Breakthroughs in Informatics, Networking, Algorithms, Research, and Yield (BINARY)
Volume 2 No 2 2026 | Sulistiani et. al | 211-227 | 2026-08-01
ISSN: 3109-5003

Classification of Tilapia Freshness Based on Visual Eye Images Using a Convolutional Neural Network Method

Sulistiani[1], Fahmi Syuhada[1], Syahrani Lonang[2]

[1] Department of Computer Science, Faculty of Science and Technology, Universitas Qamarul Huda Badaruddin Bagu, Indonesia
[2] Department of Information Technology, Faculty of Science and Technology, Universitas Qamarul Huda Badaruddin Bagu, Indonesia

Corresponding author: tiani6902@gmail.com

Submited: 22 April 2026 | Revision: 27 April 2026 | Accept : 6 June 2026 | Published : 1 August 2026

ABSTRACT: This study aims to classify the freshness levels of tilapia based on visual images using a Convolutional Neural Network (CNN) with a VGG16 architecture. Manual assessment of fish freshness tends to be subjective and inefficient, necessitating a more accurate and faster automated system. The research methods used include data collection, data preprocessing (resizing, augmentation), model design, training, and model evaluation. This study compares two models: a conventional CNN and a transfer learning-based CNN using the VGG16 architecture. The results show that the conventional CNN achieved an accuracy of 99.62% with a loss value of 0.0107, while the CNN with the VGG16 architecture achieved 100% accuracy with a loss value of 0.0002. Based on these results, it can be concluded that the use of the VGG16 architecture is capable of improving the model's performance in classifying the freshness of tilapia more accurately compared to a CNN without the architecture. The developed system can serve as a solution to assist in the rapid and objective identification of fish freshness.

Keywords : Image Classification, CNN, VGG16, Fish Freshness, Deep Learning

I. INTRODUCTION

Indonesia is an archipelago with vast potential in fishery resources, both in marine and freshwater sectors. One of the freshwater fishery commodities that is widely farmed and consumed by the public is tilapia (Oreochromis niloticus) [1]. Tilapia has high economic value, is easy to farm, and is nutritionally rich, resulting in steadily increasing demand each year. As tilapia production and consumption rise, the quality and freshness of the fish become critical factors that must be addressed, as they are directly linked to food safety and market value [2]. Fish freshness is a key indicator in determining whether fish is fit for consumption. Generally, fish freshness is assessed organoleptically by examining physical characteristics such as the eyes, gills, flesh texture, odor, and surface mucus [2]. Among these indicators, the eyes are the easiest to observe and show the quickest signs of declining quality. Fresh fish typically have clear, convex eyes that are not cloudy, while fish that are no longer fresh tend to have dull, sunken eyes [3].

The manual process of assessing fish freshness has several limitations, such as observer subjectivity, inconsistent results, and reliance on individual experience. In addition, while conventional methods such as chemical and microbiological analysis do provide accurate results, they are time-consuming, costly, and involve complex procedures [4]. Therefore, a system is needed that can quickly and accurately classify the freshness of fish.

Advances in artificial intelligence technology, particularly deep learning, have provided solutions for digital image processing to meet various classification needs. One widely used method is CNN, which has the ability to automatically extract features from images without requiring a manual feature extraction process [5]. CNN have been widely applied in various fields of computer vision, such as object detection, face recognition, and image classification, achieving high levels of accuracy. The use of transfer learning with pre-trained models, such as the VGG16 architecture, can improve the performance of CNN models. VGG16 is a CNN architecture consisting of 16 layers that has been trained on large datasets, enabling it to recognize visual patterns more effectively. This approach allows the model to learn faster and achieve high accuracy on limited datasets [6].

Several previous studies have been conducted to classify fish freshness using various methods. The KNN method, combined with color feature extraction, has shown fairly good accuracy around 90–94% but still has limitations in handling complex image patterns [7]. Other studies using CNNs have shown improved performance with accuracies exceeding 85%, but these are still limited to relatively small datasets [8]. Meanwhile, transfer learning-based studies, such as those using VGG16, have achieved higher accuracies, but few have specifically utilized images of tilapia eyes as the primary indicator of freshness [8].

Based on the problem statement and previous research, this study proposes the use of a CNN method with a VGG16 architecture to classify the freshness of tilapia based on eye images. The focus of this study lies in utilizing the fish's eye as an easily observable non-destructive indicator, as well as applying transfer learning to improve model performance. The objective of this study is to design and build a tilapia freshness classification model using CNN and VGG16, as well as to evaluate the model's performance in distinguishing between fresh and non-fresh fish based on eye images. The results of this study are expected to provide a more objective, rapid, and accurate solution for the fish freshness identification process, and to serve as a foundation for the development of automated systems in the fisheries industry.

II. RELATED WORK

Numerous studies on fish freshness classification have been conducted using a variety of approaches, ranging from conventional methods to those based on machine learning and deep learning. Traditional methods, such as color and texture analysis combined with KNN algorithms, have yielded fairly good results, with accuracy rates ranging from 90% to 94%. [9]. However, this method still relies on manual feature extraction, making it less effective at handling the complexity of image patterns.

As technology advances, deep learning-based methods such as CNNs are increasingly being used due to their ability to automatically extract features from images. Several studies have shown that CNNs can improve classification accuracy to over 85% without the need for manual feature extraction [10]. However, the performance of CNNs is heavily influenced by the size and diversity of the datasets used.

The transfer learning approach, which utilizes pre-trained models such as VGG16 and VGG19, has also been applied in various image classification training tasks. These models have been trained on large datasets, enabling them to recognize visual patterns more effectively. Previous research has shown that the use of transfer learning can improve accuracy and accelerate the model training process, particularly when working with limited datasets [11],[12].

Most studies still focus on parts of the fish's body, such as the gills or the entire fish, and few have specifically utilized images of the fish's eyes as the primary indicator of freshness. In fact, fish eyes are one of the visual indicators that change most rapidly as fish quality declines. Therefore, this study focuses on classifying the freshness of tilapia based on eye images using the CNN method and the VGG16 architecture to obtain accurate and efficient results.

III. METHOD

This study is an experimental research project aimed at developing and evaluating a classification model for determining the freshness of tilapia based on visual images using the Convolutional Neural Network method. The approach focuses on model design, the training process, and testing to measure the model's performance in classifying images into two categories: fresh and non-fresh fish. Model evaluation is conducted using accuracy, precision, recall, and F1-score metrics.

The dataset used was obtained from the Kaggle platform using the keyword "tilapia fresh", which was then focused on images of the tilapias eye. The data labeling process was conducted based on the categories available in the dataset, namely "fresh" and "not fresh". Additionally, a data selection process was conducted to ensure image quality, based on the following criteria: (1) the image clearly shows the fish's eye, (2) the image is not blurry or excessively distorted, and (3) the image has sufficient lighting so that the visual characteristics of the eye can be clearly observed.

This process aims to ensure that the data used in model training is of high quality and representative, thereby improving the model's performance in recognizing the visual patterns that distinguish fresh from non-fresh fish.

A. Research Object

The subject of this study is images of tilapia eyes used to classify the freshness level of the fish based on visual inspection of the eyes. The dataset consists of 1,500 images, comprising 750 images of un-fresh fish and 750 images of fresh fish. The dataset was obtained from the Kaggle website using the keyword “tilapia fresh” in September 2025. The dataset was then divided into three parts: 70% training data, 15% validation data, and 15% testing data. This division yielded 1,050 training data points, 224 validation data points, and 226 testing data points, with a balanced class distribution. The division was performed randomly to ensure the model could be trained and tested objectively.

B. Materials and Equipment

The tools and materials used in this study consist of hardware and software, as described in Table 1 below.

Tabel 1. Research tools and materials

Type	Specifications	Description
Hardware	Laptop (Intel Corei3, RAM 8GB, GPU NVIDIA GeForce, Windows 11)	Training and testing of CNN models.
Software	Python 3.11, Google colab, Tensorflow, Keras, NumPy, Mathlotlib, Scikit learn	Primary programming language used in the research.
Dataset	1,500 image of a tilapia eye (750 fresh, 750 non fresh)	Research data from Kaggle

The dataset used in this study consists of 1,500 images of tilapia eyes, comprising 750 images of fresh fish and 750 images of non-fresh fish. This balanced data distribution across classes aims to avoid model bias toward either class and improve the reliability of classification results. With this balance, the model can optimally learn the characteristics of each class without being influenced by the dominance of data in a particular class.

C. Research Stages

The research stages include data collection, preprocessing, model design, training, testing, and model evaluation. Figure 1 illustrates these research stages.

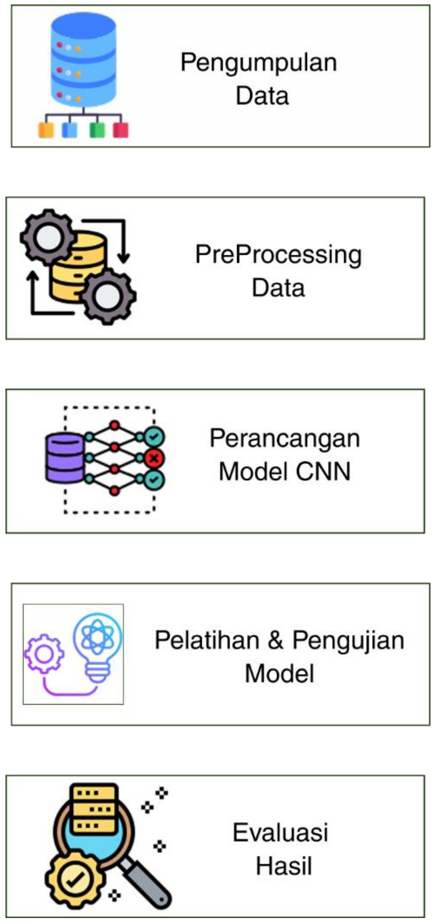


Figure 1. Research stages

As shown in Figure 1, this study was conducted in several stages, beginning with the collection of data in the form of tilapia eye images as the dataset. Next, preprocessing was performed to standardize and vary the images according to the model's requirements. The next stage involved designing a CNN model, followed by training and testing using the processed data. The final stage was evaluation to assess the model's performance based on the metrics used.

1. Data Collection

The dataset used in this study was collected from the Kaggle platform in the form of tilapia eye images in .jpg format. The eye region was selected as the primary object because it possesses the most distinct visual characteristics for indicating the fish's freshness level, such as clarity, color, and texture. Examples of fresh and non-fresh tilapia eye images are shown in Figure 2.

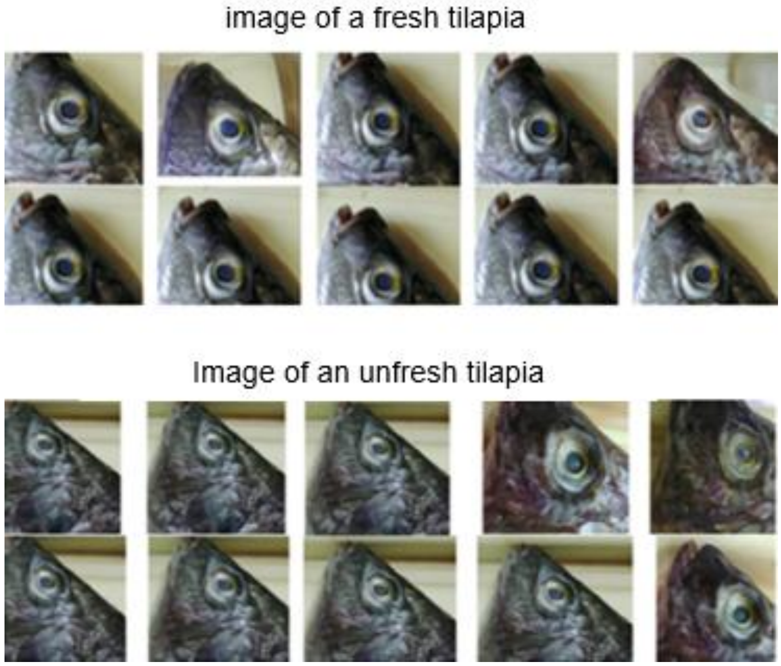


Figure 2. Images of fresh and unfresh tilapia eyes

The dataset consists of 1,500 images, evenly divided into two categories: 750 images of fresh fish and 750 images of non-fresh fish. This balanced data distribution aims to prevent model bias toward one class during the training process. Although the dataset size is sufficient for initial research, there are several limitations that need to be considered. The variety of images in the dataset is likely still limited, in terms of lighting conditions, shooting angles, and object backgrounds. Additionally, most of the data was obtained from the same source, so there is a possibility of similarity between images that could affect the model's generalization ability. Therefore, although the dataset has been balanced, the development of a more diverse and representative dataset is needed in future research so that the model can perform more optimally under real-world conditions.

2. Data Preprocessing

Data preprocessing was performed to improve the quality and consistency of the data prior to model training. The process involved:

- Resize data, that is, resizing the original image (1920 x 1080 pixels) to (128 x 128 pixels) to ensure consistency and speed up the computation process.
- Augmentation, which includes rotation (20°), scaling (0.2), and flipping to increase the diversity of the training data without adding to the original dataset.

Preprocessing steps such as image resizing and augmentation are shown in Figure 2.

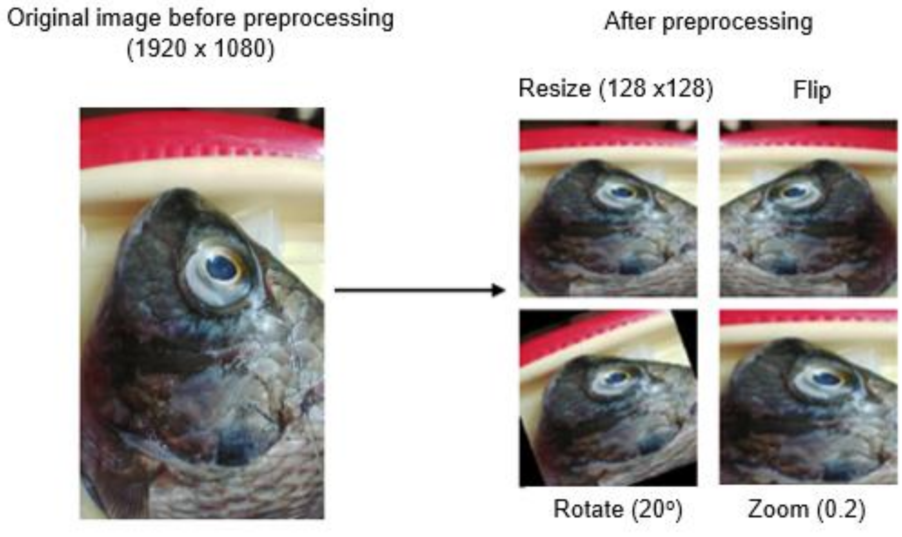


Figure 3. Image Preprocesing

3. Model Design

The classification model was built using the CNN method. The model's input consists of 128 x 128-pixel images with two output classes: "fresh" and "unfresh." The CNN architecture consists of several main stages: a convolution layer for feature extraction, a pooling layer for dimensionality reduction, a flatten layer to convert the data into a one-dimensional vector, and a fully connected layer for the classification process. The activation function used is ReLU in the hidden layers. The design process for the CNN model is shown in Figure 3.

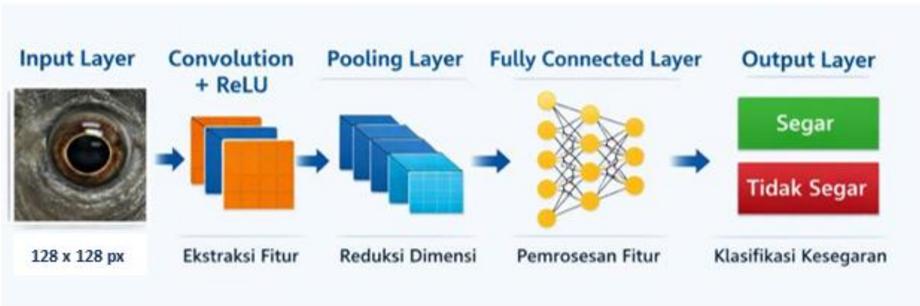


Figure 4. CNN Model Design

4. Model Training

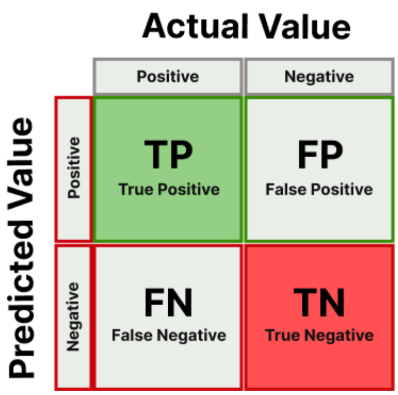
The CNN model is trained using training data through an optimization process to adjust the network's weights and biases based on the loss function. During the training process, the model's performance is monitored using validation data to prevent overfitting and ensure that the model generalizes well.

5. Model Testing

The trained model is then tested using previously unused test data. The purpose of this testing is to objectively evaluate the model's ability to classify new data.

6. Model Evaluation

The evaluation was conducted using a confusion matrix to compare the model's predicted results with the actual results. Based on the confusion matrix, evaluation metrics such as accuracy, precision, recall, and F1-score were calculated to measure the model's overall performance. The confusion matrix is shown in Figure 5 below.



Gambar 5. Confusion matrix

Description :

- TP : classification based on actual conditions.
- FP : incorrect prediction with the actual label where it should not be fresh.
- FN : incorrect prediction with the actual label where it should be fresh.
- FN : The forecast does not reflect the actual conditions.

Based on the confusion matrix obtained during testing, several evaluation metrics can be calculated. These metrics can be used to assess the performance of the tilapia freshness classification model developed in this study. The metrics are as follows:

a. Accuracy, which is used to measure how well the model classifies data correctly overall. The accuracy score is calculated based on the ratio of the number of correct predictions (TP and TN) to the total number of test data points. The calculation formula is given in Equation (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

b. Precision, indicates the proportion of data that is actually classified into the positive class out of all the data predicted as positive by the model. The calculation formula is given in equation (2).

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

c. Recall, is used to measure the model's ability to detect all data that actually belong to the positive class. The calculation formula is given in equation (3).

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

d. *F1-score,* which is a metric that combines precision and recall to strike a balance between the two. The calculation formula is given by the equation (4).

$$F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \quad (4)$$

IV. RESULT AND DISCUSSION

This Results and Discussion section presents the results of training and testing a classification model for determining the freshness of tilapia using the CNN method and a transfer-learning-based CNN with the VGG16 architecture. The evaluation was conducted to assess the model's performance in classifying images of fish eyes into fresh and non-fresh categories.

A. Models Training Result

a. CNN Model Training Result

The CNN model was trained using training data that had undergone preprocessing, including resizing and augmentation, with 10 epochs and a batch size of 16. The results of the CNN model training are shown in Figure 6.

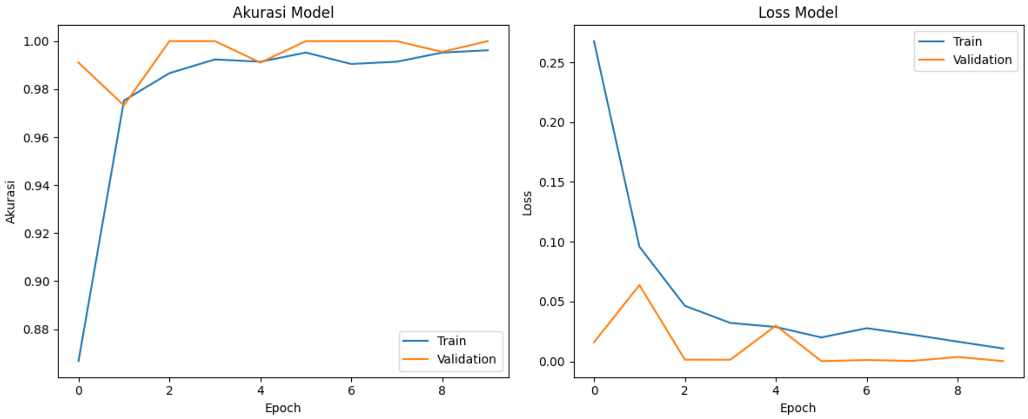


Figure 6. Results of the CNN model training

Figure 6 shows that the training accuracy increased from approximately 87% in the early epochs to 99.6% in the final epoch. The validation accuracy also showed high and relatively stable values, ranging from 97% to 100% in some epochs. Meanwhile, the training loss value decreased significantly from around 0.27 to 0.01, and the validation loss decreased to near zero.

These results indicate that the model is capable of learning data patterns very well and achieving high classification performance. The alignment between the training and validation curves also suggests that the model possesses sufficient generalization ability on the available data. However, the achievement of 100% accuracy in some epochs requires more critical analysis. This condition potentially indicates overfitting, especially if the dataset has a high degree of similarity among images and a relatively limited amount of data. The model may be memorizing data patterns rather than truly understanding the general characteristics of the objects. Therefore, although the evaluation metrics used such as accuracy, precision, recall, and F1-score show excellent results, these values must still be interpreted with caution. To support this analysis, a confusion matrix is used as a visual representation to examine the model's prediction distribution across each class, including the likelihood of misclassification. Thus, further testing using a more diverse dataset or real-time data is required to ensure that the model possesses good generalization capabilities under real-world conditions.

b. Results of CNN Model Training (VGG16 Architecture)

The CNN model with the VGG16 architecture was trained using training data that had undergone preprocessing, including resizing and augmentation, with 10 epochs and a batch size of 16. The results of training the CNN model with the VGG16 architecture are shown in Figure 7 below.

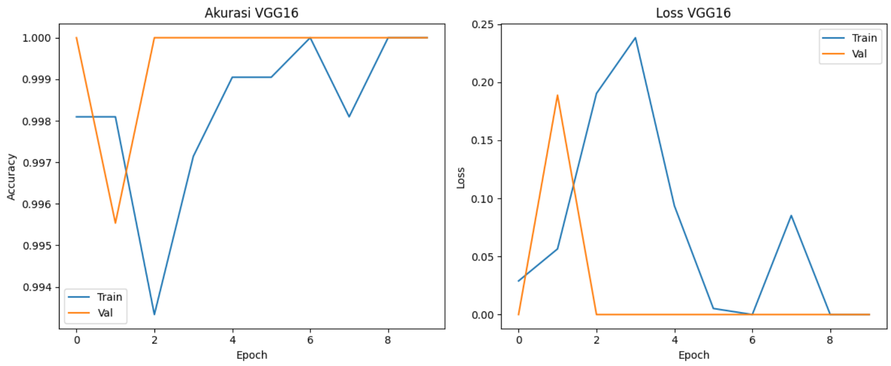


Figure 7. Results of training the CNN model using the VGG16 architecture

As shown in Figure 7, the training accuracy was high from the start of training, ranging around 99%, and increased to reach 100% by the final epoch. Validation accuracy also demonstrates stable performance, with values reaching 100% across nearly all epochs. Meanwhile, the training loss decreased to 0, despite experiencing minor fluctuations at the start of training, and the validation loss remained close to 0 for the majority of epochs. These results indicate that the VGG16 model is highly effective at learning data patterns and achieving high classification performance. This is supported by the VGG16 architecture's ability to extract features more deeply. However, accuracy and loss values approaching perfection also require more critical analysis, as they may be influenced by the similarity among similar data, potentially causing the model to memorize.

B. Model Evaluation

a. CNN Model Evaluation

The CNN model was evaluated using test data that was not used in the training process to assess the model's generalization ability. The evaluation methods used included a confusion matrix and performance metrics such as accuracy, precision, recall, and F1-score. The confusion matrix results for the CNN model are shown in Figure 8 below.

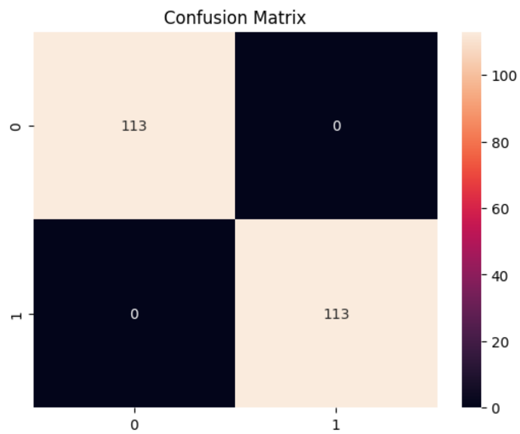


Figure 8. Confusion matrix results for the CNN model

Based on Figure 8, the True Positive (TP) value is 113 and the True Negative (TN) value is 113, with no classification errors the False Positive (FP) value is 0 and the False Negative (FN) value is 0. This indicates that all test data were successfully classified correctly by the model. The results of the evaluation metric calculations show that the precision, recall, and F1-score values for both classes reached 1.00, with an overall accuracy of 100%. Although these results indicate very high model performance, achieving perfect accuracy requires more critical analysis. In the context of machine learning, 100% accuracy may indicate that the model is not only learning general patterns but also potentially memorizing specific characteristics of the dataset (overfitting), especially if data variation is limited or there is high similarity among images.

The implication of this condition is the potential for a decline in the model's generalization ability when faced with more diverse new data in real-world environments. Therefore, although the evaluation results show excellent performance on the test data, further testing using larger and more varied datasets, as well as additional validation methods such as cross-validation, is necessary to ensure the model's overall reliability.

b. Evaluation of CNN Model (VGG16 Architecture)

The evaluation of the CNN model with the VGG16 architecture was conducted using test data not used in the training process to assess the model's generalization ability. The evaluation methods employed included a confusion matrix and performance metrics such as accuracy, precision, recall, and F1-score. The confusion matrix results for the CNN model with the VGG16 architecture are shown in Figure 9 below.

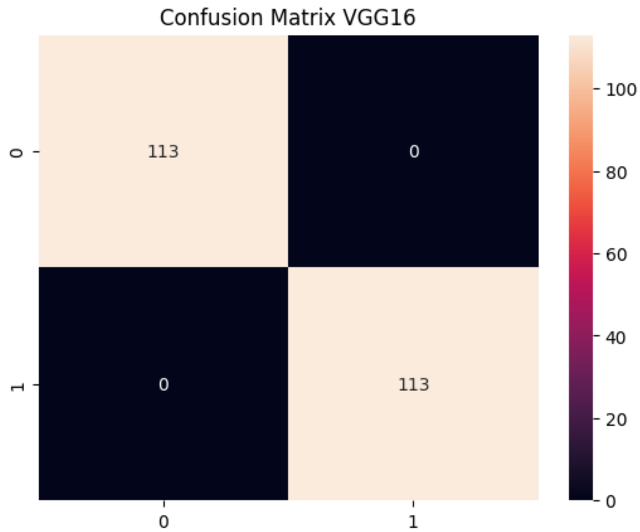


Figure 9. Confusion matrix results from the CNN model with the VGG16 architecture

Based on Figure 9, the results show TP = 113 and TN = 113, with no classification errors (FP = 0 and FN = 0). This indicates that all test data were successfully classified correctly by the model. The evaluation metrics show that the precision, recall, and F1-score values for both classes reached 1.00, with an overall accuracy of 100%. This indicates that the model performs exceptionally well in classifying the freshness level of tilapia based on visual images. However, this high performance still requires critical analysis as it may indicate overfitting. Therefore, further testing with a more diverse dataset is necessary to ensure the models ability to generalize to new data.

C. Model Performance Comparison

This study compares the performance of a simple CNN model and a CNN model based on the VGG16 architecture in classifying the freshness of tilapia based on eye images. The comparison was conducted using key evaluation metrics, namely accuracy, precision, recall, and F1-score. The comparison results show that both models the simple CNN and the VGG16-based CNN perform equally well in classifying the test data. Both models achieved an accuracy of 100% with no classification errors. A quantitative comparison of the two models performance is shown in Table 1. Based on the evaluation results shown in Figures 8 and 9, both models exhibit identical confusion matrices, in which all data were correctly classified without any FP or FN.

Table 1. Model performance comparison results

Model	Accuracy Training	Accuracy Validation	Loss Training	Loss Validation	Precision	Recall	F1-Score
CNN	99.62%	100%	0.0107	0.0002	1.00	1.00	1.00

CNN (VGG16)	100%	100%	0.0000	0.0000	1.00	1.00	1.00

Based on the test results, both models demonstrated good performance, with a validation accuracy of 100%. The precision, recall, and F1-score values for both models also reached 1.00, indicating that all test data were successfully classified correctly. The VGG16 model showed slightly better performance compared to the CNN without an architecture, as seen in the training process. This is evident from the higher training accuracy of 100% compared to 99.62% and a lower error rate of 0.0000 compared to 0.0107. This advantage is attributed to the deeper architecture of VGG16, which enables it to extract more complex image features. The accuracy values reaching 100% in both models require critical analysis as they may indicate overfitting, particularly if the dataset variation is limited. Therefore, further testing with a more diverse dataset is necessary to ensure the model's generalization capability.

The results of the study show that both simple CNN models and VGG16-based CNN are capable of achieving very high performance, with accuracy, precision, recall, and F1-score values reaching 100% on the test data. However, these results must be analyzed critically because perfect accuracy may indicate the possibility of overfitting, especially if the dataset has limited variation or similar image characteristics. The use of a dataset consisting of 1,500 images with balanced class distribution does not fully represent more complex real-world conditions, such as variations in lighting, shooting angles, and environments. However, the application of data augmentation techniques such as rotation, zooming, and flipping, as well as the division of the data into training, validation, and test sets, has helped increase data variation and maintain the objectivity of the evaluation..

D. Testing Of New Data

Model testing was also conducted using data outside the training dataset to evaluate generalization ability. The test data consisted of fish-eye images captured directly under real-world conditions and resized to 128 x 128 pixels. The results are shown in Figure 10.

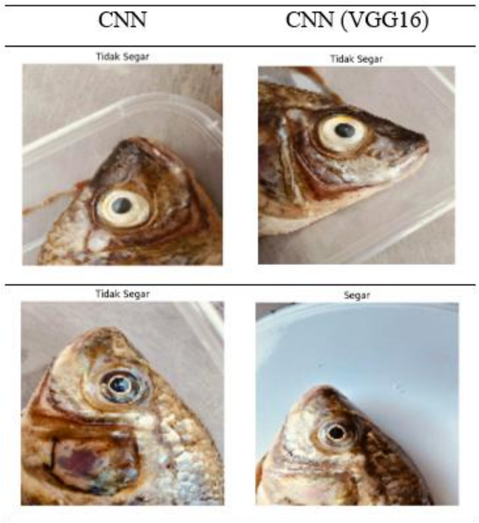


Figure 10. Test results using new data

Test results show that the CNN model without the VGG16 architecture still makes errors in classifying images in the fresh fish class, which are detected as not fresh. In contrast, the CNN model with the VGG16 architecture was able to classify images correctly according to their actual condition. This difference indicates that the VGG16 architecture has a better ability to extract complex image features, resulting in more accurate predictions. However, this testing is still limited to a small amount of data, so further testing with a more diverse dataset is needed to ensure the model's optimal generalization capability.

E. Discussion

The results of the study show that the CNN and VGG16 models are capable of classifying the freshness of tilapia with high performance. The CNN model achieved an accuracy of 99.62% with a loss of 0.0107, while VGG16 achieved 100% accuracy with a loss approaching zero, indicating superior feature extraction capabilities. Evaluation using a confusion matrix revealed no classification errors (FP = 0 and FN = 0), resulting in all evaluation metrics reaching 100%. This high performance is influenced by clear visual differences between classes as well as effective preprocessing. However, perfect accuracy potentially indicates overfitting, especially on datasets with limited variation. Although additional testing showed good results, a larger and more diverse dataset is needed to ensure the model's generalization ability. Overall, VGG16 is more recommended for image-based tilapia freshness classification.

V. CONCLUSION

This study successfully classified the freshness levels of tilapia based on visual images using the Convolutional Neural Network (CNN) method. The research stages included dataset collection, preprocessing (resizing and augmentation), and data splitting into training, validation, and testing sets.The results show that the model performs exceptionally well, with a training accuracy of 99.62% and a validation accuracy of 100%, along with a very low loss value. Evaluation using a confusion matrix indicates that all test data were correctly classified, resulting in accuracy, precision, recall, and F1-score values of 1.00 each. A comparison of models indicates that the CNN with the VGG16 architecture outperforms conventional CNNs, particularly in terms of training stability and feature extraction capabilities. Therefore, the VGG16-based model is recommended for use in image-based tilapia freshness classification. However, the very high accuracy results indicate the need for further evaluation of the model's generalization ability. Future research is suggested to use larger and more diverse datasets, as well as conduct testing under real-world conditions. Additionally, model development can be pursued by exploring other architectures or ensemble approaches, as well as applying this method to other fish species or by adding supporting features to improve the system's accuracy and reliability.

REFERENCE

[1] Cakra, Syarif Syafruddin, Gani Hamdan, Patombongi Andi, and Muh.Islah Andi, "Analisis Kesegaran Ikan Mujari dan Ikan Nila Dengan Metode Convolutional Neural Network," *Sistem Informasi dan Teknik Komputer*, vol. 7, no. 2, pp. 2502–5899, 2022.

[2] A. Prasetyo *et al.*, "Analisis Deteksi Citra Mata Ikan Nila dengan Metode Convolutional Neural Network Arsitektur Alexnet," *Jurnal Pustaka Data (Pusat Akses Kajian Database, Analisa Teknologi, dan Arsitektur Komputer)*, vol. 5, no. 1, pp. 48–53, Jun. 2025, doi: 10.55382/jurnalpustakadata.v5i1.995.

[3] S. S. Rambe, A. Asriyanik, and P. Prajoko, "Penerapan Model Convolutional Neural Network (CNN) Berbasis MobileNetV2 Untuk Klasifikasi Tingkat Kesegaran Ikan," *Jurnal Informatika dan Teknik Elektro Terapan*, vol. 13, no. 3, Jul. 2025, doi: 10.23960/jitet.v13i3.6744.

[4] R. Mahendra and R. Faurina, "Fish Freshness Prediction With Convolutional Neural Network Method Based On Fish Eye Image Analysis," *Jurnal Teknik Informatika (Jutif)*, vol. 5, no. 3, pp. 883–890, Jun. 2024, doi: 10.52436/1.jutif.2024.5.3.1351.

[5] M. Danial Purna Fiki, et al. "Classification of Central Lombok Songket Motifs Using Convolutional Neural Network ". *Breakthroughs In Informatics, Networking, Algorithms, Research, And Yield (BINARY)*, vol. 1, no. 1, Feb. 2025, pp. 13-20, https://journal.lombokscholar.org/index.php/binary/article/view/13.

[6] Ety Sutanty, Maukar, Dina Kusuma Astuti, and Handayani, "Penerapan Model Arsitektur VGG16 Untuk Klasifikasi Jenis Sampah," *Decode: Jurnal Pendidikan Teknologi Informasi*, vol. 3, no. 2, pp. 407–419, Sep. 2023, doi: 10.51454/decode.v3i2.331.

[7] H. Khamilah and M. Hardjianto, "Pengklasifikasian Kualitas Ikan Nila Berbasis Mata Ikan Dengan Metode K-Nearest Neighbors (K-NN)," vol. 3, no. 2, 2024.

[8] Y. Darnita, F. Andika Putra, S. Hendri Wibowo, S. Ade Saputera, N. David Maria Veronika, and A. Sonita, "Penerapan Metode Convolutional Neural Network Dalam Klasifikasi Kesegaran Ikan Mungkus Berdasarkan Citra Mata dan Insang Ikan," *Jurnal Informatika*, vol. 25, no. 1, pp. 59–73, 2025, doi: 10.30873.

[9] M. Sholihin, "Identifikasi Kesegaran Ikan Berdasarkan Citra Insang dengan Metode Convolution Neural Network," *JATISI (Jurnal Teknik Informatika dan Sistem Informasi)*, vol. 8, no. 3, pp. 1352–1360, Sep. 2021, doi: 10.35957/jatisi.v8i3.939.

[10] T. Dwi Novianto and I. Made Susi Erawan, “Perbandingan Metode Klasfikasi Pada Pengolahan Citra Mata Ikan Tuna,” *Prosiding SNFA(Seminar Nasional Fisika danAplikasinya)*, 2020.
[11] A. D. Putri and F. F. Rahani, “Klasifikasi Kesegaran Ikan Pada Citra dengan VGG19,” *Adopsi Teknologi dan Sistem Informasi (ATASI)*, vol. 4, no. 1, pp. 1–7, Jun. 2025, doi: 10.30872/atasi.v4i1.2888.
[12] Z. Arif and M. Lutfi, “Identifikasi Kesegaran Ikan Berdasarkan Citra Insang dengan Metode Deep Convolution Neural Network,” *Jurnal Minfo Polgan*, vol. 11, no. 2, pp. 1–6, Aug. 2022, doi: 10.33395/jmp.v11i2.11633.