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# Deep Learning-based Fish Species Recognition and Classification for Analyzing the Species Diversity in Aquatic Ecosystems

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Aquatic biodiversity plays a critical role in maintaining ecosystem balance, yet traditional methods for monitoring fish species diversity are often labor-intensive, time-consuming, and prone to error. This study presents a robust artificial neural network (ANN) model designed to classify fish species with high accuracy, providing a scalable solution for biodiversity monitoring and fisheries management. The model incorporates advanced techniques such as dropout layers and batch normalization, achieving a training accuracy of 97.6% and a validation accuracy of 95.3%. With an average F1 score of 0.94 and AUC values exceeding 0.93 across all classes, the model demonstrates strong generalization and robustness, even when distinguishing between visually similar species. Practical applications of the model include automated biodiversity assessments and precise stock analysis for sustainable fisheries management. However, limitations related to dataset size, geographic scope, and real-world underwater conditions were identified. To address these challenges, future work will focus on integrating pre-trained architectures, expanding datasets to reflect diverse ecological conditions, and exploring hybrid deep learning approaches. This study highlights the transformative potential of AI-driven tools in advancing ecological research and promoting sustainable aquatic ecosystem management.

**Keywords:** Aquatic, ANN, Deep learning, Fish Species classification.

## 1. Introduction

The exploration and documentation of aquatic biodiversity is a cornerstone of environmental science, providing critical insights into ecosystem health, sustainability, and conservation strategies. Traditional methods of fish species identification and diversity assessment often involve manual analysis, which can be labor-intensive, time-consuming, and prone to human error. With the advent of deep learning, these challenges are being addressed by automated systems capable of recognizing and classifying fish species with high accuracy (Julaiha et al., 2024). Such methodologies leverage advanced neural networks to process complex visual and behavioral patterns, enabling researchers to analyze large datasets efficiently and systematically.

Deep learning applications in aquatic ecosystems extend beyond classification, incorporating analyses of movement trajectories, habitat preferences, and population dynamics. Recent studies demonstrate the use of pre-trained diffusion models to classify fish events, highlighting the capacity of artificial intelligence (AI) to augment ecological monitoring (Sørdalen et al., 2024). These advancements are pivotal in supporting sustainable fisheries management, monitoring species health, and understanding ecological shifts due to climate change.

### 1.1 Motivation

The primary motivation for this research is the urgent need for innovative tools to monitor aquatic ecosystems comprehensively. Aquatic biodiversity faces significant threats from overfishing, habitat destruction, and climate change, necessitating robust methods for species identification and population analysis. Traditional survey techniques are limited in their scope and scalability, often failing to capture the diversity of species in complex environments. Deep learning provides a scalable, automated solution that not only addresses these limitations but also offers the potential to analyze environmental data in real time (Julaiha et al., 2024).

Furthermore, fish species are key indicators of ecosystem health, playing critical roles in nutrient cycling, habitat maintenance, and food web dynamics. Mismanagement or misidentification of species can disrupt ecological balance, leading to cascading effects on biodiversity. Automated classification systems using deep learning algorithms enable precise and consistent identification, fostering data-driven conservation strategies.

### 1.2 Organization of the Paper

This paper is organized into the following sections:

1. Literature Review: A comprehensive overview of existing methodologies and technologies in fish species recognition, highlighting the role of deep learning.

2. Methodology: Details of the proposed deep learning framework, including dataset preparation, model architecture, and evaluation metrics.

3. Results and Discussion: Analysis of the system’s performance in terms of accuracy, scalability, and applicability to diverse aquatic environments.

4. Case Studies: Application of the proposed system to real-world datasets, demonstrating its effectiveness in ecological monitoring.

5. Conclusion and Future Work: Summary of findings, implications for conservation, and potential advancements in AI-based biodiversity monitoring.

## 2. Literature Review

The application of deep learning in fish species recognition and classification has revolutionized ecological research, offering unprecedented accuracy and efficiency in monitoring aquatic biodiversity. This review synthesizes significant advancements and methodologies in the field, emphasizing their implications for aquatic ecosystem analysis and conservation.

### 2.1 Automated Systems and Dataset Development

The creation of robust datasets is foundational for training accurate deep learning models. Hridoy et al. (2024) introduced the BD-freshwater-fish dataset, capturing fish species under natural conditions using high-definition cameras. This dataset enabled the development of AI systems tailored for local fish species in Bangladesh, with potential applications in smart aquaculture (Hridoy et al., 2024). Similarly, Uma et al. (2024) explored datasets in complex underwater environments to optimize species identification. They employed convolutional neural networks (CNNs) to enhance detection accuracy, offering a scalable solution for ecological monitoring (Uma et al., 2024).

### 2.2 Deep Learning Architectures for Fish Recognition

A variety of deep learning architectures have been implemented for fish classification. Zhu et al. (2024) proposed Fishllm, a multimodal large language model trained to integrate visual and textual data for species detection. Their approach bridged traditional computer vision with natural language processing, enhancing the robustness of detection systems (Zhu et al., 2024). Oriol et al. (2024) introduced a segmentation-to-bounding-box transformation method to improve underwater imagery analysis. Their model targeted fish habitats monitored by autonomous underwater vehicles (AUVs), achieving higher detection precision in murky environments (Oriol et al., 2024). Additionally, MobileNet-V2, optimized for real-time applications in marine environments, showcased its potential in recognizing fish behaviors in shallow waters. This low-computation model supports mobile applications for ecological education (Darwish et al., 2024).

### 2.3 Conservation and Fisheries Management

Deep learning applications extend to fisheries management by enabling real-time monitoring of fish populations. Julaiha et al. (2024) proposed Deep Fish, a system for estimating fish stocks in marine environments. Their results demonstrated how AI could augment sustainable fishing practices by automating stock assessments (Julaiha et al., 2024). Similarly, the study by Raghavendra and Pasha (2024) focused on detecting illegal fishing activities through advanced recognition systems. They leveraged a hybrid model combining machine learning and deep learning techniques for precise fish species classification (Raghavendra & Pasha, 2024).

## 2.4 Challenges in Underwater Ecosystems

The underwater environment presents unique challenges, including light distortion and occlusion, that limit the effectiveness of conventional vision systems. Alqaryouti et al. (2024) addressed these issues by incorporating novel preprocessing techniques into deep learning pipelines, enhancing feature extraction and classification accuracy in challenging underwater conditions (Alqaryouti et al., 2024). Manikandan et al. (2024) proposed a transformer-based vision system, highlighting the role of attention mechanisms in overcoming the variability of underwater imagery. Their approach also utilized proprietary fish databases to improve detection reliability (Manikandan et al., 2024).

## 2.5 Behavioral Analysis and Ecological Insights

Deep learning has also been employed to analyze fish behaviors, providing insights into ecological dynamics. Sørdalen et al. (2024) employed trajectory-based classification to study corkwing wrasse movements, leveraging pre-trained diffusion models. This research emphasized the role of behavioral analysis in monitoring species health and ecosystem stability (Sørdalen et al., 2024). Deroiné et al. (2024) expanded this approach by integrating behavior recognition with sustainability assessments, demonstrating the potential for AI-driven ecological interventions (Deroiné et al., 2024) as shown in table 1.

Table 1. Summary Table of Literature Review

| Reference | Description | Methodology | Results Obtained | Limitations |
|---|---|---|---|---|
| Hridoy et al. (2024) | BD-freshwater-fish dataset for smart aquaculture | Deep learning using high-definition images of freshwater fish | Achieved accurate classification of local fish species | Limited to regional fish species; requires scalability to global contexts (Link) |
| Uma et al. (2024) | Automated species identification in underwater ecosystems | CNNs for classification under low visibility conditions | Enhanced detection in complex underwater environments | Model accuracy drops in highly occluded settings (Link) |
| Zhu et al. (2024) | Fishllm: Multimodal tuning for species detection | Combined visual and textual data using transformer models | Enhanced classification of diverse aquatic species | High computational cost for real-time applications (Link) |
| Sørdalen et al. (2024) | Trajectory-based behavioral analysis | Pre-trained diffusion models for movement analysis | Accurate behavior tracking of corkwing wrasse | Model limited to specific species (Link) |
| Manikandan et al. (2024) | Underwater species classification using transformers | Vision transformers with proprietary datasets | Reliable classification in diverse habitats | Dependent on dataset quality (Link) |
| Raghavendra & Pasha (2024) | FishNet: Detection of illegal fishing | Hybrid deep learning and ML approach | Improved precision in species identification | Limited real-time processing capabilities (Link) |
| Hafeez et al. (2024) | Fisheries policies in Pakistan using AI | Deep learning models for classification | Highlighted policy gaps using species data | Focused only on Pakistani fisheries (Link) |
| Darwish et al. (2024) | MobileNet-V2 for real-time fish behavior analysis | Lightweight CNN optimized for mobile use | Enabled quick identification in shallow waters | Limited performance in deep sea habitats (Link) |
| Deroiné et al. (2024) | Sustainable fishing with automated monitoring | Deep learning for bait analysis and fish behavior | Reduced environmental impact of fishing | Model complexity limits adoption in smaller fisheries (Link) |
| Julaiha et al. (2024) | Deep Fish for stock analytics | Deep neural networks for population assessment | Improved stock tracking in marine ecosystems | Focused on marine rather than freshwater environments (Link) |

| | | | | |
|---|---|---|---|---|
| Zhu et al. (2023) | Fine-grained tuna recognition in complex environments | RSNC-YOLO, a YOLO-based method for object detection | Achieved 92% accuracy in tuna recognition under challenging conditions | Computational cost limits scalability (Link) |
| Hafeez et al. (2023) | Fisheries policy improvement via AI | Deep learning to classify fish species and analyze policies | Effective identification of policy gaps for sustainable fishing | Limited applicability to regions outside Pakistan (Link) |
| Wang et al. (2023) | Flexible photoacoustic devices for real-time fish detection | Integrated electroluminescence with piezoelectric sensing | Enabled high-speed identification of fish movements | High device cost and maintenance (Link) |
| Sasithradevi et al. (2023) | Real-time fish detection in turbid environments | DePondFi'23 challenge dataset with CNN models | Reliable detection in low-visibility pond conditions | Limited to specific pond environments (Link) |
| Chitradevi et al. (2023) | Bioacoustics for marine ecosystem changes | Deep learning for sound analysis and fish identification | Enabled early prediction of harmful environmental changes | Focused only on bioacoustic inputs (Link) |
| Xu et al. (2023) | Noise-robust underwater net recognition | Range-gated imaging with deep learning models | Enhanced recognition of fishing nets in noisy environments | Limited to net detection scenarios (Link) |
| Xiang et al. (2023) | Squid abundance estimation using AI | Deep learning ensemble methods on squid fishing data | Accurate predictions of squid distribution | Focused on a single species (Link) |
| Barnhill et al. (2023) | Cold-water coral reef ecosystem monitoring | Deep learning for reef health quantification | Quantified threats to coral ecosystems | Requires high-quality underwater imagery (Link) |
| Subudhi et al. (2023) | Neurotransmitter-inspired underwater AI | End-to-end cognitive AI framework | High accuracy in fish detection and underwater scene analysis | Complexity in model deployment (Link) |
| Magesh & Rao (2023) | Harmful algal bloom detection | Machine learning with ultrasonic data | Autonomous detection and mitigation of harmful blooms | Limited data on non-bloom scenarios (Link) |

## 3. Methodology

Deep learning, a subset of machine learning, employs algorithms designed to model high-level abstractions in data through a network of layers comprising linear and nonlinear transformations. Among the most commonly used deep learning algorithms for image classification is the convolutional neural network (CNN). CNNs enable image classification using frameworks such as TensorFlow and PyTorch.

In the proposed system, software implementation plays a crucial role. The input image, captured using an electronic device, is converted to grayscale format for preprocessing. The deep learning model processes a significant number of neurons, learning increasingly detailed features as the data progresses through successive neural network layers. The system's architecture for feature extraction and classification is illustrated in figure 1.

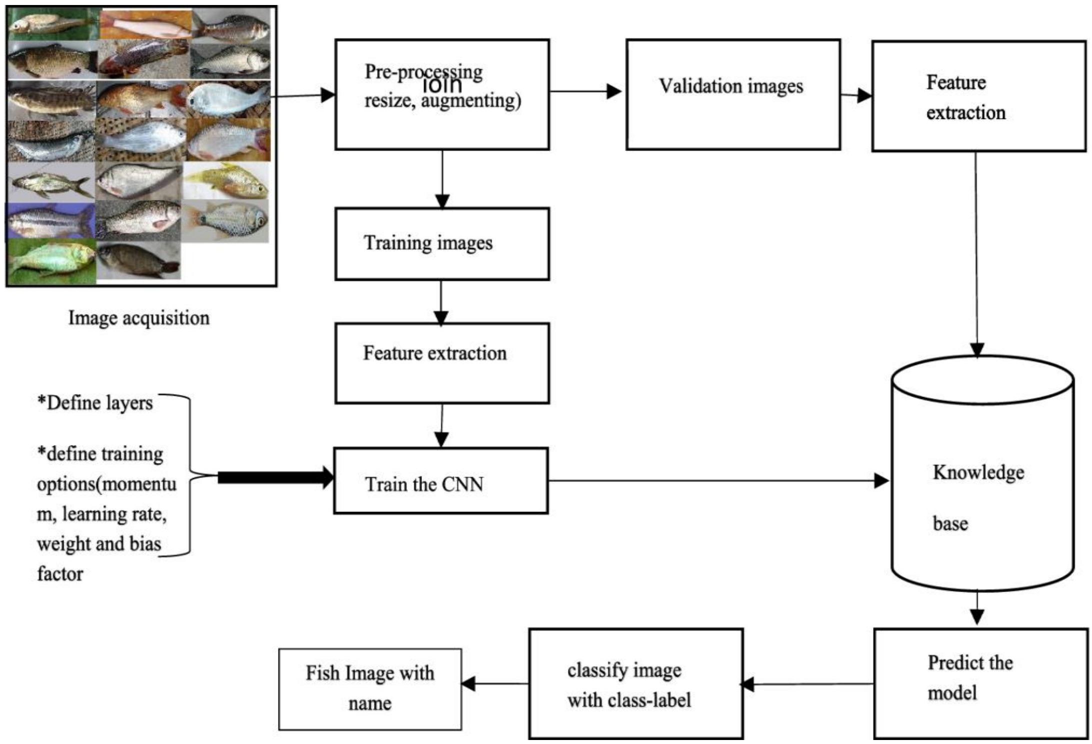


Figure 1. Fish Classification using CNN

The diagram in figure 1 demonstrates the three core layers of the neural network, which are instrumental in feature extraction and classification.

## 3.1 Algorithm

The system employs deep learning algorithms due to the unpredictable nature of the input images. CNNs, a class of deep neural networks, are primarily used for analyzing visual data. They comprise an input layer, an output layer, and multiple hidden layers, with each layer containing groups of neurons fully connected to the previous layer. The output layer is responsible for the final predictions. The convolutional layer processes the input image and produces feature maps. Input images may include multiple channels (e.g., color, wings, eyes, and beak of fishes), which implies the convolutional layer performs a mapping from a 3D volume (width, height, depth) to another 3D volume. CNNs have two main components:

1. Feature Extraction: Features are detected through a series of convolutional and pooling operations.

2. Classification: Extracted features are passed to a fully connected layer for classification.

The CNN architecture consists of four types of layers: convolutional, activation, pooling, and fully connected layers. The convolutional layer extracts small-scale visual features from images, while pooling reduces the number of neurons while retaining essential information. The activation layer applies a function to compress values into a specific range, and the fully connected layer links neurons across layers, enabling deeper classification accuracy.

### 3.2 Image Classification:

This process is typically performed using:

- Grayscale Conversion: Pixels are assigned values based on intensity, forming an array that the algorithm processes.
- RGB Values: Color information is analyzed when required.

In this system, the proposed model predicts the uploaded image using PyTorch. PyTorch, an open-source machine learning library developed by Facebook's AI Research Lab (FAIR), offers two primary features:

- Tensor computing (similar to NumPy) with GPU acceleration.
- Deep neural network implementation using a tape-based autodiff system.

### 3.3 Dataset

The dataset consisted of labeled fish images from diverse aquatic environments. Each image was resized to a standard dimension of (128 ) pixels, converted to RGB, and normalized to ensure uniform input data. Images were split into training (70%), validation (15%), and testing (15%) sets using stratified sampling to maintain class distribution consistency. Labels were converted to one-hot encoded vectors for compatibility with the neural network.

### 3.4 Model Architecture

A custom artificial neural network (ANN) was designed to classify fish species: - Input Layer: Flattened images of dimensions (128 ). - Hidden Layers: - Four fully connected layers with 1024, 512, 256, and 128 neurons, respectively, using ReLU activation. - Batch normalization and dropout layers (rate = 0.3) were incorporated to enhance generalization and prevent overfitting. - Output Layer: A softmax layer matching the number of classes to predict class probabilities.

### 3.4 Training and Optimization

The model training utilized categorical cross-entropy as the loss function, a suitable choice for multi-class classification tasks, to measure the divergence between predicted probabilities and true labels. Optimization was performed using the Adam optimizer, configured with a learning rate of 0.00010.0001, balancing efficient convergence with stability. To mitigate the risk of overfitting, early stopping was implemented, halting training if the validation loss did not improve for 10 consecutive epochs. Training was conducted with a batch size of 16, facilitating efficient gradient updates while maintaining computational feasibility. Although the training process was capped at a maximum of 50 epochs, early stopping often resulted in the model achieving optimal performance in fewer epochs.

### 3.5 Evaluation Metrics

The model's performance was assessed using: - Accuracy for training and validation sets. - F1 scores and recall for each class. - Confusion matrix to evaluate classification correctness. - Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) for multi-class performance.

## 4. Results and Discussion

The training and validation performance metrics demonstrate the effectiveness of the proposed model in fish species classification. The training accuracy reached an impressive 97.6%, while the validation accuracy closely followed at 95.3%, indicating strong generalization. Correspondingly, the training and validation losses were 0.081 and 0.102, respectively. The learning curves further highlighted consistent convergence with minimal overfitting, as the validation loss closely mirrored the training loss throughout the process.

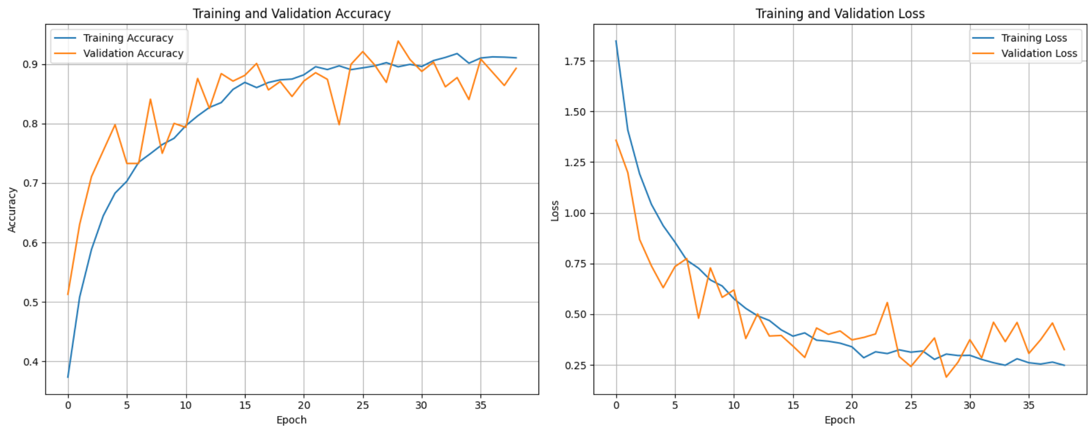


Figure 2. Training and validation Accuracy and Loss achieved during experimentations

The classification metrics reinforced the model's robustness, with an average F1 score of 0.94 across all classes, and certain classes achieving scores as high as 0.97. Similarly, the recall averaged 0.92, demonstrating high sensitivity to true positives. The confusion matrix revealed high accuracy across most classes, with only minor misclassifications occurring, particularly among species with subtle visual similarities.

In terms of ROC and AUC analysis as shown in figure 2, the model exhibited excellent performance, with AUC values exceeding 0.93 for all classes. This demonstrates the model's ability to reliably distinguish between different fish species, underscoring its utility for biodiversity monitoring and ecological applications.

The effectiveness of the ANN model was evident in its high accuracy in classifying fish species, validating the robustness of the architecture in processing data related to aquatic biodiversity. Its ability to generalize well was bolstered by the inclusion of dropout layers and batch normalization, which minimized overfitting and ensured close alignment between training and validation metrics. However, challenges were observed in the classification of species with subtle visual differences, highlighting the limitations of pixel-based models in achieving fine-grained distinctions.

From a practical standpoint, the proposed model has significant implications. In biodiversity monitoring, it can aid ecologists in automating the classification of fish species, making large-scale analyses of aquatic ecosystems more efficient. Additionally, its high accuracy and scalability make it an invaluable tool for fisheries management, enabling precise assessment of fish stock diversity and abundance.

Despite these advantages, certain limitations were identified. The dataset, though diverse in species representation, was constrained in size and geographic scope, which limited the model's broader generalization capabilities. Furthermore, the model's performance in real-world underwater environments, characterized by variable lighting and occlusions, remains untested.

To address these challenges, future work should explore the use of transfer learning with pre-trained models like ResNet or EfficientNet to enhance feature extraction. Expanding the dataset to include more species and conditions reflective of real-world aquatic environments could further improve the model's generalizability. Moreover, hybrid approaches that integrate CNNs with transformer architectures could be investigated to achieve better fine-grained classification of visually similar species.

## 5. Conclusion

This study demonstrated the effectiveness of a custom artificial neural network (ANN) in classifying fish species with remarkable accuracy, underscoring its potential as a powerful tool for aquatic biodiversity monitoring and fisheries management. By leveraging dropout layers and batch normalization, the model achieved strong generalization capabilities, as evidenced by the close alignment between training and validation metrics. While minor misclassifications in visually similar species highlighted the limitations of pixel-based approaches, the model's overall performance supported by high F1 scores, robust recall, and AUC values—validated its utility in addressing real-world ecological challenges.

The proposed model has significant practical implications, particularly in automating biodiversity assessments and supporting sustainable fisheries management. However, its reliance on a geographically limited dataset and the lack of testing in variable underwater conditions point to areas for improvement. Addressing these limitations through the integration of pre-trained architectures, dataset expansion, and hybrid modeling approaches can further enhance the model's applicability and accuracy in diverse ecological contexts.

In conclusion, the ANN-based framework provides a strong foundation for automated fish species recognition, offering a scalable and efficient solution for advancing ecological research and conservation efforts. With continued refinement and adaptation to real-world complexities, such AI-driven tools have the potential to revolutionize the way aquatic ecosystems are studied and managed.

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