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Research Article

Fish Species Classification with Deep Learning and Bayesian Optimization: Effectiveness and Comparative Results

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Abstract: This study examines the effectiveness of deep learning-based models in the classification and monitoring of fish species. A dataset obtained from the Kaggle platform, containing 31 different fish species, was used to train MobileNetV2, DenseNet121, and VGG19 models. Bayesian optimization was applied to enhance model performance and determine the optimal hyperparameters. The results indicate that models trained with Bayesian optimization achieved significantly higher accuracy compared to those trained with randomly assigned hyperparameters. Additionally, the ensemble learning approach, which combined the outputs of individual models, yielded the best classification performance. This study demonstrates that deep learning techniques serve as a crucial tool for marine ecosystem conservation and sustainable fisheries practices.

Keywords: deep learning; fish species classification; mobilenetv2; VGG19; densenet121; bayesian optimization.

Araştırma Makalesi

Balık Türü Sınıflandırmasında Derin Öğrenme ve Bayes Optimizasyonu: Model Etkinlik ve Karşılaştırmalı Sonuçlar

Özet: Bu çalışma, derin öğrenme tabanlı modellerin balık türlerinin sınıflandırılması ve izlenmesindeki etkinliğini incelemektedir. Kaggle platformundan elde edilen ve 31 farklı balık türünü içeren veri kümesi kullanılarak MobileNetV2, DenseNet121 ve VGG19 modelleri uygulanmıştır. Model performansını artırmak amacıyla Bayes optimizasyonu kullanılmış ve en iyi hiperparametreler belirlenmiştir. Sonuçlar, Bayes optimizasyonu uygulanmış modellerin rastgele hiperparametrelerle eğitilmiş modellere kıyasla önemli ölçüde daha yüksek doğruluk oranlarına ulaştığını göstermektedir. Ayrıca, bireysel modellerin çıktılarının birleştirildiği toplu öğrenme yaklaşımı, en iyi sınıflandırma başarımını sağlamıştır. Bu çalışma, derin öğrenme tekniklerinin deniz ekosistemlerinin korunması ve sürdürülebilir balıkçılık uygulamalarında kritik bir araç olduğunu göstermektedir.

Anahtar Kelimeler: derin öğrenme; balık türü sınıflandırma; mobilnetv2; VGG19; densenet121; bayes optimizasyonu.

1. Introduction

In contemporary times, environmental issues exerted an increasingly pronounced impact on the health and sustainability of ecosystems. Human activities increasingly threaten both terrestrial and marine ecosystems. These impacts cause biodiversity loss, habitat degradation, and disruption of ecological balance on a global scale. Particularly, marine ecosystems, recognized for their high biodiversity and ecological significance, continue to face threats from anthropogenic factors. Overfishing, habitat destruction, environmental pollution, and climate change are among the primary drivers of damage to marine ecosystems [1]. In this context, the effective monitoring and conservation of fish populations is critical not only for ensuring the sustainability of marine ecosystems but also for safeguarding food security and economic well-being in human societies. Addressing these challenges requires an understanding of how fish respond to environmental changes, which constitutes a crucial step toward species conservation and the maintenance of ecosystem health [2].

Accurately monitoring and understanding the responses of fish species to environmental factors constitute a fundamental knowledge base for the future of marine ecosystems. Climate change, habitat loss, and overfishing—shaped by human activities—directly influence the distribution, populations, and biodiversity of fish species [3]. For instance, climate change can increase ocean temperatures, potentially altering the reproductive cycles of certain fish species or leading to the loss of their habitats. Such changes can disrupt the balance within marine ecosystems, thereby diminishing the quality of ecosystem services [4]. A deeper understanding of these interconnections between ecosystems is crucial for the conservation of natural habitats and the promotion of sustainable fisheries.

In this context, the accurate classification and monitoring of fish species serve as a critical tool for the conservation of marine ecosystems. Identifying fish species is not only essential for assessing ecosystem health but also plays a vital role in the development of sustainable fisheries practices [5]. Traditional monitoring methods face numerous challenges in fish classification. The visual similarities among fish species, along with morphological and behavioral changes influenced by environmental factors, add complexity to the classification process. Therefore, the adoption of new technologies is essential for accurately distinguishing fish species. In recent years, artificial intelligence and deep learning algorithms have made significant advancements in the analysis of visual data, enabling the precise classification of fish species [6].

Deep learning algorithms, with their ability to process large volumes of data, can serve as an effective tool for the classification of fish species. These algorithms analyze visual features such as shape, color, and texture, enabling the rapid and accurate identification of species. Deep learning, a subset of machine learning, possesses the capacity to learn complex patterns and relationships within data. The classification of fish species is not solely based on visual characteristics but also requires the analysis of environmental changes and behavioral variations in fish populations [7]. Due to their capability to process such complex datasets, deep learning algorithms yield significantly more efficient and accurate results compared to traditional methods.

A review of the literature reveals several studies employing deep learning for fish species classification. Kaya et al. [8] introduced a novel deep learning-based model, IsVoNet8, designed to classify eight fish species commonly consumed in Turkey. The proposed model was compared with ResNet50, ResNet101, and VGG16, achieving the highest accuracy of 98.62%. It was reported that IsVoNet8, due to its lower number of layers and parameters, provided a higher accuracy rate with lower computational cost compared to other models.

In another study, Cui et al. [9] proposed a deep learning-based method for fish detection in turbid seawater using images collected from the Gulf of Mexico. The study incorporated data augmentation, network simplification, and optimization techniques to accelerate the training process, ultimately resulting in a single optimized model. Experimental results demonstrated that the proposed model improved accuracy rates and showed promise for real-time underwater applications.

Chen et al. [10] developed a two-stage deep learning-based system for fish classification. The system first detects and aligns fish to manage variations in pose and scale before classifying them. It then utilizes environmental context information to identify species. The proposed method proved effective in classifying fish under challenging real-world conditions.

Aziz et al. [11] presented a model that optimizes deep learning algorithms for fish species classification using the Chaotic Opposition-Based Whale Optimization Algorithm (CO-WOA). The study compared its performance with deep learning models such as CNN, VGG-19, and ResNet150V2, demonstrating that the proposed method achieved a 100% accuracy rate.

Furthermore, Shammi et al. [12] employed FishNet, a CNN-based model, to classify six different fish species. The study also utilized data augmentation techniques to enhance the model's accuracy. The developed model achieved an accuracy rate of 88.96%, outperforming traditional algorithms.

Kandimalla et al. [13] conducted a performance comparison of deep learning models for classifying fish images collected using DIDSON imaging sonar and optical cameras. The study employed YOLOv3, Mask-RCNN, and Norfair methods to automatically detect, classify, and count fish in passageways. The results demonstrated the potential of this system for real-time monitoring of fish species, even in challenging conditions such as low-light and turbid environments, as well as for tracking species requiring conservation.

In another study, Salman et al. [14] proposed a deep learning-based approach to address challenges in fish classification within underwater environments, such as variations in lighting, turbidity, and background complexity. The results indicated that accuracy rates exceeded 90% across various datasets.

Varalakshmi and Rachel [15] focused on solving the problem of fish category classification and localization. They utilized CNN methods to capture segmentation errors, noise, and environmental variations in images. By training the dataset with different activation functions, they achieved higher classification accuracy. Their results demonstrated 95% accuracy in fish image classification and 99% accuracy in fish localization.

Iqbal et al. [16] employed a simplified version of AlexNet for an automatic fish species classification system, aiming to facilitate fish farming and the understanding of fish habitats. While the proposed model outperformed AlexNet, it did not achieve better results compared to VGGNet. However, it attained competitive accuracy with fewer layers and reduced computational requirements.

Additionally, Deep and Dash [17] proposed a hybrid CNN-based framework for underwater fish species recognition. In this approach, CNN was used for feature extraction, while classification was performed using Support Vector Machines (DeepCNN-SVM) and K-Nearest Neighbors (DeepCNN-KNN). The model was evaluated on the Fish4Knowledge dataset, where DeepCNN-KNN achieved an accuracy of 98.79%, outperforming other compared models.

This study aims to examine the effectiveness of deep learning-based algorithms in the classification and monitoring of fish species. Specifically, investigating how these algorithms are utilized for marine ecosystem conservation and the benefits they provide will make significant contributions to the existing body of knowledge in this field. In an era of rapid technological advancements, the development of more effective methods for marine ecosystem preservation is crucial for achieving future sustainability goals. Therefore, one of the primary focuses of this study is to explore the role of innovative technologies, such as deep learning and artificial intelligence, in the monitoring and conservation of marine ecosystems.

2. Materials and Method

2.1. Dataset

The dataset utilized in this study was sourced from Kaggle and created by Mark Daniel Lampa [18]. It includes images of 31 different fish species found in Marinig Fishing Port, located in Cabuyao, Philippines. The dataset comprises 13,304 images in total. Convolutional Neural Network (CNN) architectures such as DenseNet121, VGG19, and MobileNetV2 were applied, along with ensemble learning techniques and hyperparameter optimization. Example images from the dataset are presented in Figure 1.

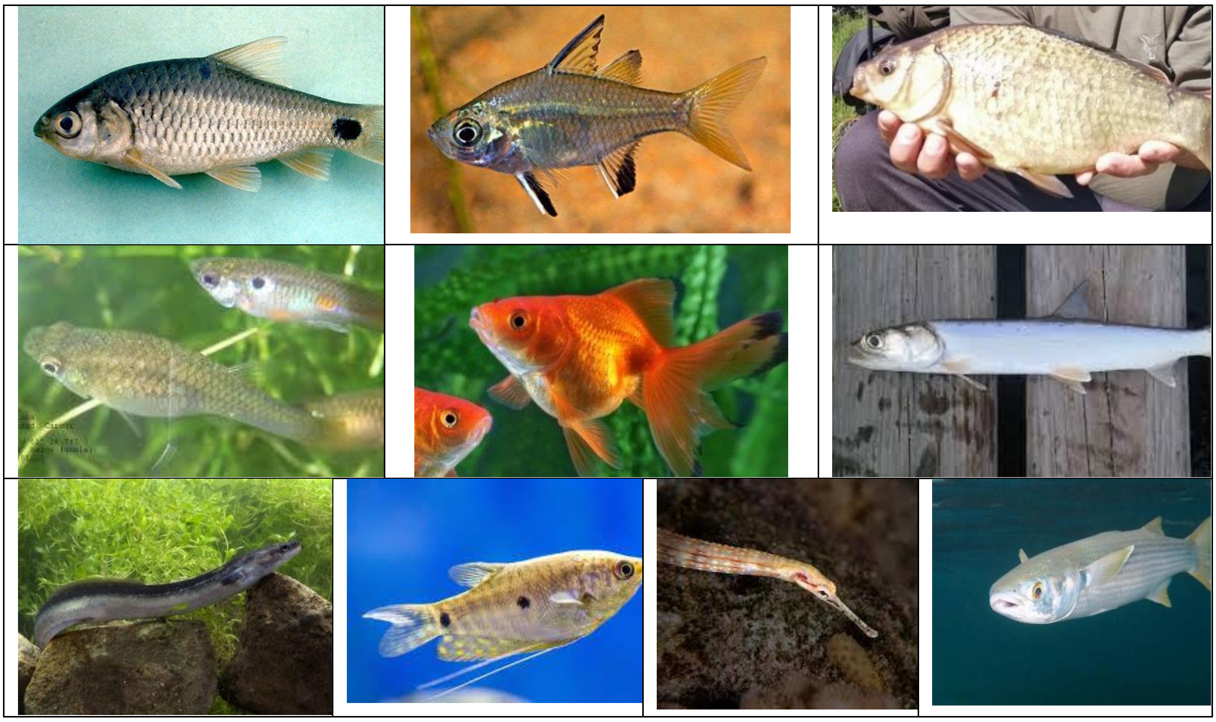

Figure 1. Sample Images from the Dataset [18]

2.2. DenseNet121

The DenseNet121 model, accepts input images with dimensions of 224×224×3 and consists of approximately 7 million trainable parameters [19]. This model effectively prevents the gradient vanishing problem, thereby enabling the construction of sufficiently deep networks. Additionally, compared to other deep learning architectures, its lower number of parameters allows for faster computational performance.

One of the key characteristics of DenseNet121 is its feed-forward connectivity, where each layer is directly connected to all subsequent layers. This structure enables a layer to use the feature maps of all preceding layers as input while passing its own feature maps as input to all subsequent layers. Although DenseNet architecture shares similarities with ResNet, it enhances information flow by allowing features extracted from one layer to be utilized as input for all deeper layers, resulting in a more efficient learning process. The structure of the DenseNet architecture is schematically illustrated in Figure 2.

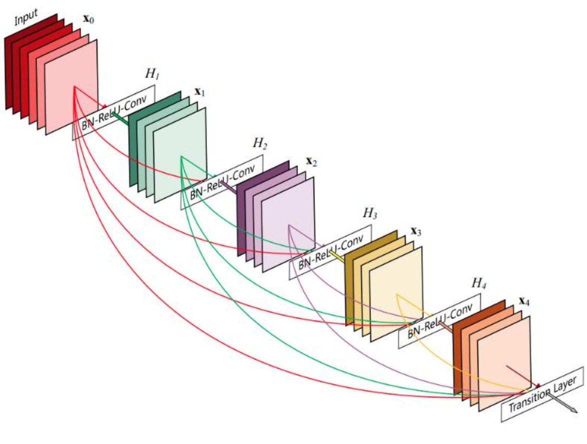

Figure 2. Structure of DenseNet [19]

2.3. VGG19

VGG is a CNN model proposed in 2014 by K. Simonyan and A. Zisserman from the University of Oxford [20]. It achieved successful results in the ILSVRC2014 competition, which utilized the ImageNet dataset large-scale dataset containing over 14 million images across 1,000 classes. The VGG19 model can be broadly described as an improved version of the AlexNet.

The VGG19 architecture consists of 16 convolutional layers and 3 fully connected layers, comprising approximately 143 million parameters. It includes MaxPooling, Fully Connected, ReLU, Dropout, and Softmax layers. Like VGG16, the input layer dimensions are 224×224×3, while the final layer serves as the classification layer. VGG19 achieved an accuracy of 88% on the ImageNet database, making it a highly effective deep learning algorithm.

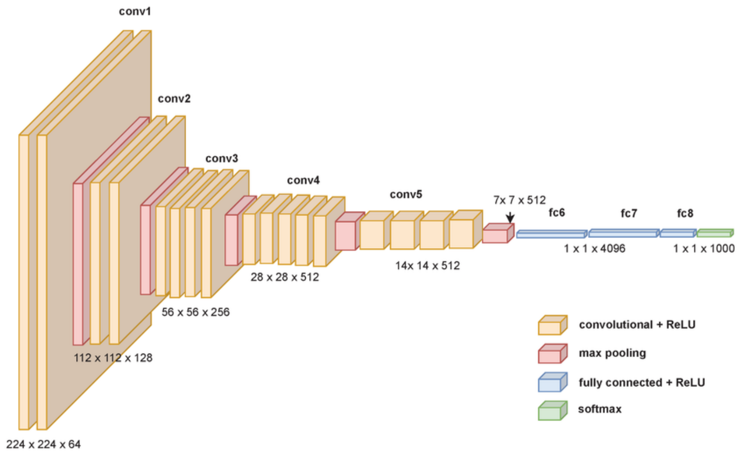

Figure 3. Structure of VGG19 [21]

2.4. MobileNetV2

MobileNet is a CNN model proposed by Howard et al [22]. It is lightweight, fast, and simple architecture designed for compatibility with mobile devices. Instead of standard convolutional blocks, MobileNet employs depthwise separable convolutional blocks. Depthwise separable convolution consists of two operations: depthwise convolution and pointwise convolution.

In depthwise separable convolutions, a filter is applied to each input channel separately, followed by a pointwise convolution, which utilizes 1×1 convolutional filters to create a linear combination of the outputs from the depthwise convolution layers. These depthwise separable convolutional blocks constitute the core of the MobileNet algorithm's performance. For instance, replacing a conventional 3×3 convolutional filter block with a 3×3 depthwise convolutional filter block can reduce computation time by approximately ninefold.

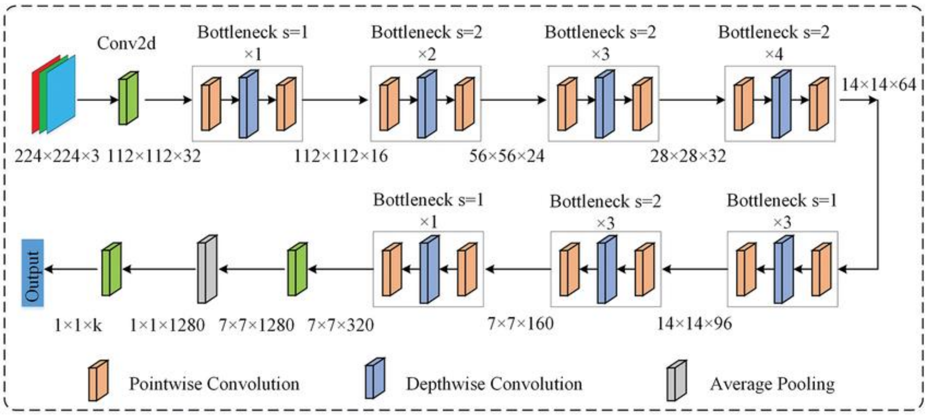

Figure 4. Structure of MobileNetV2 [23]

2.5. Bayesian Search Hyperparameters Optimization

Hyperparameter tuning for machine learning algorithms has traditionally been performed using methods such as grid search, based on cross-validation errors. While grid search is practical, it has the disadvantage of exponentially increasing search space complexity as the number of hyperparameters increases. Recent studies have demonstrated that alternative strategies, such as random search and Bayesian optimization, can be more efficient than grid search for non-trivial search spaces [24].

One of the widely used methods among existing techniques is Bayesian search, which was highlighted in a study published by Snoek in 2012 [25]. The most notable feature of this method is its ability to iteratively refine hyperparameter selection by leveraging the outcomes of previous experiments. This selection process is based on probability calculations using Bayes' theorem. Since finding optimal hyperparameter values for large datasets is computationally expensive, a proposed solution involves partitioning the dataset into smaller subsets and selecting the least costly subset to infer general conclusions about the entire dataset.

Bayesian search is more efficient than grid and random search methods as it requires fewer evaluations to converge to an optimal solution. However, its primary drawback lies in the tendency to become trapped in local optima. During the search for maximum values, the algorithm continuously samples around the highest observed value, making it susceptible to local optima [26].

2.6. Ensemble Learning

The ensemble learning model, frequently employed in machine learning and deep learning, aims to enhance performance by combining multiple predictors [27]. This technique seeks to improve generalization ability and reduce error rates by compensating for the individual weaknesses of different models. The integration of multiple algorithms helps mitigate error diversity, making it an effective strategy for addressing issues such as overfitting and underfitting.

One of the key advantages of ensemble learning methods is their ability to achieve higher accuracy rates. By aggregating the predictive power of multiple models, ensemble learning produces more balanced and generalizable results. However, this process often demands significant computational resources and time. Additionally, running multiple models simultaneously increases system complexity, making it more challenging to manage.

Voting is one of the most commonly used ensemble learning methods, in which the outputs of different classifiers are combined to make a final decision. This approach leverages the strengths of various models and is generally categorized into two subtypes: Soft Voting and Hard Voting.

Soft Voting considers the probability values generated by multiple predictors and assigns weights to them. More reliable models are given higher importance, and the final prediction is based on the highest weighted probability. This method surpasses the accuracy of individual predictions by leveraging a weighted consensus approach.

Hard Voting, on the other hand, treats each model's prediction as a vote and selects the class with the highest number of votes. Its simplicity and compatibility with different algorithms are among its major advantages. However, assuming equal weighting among models may limit its performance in certain cases.

In conclusion, voting methods are among the most widely applied ensemble learning techniques, contributing to both increased accuracy and model robustness.

2.7. Performance Evaluation Metrics

Models are evaluated using accuracy, precision, F1 score, and recall metrics [28]. These metrics are assessed with the help of a confusion matrix. In classification problems, the confusion matrix is highly useful for understanding how well a model predicts the actual classes and identifying the types of errors it makes.

In image classification tasks, the confusion matrix is used to evaluate the model's performance by determining whether each pixel or region has been correctly classified. The calculation of evaluation metrics is based on variables such as true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). TP refers to cases in which the classifier accurately identifies a positive instance as positive, while TN denotes cases where a negative instance is correctly classified as negative. Conversely, FP occurs when the classifier incorrectly labels a negative instance as positive, and FN represents cases where a positive instance is misclassified as negative. These metrics are fundamental in evaluating the performance of classification models, particularly in applications requiring high precision and recall.

Accuracy measures the proportion of correct predictions out of all instances in the dataset.

$$\boldsymbol{Accuracy} = \frac{\mathbf{TP + FN}}{\mathbf{TP + FP + TN + FN}} \tag{2.1}$$

Precision evaluates the proportion of true positives among all predicted positives, indicating how accurate the model is in making positive predictions.

$$\boldsymbol{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}} \tag{2.2}$$

Recall measures the proportion of actual positive instances that were correctly identified by the model.

$$\boldsymbol{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} \tag{2.3}$$

The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of a classifier's performance. These metrics ensure a comprehensive assessment of the model's classification capabilities.

$$\boldsymbol{F1 - Score} = \frac{\mathbf{Precision * Recall}}{\mathbf{Precision + Recall}} \tag{2.4}$$

3. Results and Discussion

In this study, the performance of MobileNetV2, VGG19, and DenseNet121 models was analyzed using the "Fish" dataset available on the Kaggle platform. During the preprocessing stage, the dataset was subjected to resizing and normalization techniques. Bayesian search optimization was employed for tuning the hyperparameters of the models. The optimized models were then combined using the Soft Voting technique to develop an ensemble learning approach.

To examine the impact of Bayesian optimization on model performance, two separate ensemble models were constructed: one with the optimization algorithm applied and the other without it. These models were then compared in terms of performance. The dataset was divided into two subsets: 80% for training and 20% for validation. To prevent overfitting, an early stopping mechanism was implemented during training.

Table 1. Parameters of DL Algorithms without Bayesian Search Optimization

Model	MobileNetV2	VGG19	DenseNet121
Epochs	15	15	15
Batch Size	32	32	32
Optimizer	Adam	Adam	Adam
Learning Rate	1,00E-06	3,00E-06	1,00E-06
Dense Layer Size	256	256	256
Dropout	0.3	0.2	0.3
Activation Functions	ReLU (Dense), Softmax (Output)	ReLU (Dense), Softmax (Output)	ReLU (Dense), Softmax (Output)
Loss Function	Categorical Crossentropy	Categorical Crossentropy	Categorical Crossentropy

Model performance was evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. Throughout the training process, validation loss and validation accuracy values were recorded, and the results were visualized using graphical representations.

The default parameter values obtained from the models without applying any hyperparameter optimization are presented in Table 1.

The optimized parameter values obtained from the models with applying a hyperparameter optimization are presented in Table 2.

Table 2. Table of the Hyperparameter Generated with Bayesian Search Optimization

Model	MobileNetV2	DenseNet121	VGG19
Epochs	15	15	15
Batch Size	32	32	32
Optimizer	Adam	Adam	Adam
Learning Rate	1,00E-05	1,31E-02	1,00E-05
Dense Layer Size	180	180	244
Dropout	0.1	0.1	0.1
Activation Function	ReLU (Dense), Softmax (Output)	ReLU (Dense), Softmax (Output)	ReLU (Dense), Softmax (Output)
Loss Function	Categorical Crossentropy	Categorical Crossentropy	Categorical Crossentropy

Table 2. presents the values obtained through Bayesian Search Optimization. The optimal values were determined within the given parameter ranges. These hyperparameter values were identified over five trials, with each trial trained for five epochs. This process was conducted separately for each model. Subsequently, the identified hyperparameter values were utilized in the final models for training.

Table 3. Performance Metrics of the Models without Bayesian Search Optimization

Model	Ensemble Model	VGG19	MobileNetV2	DenseNet121
Accuracy	0.89091	0.68523	0.86534	0.80901
Recall	0.86231	0.61587	0.83662	0.76525
Precision	0.90232	0.75573	0.86360	0.81010
F1 Score	0.88187	0.64104	0.84677	0.77647
Loss	Null	1.39851	0.57380	0.79729

According to the values presented in Table 3, among the individual models trained without Bayesian Search Optimization, MobileNetV2 achieved the highest accuracy, while VGG19 exhibited the lowest accuracy. The ensemble model, which was constructed using models trained with randomly assigned hyperparameters, outperformed all individual models by incorporating their strongest features. As a result, it demonstrated the expected performance with superior accuracy.

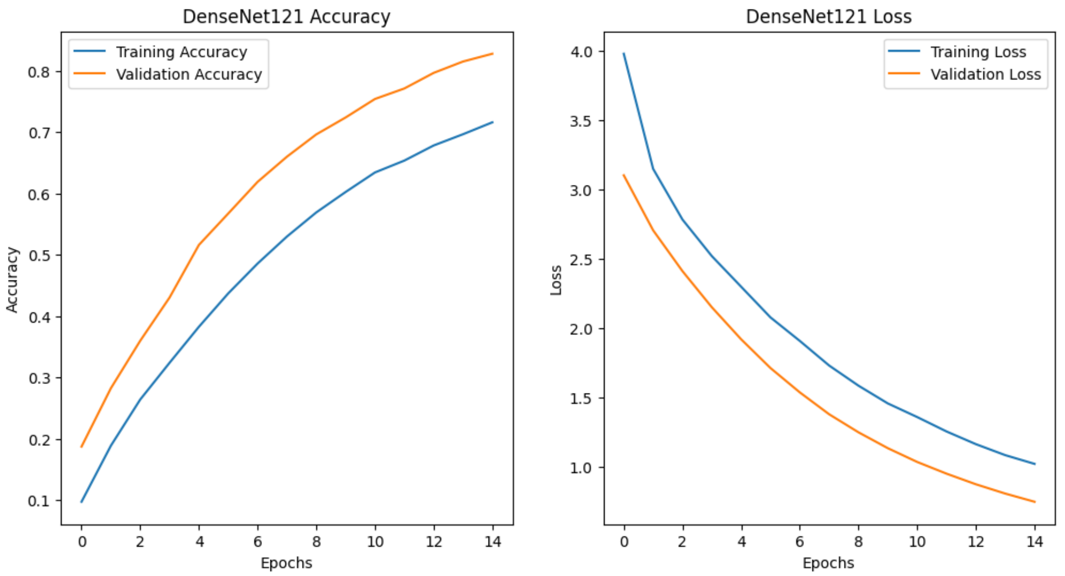

Figure 5. The Accuracy and Loss Plots for the DenseNet121 Model Obtained Without Bayesian Optimization

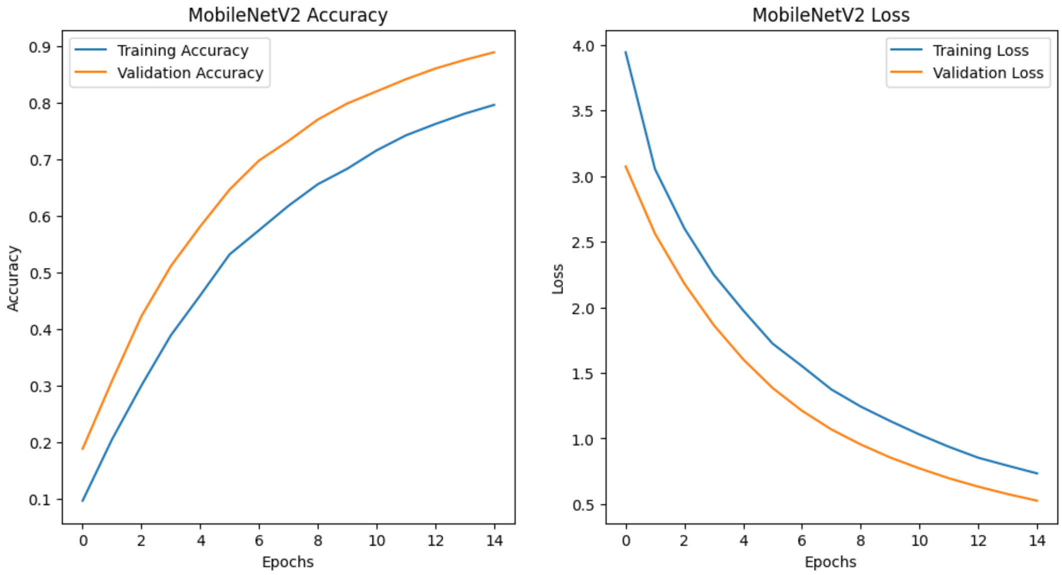

Figure 6. The Accuracy and Loss Plots for the MobileNetV2 Model Obtained Without Bayesian Optimization

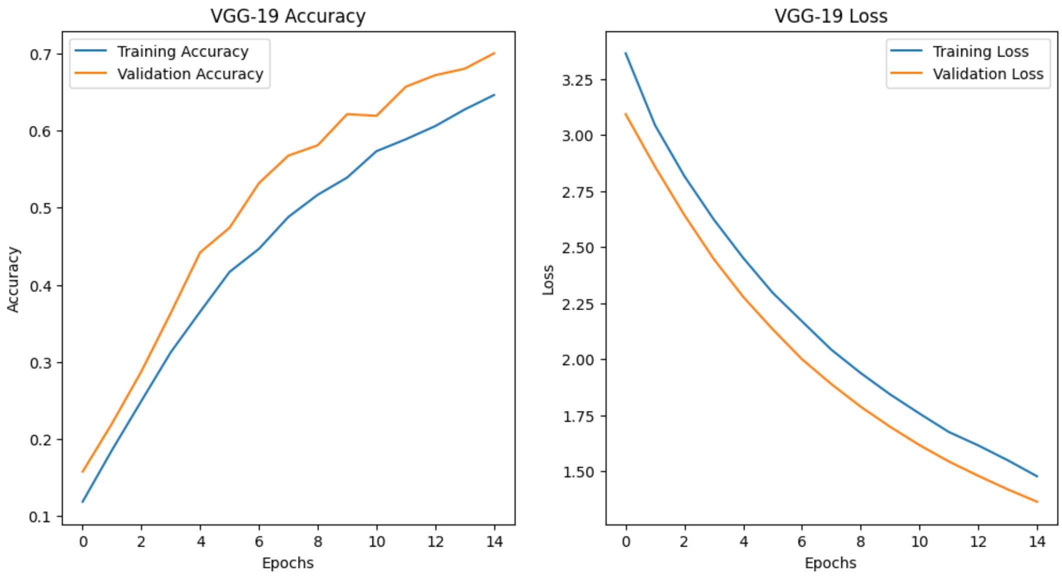

Figure 7. The Accuracy and Loss Plots for the VGG-19 Model Obtained Without Bayesian Optimization

As seen in the Figures 5,6, and 7 without applying Bayesian optimization, a comparative analysis of the accuracy and loss curves of the DenseNet121, MobileNetV2, and VGG19 models reveals notable differences in performance. Among these models, MobileNetV2 achieved the highest accuracy and exhibited a more stable learning process. While DenseNet121 demonstrated a comparable performance, VGG19 obtained the lowest accuracy values. Regarding loss curves, MobileNetV2 exhibited a consistent decrease in loss values. In contrast, VGG19 and DenseNet121 showed greater fluctuations throughout the training process. These findings indicate that models trained without Bayesian optimization have lower generalization capabilities and experience instability during the learning process.

Table 4. Performance Metrics of The Models with Bayesian Search Optimization

Model	Ensemble Model	VGG19	MobileNetV2	DenseNet121
Accuracy	0.97159	0.87841	0.96818	0.87045
Recall	0.96489	0.85580	0.96060	0.84490
Precision	0.97014	0.89145	0.96546	0.86261
F1 Score	0.96751	0.86900	0.96200	0.84972
Loss	Null	0.63590	0.12411	0.53250

According to the results presented in Table 4, Bayesian Search Optimization clearly outperformed randomly assigned hyperparameters in terms of overall performance. On a model-specific basis, MobileNetV2 once again achieved the highest accuracy. Among the three models, DenseNet121 exhibited the lowest performance, albeit by a very small margin.

For the ensemble model, the version utilizing Bayesian Search Optimization achieved a higher accuracy rate compared to the model without optimization. These findings indicate that Bayesian Search Optimization is highly beneficial in terms of both time efficiency and computational cost. The inefficiencies associated with randomly assigned hyperparameters—such as time loss and cost-effectiveness—highlight the practical advantages of using this optimization technique.

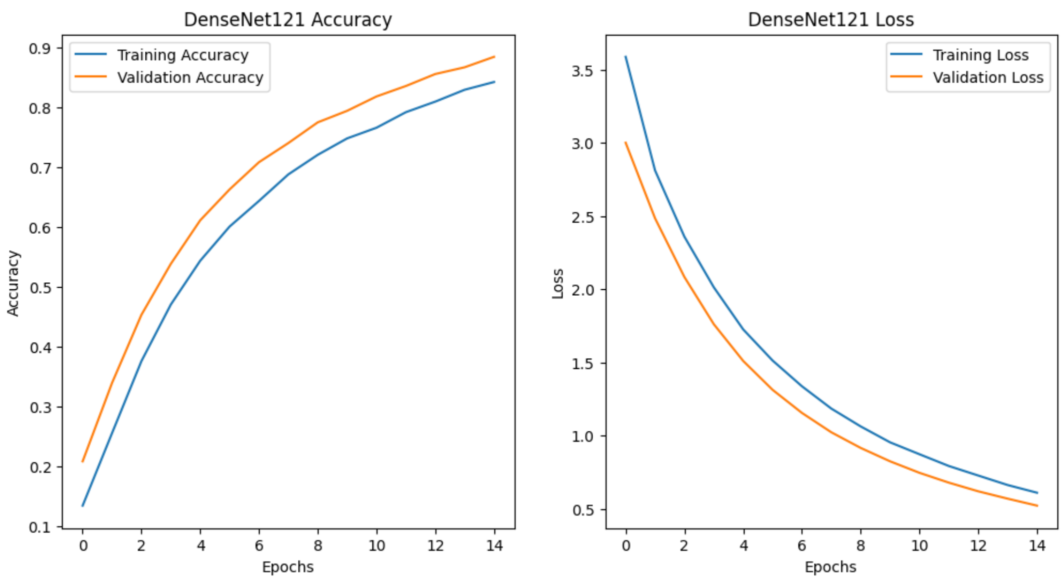

Figure 8. Accuracy and Loss Plots for the DenseNet121 Model Obtained with Bayesian Optimization for Hyperparameters

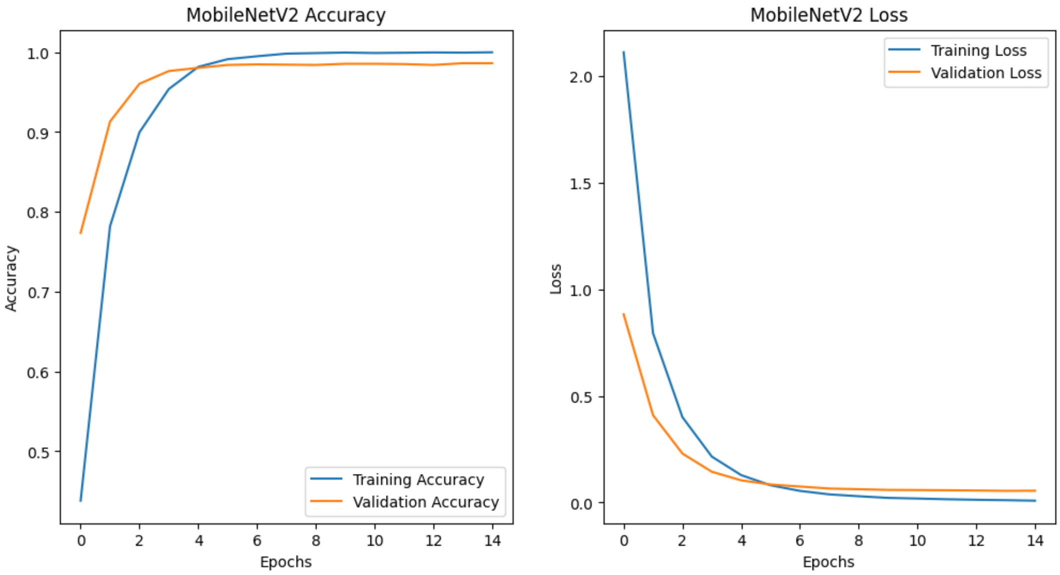

Figure 9. Accuracy and Loss Plots for the MobileNetV2 Model Obtained with Bayesian Optimization for Hyperparameters

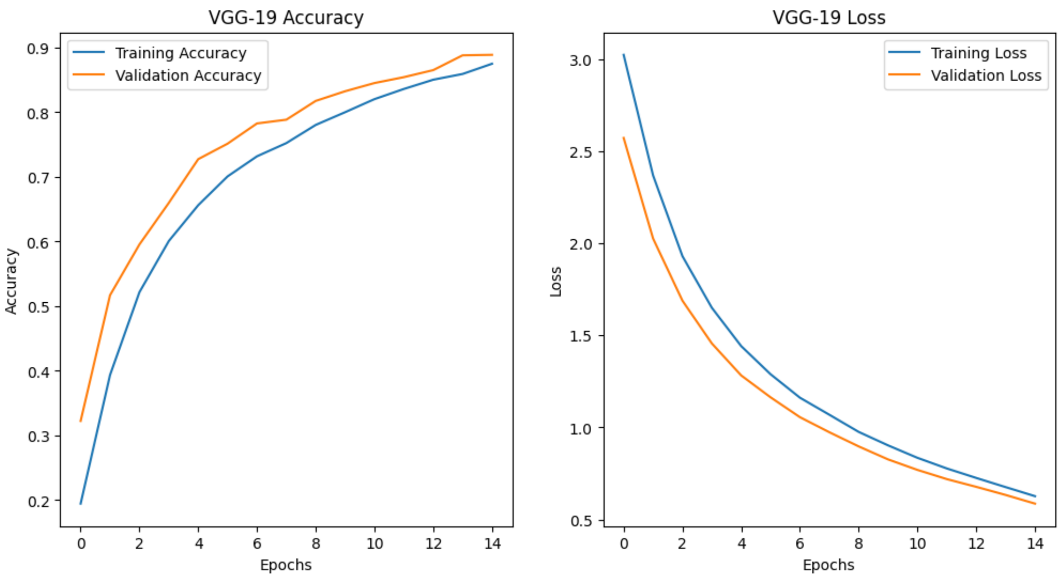

Figure 10. Accuracy and Loss Plots for the VGG-19 Model Obtained with Bayesian Optimization for Hyperparameters

As seen in Figures 8,9, and 10 with the application of Bayesian optimization, a significant increase in the accuracy rates of all models has been observed, along with a notable reduction in loss values. In particular, MobileNetV2 achieved the highest accuracy, emerging as the most successful model. Additionally, both DenseNet121 and VGG19 demonstrated improved accuracy rates and reduced loss values. Furthermore, the ensemble model obtained through the ensemble learning approach outperformed the individual models, achieving the highest classification accuracy. These findings indicate that Bayesian optimization significantly enhances hyperparameter selection, enabling deep learning models to learn in a more stable and efficient manner.

The comparative analysis of the three deep learning models indicates that MobileNetV2 consistently delivered superior performance under both optimized and non-optimized hyperparameter configurations. Its notable accuracy and robust generalization capability can be primarily attributed to its lightweight and computationally efficient architecture, which employs depth wise separable convolutions to minimize complexity without compromising classification effectiveness. DenseNet121 also demonstrated competitive results, largely due to its densely connected structure, which enhances gradient propagation and enables effective feature reuse across layers. Conversely, VGG19, despite its deep architecture, yielded comparatively lower performance likely a consequence of its high parameter count, which increases the risk of overfitting and slows convergence, particularly when dealing with datasets of limited diversity. The implementation of ensemble learning further elevated the overall classification accuracy by integrating the complementary strengths of individual models and mitigating their respective weaknesses. Additionally, Bayesian optimization significantly improved model stability and generalization, as evidenced by smoother training curves and reduced loss values. Collectively, these results highlight the critical role of model architecture, ensemble strategies, and informed hyperparameter tuning in developing accurate and reliable fish species classification systems for practical applications in ecological monitoring.

4. Conclusion

In this study, deep learning-based classification models were developed for fish species identification using a dataset obtained from the Kaggle platform, which consists of a total of 13,302 images representing 31 different fish species. The study aimed to accurately classify fish species using MobileNetV2, DenseNet121, and VGG19 models.

Accurate classification of fish species is of critical environmental and biological importance, as it facilitates the identification of invasive species, the conservation of endangered species, and the maintenance of ecosystem balance. In this context, Bayesian Search Optimization was applied to enhance the performance of the models. It was observed that hyperparameter optimization significantly improved accuracy and other performance metrics across all three models.

Among the individual models, MobileNetV2 achieved the highest classification accuracy for fish species. However, the ensemble learning approach, which combined multiple models, outperformed the individual models and yielded the best overall results. The ensemble model particularly improved the correct prediction rate and minimized classification errors.

The findings indicate that hyperparameter optimization not only enhances accuracy but also strengthens the generalization capabilities of the models. Additionally, the implementation of an early stopping mechanism during training prevented overfitting, enabling the models to achieve more balanced performance.

This study demonstrates the effectiveness of deep learning techniques in fish species classification and highlights the value of ensemble learning approaches. Moreover, the developed models hold significant real-world application potential. They can be directly integrated into real-time marine monitoring systems, support early detection of invasive fish species, and assist in the automation of aquaculture practices. These capabilities are vital for sustainable fishery management, biodiversity preservation, and the protection of marine ecosystems against anthropogenic threats. Future research can further improve model performance by expanding the dataset, integrating different deep learning architectures, and applying transfer learning techniques. Moreover, the broader application of such models in environmental and biological fields could contribute significantly to ecosystem conservation and sustainability.

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Conflict of Interest

Authors approve that to the best of their knowledge, there is not any conflict of interest or common interest with an institution/organization or a person that may affect the review process of the paper.

Research and Publication Ethics Statement

The authors declare that this study complies with research and publication ethics.

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