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Research paper

A Novel Method for Fish Spoilage Detection based on Fish Eye Images using Deep Convolutional Inception-ResNet-v2

Sekineh Asadi Amiri[1,*], Mahda Nasrolahzadeh[2], Zeynab Mohammadpoory[3], Abdolali Movahedinia [4] and Amirhossein Zare Kordkheili[1]

1,5. Department of Computer Engineering, University of Mazandaran, Babolsar, Iran
2. Department of Biomedical Engineering, Hakim Sabzevari University, Sabzevar, Iran
3. Department of Electrical Engineering, Shahrood University of Technology, Shahrood, Iran
4. Department of Marine Biology, University of Mazandaran, Babolsar, Iran.

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Corresponding author: s.asadi@umz.ac.ir, asadi_amiri@yahoo.com (S. Asadi Amiri).

Abstract

Improving the quality of food industries and the safety and health of the people's nutrition system is one of the important goals of governments. Fish is an excellent source of protein. Freshness is one of the most important quality criteria for fish that should be selected for consumption. It has been shown that due to improper storage conditions of fish, bacteria, and toxins may cause diseases for human health. The conventional methods of detecting spoilage and disease in fish, i.e. analyzing fish samples in the laboratory, are laborious and time-consuming. In this paper, an automatic method for identifying spoiled fish from fresh fish is proposed. In the proposed method, images of fish eyes are used. Fresh fish are identified by shiny eyes, and poor and stale fish are identified by gray color changes in the eye. In the proposed method, the Inception-ResNet-v2 convolutional neural network is used to extract features. To increase the accuracy of the model and prevent overfitting, only some useful features are selected using the mRMR feature selection method. The mRMR reduces the dimensionality of the data and improves the classification accuracy. Then, since the number of samples is low, the k-fold cross-validation method is used. Finally, for classifying the samples, Naïve Bayes and Random forest classifiers are used. The proposed method has reached an accuracy of 97% on the fish eye dataset, which is better than previous references. This research contributes significantly to the field of food safety, offering a more efficient and accurate approach to fish spoilage detection. This method could revolutionize quality control procedures in the seafood industry, improving the safety and health of people's nutrition systems.

1. Introduction

Nowadays the demand for fish consumption has increased worldwide due to its high nutritional value. It is mainly because fish is known as one of the best sources of omega-3 fatty acids, which can reduce the risk of heart disease and stroke [1, 2]. Moreover, it has been demonstrated that their consumption is necessary for the growth and development of the brain. Since the human body cannot produce it, doctors recommend consuming fish at least twice a week [3]. Therefore, many people replace the consumption of fish with chicken and beef to meet their daily need for such a healthy protein with low unsaturated fat [4]. Studies show that as much as local markets typically display two-week-old fish from the seas for sale, consumers also tend to purchase freshly caught fish. In addition, it has been determined that there are pathogenic bacteria and toxins in fish that are kept in inappropriate conditions or transported with wrong logistic manners, which are dangerous for human health [5]. Therefore, to ensure the safety of fish consumers, it is necessary to practically check the quality indicators based on the freshness of the fish. Fish eye evaluation is among the traditional methods that are used to determine the freshness of fish [6]. Although this factor is visible to the naked eye, a common consumer, or even a highly skilled expert, often cannot correctly determine the freshness of fish. In addition, analyzing fish samples in the laboratory is laborious and time-consuming [7, 8]. Figure 1 shows some examples of healthy and rotten fish eyes. From the figure, a fresh fish is characterized by shiny, black eyes, white skin, and healthy fins. On the other hand, a poor quality and old fish is identified by a gray color change in the eyes, red skin, and swollen belly. To overcome such problems, it is necessary to develop an objective, fast, and robust automatic system that can not only solve the problem of corruption detection but also reduce the economic burden of sellers.

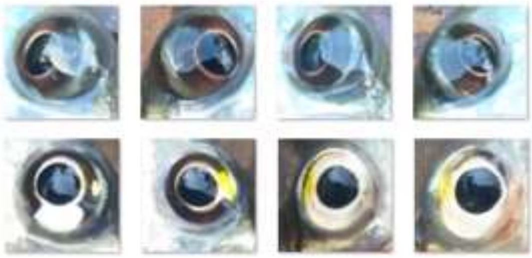


Figure 1. Some examples of fish eyes, the first row belongs to the eyes of some healthy fish, and the second row belongs to the eyes of some rotten fish.

In recent years, several algorithms have been proposed for automatic fish image analysis [9]. In general, the pipeline of these computer-aided detection techniques usually consists of three parts: i) image acquisition; ii) image pre-processing; and iii) classification procedures. Moreover, classification procedures are separated into two categories, i.e., conventional machine learning and deep learning [10]. Although conventional machine learning methods including support vector machine (SVM) [11], artificial neural networks (ANN) [12], and principal component analysis (PCA) [13] in fish classification have yielded impressive performance, they are heavily dependent on handcrafted feature engineering. In contrast, deep learning models as a fresh research framework in the domain of machine learning have attracted wide interest in fish categorization [14]. In deep models, it does not need prior knowledge about the original image so the raw image is directly fed to the network for feature design and parameter optimization [15]. Moreover, deep learning combines the two stages of feature extraction and classification for the initial stages of image processing. Because deep learning models need powerful computing resources and large datasets for training [16], some of these deep models use the transfer learning approach to address these limitations.

This study introduces a new automatic method to identify fresh fish from rotten fish based on fish eye images. The proposed method uses an Inception-ResNet-v2 convolutional neural network to extract effective features. For each image, a feature vector of length 1536 is extracted. To increase the accuracy of the model and reduce the computational load, the mRMR feature selection method is used to remove redundant and irrelevant features. Since the number of samples in the database is small, the evaluation of the proposed method is performed using the k-fold cross-validation approach. Finally, naïve base and random forest models are used as classifiers to recognize fresh fish images. Experimental results support that the proposed method compared to existing methods surpasses performance.

The rest of this paper is organized as follows: In Section 2, a review of related works on fish freshness classification is provided. In Section 3, the proposed algorithm is explained in detail. In section 4, the experimental results and discussions are reported. Finally, the conclusions and future works are given in Section 5.

2. Related work

In recent years, fish eyes have attracted wide attention as a powerful feature in identifying and classifying the freshness of fish. It is mainly because studies have reported that the visual appearance of fresh and non-fresh fish eyes is different, so it can be considered as a useful indicator to identify the freshness of fish [17]. For example, Issac et al. presented an automatic segmentation method of fish gills from images of fish. In the proposed method, an evaluation model was designed using a statistical relation of the segmented gill area to identify the freshness of the fish. The results showed that out of a total of eight fish with 144 data samples, the classification results yielded negative for two data samples [18]. In the framework of a supervised learning method, Lalabadi et al. extracted multiple color space-based features from the gills and eyes of fish in L*a*b*, HSV, and RGB color spaces and classified them to evaluate the freshness of fish. The classification accuracies of 96% and 84% were respectively obtained with ANN and SVM for the freshness of fish in this study [19]. Jarmin et al. proposed the

RGB color indices to detect the freshness of fish. In the method, a sensor named Torrymeter was used to measure the freshness of three kinds of fish species. The results of the study showed that the proposed features based on RGB color space were capable of detecting spoilage of fish after three days [20]. Tolentino et al. developed a method to determine the freshness of fish by using the characteristics of the eyes and gills of fish. In this study, the freshness quality level of fish was classified using SVM and resulted in an accuracy of 98% [21]. Prasetyo et al. introduced the Cosine K-Nearest Neighbors classification method for fish freshness detection. In this study, fish eye features were extracted from 71 images, and the obtained classification accuracy was reported as 96.79% [22]. Cengizler presented an unsupervised clustering algorithm for feature extraction from fish eye images. The method divided each image into three parts based on the color distribution and then the freshness was calculated according to the intensity diversity amongst the clusters. The accuracy obtained in this study was 95% [23].

Needless to say, different from methods that deal with hand-crafted features, deep learning models such as convolutional neural networks (CNNs) have made a widespread presence in the tasks of detecting the freshness of fish from images. For example, Taheri-Garavand et al. utilized VGG-16 architecture as a feature extractor from fish eye images automatically. The classification accuracy reached up to 98.21% in this study [24]. Prasetyo et al. presented a MobileNetV1 Bottleneck CNN model for categorizing the freshness of fish eyes. The method achieved 63.21% classification accuracy [25]. Lanjewar and Panchbhai combined NasNet and LSTM models to extract features from fish eye images. The method achieved Cohen's kappa coefficient and Matthew's correlation coefficient of 91%. Moreover, the two mentioned coefficients yielded a value of 97% using the 5-fold cross-validation method for identifying the freshness of fish [26].

3. Proposed method

The appearance of fish eyes undergoes a significant change during the spoilage process. The fish eyes can be a good representor of its quality and its freshness. Fresh fish usually have shiny and clear eyes, while spoiled fish have sunken, cloudy, and colorless eyes [23]. In this paper, a novel automated freshness assessment method is proposed using the fish eyes. The flowchart of the proposed method is illustrated in Figure 2. To classify the quality of fish eyes, we use a pre-trained convolutional neural network to extract important features from the deep layers. However, some of these features are not relevant, so the mRMR method is applied to select the most informative ones. Then, Naïve Bayes (NB) and Random Forest (RF) classifiers are employed to perform the final classification. The details of the proposed method are described as follows:

3.1. Inception-ResNet-v2 convolutional neural network

In this paper, we propose a new method for identifying fresh fish from spoiled fish based on fish eye images. We use a pre-trained convolutional neural network (CNN) that has learned features from the ImageNet dataset, which contains over 14 million images of 20000 classes, some of which have bounding box annotations for object localization. We use the Inception ResNet-v2 architecture [27], which combines the Inception modules with different convolutional filter sizes and the ResNet residual connections, which improve the training speed and accuracy of the network. The network consists of seven main modules. Figure 3 represents the flowchart of Inception-ResNet-v2.

Figure 2. The flowchart of our proposed method for identifying fish freshness.

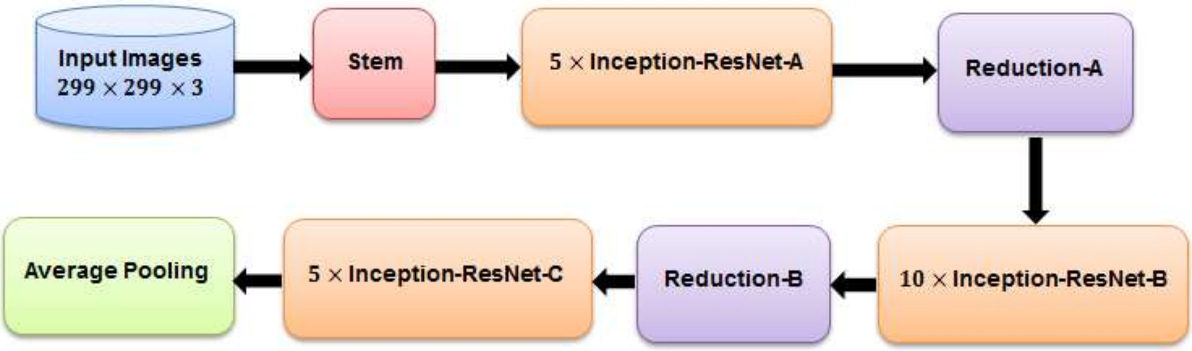


Figure 3. The flowchart of Inception-ResNet-v2.

The input of the network is an image of size $299 \times 299 \times 3$. The first component of the network is the stem module, which performs several operations on the input image, such as convolutions, max-pooling, and batch normalization. The stem module reduces the size of the image and increases the number of features. The output of the stem module is a tensor of size $35 \times 35 \times 256$. The second component of the network is the Inception-ResNet-A module, which contains 10 blocks of Inception-ResNet-A. The third component of the network is the reduction-A module, which applies a max-pooling operation and three branches of convolutions with different filter sizes and concatenates their outputs. The output of the reduction-A module is a tensor of size $17 \times 17 \times 1088$. The fourth component of the network is the Inception-ResNet-B module, which consists of 20 blocks of Inception-ResNet-B. The fifth component of the network is the reduction-B module, which applies a max-pooling operation and four branches of convolutions with different filter sizes and concatenates their outputs. The reduction-B module reduces the spatial dimensions and increases the number of channels of the image. The output of the reduction-B module is a tensor of size $8 \times 8 \times 1536$. The sixth component of the network is the Inception-ResNet-C module, which consists of 9 blocks of Inception-ResNet-C. The seventh component of the network is the global average pooling layer, which applies a global average pooling operation to the output of the Inception-ResNet-C module. This reduces the spatial dimensions to 1×1 and preserves the number of channels. The output of the global average pooling layer is a vector of size 1536.

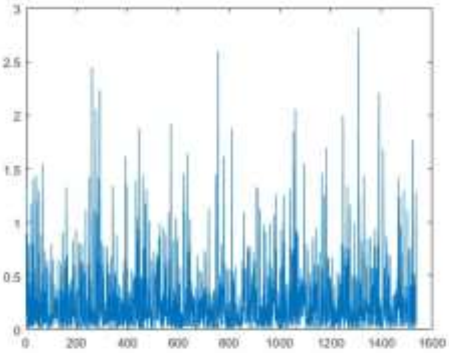
In this paper, the Inception-ResNet-v2 neural network is utilized to extract features from fish eye images [28]. We gave an image of a fish eye as input to this network and extracted a feature vector of length 1536 from it. This feature vector provides us with good information about the color, edge, and structure of the image. Figure 4 shows the 1536-element feature vector obtained from the Inception ResNet v2 neural network for two images of healthy and rotten fish eyes, in the form of a chart. This chart shows that the proposed feature vector can separate healthy and spoiled fish.

The purpose of Figure 4 is to demonstrate the capability of the pre-trained Inception-ResNet-v2 neural network in feature extraction. The output of the Inception-ResNet-v2 network for each image is a feature vector of length 1536. We plotted the distribution of these feature vectors for two images from different classes to show that the features extracted by Inception-ResNet-v2 are distinct for different classes. Therefore, the distributions of the two plots for the two different classes are different. The goal is to show that the features extracted from the pre-trained Inception-ResNet-v2 network have good discriminative ability for class separation.

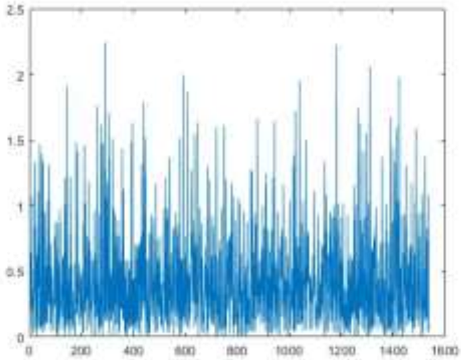
It should be noted that in this study, the pre-trained Inception-ResNet-v2 neural network was not used to train our dataset, but only as a feature extractor. As a result of applying the aforementioned network to the dataset, a feature vector with a length of 1536 has been obtained.

a) A sample of fresh fish eye.

b) A sample of spoiled fish eye.



c) Feature vector of image a).



d) Feature vector of image b).

Figure 4. Display of two fish-eye images along with feature vector.

3.2. mRMR feature selection method

The mRMR stands for Minimum Redundancy Maximum Relevance, which is a filter-based feature selection method that uses mutual information as a criterion to select the most relevant and least redundant features for a given task [29]. Mutual information measures the amount of information that one variable contains about another variable, and it is based on the probability distributions of the variables. Mutual information between two variables x and y can be defined according to the following equation:

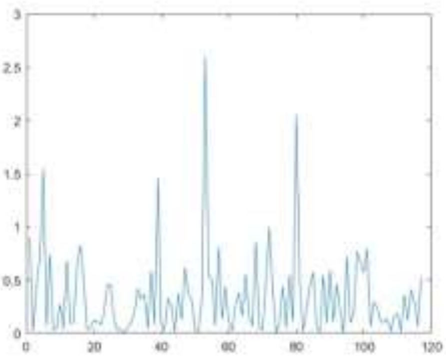
$$I(x,y)=\sum_{y\in Y}\sum_{x\in X}P(x,y)\log(\frac{P(x,y)}{P(x),P(y)}) \qquad (1)$$

The mRMR criterion can be defined as:

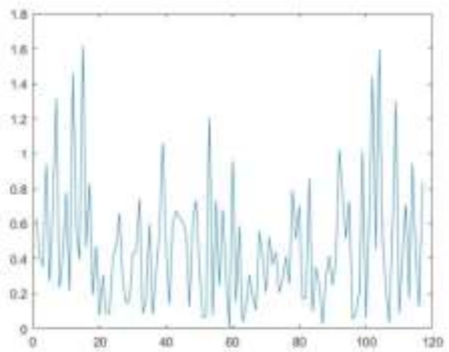
$$M(S,c)=\frac{1}{|S|}\sum_{\chi_i\in S}I(\chi_i;c)-\frac{1}{|S|^2}\sum_{\chi_i,\chi_j\in S}I(\chi_i;\chi_j) \qquad (2)$$

where X is a feature vector, x_i is a feature in X, S is the subset of selected features and c is a target class. Also, $I(\chi_i;c)$ is the mutual information between x_i and c, and $I(\chi_i;\chi_j)$ is the mutual information between χ_i and χ_j.

The mRMR criterion selects features that are correlated to the class and non-correlated with each other. This means that mRMR picks features that have a maximum average mutual information with the class, and a minimum average mutual information with each other. The mRMR can reduce the dimensionality of features and increase the classification accuracy. Threshold is an important parameter in mRMR that determines the number of features that can be selected. A high threshold value causes a small number of features to be selected, while a lower threshold value causes more features to be chosen. In this paper, we used a zero threshold in mRMR to select the useful features. This threshold value decreased the number of features from 1536 to 117. Figure 5 shows the reduced feature vector with mRMR for the previous figure. In this figure, we demonstrated the effect of the MRMR feature reduction method. Even with the removal of a significant number of features, the remaining features of the two classes are still distinguishable and can be used for class separation.



a) Result of mRMR of Figure 4.c.



b) Result of mRMR of Figure 4.d.

Figure 5. Result of MRMR feature selection for Figure 4.

3.3. Classification of fresh fish and spoiled fish

The classifier is an extremely important part of a recognition system so its performance can directly affect the accuracy of the system [30]. In this study, two well-known classifiers, namely NB and RF, are used. In the following two classifiers used to discriminate fresh fish from spoiled ones are explained.

3.3.1. NB classifier

NB is a simple and strong classifier used in many machine-learning applications [11]. This algorithm uses Bayes' rule together with an assumption that the features are conditionally independent given the class. With this assumption, NB can be defined as follows:

$$P(y \mid x) = \frac{P(y)\prod_{i=1}^{n} P(x_i \mid y)}{P(x)} \tag{3}$$

where n is the number of features and x_i is the ith feature of object x. With this formula, the probability of an object belonging to each class can be calculated and then the class with the highest probability can be chosen (Eq. 4). This class is known as the maximum likelihood or MAP class.

$$y_{MAP} = \arg\max_y P(y)\prod_{i=1}^{n} P(x_i \mid y) \tag{4}$$

3.3.2. RF classifier

A random forest is a type of ensemble learning method, which means it uses multiple models to improve the accuracy and robustness of the prediction [11]. In this case, the models are decision trees, which are graphical representations of the logic behind the classification. Bagging decreases the variance of each tree and leads to less prone to overfitting. A low variance indicates that the model is robust to the noise and outliers in the data. However, high variance implies that the model is sensitive to the noise and outliers in the data and it may overfit the data. Overfitting means that the model has high accuracy on the training data, but low accuracy on the unseen data. Feature selection means that each decision tree considers a random subset of the features rather than all the original features. This process causes less correlation in the trees and more diversity. Diversity has benefits for ensemble methods because it means that the trees can learn different aspects of the data and boost each other. This may lead to more accuracy and generalization than a single tree. Finally, a random forest makes votes to reach the final decision [31].

In the proposed method, the NB and RF classifiers are implemented by using the Weka software [11], applying the default values for the parameters.

4. Experimental Results and Discussion

In this section, we present and discuss the results of our experiments on fish eye spoilage detection using the Inception-ResNet-v2 network. The goal of this study is to evaluate the performance and robustness of the proposed method as well as compare it with state-of-the-art methods.

4.1. Dataset

The dataset used in the present study consists of 40 fish eye images, half of which are fresh and half spoiled [32]. The images are taken with a Samsung A6+ cellphone camera at 10 cm distance from the eyes, with a resolution of 4608 × 3456 pixels (f/1.7, 26mm wide). The camera focuses on the pupil of the eye, and the images are cropped from the original data to have a fixed size of 500 × 500 pixels.

4.2. Performance metric

This study proposes a method for classifying fish eye images as fresh or spoiled, based on the color, brightness, and sharpness of the eye. The performance of the proposed method is assessed using the accuracy, precision, recall, and the F1-score as the evaluation metrics. These metrics are defined as follows [33]:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \quad (5)$$

$$\Pr ecision = \frac{TP}{TP + FP} \quad (6)$$

$$\text{Re}\,call = \frac{TP}{TP + FN} \quad (7)$$

$$F1 - score = \frac{2TP}{2TP + FN + FP} \quad (8)$$

$$Specificity = \frac{TN}{TN + FP} \quad (9)$$

where TP, FP, FN and TN are the numbers of true positives, false positives, false negatives, and true negatives, respectively.

4.3. Results and Discussion

As discussed throughout this study, the purpose of the proposed method was to detect fish freshness through fish eye images. Since the dataset used is small, we used a 5-fold cross-validation procedure [34] to evaluate our proposed method. By dividing the data into 5 folds with equal sizes, 5 training and testing rounds were performed. In each round, one of the folds was kept as a fold test, while the other 4 folds were used as training. The K-fold validation technique is especially beneficial for smaller datasets as it optimizes the use of both training and testing data. This strategy facilitated the optimal tuning of the classifier parameters, notwithstanding the constraints imposed by the limited number of images. In addition, NB and RF classifiers tested and evaluated the performance of the proposed method. The results obtained from the two mentioned classifiers were the same. Therefore, we reported only one result for our proposed method.

A Receiver Operating Characteristic (ROC) curve is a plot that shows how well a binary classifier model performs at different threshold values. It is a way to visualize the trade-off between the true positive rate (TPR) and false positive rate (FPR) of a binary classifier model. The area under the curve (AUC) is a measure of the classifier's performance, with a value of 1 indicating perfect classification and a value of 0.5 indicating random guessing. The proposed method achieved an AUC of 0.975, as shown in Figure 6. The AUC value indicates that our method has a very good performance.

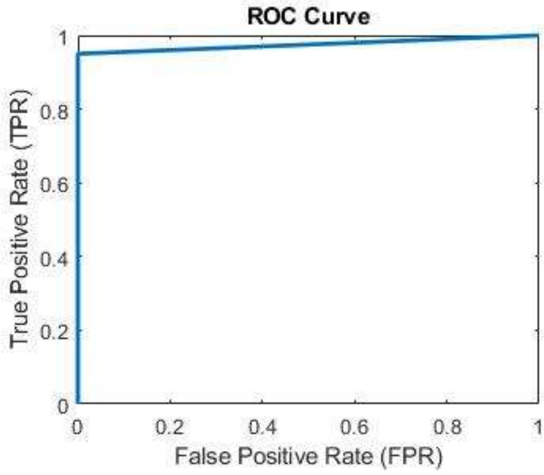


Figure 6. ROC result of our proposed method.

Table 1 shows the comparison of the performance of the proposed method and the results presented in [23] on the eye fish dataset described in section 4.1. As can be seen, our proposed method performs better than the method presented in [23] in terms of accuracy, precision, recall, F1-score, and specificity. Hence, our method can reliably classify fresh and spoiled fish eye images.

Table 1. Comparison result of our proposed method with the reference [23].

Method	Year	Database	Accuracy	Precision	Recall	F1 − score	Specificity
Cengizler, C. [23]	2023	Kaggle	0.95	1	0.9	0.947	1
Proposed method	2024	Kaggle	0.97	1	0.95	0.97	1

5. Conclusion and future works

This article introduces a novel method for differentiating between fresh and spoiled fish, utilizing eye images of fish as the primary data source. The method employs the Inception-ResNet-v2 neural network, a powerful tool in the field of image classification, to extract pertinent features from these images. The mRMR feature selection method is then applied to filter out irrelevant features, thereby enhancing the accuracy of the classification process. The evaluation results on the fish dataset demonstrate that the proposed method outperforms existing methods in terms of accuracy, underscoring its effectiveness.

The findings of this study have significant implications. Our proposed method provides a non-destructive and automated solution for detecting fish spoilage, which has the potential to transform quality control procedures in the seafood industry. In future work, we aim to further enhance our method by incorporating image augmentation techniques. This would involve generating a larger number of training examples through transformations such as rotation and flipping, to increase the classifier's accuracy and robustness, especially in the context of detecting fish spoilage from eye images.

Additionally, our research paves the way for new directions in future work. One such direction could be to explore the feasibility of determining fish freshness based on other parts of the fish, such as the gills. This could potentially expand the applicability of our method, making it a more comprehensive tool for detecting fish spoilage. However, implementing these enhancements would require a larger dataset for training the supervised machine learning algorithm, indicating a potential avenue for future research in this field.

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شناسایی فساد ماهی براساس چشم ماهی با استفاده از شبکه عصبی عمیق Inception-ResNet-v2

سکینه اسدی امیری[۱،*]، مهدا نصراله زاده[۲]، زینب محمدپوری[۳]، عبدالعلی موحدی نیا[۴] و امیرحسین زارع کردخیلی[۱]

[۱] گروه مهندسی کامپیوتر، دانشگاه مازندران، بابلسر، ایران.

[۲] گروه مهندسی پزشکی، دانشگاه حکیم سبزواری، سبزوار، ایران.

[۳] گروه الکترونیک، دانشگاه صنعتی شاهرود، شاهرود، ایران.

[۴] گروه زیست شناسی دریا، دانشگاه مازندران، بابلسر، ایران.

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چکیده:

تقویت کیفیت صنایع غذایی و ایمنی و سلامتی سیستم تغذیه مردم یکی از اهداف مهم دولت‌ها است. ماهی منبع عالی پروتئین است. تازگی یکی از مهمترین معیارهای کیفیت برای ماهی است که باید برای مصرف انتخاب شود. به دلیل شرایط نامناسب نگهداری ماهی، باکتری ها و سموم می‌توانند برای سلامتی انسان بیماری ایجاد کنند. روش‌های سنتی تشخیص فساد و بیماری در ماهی، یعنی تجزیه و تحلیل نمونه های ماهی در آزمایشگاه، زمان‌بر و پر هزینه هستند. در این مقاله، یک روش خودکار برای شناسایی ماهی‌های فاسد از ماهی‌های تازه ارائه شده است. در روش پیشنهادی، تصاویر چشم ماهی ها استفاده می‌شود. ماهی‌های تازه با چشمان درخشان شناسایی می‌شوند و ماهی‌های کهنه با تغییرات رنگ خاکستری در چشم شناسایی می شوند. در روش پیشنهادی، شبکه عصبی کانولوشنی Inception-ResNet-v2 برای استخراج ویژگی‌ها استفاده می شود. برای افزایش دقت مدل و جلوگیری از بیش برازش، فقط برخی از ویژگی‌های مفید با استفاده از روش انتخاب ویژگی mRMR انتخاب می‌شوند. mRMR ابعاد داده ها را کاهش می‌دهد و دقت طبقه‌بندی را بهبود می‌بخشد. سپس، از آنجا که تعداد نمونه‌ها کم است، از روش اعتبار سنجی متقابل k-fold استفاده می شود. در نهایت، برای طبقه‌بندی نمونه‌ها، طبقه‌بندهای Naïve bayes و Random forest استفاده می‌شود. روش پیشنهادی به دقت ۹۷٪ در مجموعه داده چشم ماهی به دست آمده است که بهتر از مراجع قبلی است.

کلمات کلیدی: چشم ماهی، تشخیص فساد، انتخاب ویژگی mRMR، Inception-ResNet-v2 .