

XGBoost Implementation for Marine Fish Image Classification Using VGG19-Based Transfer Learning

Anggito Wahyu Adi¹, Florentina Yuni Arini^{1*}

¹Informatics Engineering Study Program, Faculty of Mathematics and Natural Sciences,
Universitas Negeri Semarang, Indonesia

Abstract. Accurate identification of fish species is important for trade supervision, marine biology, and fisheries management. This study develops a classification system for nine marine fish species by combining VGG19-based feature extraction with XGBoost. Using 9,000 balanced RGB images from the Kaggle Large-Scale Fish Dataset, the workflow includes EDA, preprocessing, an 80:20 data split, feature extraction, and model training. EDA showed that Red Mullet and Striped Red Mullet share similar visual characteristics, while the Shrimp class appears more distinct. The model achieved 97% accuracy and was deployed through a Flask web application that processes, extracts features, and classifies images. These findings demonstrate that integrating VGG19 with XGBoost offers an effective and efficient approach for marine fish image classification.

Purpose: The primary objective here is to build a hybrid classification model for marine fish that is both efficient and robust, merging deep feature extraction from the VGG19 architecture with the XGBoost classifier. Specifically, this research seeks to improve classification accuracy while reducing computational overhead, thereby providing a reliable automated identification system that can support fisheries management, ecological monitoring, and marine biological research.

Methods: This research employed a dataset of 9,000 images representing nine marine fish species. The preprocessing stage included resizing each image to 224×224 pixels and applying normalization. Deep feature representations were obtained using a pre-trained VGG19 model, utilizing only its convolutional layers to extract semantic features. These features were then classified with the XGBoost algorithm, chosen for its efficiency, resilience, and strong performance on structured data. The model was trained using an 80:20 split for training and testing, and its performance was assessed through accuracy, precision, recall, F1-score, and a confusion matrix.

Result/Findings: The combination of VGG19 feature extraction with XGBoost produced strong results, achieving an accuracy of about 97%. This performance was further supported by consistently high precision, recall, and F1-scores across all nine species.

Novelty/Value: A hybrid architecture integrating VGG19-based transfer learning with the XGBoost classifier is presented an approach rarely explored in this domain. This combination capitalizes on deep semantic feature extraction from VGG19 alongside efficient structured classification via XGBoost, producing a model that delivers high accuracy with significantly reduced computational costs. Additionally, the hybrid approach proposed in this study remains competitive with fully end-to-end deep learning models, yet operates with fewer parameters and reduced training demands. These results illustrate that well-designed hybrid pipelines can match the performance of conventional deep learning architectures while providing clear benefits in terms of training efficiency, interpretability, and scalability.

Keywords: XGBoost, VGG19, Transfer Learning, Image Classification, Marine Fish, Deep Learning

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INTRODUCTION

Indonesia, distinguished as an archipelagic nation, possesses extraordinary aquatic biodiversity, including over 1,500 freshwater species and more than 2,000 marine fish species. This biological wealth is pivotal to the country's cultural identity and economic stability, particularly within the fisheries sector, which serves as a primary income source for coastal communities[1], [2]. Effective management of these resources relies heavily on precise data regarding stock and species distribution to formulate policies that balance economic exploitation with ecological preservation. Given the rapid growth of the fisheries industry, the need for accurate and efficient species identification methods has become increasingly urgent to support sustainable management practices. Nevertheless, the extensive diversity of species creates substantial obstacles for identification and classification processes. This issue is particularly pronounced considering the inherent

*Corresponding author.

Email addresses: floyuna@mail.unnes.ac.id (Arini)

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limitations of manual observation methods, which are frequently susceptible to subjectivity and observer fatigue [3], [4].

A prominent obstacle in fish classification arises from the high morphological resemblance among certain groups, known as cryptic species. For instance, distinguishing members within the Mullidae family or differentiating between *Rastrelliger* species remains an arduous task. Misidentification in these contexts can lead to distorted catch data and ineffective management policies, a critical issue in regions where marine resources already face stress from unsustainable exploitation practices, as highlighted in marine ecosystem studies [5]. Consequently, precise classification is imperative not merely for biodiversity conservation but also for guaranteeing the traceability of fishery products in the global market. In recent years, Machine Learning (ML) and Artificial Intelligence (AI) have emerged as promising instruments for automating species recognition, offering the potential to enhance both accuracy and operational efficiency in fisheries management [6], [7].

In the domain of fish image classification, traditional models such as Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN) have been extensively applied. Previous investigations utilizing SVM with Radial Basis Function (RBF) features reported an accuracy of 78.75% [8], whereas approaches integrating K-NN with Principal Component Analysis (PCA) achieved accuracies up to 85% accuracy [9]. Other attempts using Naïve Bayes for freshness identification reached 79.37% [10]. However, these conventional machine learning frameworks often struggle to capture the complex, high-level visual features required to distinguish morphologically similar species, largely due to their reliance on manual feature extraction or simple geometric properties.

To address these limitations, contemporary advancements in computer vision have increasingly pivoted toward Deep Learning, specifically Convolutional Neural Networks (CNNs), which are distinguished by their capacity to automatically learn hierarchical feature representations. Architectures such as R-CNN have been shown to achieve improved accuracy of up to 85% in underwater environments [11]. Additionally, models like SVM have shown significant performance gains when combined with Histogram of Oriented Gradients (HOG) features, achieving an accuracy of 94.8% [12]. Further enhancements in feature fusion, such as the FFM-ViT model, have successfully attained an accuracy of 90.2% [13]. Nevertheless, training deep CNN models from scratch necessitates large-scale datasets and substantial computational resources, presenting barriers to practical deployment in resource-constrained settings. Moreover, end-to-end deep learning models may impose intensive computational demands during real-time inference.

Building on these advances, this research proposes a hybrid classification system for marine fish species using a Transfer Learning approach with VGG19 enhanced by Extreme Gradient Boosting (XGBoost). Previous studies have demonstrated that transfer-learning-based CNN architectures are effective for marine fish classification across multiple species [14]. By leveraging VGG19 pre-trained on ImageNet to extract robust high-dimensional visual features [15], and using XGBoost, a highly efficient and scalable gradient-boosting classifier [16], this approach aims to combine the feature-extraction power of deep learning with the classification efficiency of ensemble learning. This research targets the classification of nine distinct fish species from 'A Large-Scale Fish Dataset' aiming to improve classification accuracy beyond traditional benchmarks while maintaining a system architecture suitable for practical application.

METHODS

This research is executed through a series of systematic stages designed to construct the final classification model. The comprehensive workflow of the analytical process and model development is depicted in the subsequent flowchart, which provides a lucid overview of how the dataset progresses through each phase, spanning from preprocessing and feature extraction to model training and evaluation. The comprehensive workflow of the analytical process and model development spanning from data preprocessing and feature extraction to model training and evaluation is illustrated in Figure 1.

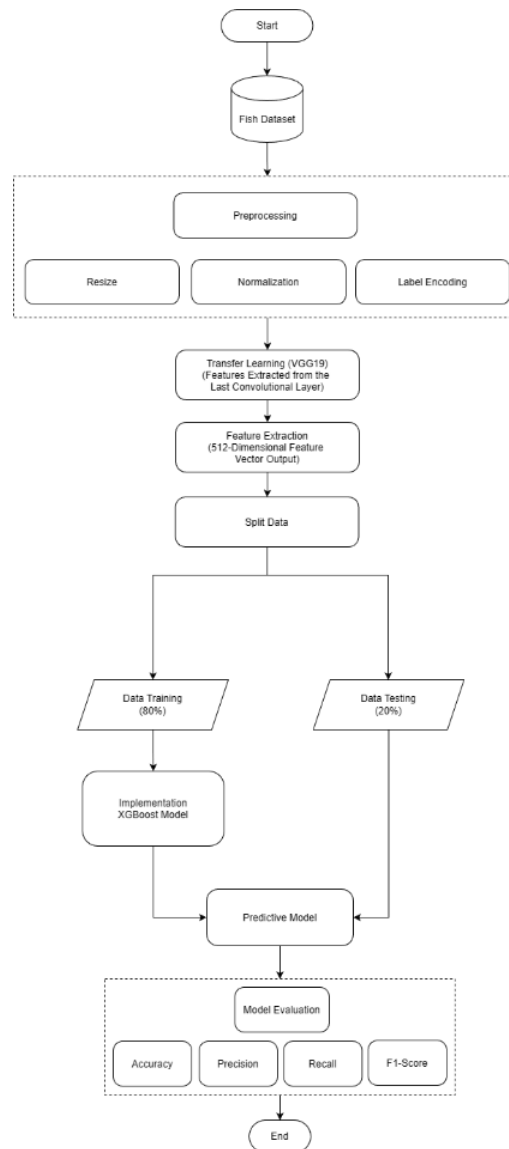


Figure 1. Research model step

Dataset

This research utilizes "A Large-Scale Fish Dataset" obtained from the Kaggle repository, comprising 9,000 RGB images evenly distributed across nine marine fish species, with 1,000 images class [17]. The images were captured using Kodak Easyshare Z650 and Samsung ST60 digital cameras, resulting in varying original resolutions such as 2832×2128 and 1024×768 pixels, providing diverse lighting conditions, backgrounds, and orientations. All images were standardized through preprocessing by resizing them to 224×224 pixels to match the VGG19 input specification, and the dataset was divided into an 80:20 train–test split to ensure balanced evaluation of model performance.

Table 1. Summary of the A Large Scale Fish Dataset

Description	Value
Total number of images	9000
Number of classes	9
Image per class	1000
Image format	RGB
Train/Validation/Test split	80 : 20

Preprocessing

To prepare the dataset for optimal feature extraction and classification, a comprehensive preprocessing pipeline was implemented to ensure uniformity, numerical stability, and compatibility with both the VGG19 architecture and the XGBoost classifier [13]. This phase is designed to standardize visual inputs, enhance the quality of extracted features, and maintain balanced class representation, thereby supporting the development of a reliable and high-performance hybrid classification model.

The procedure commenced with image resizing, addressing the varying resolutions of the source images such as 2832×2128 and 1024×768 pixels by standardizing them to 224×224 pixels. This step satisfies the input requirements of VGG19, ensuring consistent spatial representation while preserving the essential morphological details needed for accurate feature extraction. After resizing, pixel normalization was applied by scaling values from the original 0–255 range to 0–1. This process improves numerical stability during feature extraction, accelerates model convergence, and prevents disproportionately large pixel values from skewing the feature space.

Following this, label encoding was performed to convert the nine fish species, initially represented as categorical strings like Sea Bass and Red Mullet, into numerical labels ranging from 0 to 8. This transformation is necessary because XGBoost requires numerical target values for multi-class classification. A summary of the complete preprocessing workflow is presented in Table 2.

Table 2. Summary of the preprocessing steps applied to the A Large Scale Fish Dataset

Description	Value
Image Resizing	Resized all images to 224×224 pixels
Normalization	Normalized pixel values to the range [0, 1].
Label Encoding	Converted image into numerical labels 0–8

Feature Extraction Using VGG19

After completing the resizing and normalization steps, feature extraction was performed using the VGG19 model pre-trained on the ImageNet dataset. In this research, VGG19 was used only as a feature extractor, where the fully connected layers were removed (include_top=False) and Global Average Pooling was applied to obtain compact feature vectors.

Each input image sized 224×224 pixels was converted into a NumPy array and normalized before being passed through the VGG19 convolutional layers. These layers progressively learn visual patterns, evolving from simple edges and textures to higher-level semantic features related to fish morphology. The network's final output is a 512-dimensional feature vector representing the essential visual characteristics of each image. These feature vectors subsequently served as the input for the XGBoost classifier in the following stage.

To provide a clearer representation of the convolutional hierarchy and the flow of feature extraction, the complete architecture of the VGG19 model used in this research is presented in Figure 2. This figure illustrates how the convolutional and pooling layers progressively transform the input image into a 512-dimensional feature vector that serves as input to the XGBoost classifier [18].



Figure 2. VGG19 architecture.

XGBoost Classifier

The classification stage in this research was carried out using the Extreme Gradient Boosting (XGBoost) algorithm. XGBoost was selected due to its strong performance, scalability, and ability to effectively handle high-dimensional numerical features produced by the VGG19 feature extractor [19]. The 512-dimensional

feature vectors generated from each image, together with the encoded class labels, were used as the primary inputs to the model.

Before the model was trained, the dataset was divided into separate training and testing sets to ensure that the evaluation process remained objective and free from bias. XGBoost was then trained to recognize and categorize the images by learning patterns embedded within the extracted feature representations. Following the completion of training, the model's effectiveness was measured using several evaluation metrics. If the performance obtained fell short of expectations, additional adjustments or fine-tuning procedures were implemented. After achieving satisfactory performance levels, the model was retrained using the complete training subset before being subjected to final testing.

Model Evaluation

Evaluating the model's performance is essential to determine how accurately the classifier is able to assign the correct labels to each input image. [20]. This assessment is carried out by comparing the prediction results generated by the model with the true labels assigned to each sample. Classification problems typically rely on several key terms to explain the different possible outcomes of a prediction. A True Positive (TP) occurs when a positive sample is correctly recognized as such, whereas a True Negative (TN) indicates that a negative sample has been accurately identified. Conversely, a False Positive (FP) happens when a negative instance is mistakenly labeled as positive, and a False Negative (FN) takes place when a positive instance is incorrectly predicted as negative.

Using these foundational concepts, a number of quantitative metrics such as accuracy, precision, recall, and F1-score are utilized to measure the classifier's overall performance. Together, these metrics offer a broad perspective on how well the model performs, especially in multi-class tasks like marine fish classification. The final performance values are derived from the counts of TP, TN, FP, and FN, which are summarized in the confusion matrix. The evaluation matrix equations are shown below.

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

Accuracy measures the proportion of correctly predicted instances out of all predictions made. It provides an overall indication of how well the model performs. The calculation is shown in Eq. (1).

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

Precision measures the proportion of correctly predicted positive instances among all instances predicted as positive. This metric is particularly important when false positives carry a high cost. Its formulation is presented in Eq. (2).

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

Recall measures the proportion of correctly identified positive instances among all actual positive instances. It is crucial when false negatives are more costly. The computation is shown in Eq. (3).

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

F1-Score represents the harmonic meaning of Precision and Recall. This metric is useful in situations involving class imbalance because it balances both Precision and Recall. The formula is provided in Eq. (4).

RESULT AND DISCUSSION

A preliminary review of the dataset is crucial for understanding the model's expected performance and identifying whether further preprocessing or data adjustments are necessary. Through Exploratory Data Analysis (EDA), it was observed that the dataset is perfectly balanced, with each of the nine fish species represented by exactly 1,000 images. This uniform distribution is particularly beneficial for classification since it reduces the likelihood of bias toward dominant classes and ensures that the model can learn features

from all categories evenly. Consequently, evaluation metrics such as accuracy become more meaningful because they are not skewed by class imbalance. The balanced dataset also removes the necessity for specialized handling methods like class-weighting or oversampling, which are commonly used to address imbalance issues. The distribution of image counts for all classes is illustrated in Figure 3, where a uniform horizontal bar plot clearly demonstrates the equal presence of 1,000 samples for each category, further confirming the dataset’s suitability for developing and evaluating the classification model.

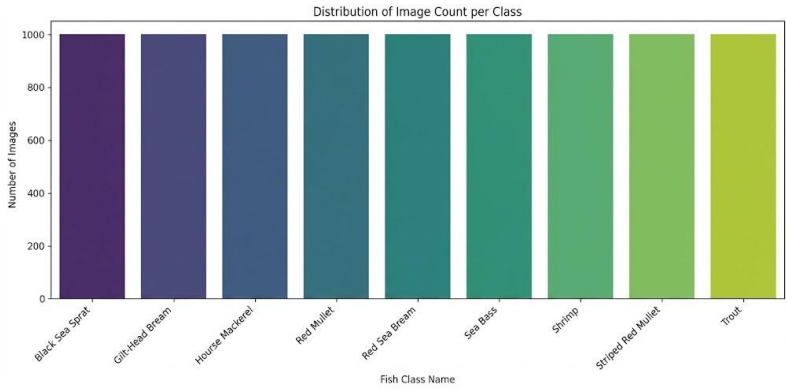


Figure 3. Distribution of Data Amount per Class

The performance of the final VGG19+XGBoost model was evaluated in detail using a confusion matrix to examine the distribution of classification errors across classes. As illustrated in Figure 4, the heatmap of the confusion matrix shows a strong dominance along the main diagonal, indicating a high number of correct predictions across all fish species. However, the off-diagonal elements provide important diagnostic insights. Misclassifications were primarily concentrated between the Striped Red Mullet and Red Mullet classes, where a small number of images from each class were incorrectly predicted as the other. This observation aligns with the visual similarity between the two species and reflects the inherent challenge in distinguishing subtle morphological differences.

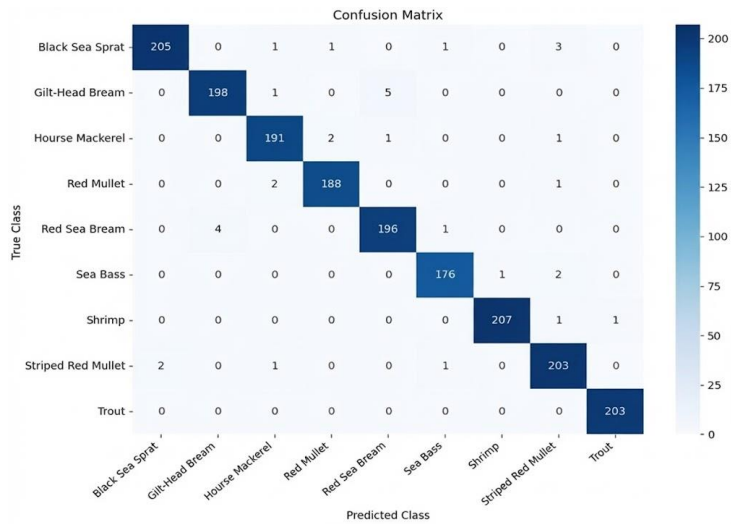


Figure 4. Heatmap of XGBoost+VGG19 model evaluation results

The detailed classification report further confirms the robustness of the VGG19+XGBoost model. As shown in Table 3, most fish species achieved precision, recall, and F1-scores ranging from 0.95 to 0.99, indicating highly consistent predictive performance across classes. Species such as Horse Mackerel, Shrimp, and Trout reached near-perfect scores, demonstrating the model’s ability to correctly identify species with distinct morphological features. Meanwhile, Striped Red Mullet and Red Mullet exhibited slightly lower values although still above 0.95 reflecting the classification challenges previously observed in the confusion matrix. The overall accuracy of 0.98 further validates the effectiveness of the hybrid

architecture, supported by macro and weighted averages that remain uniformly high at 0.98, demonstrating balanced performance even across classes with subtle visual differences.

Table 3. Model evaluation results on test data

Fish Species	Precision	Recall	F1-Score	Support
Black Sea Sprat	0.96	0.98	0.97	211
Gilt-Head Bream	0.95	0.94	0.95	204
Horse Mackerel	0.98	0.98	0.98	195
Red Mullet	0.96	0.97	0.97	191
Red Sea Bream	0.94	0.96	0.95	201
Sea Bass	0.98	0.97	0.98	179
Shrimp	0.99	0.99	0.99	209
Striped Red Mullet	0.96	0.93	0.94	207
Trout	1.00	1.00	1.00	203
Accuracy			0.97	1800
Macro avg	0.97	0.97	0.97	1800
Weighted avg	0.97	0.97	0.97	1800

The accuracy result of the purpose method XGBoost and VGG19 shows in Table 4. Showing clear differences in methodological approaches, feature extraction strategies, and accuracy results. The study by Pandiyan et al. [8], which implemented an SVM model with an RBF kernel, achieved an accuracy of only 78.75%, highlighting the limitations of traditional SVM approaches when dealing with fish species that exhibit highly similar visual patterns. These limitations often arise from the model's dependency on manually crafted features, which may not fully capture the subtle variations among species.

Nuraini et al. [9] attempted to enhance classification performance by combining K-NN with PCA for dimensionality reduction. This hybrid method produced a higher accuracy of 85%, demonstrating that simplifying high-dimensional image data can improve the discriminative ability of classical machine learning models. In another study, Saputra et al. [10] utilized the Naïve Bayes algorithm to identify fish freshness levels and obtained an accuracy of 79.37%. However, the method remains constrained by the assumption that input features are independent an assumption that rarely holds true for image-based datasets where pixel relationships are strongly correlated.

Meanwhile, the comparative work by Nababan et al. [21] evaluated various machine learning algorithms, including SVM, K-NN, Naïve Bayes, Decision Tree, and Multilayer Perceptron (MLP). The highest accuracy achieved was 66% using the MLP model, indicating that traditional handcrafted features combined with standard classifiers may struggle to generalize effectively on more challenging datasets. Raja et al. [11] further explored region-based convolutional techniques and achieved an accuracy of 85%, reinforcing the potential of region-focused deep learning approaches for capturing more complex spatial structures.

Compared to all these studies, the method proposed in the present research integrating VGG19 as a deep feature extractor with XGBoost as the classifier shows a substantial improvement in performance. By leveraging transfer learning, the model benefits from rich, high-level feature representations, while gradient boosting enhances predictive accuracy. The final model achieved an accuracy of 97%, significantly outperforming existing approaches and demonstrating its effectiveness as a practical, robust, and highly competitive solution for image-based fish classification.

Table 4. Proposed Method VS Previous Studies

Author	Method	Accuracy (%)
Pandiyan et al., 2020 [8]	Support Vector Machine (SVM)	78
Nuraini et al., 2023 [9]	KNN + PCA	85
Saputra et al., 2022[10]	Naïve Bayes	79
Nababan et al., 2023 [21]	SVM, Naive Bayes, KNN, Decision Tree, Multilayer Perceptron	66
Raja et al., 2023 [11]	Region-based Convolutional Neural Network (R-CNN)	85
Proposed Method	XGBoost + VGG19	97

CONCLUSION

This research demonstrates that the hybrid approach combining VGG19-based transfer learning with the XGBoost classifier is highly effective for classifying nine species of marine fish, achieving an overall accuracy of approximately 97%. The VGG19 feature extractor successfully generated 512-dimensional representations that captured essential visual characteristics, enabling XGBoost to deliver strong and consistent predictive performance across most classes. Species with distinct morphology, such as Trout and Shrimp, were identified accurately, while visually similar species such as Red Mullet and Striped Red Mullet remained challenging due to subtle inter-species similarities. Although the proposed method is computationally efficient and performs competitively compared to end-to-end deep learning models, the absence of hyperparameter tuning indicates that further optimization could potentially enhance performance. Overall, the findings highlight the potential of hybrid deep feature extraction and gradient boosting techniques as a practical and scalable solution for marine fish image classification.

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