the same task will not be easy. A method of determining the freshness of fish using deep learning techniques proposed in this study. In the conducted research, a dataset was used to classify fish body freshness into two categories, as fresh or stale to determine whether a fish was fresh or stale. Several deep learning algorithms were used in training machine learning models, including SqueezeNet, and InceptionV3.

The results showed that the dataset was effective in successfully determining the freshness of the fish. The results were impressive, as the proposed model used a total of 4476 images of fresh and stale fish. For each of the algorithms (SqueezeNet, and InceptionV3), various machine learning models (k-NN, SVM, LR, RF, and ANN) were used. Briefly the dataset extracted its features with the mentioned deep learning separately then the results were trained by the machine learning one by one. The machine learning models achieved high accuracy rates, ranging from 99.6 to 100%, for evaluating the freshness of fish using SqueezeNet and InceptionV3 feature extraction. The results demonstrate the effectiveness of the approach in objectively determining fish freshness.

Numerous research studies have been conducted on detecting fish and categorizing its freshness using various approaches such as chemical or biological methods or different sensor types. Furthermore, research studies using deep learning algorithms to detect freshness have been conducted. This study's unique aspect is that it utilized the same dataset as previous studies, without modifying the dataset, and achieved a higher success rate using methods other than the VGG-16 neural network architecture and Bi-directional Long Short-Term Memory model which is used in the previous study.

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Author contributions ETY: conceptualization, methodology, software, validation, formal analysis, writing—review and editing. IAO: conceptualization, methodology, software, validation, formal analysis, writing. MK: conceptualization, methodology, software, validation, formal analysis, writing.

Data availability Contacting the corresponding authors Abu Rayan [33], or accessing to the study's dataset can be found here,https://www.kaggle.com/datasets/muhammadaburayan/fish-freshness-classification

Declarations

Conflict of interest The authors have stated that they do not have any known financial interests or personal relationships that could potentially affect the work presented in this report.

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