Performance Comparison of Regularization Methods on Transfer Learning Algorithm for Fish Species Classification

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***Abstract*—Automatic fish classification played an essential role in the fisheries sector, particularly in underwater environments where visual quality was often degraded. This study addressed challenges related to low-contrast underwater images and limited dataset conditions by integrating Contrast Limited Adaptive Histogram Equalization (CLAHE) with a VGG16-based transfer learning model with regularization approaches including L1, L2, and Dropout. The dataset consisted of multiple fish species, including Bream, Sea Bass, Horse Mackerel, Red Mullet, and Black Sea Sprat. To enhance dataset diversity, data augmentation was performed using geometric transformations such as rotation, flipping, cropping/resizing, translation, shearing, and zooming. The dataset was divided into training (70%, 18,900 images), validation (20%, 5,400 images), and testing (10%, 2,700 images). Experimental results showed that the VGG16-CLAHE-Dropout model achieved the best overall performance, with training, validation, and testing accuracies of 99.15%, 98.37%, and 97.07%, respectively. CLAHE was implemented using a clip limit of 2.0 and a tile grid size of 8×8 to enhance image contrast, while the model was optimized using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. These findings demonstrated that combining contrast enhancement with appropriate regularization techniques significantly improved deep learning performance for underwater fish species classification.**

***Keywords*—Fish classification; underwater image; VGG16; CLAHE; regularization; transfer learning**

I. Introduction

Automatic fish classification is important because it allows the fish industry to be more productive through automation. In addition, the challenges of increasing food demand and potential food scarcity in the future urgently require automatic fish classification [1]. Fish species identification research is important for researchers in various fields such as ecologists, taxonomists, and geneticists to avoid mistaken identification [2]. In addition, automatic fish classification is important in freshwater environments where different species may be similar to each other, making manual identification difficult and prone to error [3]. To increase productivity, support research, ensure accurate species identification, and understand the health benefits of fish is the urgency of automated fish classification research using artificial intelligence [4], [5].

Detection of fish species is important to support fish biodiversity monitoring activities that are used as indicators of the health of seawater ecosystems [6]. Several studies have been conducted to solve the problems that exist in the detection of fish species [7], [8], [9], [10], [11]. In addition, fish species detection research can be useful for calculating the total and type of fish caught as a report to avoid overfishing in a particular area [12].

Unlike other types of data, videos and images cannot be immediately used for automatic detection [13], [14], [15]. The images collected are usually analyzed by manually trained human resources for reporting on the health of marine ecosystems or reporting on fishing areas, which is costly and time-consuming [16]. To overcome this problem, there is a need for an approach in modeling fish species detection technology [17]. This model can be used to help extract information about fish species and their numbers according to the actual situation [18].

Recent studies on fish species classification using deep learning demonstrated notable improvements in performance alongside the evolution of network architectures. ResNet50 and ResNet101 performance remained relatively limited in certain scenarios, with reported accuracies of 91.37% for ResNet50 and 86.12% for ResNet101 [19]. In contrast, MobileNetV2 achieved an accuracy of 96.56% [20], while MobileNetV3 further improved performance to 97.20% [21]. Additionally, integrating image enhancement techniques proved beneficial; for instance, the combination of ESRGAN with VGG16 achieved 96.50% accuracy [22], demonstrating that super-resolution preprocessing significantly improved feature quality in low-resolution images [23].

However, many fish classification techniques rely on transfer learning to improve accuracy. The VGG16 model has been used for fish classification in previous studies. Previous research proposes a framework combining the VGG16 transfer classification method and object localization that proposes rapid classification performance for fish image classification processing [4], [24], [25], [26], [27], [28].

In a study comparing several different transfer learning models, VGG16 achieved the highest accuracy scores, with a testing accuracy of 98.07% without fine-tuning and 96.56% with fine-tuning [20]. However, some previous studies have not discussed the comparative effectiveness of regularization methods applied to VGG16 for fish classification.

Classification of fish species in underwater images is a challenging task due to the phenomenon of illumination in seawater that causes low-contrast imagery. In addition, the scarcity of sufficient species datasets of fish imagery poses a serious problem for training a classification model. To overcome this problem, transfer learning-based methods need to be applied contrast enhancement methods to improve classification accuracy [18], [29].

The contrast enhancement approach that can be used is Contrast Limited Adaptive Histogram Equalization (CLAHE). By applying the CLAHE method, it is expected to overcome the problem of limited contrast fish species datasets and provide solutions for accurate fish identification. In addition, this study will use the regularization method on VGG16 to reduce overfitting when processing image datasets from contrast enhancement results. In this study, VGG16 was regularized and optimized with the CLAHE method. This proposed research aims to improve the performance of VGG16 in processing species image datasets with low contrast due to lighting conditions in seawater.

II. Research Methodology

The study employed a structured methodology starting with the dataset collection of fish species images, followed by data preprocessing using CLAHE to enhance image quality, and model development using transfer learning based on VGG16 with the application of regularization techniques, including Dropout, L1, and L2. Subsequently, performance evaluation was conducted through benchmarking to compare the effectiveness of each regularization method in improving classification accuracy. In this study, a comparison of different regularizations is proposed to be applied to the VGG16 model layer. The research stage can be seen in Fig. 1.

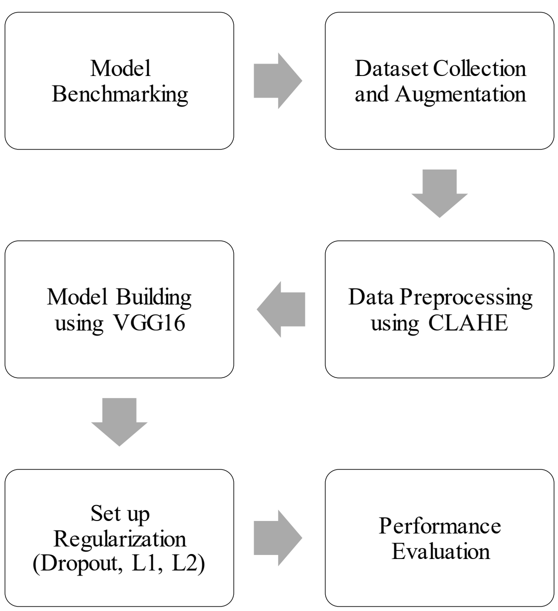

Fig. 1. Research phase

The data classes in this study consisted of Bream, Red Sea Bream, Sea Bass, Red Mullet, Horse Mackerel, Black Sea Sprat, and Striped Red Mullet, while the training and validation datasets were obtained from [30]. Data augmentation was applied to increase dataset diversity and reduce overfitting by performing geometric transformations including rotation, flipping, cropping/resizing, translation, shearing, and zooming. The dataset was divided into three subsets with a composition of 70% (18,900 images) for training, 20% (5,400 images) for validation, and 10% (2,700 images) for testing. The example of dataset can be seen in Fig. 2.

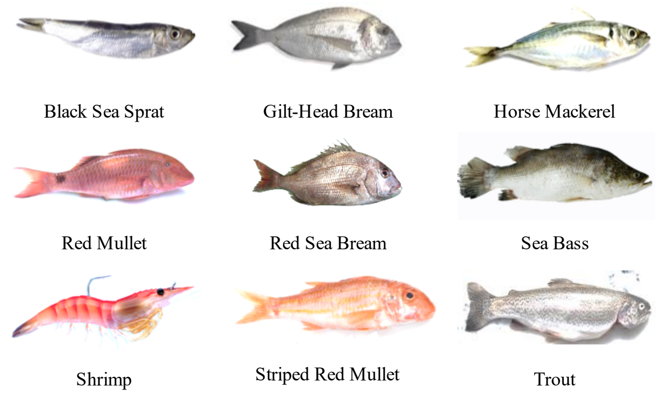

Fig. 2. Fish dataset class

Due to the presence of illumination distortions and low-contrast characteristics typical of underwater imaging, the collected dataset underwent a preprocessing stage employing Contrast Limited Adaptive Histogram Equalization (CLAHE) with a clip limit of 2.0 and a tile grid size of (8×8) to improve image quality. Model construction was performed using the VGG16 architecture with three regularization strategies, i.e., Dropout, L1, and L2, which were implemented in separate experimental configurations. The architecture of VGG16 that is used in this experiment can be seen in Fig. 3.

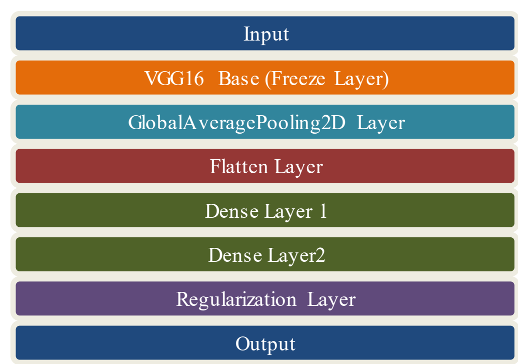

Fig. 3. VGG6 model experiment

Model performance evaluation was conducted using the testing subset through quantitative metrics such as accuracy, confusion matrix, precision, recall, and F1-score.

III. Results and Discussion

The study first conducted a baseline experiment using VGG16 without CLAHE to determine the optimal hyperparameter configuration. Subsequently, CLAHE was applied as a preprocessing technique, and the model was evaluated with different regularization methods. Each configuration was trained and tested under the same experimental settings to ensure a fair comparison.

A. *VGG16 Experiment*

The experiment evaluated the performance of regularization methods on a transfer learning model based on VGG16 for fish species classification, with the number of epochs fixed at 50. The learning rate was set to 0.0001, while the optimizer (Adam and SGD) and batch size (16, 32, and 64) were systematically varied to generate six experimental scenarios. The result of experiment is presented in Table I.

TABLE I. VGG16 EXPERIMENT RESULT

No	Learning Rate	Optimizer	Batch Size	Testing Accuracy
1	0.0001	Adam	16	94.85
2	0.0001	Adam	32	95.92
3	0.0001	Adam	64	95.40
4	0.0001	SGD	16	93.75
5	0.0001	SGD	32	94.88
6	0.0001	SGD	64	92.60

The experimental results demonstrated that the choice of optimizer and batch size significantly influenced the performance of the fish classification model. Using the Adam optimizer with a learning rate of 0.0001 consistently produced higher testing accuracy compared to SGD across all batch sizes. The highest accuracy of 95.92% was achieved with a batch size of 32, while batch sizes of 16 and 64 resulted in slightly lower accuracies of 94.85% and 95.40%, respectively. These findings indicated that a moderate batch size provided a better balance between stable gradient updates and generalization capability.

In contrast, the SGD optimizer yielded lower performance overall, with testing accuracies ranging from 92.60% to 94.88%. The best result using SGD was obtained with a batch size of 32 (94.88%), while the lowest accuracy was observed at a batch size of 64 (92.60%). This suggested that SGD was less effective in handling the complexity of underwater fish image classification under the given configuration. Overall, the results confirmed that the Adam optimizer, combined with an appropriate batch size, particularly 32 for fish species classification tasks.

B. VGG16-CLAHE-L1

The accuracy results of the VGG16-CLAHE-L1 model showed that the training process initially started with 0.19 for training and 0.18 for validation, but it quickly decreased and stabilized around 0.10–0.11 for both training and validation in subsequent epochs. Throughout the training process up to 50 epochs, the accuracy values fluctuated slightly but remained relatively constant. The accuracy results for experiments using the VGG16-CLAHE-L1 model can be seen in Fig. 4.

The confusion matrix was used to evaluate the performance of the VGG16-CLAHE-L1 model during the testing phase in classifying fish species across nine categories. The results showed that the model correctly classified certain classes with relatively high accuracy, particularly Horse Mackerel (HM), which achieved 298 correct predictions out of 300 samples. Similarly, Gilt-head Bream (GHB) and Red Mullet (RM) recorded moderate correct classifications with 203 and 112 correctly predicted samples, respectively. However, some classes, such as Black Sea Sprat (BSS) and Sea Bass (SB), were not correctly classified, as all their samples were misclassified, primarily into the Horse Mackerel (HM) class. This indicated that the model had difficulty distinguishing between visually similar species, as presented in Fig. 5.

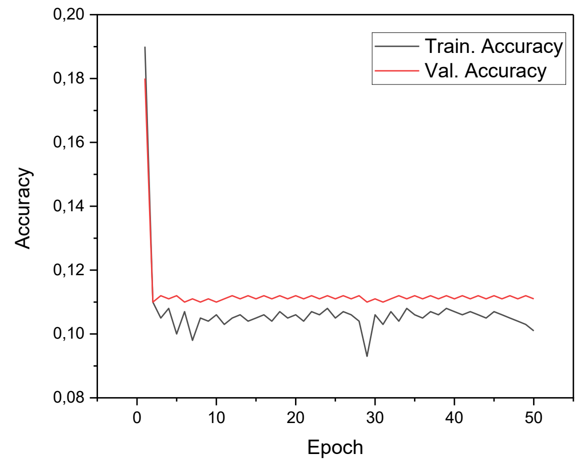

Fig. 4. Accuracy of VGG16-CLAHE-L1 model.

True \ Pred	BSS	GHB	HM	RM	RSB	SB	SH	SRM	TR
BSS	0	0	300	0	0	0	0	0	0
GHB	0	203	97	0	0	0	0	0	0
HM	0	2	298	0	0	0	0	0	0
RM	0	48	140	112	0	0	0	0	0
RSB	0	246	38	0	16	0	0	0	0
SB	0	98	202	0	0	0	0	0	0
SH	0	15	242	5	0	0	38	0	0
SRM	1	19	268	11	0	0	1	0	0
TR	0	141	154	0	0	0	0	0	5

BSS = Black Sea Sprat; GHB = Gilt-head Bream; HM = Horse Mackerel; RM = Red Mullet; RSB = Red Sea Bream; SB = Sea Bass; SH = Shrimp; SRM = Striped Red Mullet; TR = Trout.

Fig. 5. Confusion matrix of VGG16-CLAHE-L1.

Furthermore, substantial misclassification was observed across multiple classes, where a considerable number of samples were incorrectly predicted as Horse Mackerel (HM). For example, Trout (TR), Sea Bass (SB), and Shrimp (SH) were largely misclassified into the HM category, indicating a strong bias of the model toward this dominant class. In addition, Red Sea Bream (RSB) and Striped Red Mullet (SRM) demonstrated low classification performance, with only a small number of correctly identified instances. Based on the confusion matrix, further performance evaluation was conducted using precision, recall, and F1-score metrics, and the results obtained from the VGG16-CLAHE-L1 model were presented in Table II.

The classification performance of the VGG16-CLAHE-L1 model was assessed using precision, recall, and F1-score metrics for each fish species class. The results indicated substantial disparities in performance, where several classes exhibited extremely low or zero effectiveness. Specifically, Black Sea Sprat (BSS), Sea Bass (SB), and Striped Red Mullet (SRM) recorded zero values across all evaluation metrics, demonstrating that these classes were entirely misclassified. Meanwhile, Gilt-head Bream (GHB) and Red Mullet (RM) showed moderate performance, with F1-scores of 0.38 and 0.52, respectively, indicating partial classification capability.

TABLE II. PRECISION, RECALL, F1-SCORE OF VGG16-CLAHE-L1

Class	Precision	Recall	F1-Score	Support
Black Sea Sprat	0.00	0.00	0.00	300
Gilt-Head Bream	0.26	0.68	0.38	300
Horse Mackerel	0.17	0.99	0.29	300
Red Mullet	0.88	0.37	0.52	300
Red Sea Bream	1.00	0.05	0.10	300
Sea Bass	0.00	0.00	0.00	300
Shrimp	0.97	0.13	0.22	300
Striped Red Mullet	0.00	0.00	0.00	300
Trout	1.00	0.02	0.03	300

In contrast, certain classes displayed imbalanced metric distributions. Red Sea Bream (RSB) and Trout (TR) achieved perfect precision (1.00), yet their very low recall values resulted in poor F1-scores, indicating that only a few instances were correctly identified despite highly accurate predictions. Similarly, Horse Mackerel (HM) achieved a high recall of 0.99 but suffered from low precision (0.17), suggesting that many samples from other classes were incorrectly predicted as HM. Shrimp (SH) also exhibited high precision (0.97) but low recall (0.13), reinforcing the presence of class imbalance and misclassification bias.

C. *VGG16-CLAHE-L2*

The experimental results of the VGG16-CLAHE-L2 model demonstrated a consistent improvement in accuracy throughout the training process. Initially, both training and validation accuracies were relatively low, but they increased rapidly during the early epochs, indicating that the model effectively learned relevant features from the dataset. As the training progressed, the training accuracy continued to improve gradually, reaching approximately 0.89–0.90, while the validation accuracy fluctuated within the range of 0.70 to 0.76. These trends suggested that the model was able to capture underlying patterns in the data, although some variability in validation performance remained. The detailed accuracy results of the VGG16-CLAHE-L2 experiments were presented in Fig. 6.

Beyond assessing training and validation, the performance model during the testing phase was further evaluated using a confusion matrix. This approach was employed to assess how well the VGG16-CLAHE-L2 model predicted each fish species class correctly or incorrectly across the entire dataset. The confusion matrix results revealed that several classes were classified with high accuracy, such as Horse Mackerel (HM) and Trout (TR), which achieved perfect classification with 300 correct predictions each. Similarly, Red Sea Bream (RSB) and Shrimp (SH) showed strong performance with 298 and 297 correctly classified samples, respectively. Other classes, such as Gilt-head Bream (GHB) and Red Mullet (RM) also demonstrated relatively high correct predictions, indicating improved discriminative capability of the model compared to previous configurations. The detailed results of this evaluation were illustrated in Fig. 7.

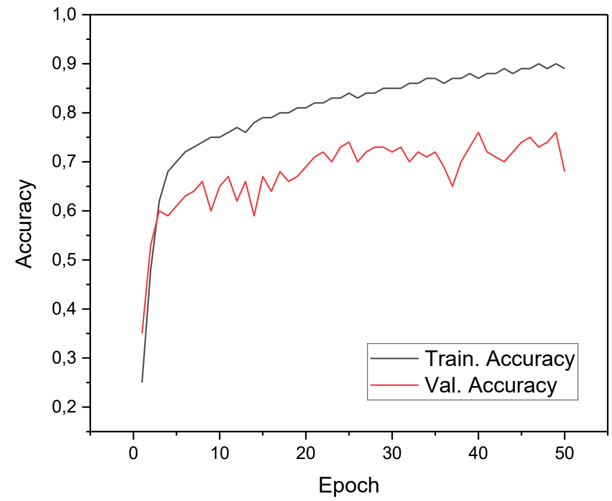

Fig. 6. Accuracy of VGG16-CLAHE-L2.

True \ Pred	BSS	GHB	HM	RM	RSB	SB	SH	SRM	TR
BSS	285	0	2	0	0	1	0	12	0
GHB	0	288	4	0	6	1	0	0	1
HM	0	0	300	0	0	0	0	0	0
RM	0	0	0	243	0	0	0	57	0
RSB	0	2	0	0	298	0	0	0	0
SB	29	5	0	0	0	254	0	0	12
SH	0	0	0	0	0	0	297	3	0
SRM	39	0	24	2	0	0	17	218	0
TR	0	0	0	0	0	0	0	0	300

BSS = Black Sea Sprat; GHB = Gilt-head Bream; HM = Horse Mackerel; RM = Red Mullet; RSB = Red Sea Bream; SB = Sea Bass; SH = Shrimp; SRM = Striped Red Mullet; TR = Trout

Fig. 7. Confusion matrix of VGG16-CLAHE-L2.

Although several classes were classified correctly, a certain level of misclassification was still observed across some categories. Black Sea Sprat (BSS) was occasionally predicted as Striped Red Mullet (SRM), while Sea Bass (SB) showed confusion with both Black Sea Sprat (BSS) and Trout (TR). In addition, Striped Red Mullet (SRM) was misclassified into multiple classes, including BSS and Horse Mackerel (HM), indicating the presence of similar visual features among these species. Despite these limitations, the overall pattern of predictions demonstrated that the VGG16-CLAHE-L2 model achieved a more balanced and reliable performance compared to the L1-based approach. Further evaluation based on the confusion matrix was conducted using precision, recall, and F1-score metrics, where the Red Sea Bream (RSB) class achieved the highest performance across all metrics. The detailed evaluation results for each fish species class were presented in Table III.

The performance of the VGG16-CLAHE-L2 model was evaluated using precision, recall, and F1-score metrics for each fish species class, and the results indicated a substantial improvement compared to the L1-based model. Most classes achieved high and balanced metric values, demonstrating strong classification capability. Red Sea Bream (RSB) recorded the best overall performance with precision, recall, and F1-score values close to perfect (0.98, 0.99, and 0.99, respectively). Similarly, Trout (TR) and Horse Mackerel (HM) achieved excellent recall values of 1.00, with high precision and F1-scores, indicating that these classes were accurately and consistently classified.

TABLE III. PRECISION, RECALL, F1-SCORE OF VGG16-CLAHE-L2

Class	Precision	Recall	F1-Score	Support
Black Sea Sprat	0.81	0.95	0.87	300
Gilt-Head Bream	0.98	0.96	0.97	300
Horse Mackerel	0.91	1.00	0.95	300
Red Mullet	0.99	0.81	0.89	300
Red Sea Bream	0.98	0.99	0.99	300
Sea Bass	0.90	0.85	0.91	300
Shrimp	0.95	0.99	0.97	300
Striped Red Mullet	0.75	0.73	0.74	300
Trout	0.96	1.00	0.98	300

In addition, Gilt-head Bream (GHB), Shrimp (SH), and Red Mullet (RM) showed strong performance with F1-scores above 0.89, reflecting reliable classification across these categories. Sea Bass (SB) and Black Sea Sprat (BSS) also demonstrated good performance, although slightly lower compared to the top-performing classes. However, Striped Red Mullet (SRM) recorded the lowest performance among all classes, with an F1-score of 0.74, indicating that some misclassification issues persisted.

D. *VGG16-CLAHE-Dropout*

From the experimental results, the accuracy results of the VGG16-CLAHE-Dropout model showed a strong and consistent improvement throughout the training process. At the initial epochs, both training and validation accuracy started at moderate levels, then increased rapidly as the model learned relevant features from the data. The training accuracy steadily improved and reached approximately 0.94–0.95 in the final epochs, indicating effective learning. The validation accuracy also increased and stabilized in the range of 0.80–0.85, although it exhibited slight fluctuations across epochs. The accuracy results and loss results for experiments using the VGG16-CLAHE-Dropout model can be seen in Fig. 8.

The model performance at the testing stage was further analyzed using a confusion matrix. This evaluation approach was employed to measure how accurately the VGG16-CLAHE-Dropout model classified each fish species across all categories. The results indicated that most classes were correctly predicted with high accuracy, as shown by the dominant diagonal values in the confusion matrix. In particular, Red Sea Bream (RSB) and Shrimp (SH) achieved perfect classification with 300 correct predictions each, while Trout (TR), Gilt-head Bream (GHB), and Sea Bass (SB) also demonstrated near-perfect classification performance, as depicted in Fig. 9.

Nevertheless, a small number of misclassifications were still observed in certain classes. For example, Striped Red Mullet (SRM) was occasionally misclassified into classes such as Black Sea Sprat (BSS) and Horse Mackerel (HM), while minor confusion occurred between Horse Mackerel (HM) and Red Sea Bream (RSB). Despite these errors, the overall classification performance remained highly reliable and balanced across all classes. The next evaluation was conducted using precision, recall, and F1-score metrics. The detailed results for each fish species class were presented in Table IV.

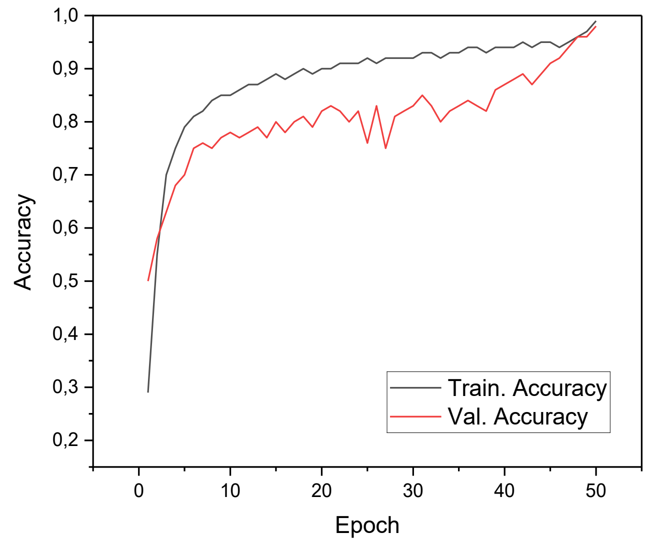

Fig. 8. Accuracy of VGG16-CLAHE-Dropout.

True \ Pred	BSS	GHB	HM	RM	RSB	SB	SH	SRM	TR
BSS	295	0	1	0	0	3	0	1	0
GHB	0	294	0	0	6	0	0	0	0
HM	0	4	288	0	8	0	0	0	0
RM	0	0	0	285	0	0	0	15	0
RSB	0	0	0	0	300	0	0	0	0
SB	5	0	0	0	2	292	0	1	0
SH	0	0	0	0	0	0	300	0	0
SRM	12	0	10	2	1	1	6	268	0
TR	0	0	0	0	0	1	0	0	299

BSS = Black Sea Sprat; GHB = Gilt-head Bream; HM = Horse Mackerel; RM = Red Mullet; RSB = Red Sea Bream; SB = Sea Bass; SH = Shrimp; SRM = Striped Red Mullet; TR = Trout

Fig. 9. Confusion matrix of VGG16-CLAHE-Dropout.

TABLE IV. PRECISION, RECALL, F1-SCORE OF VGG16-CLAHE-DROPOUT

Class	Precision	Recall	F1-score
Black Sea Sprat	0.95	0.98	0.96
Gilt-Head Bream	0.99	0.98	0.98
Horse Mackerel	0.96	0.96	0.96
Red Mullet	0.99	0.95	0.97
Red Sea Bream	0.95	1.00	0.97
Sea Bass	0.98	0.97	0.98
Shrimp	0.98	1.00	0.99
Striped Red Mullet	0.94	0.89	0.92
Trout	1.00	1.00	1.00

Most classes achieved excellent and well-balanced metric values, indicating strong generalization capability of the model. Trout (TR) recorded perfect performance with precision, recall, and F1-score all reaching 1.00, while Shrimp (SH) and Red Sea Bream (RSB) also achieved near-perfect results, with recall values of 1.00 and high precision and F1-scores. Additionally, Gilt-head Bream (GHB), Sea Bass (SB), and Red Mullet (RM) showed strong and stable performance, with F1-scores ranging from 0.97 to 0.98. Furthermore, Black Sea Sprat (BSS) and Horse Mackerel (HM) demonstrated high classification accuracy with balanced precision and recall values around 0.95–0.98. Although Striped Red Mullet (SRM) recorded the lowest performance among all classes, with an F1-score of 0.92, its results remained relatively strong compared to previous models.

E. Discussion

Previous studies proposed various frameworks for fish image classification, including approaches that combined VGG16-based transfer learning to achieve accurate classification performance. Other studies compared multiple transfer learning architectures. However, most of these works did not explore the comparative effectiveness of different regularization techniques applied specifically to the VGG16 architecture. In this study, several configurations of VGG16 were evaluated, including the baseline model and variants integrated with CLAHE and different regularization methods, and the experimental results were summarized in Table V.

TABLE V. COMPARISON OF RESULTS WITH PREVIOUS STUDIES

Source	Model	Testing Accuracy
This research	VGG16	95.92
This research	VGG16-CLAHE-L1	24.89
This research	VGG16-CLAHE-L2	91.96
This research	VGG16-CLAHE-Dropout	97.07
[19]	ResNet50	91.37
[19]	ResNet101	86.12
[20]	MobileNetV2	96.56
[22]	ESRGAN-VGG16	96.50
[21]	MobileNetV3	97.20

The experimental results indicated that the proposed VGG16-CLAHE-Dropout model achieved the highest testing accuracy of 97.07%, outperforming the baseline VGG16 (95.92%) as well as other variants, including VGG16-CLAHE-L2 (91.96%) and VGG16-CLAHE-L1 (24.89%). When compared with prior studies, the proposed approach demonstrated competitive performance, closely approaching MobileNetV3 (97.20%) and surpassing MobileNetV2 (96.56%), ESRGAN-VGG16 (96.50%), and ResNet-based models such as ResNet50 (91.37%) and ResNet101 (86.12%). These findings suggested that the integration of CLAHE and Dropout regularization within the VGG16 framework significantly enhanced classification accuracy and robustness. Furthermore, the architecture of the proposed VGG16-based framework was presented in Table VI.

The proposed framework for fish classification was designed based on a VGG16-based architecture with additional layers for feature refinement and regularization. The model took input images of size 224 × 224 × 3, which were processed through the pre-trained VGG16 convolutional base to extract high-level feature representations. The convolutional layers were frozen to preserve the learned features, followed by a GlobalAveragePooling2D layer that reduced the spatial dimensions into a compact feature vector. Subsequently, a flatten layer was applied to prepare the features for the fully connected layers. The classification stage consisted of two dense layers with 4096 and 1072 neurons, respectively, which enhanced the model's ability to learn complex patterns. A dropout layer was incorporated to reduce overfitting by randomly deactivating neurons during training.

TABLE VI. PROPOSED FRAMEWORK FOR FISH CLASSIFICATION

No	Layer	Layer Type	Output Shape
1	Input	Input Layer	(224, 224, 3)
2	VGG16 Base	Convolutional Blocks	(7, 7, 512)
3	Freeze Layers	-	-
4	GlobalAveragePooling2D	Pooling	512
5	Flatten	Flatten	512
6	Dense 1	Fully Connected	4096
7	Dense 2	Fully Connected	1072
8	Dropout	Regularization	1072
9	Output	Dense	9

IV. CONCLUSION

In conclusion, the training process was conducted to optimize the VGG16 model by minimizing the discrepancy between predicted outputs and ground truth labels, while incorporating a comparative analysis of regularization techniques within the network. The experimental results demonstrated that the VGG16-CLAHE-Dropout model achieved the highest testing accuracy of 97.07%, outperforming the baseline VGG16 (95.92%), VGG16-CLAHE-L2 (91.96%), and VGG16-CLAHE-L1 (24.89%). The model was trained for 50 epochs, and CLAHE was applied using a clip limit of 2.0 and a tile grid size of 8 × 8 to enhance image contrast. Furthermore, the optimization process was carried out using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32.

Future research will focus on improving the robustness and generalization capability of the VGG16-CLAHE framework by exploring more advanced regularization strategies, as well as utilizing larger and more diverse underwater datasets. Additional contrast enhancement techniques tailored for complex aquatic environments will be investigated to further improve feature representation. Moreover, subsequent studies will integrate modern architectures such as EfficientNet, Vision Transformers, and hybrid CNN–Transformer models to evaluate whether they will outperform VGG16 in handling low-contrast fish images.

ACKNOWLEDGMENT

This research is fully supported by the Universitas Dian Nusantara and Direktorat Riset, Teknologi, dan Pengabdian

Kepada Masyarakat, Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia through research funding with No.792/LL3/AL.04/2024 c.q. No.11/136/H-SPK/VI/2024.

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