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CLASSIFICATION OF MOLLY ORNAMENTAL FISH USING VGG16 ARCHITECTURE

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Abstrak

Ikan molly (*Poecilia sphenops*) merupakan salah satu jenis ikan hias yang banyak dibudidayakan. Penelitian ini bertujuan untuk mengembangkan sistem klasifikasi ikan hias molly menggunakan model VGG16 yang dilatih dengan teknik augmentasi data *on-the-fly* (*flip, zoom, rotasi, dan translasi*). Dataset yang digunakan terdiri dari 1.750 gambar ikan molly yang dibagi ke dalam tujuh spesies berbeda, yaitu Black, Blue Electric, Calico, Dalmatian, Golden Black, Platinum, dan Sunkist. Augmentasi data dilakukan secara dinamis selama proses pelatihan tanpa menyimpan hasil transformasi, yang bertujuan untuk meningkatkan keragaman data dan membantu model mengenali pola dengan lebih akurat. Hasil eksperimen menunjukkan bahwa kombinasi parameter optimal, yaitu laju pembelajaran 1e-5, ukuran batch 32, dan 50 epoch, menghasilkan akurasi pelatihan sebesar 97,80%, akurasi validasi sebesar 99,61%, serta akurasi pengujian sebesar 99,62%. Selain itu, nilai precision sebesar (99,63%), recall (99,62%), dan F1-Score (99,62%) yang sangat tinggi juga berhasil dicapai. Meskipun terdapat sedikit kesalahan klasifikasi pada kelas "Black" yang diprediksi sebagai "Sunkist", kesalahan ini sangat minim dan tidak mempengaruhi hasil secara keseluruhan. Penelitian ini menunjukkan bahwa dengan pengaturan parameter yang tepat dan penggunaan teknik augmentasi, model VGG16 dapat memberikan hasil klasifikasi yang memiliki hasil akurasi yang cukup tinggi untuk ikan hias molly. Model ini juga memiliki potensi untuk diterapkan dalam industri akuakultur ikan hias, khususnya dalam sistem deteksi otomatis berbasis gambar.
Kata kunci: augmentasi data, CNN, ikan hias molly, klasifikasi, VGG16

Abstract

Molly fish (Poecilia sphenops) is one of the ornamental fish species that is widely cultured. This study aims to develop a classification system for ornamental molly fish using the VGG16 model, trained with on-the-fly data augmentation techniques (flip, zoom, rotation, and translation). The dataset used consists of 1,750 images of molly fish, divided into seven different species: Black, Blue Electric, Calico, Dalmatian, Golden Black, Platinum, and Sunkist. Data augmentation is performed dynamically during the training process without saving the transformation results, aiming to increase data diversity and help the model recognize patterns more accurately. The experimental results show that the optimal combination of parameters, namely a learning rate of 1e-5, a batch size of 32, and 50 epochs, achieved a training accuracy of 97.80%, validation accuracy of 99.61%, and test accuracy of 99.62%. Additionally, very high precision (99.63%), recall (99.62%), and F1-Score (99.62%) values were achieved. Although there were minor classification errors in the "Black" class predicted as "Sunkist," these errors were minimal and did not affect the overall results. This study shows that with the right parameter settings and the use of augmentation techniques, the VGG16 model can provide classification results with fairly high accuracy for molly ornamental fish. This model also has the potential to be applied in the ornamental fish aquaculture industry, particularly in image-based automatic detection systems.

Keywords: *CNN, classification, data augmentation, ornamental molly fish, VGG16*

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INTRODUCTION

The Molly fish (*Poecilia sphenops*) is one of the most popular freshwater ornamental fish among aquarium enthusiasts. This fish originates from Central and South America, where it is mainly found in low-salinity or freshwater environments such as rivers, lakes, and ponds (Andriyono et al., 2025). This ornamental fish is known for its aesthetic appeal and visual beauty, making it a highly sought-after commodity in the aquaculture market. The diversity of ornamental fish species spread across various aquatic habitats, both freshwater and marine, makes ornamental fish a favorite choice for hobbyists and aquarium enthusiasts. Among the many species, molly fish are one of the most popular. Molly fish are known for their relatively larger size compared to guppy fish, as well as their ability to adapt to various water conditions. This makes them an ideal choice for both beginners and experienced hobbyists (Islamy et al., 2023)

All species of molly fish are known to hybridize with each other, resulting in a wide variety of colors and body patterns (A-Z Animals, 2024). This diversity of physical characteristics including color, pattern, and body texture often makes manual identification difficult. However, accurate classification is essential to support breeding, trade, and conservation efforts. Based on available sources, there are 27 types of molly fish that are popular in the aquarium market, each with distinctive color and body shape characteristics, as described in the article *27 Types of Popular Molly Ornamental Fish* (Hidayat, 2024). From this number, this study selected 7 species of molly fish as samples to be classified using the Convolutional Neural Networks (CNN) method.

In this context, artificial intelligence (AI) based technology can provide an effective solution. AI has been widely used in various fields to recognize and classify objects with a high degree of accuracy, including image recognition (Xu et al., 2024). With its wide range of applications, AI, particularly through Convolutional Neural Networks (CNN), has proven to be effective in processing images and recognizing objects, even with complex visual variations. One potential solution is the use of Convolutional Neural Networks (CNN), an artificial intelligence method that has proven effective in various image recognition applications. CNN is capable of automatically extracting important features from images without requiring manual processing, making it more reliable in identifying objects with complex visual variations (Putra, 2023). This advantage makes CNNs particularly suitable for classifying fish species with diverse colors and body patterns.

Previous research also supports the effectiveness of CNN in ornamental fish classification. One such study is (Marshanda et al., 2025) entitled “Classification of Guppy Fish Types Using Convolutional Neural Network (CNN)”, which used the pretrained ImageNet VGG16 architecture to classify six classes of guppy fish. Data augmentation techniques such as rotation, translation, zoom, and horizontal flipping were applied and produced excellent classification performance. However, the study did not apply the more efficient on-the-fly dynamic augmentation technique in terms of storage and training time usage.

Another study by (Muslem R & Johan, 2023) entitled “Fish Image Classification Using a Convolutional Neural Network Algorithm with VGG-16 Architecture” used 1,088 fish images in four classes, namely Bangus, Glass Perchlet, Gold Fish, and Gourami. This study utilized the VGG16 architecture on the Orange Data Mining platform for feature extraction and classification, and produced excellent accuracy rates. However, this study still has limitations in the form of a small number of classes and does not apply data augmentation techniques, so opportunities for further development are still open, especially for a more diverse number of classes.

Based on these findings, this study proposes a molly fish classification system by applying dynamic image augmentation techniques on-the-fly augmentation during the training process without explicitly storing the augmentation results. The augmentation techniques used include flip, zoom, rotation, and translation. The main dataset consists of seven species of molly fish. The system was developed using the VGG16 architecture with the aim of improving classification accuracy. In addition, this study also conducted a comparative evaluation of the performance of the CNN model used, so that it can be an important reference for further research.

LITERATURE REVIEW

Deep learning, particularly Convolutional Neural Networks (CNN), has demonstrated significant advancements in image classification, especially in tasks requiring species identification based on visual characteristics such as color, shape, and body patterns. CNN models excel due to their ability to automatically extract hierarchical features, making them highly suitable for classifying ornamental fish, which often exhibit subtle inter-species variations.

Among commonly used architectures, VGG16 remains one of the most popular due to its simplicity and strong capability in extracting fine visual details. Several studies have reported excellent performance using VGG16. (Adi Laksono et al., 2024) achieved 100% accuracy in betta fish classification, while (Karina Auliasari et al., 2023) obtained 98.33% accuracy on a large fish dataset using transfer learning. (Setyawan et al., 2023) also demonstrated the effectiveness of a modified VGG16 model, achieving high training accuracy (99.30%) and substantial validation performance (84.07%). These studies confirm that VGG16 remains reliable across diverse datasets and image conditions.

Data augmentation plays a crucial role in enhancing CNN generalization, especially when datasets are limited. (Zuhari et al., 2022) showed that augmentation significantly improved classification results in shark species identification, achieving 91.80% accuracy. Similarly, (Setia, 2023) found that MobileNetV2 outperformed other CNN models in koi fish classification, achieving 92% accuracy, emphasizing that proper augmentation and lightweight architectures can boost performance.

Recent works also highlight the strengths of alternative CNN architectures. (Wijayanto et al., 2025) achieved 99.4% accuracy in betta fish classification using MobileNetV2, while (Mohammadisabet et al., 2025) demonstrated that DenseNet121 achieved 90.2% accuracy in challenging conditions involving class imbalance and environmental variability. Despite these strong results, certain studies revealed limitations. (Hanggara et al., 2021), using a CNN-based CBIR approach for koi fish recognition, achieved only 65% retrieval accuracy, indicating that classification performance can drop in retrieval-based systems. Meanwhile, (Lubis, 2022) achieved 99.1% accuracy in general fish classification tasks, confirming the robustness of CNNs across broader datasets.

CNN models have also shown resilience in challenging imaging conditions. (Sudhakara et al., 2022) demonstrated that CNNs can still achieve 77% accuracy in underwater images affected by poor lighting and noise, highlighting the need for robust preprocessing and well-designed model architectures.

Overall, the literature demonstrates that CNN-based models including VGG16, MobileNetV2, and DenseNet121 consistently outperform traditional methods in fish species classification. These findings provide a strong theoretical foundation for the present study, which applies VGG16 with on-the-fly augmentation to improve classification performance for seven molly fish species.

METHOD

This section explains in detail the stages that will be carried out in the research, from problem formulation to drawing conclusions. The overall research methodology flow can be seen in Figure 1.

Fig. 1 Research Methodology Flowchart

Literature Study

This stage of aims to collect references that discuss the topic of ornamental fish classification, whether through books, theses, journals, or other scientific works. The focus of the literature includes the introduction of ornamental fish images, challenges in visual identification, and the application of learning techniques such as CNN for species classification. The references found will provide a theoretical basis for designing an effective and accurate ornamental fish classification system.

Dataset Collection

The dataset was created by capturing images of seven types of molly ornamental fish: Black, Blue Electric, Calico, Dalmatian, Golden Black, Platinum, and Sunkist. Each variety consisted of 250 images, resulting in a total of 1,750 raw images before the augmentation process. The fish were photographed using an iPhone 15 smartphone in standard mode. The photography took place indoors using an acrylic selfie setup, with additional lighting of 1699 lux to ensure optimal image quality. The photos were taken from a distance of approximately 15 cm, with the camera directed at the front of the acrylic surface. To ensure a clean and uniform background, transparent acrylic was used during the photography process. An example of the image capture setup is illustrated in Figure 2.

Fig. 2 Dataset Collection Process

The processed dataset was then divided into three parts: 70% for training data, 15% for validation data, and 15% for test data. During the training stage, the training data underwent on-the-fly augmentation techniques to increase data variation. The model used in this study was the VGG16 architecture, which served to classify the types of Molly fish based on the dataset. The discussion on the dataset division for the ornamental molly fish is presented in Table 1.

Table 1. Division of the Molly Ornamental Fish Dataset

Number	Molly Ornamental Fish Dataset Division		
	Training Data	Validation Data	Test Data
Percentage	70%	15%	15%
Number of Images	1225	259	266
Total Original Image	1750		
Total epoch (initial Epoch set = 50 or 100)	50 epoch * 1225 100 epoch * 1225		
Total Overall Data Train After Augmentation	50 epoch = 61.250 100 epoch = 122.500		

The dataset division of 70% for training data, 15% for validation data, and 15% for testing data is a standard practice commonly used in deep learning research. This aims to ensure the model receives sufficient data for training while maintaining an unbiased dataset for validation and testing (Iqtait et al., 2024) This division allows for more objective model evaluation and helps prevent overfitting during the training process.

Due to the use of on-the-fly data augmentation techniques, the amount of training data depends on the number of epochs used. Only the model can observe the random combinations of the data augmentation techniques, as the data is not stored permanently during the training process. This approach helps save memory storage while ensuring efficient and fast computation.

Design

The design stages will include processing the dataset to form the VGG16 model that will be used to classify types of Molly ornamental fish. The design scheme that has been compiled can be seen in Figure 3.

Fig. 3 VGG16 Model Design Scheme

In the initial stage, the photographed fish images will undergo a background removal process. Then, a dataset consisting of 1,750 fish images will be uploaded and organized into 7 folders based on their types: Black Molly, Electric Blue Molly, Calico Molly, Dalmatian Molly, Golden Black Molly, Platinum Molly, and Sunkist Molly. The dataset will then go through two preprocessing stages: resizing the images to 224x224 pixels and rescaling the data to normalize it within a range of [0, 1]. After that, the data will be split into three parts: training data, validation data, and test data. On-the-fly augmentation will be applied to the training data to increase data diversity and assist the model in the learning process.

In the next stage, the model will be trained using the VGG16 architecture with the augmented training data. The validation data will be used to evaluate the model's performance and to prevent underfitting or overfitting. The Adam optimizer will be employed to help adjust the model's weights when underfitting or overfitting occurs, with a learning rate range of 1e-1 to 1e-5, batch sizes of 32 and 64, and epochs of 50 and 100.

After the model has been trained, a testing phase will be conducted to assess the performance of the model in classifying the Molly fish types using the provided test data. The test results will offer insights into the model's ability to classify Molly ornamental fish types, completing the training and testing process.

Implementation

The implementation phase focused on classifying ornamental molly fish based on species using the VGG16 model, which was trained with on-the-fly augmentation techniques to improve model performance and generalization.

Evaluation

After the trial phase, the test results were analyzed using the Confusion Matrix to determine the success rate of the method. The following metrics were calculated: (1) Precision, which indicates the proportion of positive predictions that are correct, (2) Recall, which measures the proportion of actual positive cases correctly identified by the model, (3) F1-Score, which is the harmonic mean of Precision and Recall, and (4) Accuracy, which represents the percentage of correct predictions out of the total number of predictions made.

$$Precision = \frac{TP}{TP + FP} \times 100\% \ (1)$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \ (2)$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \ (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \ (4)$$

RESULT AND DISCUSSION

This section presents an in-depth analysis of the experimental results with the aim of identifying the most effective hyperparameter configuration for the VGG16 architecture in classifying Molly ornamental fish species. The experiment was conducted using a dataset consisting of 1,750 fish images, where the number of images in the training data increased with the number of epochs thanks to the application of on-the-fly augmentation techniques. This technique dynamically generates new image variations during the training process. As a result, the number of images in the 50 epoch became 61,250, and in the 100 epoch, it increased to 122,500 images. This entire dataset was allocated to seven different types of Molly fish: Black, Blue Electric, Calico, Dalmatian, Golden Black, Platinum, and Sunkist. The distribution and composition of classes can be seen in Table 2.

To comprehensively analyze model performance, this experiment also aims to find the best hyperparameter configuration for the VGG16 architecture. A total of twenty experimental scenarios were tested by varying several critical hyperparameters, such as batch size, number of training epochs, and learning rate. These variations were designed to observe their impact on model performance, stability, and generalization ability under various training, validation, and testing conditions.

To support open research and encourage further exploration in the field of ornamental fish classification using deep learning, this complete dataset is publicly available. The dataset can be accessed and downloaded for free via the following DOI link: https://doi.org/10.5281/zenodo.17348065. The open availability of this dataset ensures transparency, enables reproducibility of results, and provides a valuable resource for researchers who wish to compare or expand upon this research.

Table 2. Details of the Dataset Used

Number	Molly Fish	Epoch	Count	Example Image
1	Black	50	8.750	
		100	17.500	
2	Blue Electric	50	8.750	
		100	17.500	
3	Calico	50	8.750	
		100	17.500	
4	Dalmatian	50	8.750	
		100	17.500	
5	Golden Black	50	8.750	
		100	17.500	
6	Platinum	50	8.750	
		100	17.500	
7	Sunkist	50	8.750	
		100	17.500	

Table 3 shows the results of testing the VGG16 model with various combinations of hyperparameters, such as learning rate, batch size, and number of epochs. Each combination produces different results, with evaluation metrics such as training accuracy, validation accuracy, testing accuracy, precision, recall, and F1-Score calculated for each scenario. These results are visualized in Figure 4 using bar charts, which provide a clearer picture of the model's performance based on various parameter combinations. These charts make it easy for readers to directly compare the results obtained from each setting, allowing for visual identification of the best parameters.

Table. 3 VGG16 Test Result

Number	Learning Rate	Batch Size	Epoch	Train Accuracy	Validation Accuracy	Testing Accuracy	Precision	Recall	F1-Score
1	1e-1	32	50	48.08%	66.02%	14.29%	0.0204	0.1429	0.0357
2	1e-1	32	100	50.37%	66.41%	19.17%	0.3072	0.1917	0.1132
3	1e-1	64	50	43.92%	62.16%	15.04%	0.1634	0.1504	0.0502
4	1e-1	64	100	34.78%	39.38%	15.41%	0.1635	0.1541	0.0570
5	1e-2	32	50	87.76%	100%	100%	1.0000	1.0000	1.0000
6	1e-2	32	100	93.80%	100%	96.99%	0.9752	0.9699	0.9700
7	1e-2	64	50	94.29%	100%	100%	1.0000	1.0000	1.0000
8	1e-2	64	100	89.88%	100%	97.37%	0.9749	0.9737	0.9738
9	1e-3	32	50	97.47%	100%	100%	1.0000	1.0000	1.0000
10	1e-3	32	100	94.94%	100%	100%	1.0000	1.0000	1.0000
11	1e-3	64	50	98.37%	100%	99.62%	0.9963	0.9962	0.9962
12	1e-3	64	100	94.86%	100%	100%	1.0000	1.0000	1.0000
13	1e-4	32	50	96.16%	100%	100%	1.0000	1.0000	1.0000
14	1e-4	32	100	97.06%	100%	100%	1.0000	1.0000	1.0000
15	1e-4	64	50	96.57%	100%	99.62%	0.9963	0.9962	0.9962
16	1e-4	64	100	95.51%	100%	100%	1.0000	1.0000	1.0000
17	1e-5	32	50	97.80%	99.61%	99.62%	0.9963	0.9962	0.9962
18	1e-5	32	100	95.67%	100%	100%	1.0000	1.0000	1.0000
19	1e-5	64	50	94.20%	99.61%	99.25%	0.9927	0.9925	0.9924
20	1e-5	64	100	97.96%	99.23%	99.62%	0.9963	0.9962	0.9962

Table 3 presents the results of testing the VGG16 model with various combinations of parameters, namely learning rate, batch size, and epoch, as well as important metrics such as training, validation, and testing accuracy, precision, recall, and F1-Score. For example, in row 17 with a combination of learning rate 1e-5, batch size 32, and epoch 50, the model achieved a test accuracy of 99.62%, with very high precision, recall, and F1-Score, namely 0.9963, 0.9962, and 0.9962. This combination of parameters provides the best results among the other combinations tested.

The VGG16 model with on-the-fly augmentation achieved an accuracy of 99.62%, precision of 99.63%, recall of 99.62%, and an F1-Score of 99.62%. This performance is higher than that of the study (Muslem R & Johan, 2023), which used VGG16 without augmentation and only achieved an accuracy of 94%. These findings are also in line with the research (Marshanda et al., 2025) that applied static augmentation to guppy fish classification, as well as (Zuhari et al., 2022) which showed that augmentation techniques increased the accuracy of shark species classification to 91.8%.

The main advantage of on-the-fly augmentation is its ability to generate new image variations at each epoch, which expands the distribution of data seen by the model. This makes the model more resistant to overfitting and able to generalize better on previously unseen data.

Despite its high performance, the confusion matrix shows classification errors in the Black class, which is predicted as Sunkist. This error can be explained by the strong visual similarities between the two species, especially in body color and pattern. A similar challenge was reported by (Hidayat, 2024), who emphasized the difficulty in identifying molly variants with similar physical characteristics. To overcome this, further research could explore preprocessing such as segmentation or contrast enhancement, as well as consider alternative architectures such as DenseNet, ResNet, or MobileNet, which have proven effective in distinguishing subtle visual details.

Overall, this study confirms that VGG16 with on-the-fly augmentation is a highly effective approach for classifying molly ornamental fish. In addition to its academic contribution, this model also has great potential for application in image-based automatic detection systems in the ornamental fish farming industry.

Fig 4. VGG16 Result

Figure 4 provides a visual representation of the results in Table 3. The bar chart in Figure 4 allows readers to easily compare the results obtained from the various combinations of parameters tested. Each category (learning rate, batch size, and epoch) on the horizontal axis represents a different setting, while the values on the vertical axis show the accuracy percentage and other metrics, such as precision, recall, and F1-Score. Using this bar chart makes it easier to visually understand the comparisons between parameter combinations. Although both sources of information, Table 3 and Figure 4, present the same data, Table 3 provides more complete and detailed numerical details, while Figure 4 provides a more intuitive and clearer visual overview of how parameter settings affect model performance.

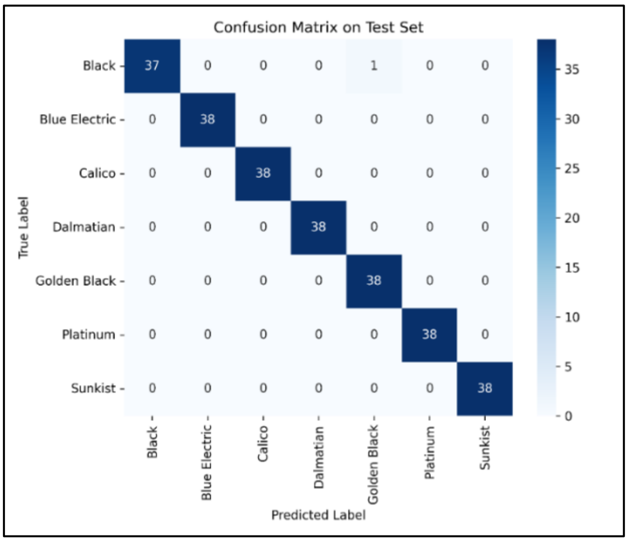

Fig. 5 Confusion Matrix

Figure 5 shows the Confusion Matrix that illustrates the results of testing the classification model for ornamental molly fish species. In this matrix, each row represents the true label, while each column shows the label predicted by the model. The numbers in the matrix indicate the number of samples that were classified correctly or incorrectly based on the combination of the true label and the model's prediction. Most of the numbers are on the main diagonal, which indicates that the model successfully classified most classes very well. However, there was one prediction error in the "Black" class, which was predicted as "Sunkist." Despite this error, it was very small, as the model successfully classified 37 out of 38 samples correctly for the "Black" class. Overall, this Confusion Matrix shows that the model has a very low error rate in classifying molly fish species, with most classes predicted accurately. This indicates that the model is able to recognize patterns in the test data very well, despite a few minor errors. This matrix also provides a more in-depth picture of the model's performance in recognizing each fish species, showing the extent to which the model is able to avoid classification errors.

CONCLUSION

This study successfully demonstrated that the VGG16 model, applied with on-the-fly augmentation, was able to classify molly fish species with a very high accuracy rate of 99.62%. This model, using a learning rate of 1e-5, batch size of 32, and 50 epochs, achieved a training accuracy of 97.80%, a validation accuracy of 99.61%, test accuracy of 99.62%, and precision 99.63%, recall 99.62%, and F1-Score 99.62%. These results demonstrate the effectiveness of this approach in improving classification performance.

However, this study has several limitations. First, the dataset used is limited to seven species of molly fish, which may not fully cover the diversity of ornamental fish species. In addition, although on-the-fly augmentation has been shown to improve model generalization, the model still experiences classification errors in very similar species, such as errors between Black and Sunkist. Another limitation is the use of images with varying lighting conditions, which may affect the quality of the classification results. The model developed in this study has great potential for application in the ornamental fish aquaculture industry, especially in image-based automatic detection systems for fish classification.

Further research could expand the dataset to include more ornamental fish species and address the challenge of classifying highly similar species. The application of further augmentation techniques, such as feature-based augmentation or the use of more complex models, could help reduce classification errors. In addition, further research could explore the use of this model in real-world conditions, such as in environments with less-than-ideal lighting or low-quality images.

REFERENCES

A-Z Animals. (2024). *Molly*. https://a-z-animals.com/animals/molly/

Adi Laksono, S., Rahmat, B., & Nugroho, B. (2024). Identifikasi jenis ikan cupang berdasarkan gambar menggunakan metode convolutional neural network. *JATI (Jurnal Mahasiswa Teknik Informatika), 8*(3), 3331–3338. https://doi.org/10.36040/jati.v8i3.9676

Andriyono, S., Pramono, H., Hapsari, R. S., Riza, A., Hakim, A. N., & Pangestu, C. T. (2025). *Membangun masa depan perikanan Tulungagung*. Airlangga University Press. https://books.google.co.id/books?id=UNZ4EQAAQBAJ

Hanggara, N. R., Niswatin, R. K., & Kasih, P. (2021). Penerapan content-based image retrieval untuk pengenalan jenis ikan koi. *[Nama jurnal/prosiding tidak tersedia]*.

Hermanto, D., & Nurrahman, A. A. (2025). *Molly fish dataset* (Version 1.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.17348065

Hidayat, A. (2024). *27 jenis ikan molly hias populer beserta foto lengkap di kalangan penghobi ikan hias dan aquascape*. Iwak Buncit. https://www.iwakbuncit.com/2024/04/27-jenis-ikan-molly-hias-populer.html

Iqtait, M., Alqaryouti, M. H., & Sadeq, A. E. (2024). Enhanced fish species detection and classification using a novel deep learning approach. *International Journal of Advanced Computer Science and Applications, 15*(10), 1–10. https://doi.org/10.14569/IJACSA.2024.01510108

Islamy, R. A., Hasan, V., Valen, F. S., & Serdiati, N. (2023). *Ikan hias dan akuaskap: Buku ajar*. Universitas Brawijaya Press. https://books.google.co.id/books?id=mYHeEAAAQBAJ

Karina Auliasari, W., Wasef, M., & Kertaningtyas, M. (2023). Leveraging VGG16 for fish classification in a large-scale dataset. *Brilliance: Research of Artificial Intelligence, 3*(2), 316–328. https://doi.org/10.47709/brilliance.v3i2.3270

Lubis, C. (2022). Klasifikasi citra ikan menggunakan convolutional neural network. *Jurnal Ilmu Komputer dan Sistem Informasi (JIKSI), 10*(1), 1–8. https://doi.org/10.24912/jiksi.v10i1.17827

Marshanda, F., Santoso, B., & Armanto. (2025). Klasifikasi jenis ikan guppy menggunakan convolutional neural network (CNN). In *Proceedings of ESCAF (Economic, Social Science, Computer, Agriculture and Fisheries)* (pp. 967–974).

Mohammadisabet, A., Hasan, R., Dattana, V., & Mahmood, S. (2025). CNN-based optimization for fish species classification: Tackling environmental variability, class imbalance, and real-time constraints. *[Preprint/manuscript]*, 1–33.

Muslem R., I., & Johan, T. (2023). Klasifikasi citra ikan menggunakan algoritma convolutional neural network dengan arsitektur VGG-16. *Kajian Ilmiah Informatika dan Komputer, 4*(2), 978–983. https://doi.org/10.30865/klik.v4i2.1209

Putra, M. S. S. (2023). *Perbaikan dan peningkatan kualitas citra menggunakan convolutional neural network. [Laporan/skripsi tidak dipublikasikan]*.

Setia, A. (2023). Classifying types of koi fish using convolutional neural network (CNN). *[Prosiding/jurnal tidak tersedia]*, 1–8.

Setyawan, W. D., Nilogiri, A., & A'yun, Q. (2023). Implementasi convolutional neural network (CNN) untuk klasifikasi pada citra ikan cupang hias. *JTIK (Jurnal Teknik Informatika Kaputama), 7*(1), 101–110. https://doi.org/10.59697/jtik.v7i1.45

Sudhakara, M., Meena, M. J., Reddy, O., Mahalakshmi, V., & Balobaid, A. (2022). A study on fish classification techniques using convolutional neural networks on highly challenged underwater images. *International Journal on Recent and Innovation Trends in Computing and Communication, 10*(4), 1–9. https://doi.org/10.17762/ijritcc.v10i4.5524

Wijayanto, B., Mahendra, R. M., & Salam, M. I. (2025). Identifikasi jenis ikan cupang menggunakan metode CNN dengan arsitektur MobileNetV2 berbasis mobile. In *Prosiding Seminar Nasional Teknologi dan Sains* (Vol. 4, pp. 519–525).

Xu, P., Wang, J., Jiang, Y., & Gong, X. (2024). Applications of artificial intelligence and machine learning in image processing. *Frontiers in Materials, 11*, 1431179. https://doi.org/10.3389/fmats.2024.1431179

Zuhari, A. B., Maulana, D. I., & Maheswara, E. S. (2022). Optimization image classification pada ikan hiu dengan metode convolutional neural network dan data augmentasi. *[Prosiding/jurnal tidak tersedia]*, 1–11.