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Article

Advanced Image Enhancement and Transfer Learning Optimization for Freshwater Fish Classification

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Abstract: This study proposed an enhanced computer vision framework for fish image classification to support potential fishing zones identification. The research workflow consisted of literature review, data collection, data augmentation, image enhancement, transfer learning experiments, hyperparameter optimization, and comprehensive evaluation. Image data were collected for five freshwater fish species, namely Clarias sp., Pangasius sp., Oreochromis niloticus, Osphronemus goramy, and Cyprinus carpio. Four pretrained convolutional neural network architectures, i.e. ResNet50, MobileNetV2, DenseNet, and EfficientNet. In addition, four image enhancement pipelines were evaluated, namely bilateral filtering (BF), bilateral filtering with color constancy (BFCC), bilateral filtering with colour constancy and dark channel prior (BFC2DCP), and the proposed BFC2DCP-SRGAN method. Further experiments focused on optimizing the ResNet50 model using combinations of Dropout and L2 regularization with Adam, SGD, and RMSprop optimizers. Experimental results demonstrated that the BFC2DCP-SRGAN approach achieved the best performance, yielding training, validation, and test accuracies of 95.75%, 94.54%, and 89.54%, respectively.
Keywords: SRGAN, ResNet50, Fish, Image enhancement, Transfer learning

1. Introduction

Freshwater ecosystem monitoring has been considered a critical component in supporting sustainable fisheries management, optimizing harvesting efficiency, and minimizing the risk of overexploitation [1], [2]. Traditional approaches for assessing freshwater fish populations, including manual observation and net sampling as well as acoustic-based surveys, were often limited by high operational costs, time inefficiency, and susceptibility to subjective bias [3], [4]. Consequently, recent studies increasingly adopted computer vision and deep learning techniques as automated and scalable solutions for freshwater fish detection and population estimation from image and video data [5].

Deep convolutional neural networks (CNNs) such as ResNet50, MobileNetV2, DenseNet, and EfficientNet had been widely applied to image classification tasks due to their strong capability in learning discriminative visual features [6]. In the context of marine and underwater imagery, these architectures demonstrated promising performance in fish species recognition [7]. However, their effectiveness was strongly influenced by the quality of input images. Fish images acquired in marine environments frequently exhibited low contrast, uneven illumination, colour degradation, haze, and noise caused by light absorption and scattering in water [8]. These degradations significantly reduced feature clarity and negatively impacted classification accuracy, particularly in PFZ conditions with dynamic and heterogeneous environmental characteristics.

Previous studies addressed these challenges by applying individual image enhancement techniques such as noise filtering, color correction, dehazing, or super-resolution prior to classification [9]. Bilateral filtering was shown to suppress noise while preserving edge information, color constancy methods normalized illumination variations, and Dark Channel Prior (DCP) effectively enhanced visibility in hazy marine images [10]. In parallel, Super-Resolution Generative Adversarial Networks (SRGAN) were employed to reconstruct high-resolution images and recover fine-grained spatial details. Nevertheless, most existing works investigated these methods in isolation or focused primarily on terrestrial or general underwater datasets, without systematically analysing their combined influence on deep CNN-

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based fish classification [11], [12].

To record data on fish species found in specific areas, image processing technology is required, specifically for classifying fish species based on underwater images [13]. In fish image classification research, the use of ResNet-50 has proven effective in recognizing patterns in images with its CNN architecture, which includes 50 layers that help identify complex features in images [14]. Studies by Mathur & Goel (2021), Teja et al. (2023), and Gong et al. (2023) have applied the ResNet-50 model for fish classification. However, these studies did not focus on improving the quality of limited underwater images [15], [16], [17].

This study combined the use of the Super-Resolution Generative Adversarial Network (SRGAN) model with ResNet-50 to improve the quality of underwater images, thereby increasing the accuracy of fish species classification. The Generative Adversarial Network (GAN) method had been applied in previous research to enhance image quality by generating higher-quality images from low-resolution input images [15], [16], [17].

To enhance the performance of SRGAN, modifications were made by adding filters during the pre-reconstruction and post-reconstruction stages. The application of the bilateral filter (BF) at the pre-reconstruction stage was chosen to reduce noise while preserving object edges, and it had been successfully applied to underwater images with different objects in previous studies [18], [19].

The colour constancy (CC) algorithm played a key role in correcting colour distortions that are often present in underwater images, allowing fish objects to appear with more realistic colors. A previous study by Yin (2023) successfully applied colour constancy (CC) to recognize seagrass or eelgrass in underwater images [20]. Furthermore, the dark channel prior (DCP) algorithm had been used to reduce the effects of excessive light and enhance contrast in darker areas, which are commonly observed in underwater images [21], [22].

Despite the growing body of research on underwater image enhancement and deep learning-based classification, limited studies comprehensively examined the synergistic integration of BF, CC, DCP, and SRGAN within a unified preprocessing framework for fish image detection in PFZ. Furthermore, comparative evaluations across multiple CNN architectures under identical enhancement conditions remained scarce, leaving uncertainty regarding model robustness and generalization when advanced enhancement pipelines were applied.

From a theoretical perspective, the effectiveness of the proposed BFC2DCP-SRGAN framework can be explained through its impact on feature quality and representation learning in deep convolutional neural networks. CNN classifiers rely heavily on the extraction of hierarchical features such as edges, textures, and semantic patterns, which are highly sensitive to image degradation, including noise, low contrast, and colour distortion commonly observed in underwater environments [23].

Each enhancement component in the proposed pipeline addresses a specific degradation mechanism. Bilateral filtering reduces high-frequency noise while preserving edge information, thereby improving local gradient consistency [24]. Colour constancy corrects wavelength-dependent attenuation in underwater imaging, restoring chromatic balance and improving inter-class colour separability [25]. Dark Channel Prior enhances global contrast by estimating and compensating for light scattering effects, which increases structural visibility [26]. Finally, SRGAN reconstructs high-frequency spatial details, allowing CNNs to learn richer and more discriminative feature representations [27]. By sequentially improving signal-to-noise ratio, colour fidelity, contrast, and spatial resolution, the proposed enhancement framework theoretically increases intra-class feature compactness and inter-class feature separability in the learned CNN embedding space, which directly contributes to improved classification performance.

To address these gaps, this study proposed a novel BFC2DCP-SRGAN enhancement framework that integrated Bilateral Filtering, Colour Constancy, Dark Channel Prior, and SRGAN as a sequential preprocessing pipeline for fish image classification. Unlike previous approaches, the proposed framework explicitly investigated the impact of this enhancement-based novelty model on ResNet50 performance and comparatively evaluated its effectiveness against MobileNetV2, DenseNet, and EfficientNet under both enhanced and non-enhanced image conditions.

In alignment with the research objectives, this study aimed (1) to compare the classification performance of ResNet50, MobileNetV2, DenseNet, and EfficientNet for fish image detection, and (2) to analyze the influence of the proposed BFC2DCP-SRGAN enhancement pipeline on ResNet50-based classification accuracy. The findings of this study were expected to contribute to the advancement of intelligent fisheries monitoring systems and provide methodological insights for integrating image enhancement and deep learning models in real-world marine applications.

This study is positioned as a preliminary investigation toward the development of a vision-based system for freshwater fish classification, with a specific focus on fish image classification as a fundamental building block of the

overall model pipeline. The proposed BFC2DCP-SRGAN-enhanced ResNet50 framework is evaluated in a controlled aquarium environment to ensure reliable and reproducible validation of classification performance. Although the experimental setting does not yet incorporate fish counting, detection, or tracking mechanisms, the employed dataset represents a replicated approximation of real-world fishing locations, incorporating variations in illumination, viewpoint, water-induced distortion, and image quality degradation commonly encountered in natural aquatic environments.

This paper is organized as follows. Section 2 presents the research methodology, detailing the data collection setup (Section 2.1), experimental environment (Section 2.2), research workflow (Section 2.3), and parameter configuration (Section 2.4). Section 3 reports the experimental results and discusses the performance evaluation of the proposed approach. Finally, Section 4 concludes the paper by summarizing the main findings and outlining directions for future research.

2. Materials and Methods

The overall research workflow was structured into a series of systematic stages to ensure methodological rigor and reproducibility, beginning with a comprehensive literature review in which relevant studies were retrieved from ScienceDirect, IEEE Xplore, and Google Scholar to identify state-of-the-art methods in fish image classification, image enhancement, and transfer learning. Image datasets were then collected for five freshwater fish species, namely *Clarias sp*., *Pangasius sp*., *Oreochromis niloticus*, *Osphronemus goramy*, and *Cyprinus carpio*, followed by extensive data augmentation. The complete research phase as illustrated in **Figure 1**.

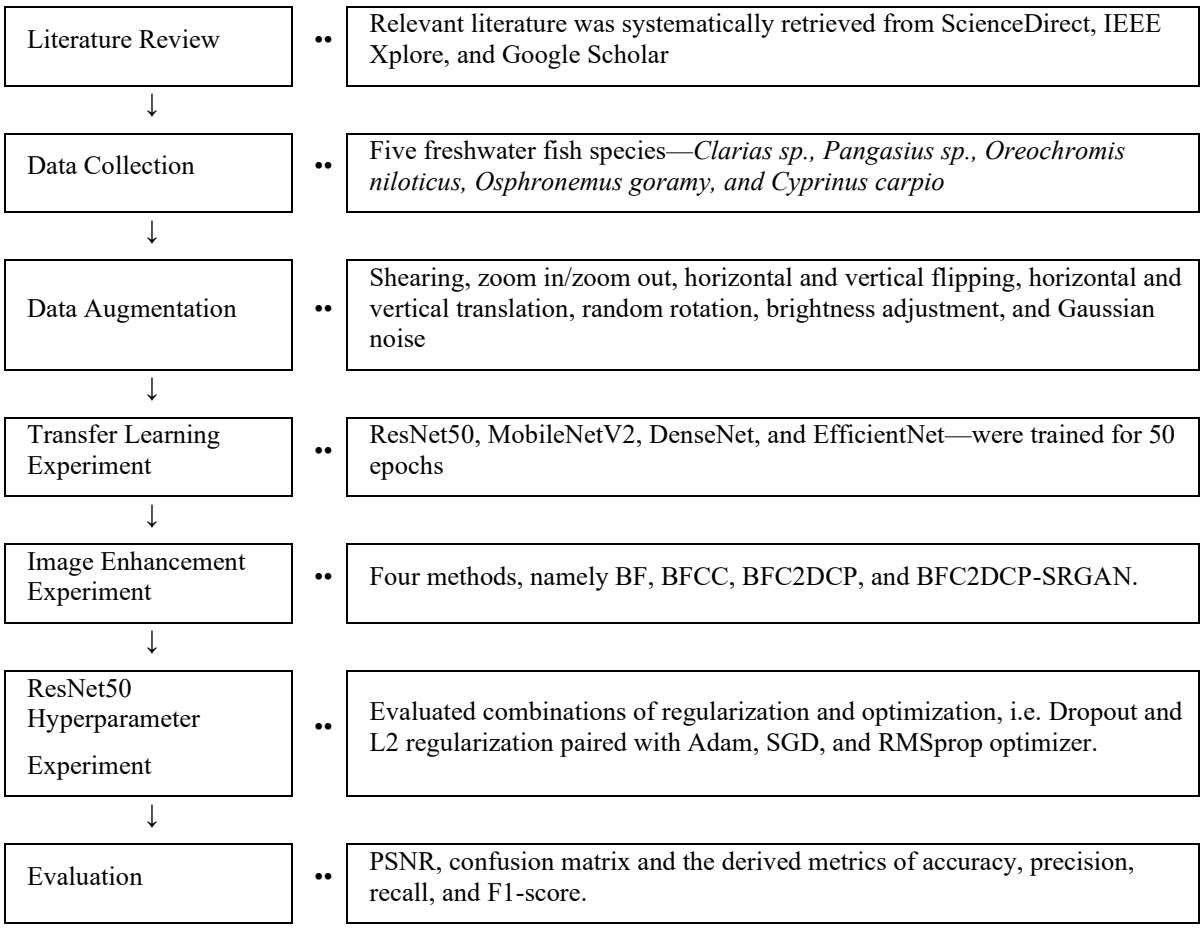


Figure 1. Research phase

Data collection was conducted in a 60-liter aquarium with dimensions of 60 cm × 29.5 cm × 35.5 cm. The aquarium was equipped with adjustable lighting systems to simulate illumination conditions resembling the natural habitat of freshwater fish, thereby minimizing illumination bias during image acquisition with setup that illustrated in **Figure 2**.



Figure 2. Data collection tools for research

Image data were captured using an iPhone 11, which features a dual 12 MP ultra-wide camera system. This camera configuration enabled image acquisition under low-light conditions while maintaining a wide field of view, ensuring full coverage of the aquarium area and reducing perspective distortion. All collected datasets were validated by the Department of Marine Affairs and Fisheries of South Sumatra Province, Indonesia, to ensure species correctness and dataset reliability.

All image processing and classification experiments were performed using a Dell XPS 13 9310 laptop equipped with an Intel Core i7-1185G7 processor (4 cores, up to 4.8 GHz), 16 GB LPDDR4x RAM, and a 512 GB SSD. This hardware configuration provided sufficient computational resources for deep learning training, image enhancement, and evaluation tasks. Python was used as the primary programming language, with TensorFlow and PyTorch frameworks employed for image enhancement implementation, transfer learning, and model optimization.

Subsequently, transfer learning experiments were conducted using four pretrained convolutional neural network architectures, ResNet50, MobileNetV2, DenseNet, and EfficientNet, each trained for 50 epochs, while image enhancement experiments evaluated four processing pipelines: bilateral filtering (BF), bilateral filtering with color constancy (BFCC), bilateral filtering with color constancy and dark channel prior (BFC2DCP), and the proposed BFC2DCP-SRGAN method.

The bilateral filter (BF) was applied to suppress noise while preserving edge information in underwater fish images. The filter parameters consisted of a diameter (d) of 7 pixels, a spatial standard deviation ($\sigma_{spa}c_e$) of 2 pixels, and a colour standard deviation (σc_{olor}) of 25. The diameter defined the local neighbourhood used in filtering, while $\sigma_{spa}c_e$ controlled the influence of spatial proximity and σc_{olor} regulated sensitivity to intensity differences. This parameter configuration enabled effective smoothing in homogeneous regions while maintaining sharp object boundaries, which is essential for preserving fish contours and fine structural details. To further address colour distortion caused by uneven illumination and water absorption, a colour constancy (CC) algorithm based on the grey-world assumption was employed, using a correction coefficient of $\sigma_{value} = 2$.

In addition, the dark channel prior (DCP) algorithm was utilized to enhance contrast in darker regions and reduce excessive light scattering effects commonly found in underwater environments. The DCP parameters included a patch size of 21 pixels and a threshold value of 0.2, which defined the local region for dark channel estimation and limited the extent of intensity correction. These values were selected to prevent over-enhancement while maintaining global contrast consistency and local detail preservation. For further visual quality improvement, SRGAN-based super-resolution was incorporated with specific parameter settings. The loss weight ($\alpha = 0.01$) regulated the contribution of additional loss. The spatial parameter ($\sigma_s = 1$) while the range parameter ($\sigma_r = 25$). For classification, the ResNet50 architecture was trained using a batch size of 32 for 50 epochs.

The classification experiments were conducted to evaluate the performance of different deep learning architectures for underwater fish image classification. Four pretrained convolutional neural network models, namely ResNet50, MobileNetV2, DenseNet, and EfficientNet, were employed as backbone architectures. All models were initialized with ImageNet pretrained weights and fine-tuned on the target dataset.

To ensure a fair and controlled comparison, all architectures were trained under identical experimental conditions. Each model was trained for 50 epochs using the same training–validation split, batch size, input image resolution, and data augmentation strategy. The initial learning rate was set to 0.0001 for all networks, following commonly adopted practices in previous deep learning studies on image classification. To mitigate overfitting during fine-tuning, regularization strategies were applied in the form of dropout and L2 weight decay. Specifically, a dropout rate of 0.5 was applied to the fully connected layer of ResNet50, while MobileNetV2 employed a lower dropout rate of 0.3 due to its lightweight architecture. DenseNet utilized a dropout rate of 0.5 to address potential overfitting arising

from its dense connectivity, whereas EfficientNet adopted a moderate dropout rate of 0.4 to complement its compound scaling design. In addition, L2 weight decay with a coefficient of 1×10^{-4} was consistently applied across all models. The optimization configuration, including optimizer type, learning rate, and regularization, followed commonly adopted settings reported in previous related studies [6], [28].

Further optimization focused on the ResNet50 model by examining combinations of Dropout and L2 regularization with Adam, SGD, and RMSprop optimizers to assess their impact on classification accuracy and convergence stability. Finally, model performance was comprehensively evaluated using PSNR, confusion matrices, and derived metrics including accuracy, precision, recall, and F1-score.

3. Results

All collected datasets were validated by the Department of Marine Affairs and Fisheries of South Sumatra Province to ensure species correctness and overall dataset reliability. Image acquisition was performed using an iPhone 11 equipped with a dual 12 MP ultra-wide camera system, enabling consistent image quality and adequate coverage of the aquarium environment. The final dataset consisted of four freshwater fish species with a balanced distribution, comprising 500 images for each class, i.e. *Clarias sp*., *Pangasius sp*., *Oreochromis niloticus*, and *Osphronemus goramy*. The process of data collection is illustrated in rich picture that depicted in **Figure 3**.

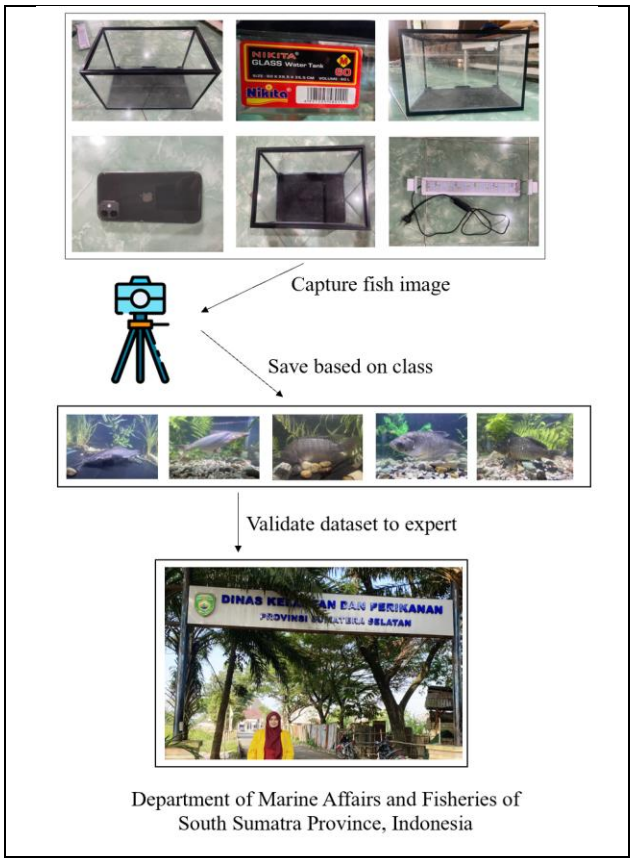


Figure 3. Rich picture of data collection process

The initial data collection process produced a balanced dataset consisting of 500 images per class for each freshwater fish species. To enhance dataset diversity and improve model generalization., an extensive data augmentation strategy was applied. The real data composition as depicted in **Table 1**.

Table 1. Dataset research composition

Scientific Name	Train. (70%)	Val. (15%)	Test. (15%)
Clarias sp.	350	75	75
Pangasius sp.	350	75	75
Oreochromis niloticus	350	75	75

Osphronemus goramy	350	75	75
Cyprinus carpio	350	75	75

The original dataset was first split at the image level into training, validation, and test subsets to prevent any overlap between splits and to eliminate the risk of data leakage. Data augmentation was applied exclusively to the training set, while the validation and test sets remained unchanged and contained only original images. The augmentation techniques included shearing (0.2), zoom in/zoom out (0.2), horizontal and vertical flipping, horizontal and vertical translation (0.2), random rotation up to 15°, brightness adjustment in the range of 0.5–1.5, and the addition of Gaussian noise with $\sigma = 0.01$. As a result of this augmentation pipeline, the number of training images per class increased from 500 to 5,000, while the validation and test sets preserved their original distributions, ensuring fair and unbiased performance evaluation.

The next stage, BF (Bilateral Filter), was applied to reduce noise while preserving the edges of fish objects. The second scheme, BFCC (Bilateral Filter ⊕ Color Constancy), incorporated color correction to address color distortion caused by uneven illumination and underwater light absorption. The third scheme, BFC2DCP (Bilateral Filter ⊕ Color Constancy ⊕ Dark Channel Prior), was designed to enhance contrast and improve the visibility of darker regions by suppressing underwater light scattering effects. Finally, the most comprehensive scheme, BFC2DCP-SRGAN (Bilateral Filter ⊕ Color Constancy ⊕ Dark Channel Prior ⊕ SRGAN), was employed to further improve spatial resolution and fine texture details of underwater fish images using a generative adversarial network–based super-resolution approach. These experiments result of image enhancment can be seen **Figure 4.**

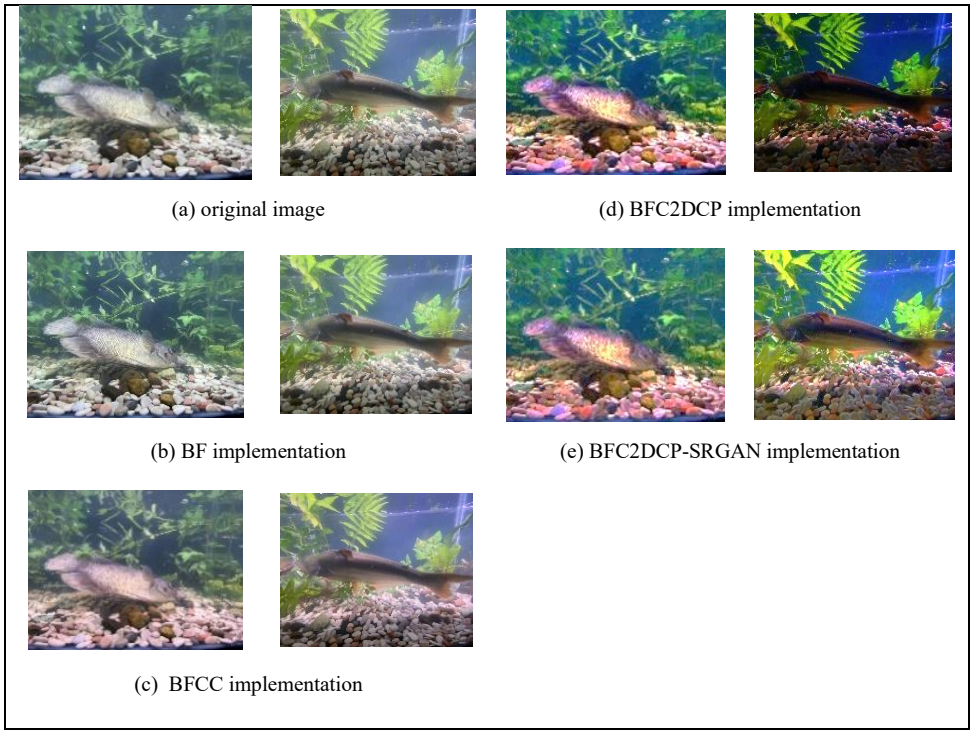


Figure 4. Result of image enhancement

The PSNR results for underwater fish images demonstrated the impact of each image enhancement method on reconstruction quality. The original images achieved a PSNR value of 24.1048 dB, serving as the baseline reference. The application of the Bilateral Filter resulted in a slight decrease in PSNR to 22.8905 dB, which indicated noise reduction but also minor smoothing effects that reduced pixel-level similarity to the original image. When Color Constancy was combined with the Bilateral Filter, the PSNR further decreased to 19.8114 dB, reflecting substantial intensity and color redistribution caused by illumination correction. A more pronounced reduction was observed in the BFC2DCP method, which yielded a PSNR of 17.3789 dB, due to aggressive contrast enhancement and haze suppression that significantly altered pixel intensities. In contrast, the proposed BFC2DCP-SRGAN method achieved the highest PSNR value of 25.6162 dB, exceeding that of the original images. The comparation of PSNR can be seen in **Figure 5**.

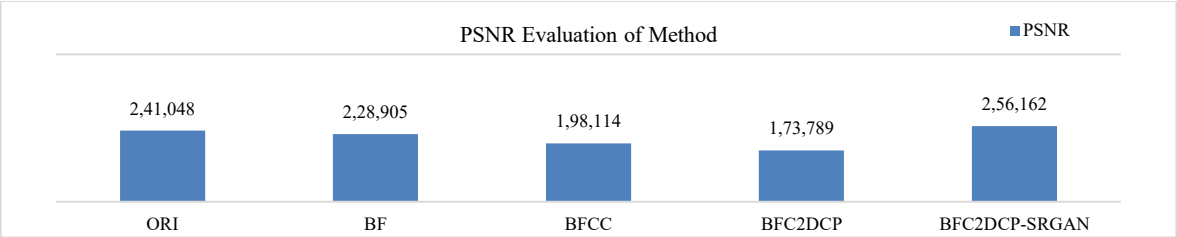


Figure 5. Comparation of PSNR

The classification experiment was conducted to evaluate the performance of different deep learning architectures on underwater fish image classification. Four pretrained convolutional neural network models, i.e. ResNet50, MobileNetV2, DenseNet, and EfficientNet, were trained for 50 epochs under the same experimental settings to ensure a fair comparison. The results showed that ResNet50 achieved the highest performance, with a training accuracy of 94.55%, a validation accuracy of 92.34%, and a testing accuracy of 87.14%, indicating strong feature extraction capability and stable generalization. MobileNetV2 demonstrated competitive performance with lower computational complexity, achieving 93.17% training accuracy, 91.67% validation accuracy, and 85.87% testing accuracy. DenseNet and EfficientNet produced slightly lower results, with testing accuracies of 84.45% and 84.10%, respectively, which suggested that their feature reuse and compound scaling strategies were less effective for this specific underwater fish dataset.

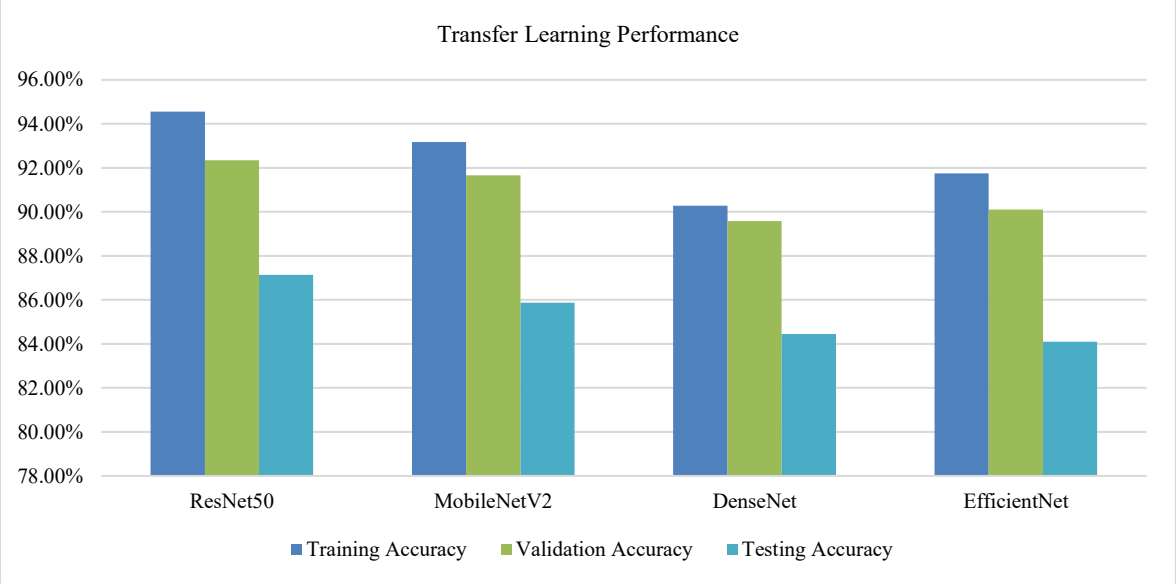


Figure 6. Comparation of transfer learning accuracy

The hyperparameter optimization experiment was conducted on the ResNet50 model to evaluate the effects of different regularization techniques and optimization algorithms on underwater fish image classification performance. Two regularization strategies, namely Dropout and L2 regularization, were combined with three optimizers: Adam, SGD, and RMSprop. The experimental results showed that the Dropout–Adam configuration achieved the best overall performance, with training, validation, and testing accuracies of 95.75%, 94.54%, and 89.54%, respectively.

Other dropout configurations also produced competitive results, with the Dropout–SGD and Dropout–RMSprop setups yielding testing accuracies of 87.78% and 87.45%. In contrast, models employing L2 regularization achieved slightly lower performance across all optimizers. The L2–Adam configuration resulted in a testing accuracy of 87.50%, while L2–SGD and L2–RMSprop achieved 86.17% and 86.58%, respectively. The best experimental configuration was achieved using the BFC2DCP-SRGAN image enhancement pipeline combined with the ResNet50 model, optimized using Dropout regularization and the Adam optimizer, which resulted in training, validation, and testing accuracies of 95.75%, 94.54%, and 89.54%, respectively.

Following the identification of the optimal model configuration, further evaluation was conducted using a confusion matrix to analyze class-wise classification performance. The test dataset consisted of 15% of the total

augmented data, with a balanced distribution of 750 images per species, including *Clarias sp*., *Pangasius sp*., *Oreochromis niloticus*, *Osphronemus goramy*, and *Cyprinus carpio*. The confusion matrix analysis provided detailed insights into correct and incorrect predictions across species, allowing for the assessment of inter-class confusion and misclassification patterns, that depicted in **Fig. 7**.

Class	*Claria*	*Pang*	*Oreoc*	*Osph*	*Cyp*
Clarias sp.	**650**	30	20	25	25
Pangasius sp.	30	**670**	25	5	20
Oreochromis niloticus	27	20	**673**	10	20
Osphronemus goramy	5	20	25	**690**	10
Cyprinus carpio	25	5	20	25	**675**

Figure 7. Confusion matrix of BFC2DCP-SRGAN-ResNet50

The performance evaluation of the proposed BFC2DCP-SRGAN–ResNet50 model demonstrated strong and consistent classification capability across all underwater fish classes, as reflected by the precision, recall, and F1-score metrics. *Clarias sp.* achieved a precision of 0.88, recall of 0.86, and F1-score of 0.87. *Pangasius sp.* showed high robustness with a precision of 0.89 and the highest recall value of 0.92, resulting in an F1-score of 0.90. The complete evaluation is presented in **Table 2**.

Table 2. Evaluation of BFC2DCP-SRGAN-ResNet50

Class	Precision	Recall	F1-Score
Clarias sp.	0.88	0.86	0.87
Pangasius sp.	0.89	0.92	0.90
Oreochromis niloticus	0.87	0.90	0.89
Osphronemus goramy	0.87	0.92	0.89
Cyprinus carpio	0.90	0.90	0.90

Similarly, *Oreochromis niloticus* and *Osphronemus goramy* achieved balanced performance, each obtaining F1-scores of 0.89, supported by recall values of 0.90 and 0.92, respectively. These results indicated strong sensitivity in recognizing fish objects despite variations in pose, illumination, and underwater visual distortion. *Cyprinus carpio* achieved the most stable performance, with precision, recall, and F1-score all reaching 0.90, demonstrating consistent classification accuracy. Overall, the class-wise evaluation confirmed that the integration of BFC2DCP-SRGAN image enhancement with the ResNet50 architecture significantly improved feature discrimination and classification reliability for underwater fish images, validating the effectiveness of the proposed approach for practical aquatic monitoring applications.

4. Discussion

The results demonstrated that the proposed BFC2DCP-SRGAN–ResNet50 framework provided an effective approach for freshwater fish classification under underwater imaging conditions. The dataset was constructed with a balanced distribution of five fish species, with 500 original images per class, and was subsequently augmented to increase the training data to 5,000 images per class. The use of image-level splitting before augmentation prevented overlap between the training, validation, and test data and reduced the potential for data leakage. In addition, the validation of the collected images by the Department of Marine Affairs and Fisheries of South Sumatra Province strengthened the reliability of the species labels. These characteristics provided a controlled experimental setting for evaluating the effects of underwater image enhancement and transfer learning on classification performance.

The comparison of image enhancement methods indicated that conventional pixel-level similarity metrics such as PSNR did not necessarily correspond directly to visual enhancement effectiveness. The original images achieved a PSNR of 24.1048 dB, while BF, BFCC, and BFC2DCP produced progressively lower values of 22.8905, 19.8114, and 17.3789 dB, respectively. This reduction was attributed to the increasingly substantial modifications in illumination, color distribution, contrast, and underwater haze. In contrast, BFC2DCP-SRGAN achieved the highest

PSNR of 25.6162 dB, indicating that the super-resolution stage reconstructed image details while maintaining greater similarity to the reference image. These results suggested that the combination of denoising, color correction, dehazing, and super-resolution was more suitable for preserving useful visual information than the application of individual enhancement techniques.

The transfer learning experiment further confirmed the importance of selecting an appropriate CNN architecture for underwater fish classification. ResNet50 achieved the highest testing accuracy of 87.14%, followed by MobileNetV2 at 85.87%, DenseNet at 84.45%, and EfficientNet at 84.10%. The superior performance of ResNet50 was attributed to its residual learning mechanism, which facilitated the extraction of hierarchical and discriminative features from images containing complex backgrounds and variations in fish appearance. Although MobileNetV2 achieved competitive performance with lower computational complexity, the performance gap indicated that the deeper residual architecture was better able to represent subtle morphological differences among the fish species. Therefore, ResNet50 was selected as the baseline architecture for subsequent optimization.

The hyperparameter optimization results showed that regularization and optimizer selection substantially influenced ResNet50 performance. The Dropout–Adam configuration achieved the highest training, validation, and testing accuracies of 95.75%, 94.54%, and 89.54%, respectively. Compared with the initial ResNet50 result, the testing accuracy increased from 87.14% to 89.54%, demonstrating the benefit of combining Dropout with the Adam optimizer. Dropout reduced overfitting by preventing excessive dependence on particular neurons, while Adam provided adaptive parameter updates during training. In comparison, the L2 configurations produced lower testing accuracies, ranging from 86.17% to 87.50%. Therefore, the results indicated that Dropout was more effective than L2 regularization for improving the generalization capability of the model.

The confusion matrix provided further evidence of the robustness of the proposed model across the five species. The diagonal values indicated that most test samples were correctly classified, with 650 *Clarias sp.*, 670 *Pangasius sp.*, 673 *Oreochromis niloticus*, 690 *Osphronemus goramy*, and 675 *Cyprinus carpio* samples correctly predicted. The remaining errors were distributed among several classes rather than being concentrated in a single category, suggesting that the model did not exhibit severe bias toward a particular species. The class-wise metrics also supported this observation. *Pangasius sp.* and *Cyprinus carpio* achieved F1-scores of 0.90, while *Oreochromis niloticus* and *Osphronemus goramy* achieved F1-scores of 0.89. *Clarias sp.* obtained an F1-score of 0.87, indicating that this species was comparatively more difficult to distinguish from the other classes. The relatively balanced precision and recall values demonstrated that the model maintained reliable positive predictions and sensitivity across the evaluated species.

Overall, the experimental findings indicated that the integration of BFC2DCP-SRGAN image enhancement with ResNet50, Dropout regularization, and the Adam optimizer provided a promising solution for underwater freshwater fish classification. The improvement from the baseline ResNet50 testing accuracy of 87.14% to 89.54% demonstrated that image preprocessing and model optimization jointly contributed to improved generalization. The enhanced images provided more informative spatial and texture features, while ResNet50 effectively learned discriminative representations from these improved inputs. Nevertheless, the remaining misclassifications indicated that species with visually similar morphological characteristics still presented classification challenges. Future research could therefore have investigated larger and more geographically diverse datasets, additional underwater imaging conditions, attention-based architectures, and real-time deployment to further evaluate the robustness and practical applicability of the proposed framework for aquatic monitoring.

5. Conclusion

This study presented an enhanced computer vision framework for freshwater fish image classification to support fish population analysis under challenging underwater imaging conditions. The proposed framework is theoretically grounded in the principle that improving low-level visual quality directly enhances high-level feature learning in convolutional neural networks. Underwater images commonly suffer from illumination inconsistency, color distortion, low contrast, and loss of fine details, which violate the assumptions of standard feature extraction mechanisms in deep learning models.

From a theoretical perspective, the proposed BFC2DCP-SRGAN pipeline addresses these issues in a complementary and hierarchical manner. Among the evaluated enhancement methods, the proposed BFC2DCP-SRGAN pipeline consistently outperformed other configurations, achieving the highest training, validation, and testing accuracies of 95.75%, 94.54%, and 89.54%, respectively, when integrated with the ResNet50 model. These results confirmed that the combination of bilateral filtering, colour constancy, dark channel prior, and super-resolution effectively enhanced visual quality and discriminative feature extraction for underwater fish images.

Direct quantitative comparison with state-of-the-art cannot be conducted in this study due to fundamental differences in the datasets used. Most recent works employ benchmark or proprietary datasets that differ significantly in terms of image acquisition conditions, number of classes, image resolution, class distribution, and preprocessing pipelines. These discrepancies make a fair and reproducible numerical comparison infeasible. Based on these analyses, the obtained results confirm that the proposed technique provides a meaningful performance improvement within the defined experimental scope. Future work will focus on evaluating the proposed method on publicly available benchmark datasets to enable direct quantitative comparison with state-of-the-art methods.

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