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Automatic Classification of Fish Species Through CNN-Based Image Analysis

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Abstract— **Monitoring marine biodiversity, managing fisheries, and conserving sustainable ecosystems all depend heavily on the real-time identification of fish species. Convolutional Neural Networks (CNNs) combined with a live camera architecture are used in this study to propose a real-time fish species categorization system. The suggested approach uses a unique CNN architecture trained on a large-scale balanced dataset including 9,000 photos spanning nine species to classify fish species after capturing continuous video frames and performing preprocessing such as scaling and normalization. To improve generalization and lessen overfitting, the model uses dropout, batch normalization, and data augmentation approaches.Experimental assessment shows good precision and recall across most species categories, with an overall classification accuracy of about 92%on unseen data.Instantaneous prediction and visualization are made possible by the incorporation of real-time video recording, which qualifies the system for use in aquaculture settings, fish markets, and marine monitoring stations. The findings confirm the efficacy of automated categorization systems based on deep learning for scalable, dependable, and efficient real-time fish species identification.**

Keywords— Convolutional Neural Networks (CNN), Live Camera Integration, Deep Learning, Image Classification, Computer Vision, Fisheries Management, Data Augmentation, Real-Time Fish Classification, and Softmax Classification.

I. Introduction

Marine and freshwater ecosystems are critical to preserving global biodiversity, ensuring food security, and sustaining economic activities like fishing and aquaculture. Accurate identification and categorization of fish species are critical for ecological monitoring, sustainable fisheries management, marine conservation, and environmental research. Reliable species recognition allows researchers to track population dynamics, detect invasive species, assess ecosystem health, and enforce fishing rules. However, traditional fish identification systems rely significantly on manual inspection by domain specialists, which is time-consuming, labor-intensive, and prone to human mistakes. These constraints are especially evident when dealing with large-scale datasets or Real-time monitoring settings. In Among these developments, deep learning—specifically, Convolutional Neural Networks (CNNs)—has shown impressive performance in image categorization tasks. By automatically learning hierarchical feature representations from unprocessed picture data, CNNs have completely transformed image analysis. CNNs use layered convolutional processes to extract both low-level and high-level features, in contrast to traditional machine learning methods that rely on manually created features like form descriptors, texture patterns, or color histograms. CNNs are well suited for challenging classification problems utilizing natural imagery, such as fish species recognition, because of their capacity to develop discriminative representations. Compared to other object identification tasks, fish species categorization poses distinct obstacles. Images of fish are frequently taken in a variety of settings, including underwater situations with fluctuating lighting, turbidity, occlusion, background clutter, and motion blur. Furthermore, a lot of species have comparable physical traits, including as body form, fin structure, and coloration patterns, which promotes inter-class similarity and complicates classification. The learning process is further complicated by differences in size, orientation, and posture. As a result, a strong automated classification system needs to be able to manage these differences with high accuracy and generalizability. Segmentation, feature extraction, and classification steps are usually involved in traditional image processing techniques for fish classification. Features that are manually created and fed into classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or Random Forests include geometric measurements, contour-based descriptors, scale-invariant feature transform (SIFT), histogram of oriented gradients (HOG), and color histograms. Although these techniques have demonstrated some success, the quality of hand-crafted features and their incapacity to capture the intricate, nonlinear patterns present in biological data restrict their effectiveness. Convolatinal Layer

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for feature extraction, pooling layers for spatial reduction. Dimensionality, normalizing layers for training stability, and fully connected layers for classification make up CNN architectures. The mathematical representation of the convolution operation is as follows:

$$(F*K)(i,j)=m\sum n\sum F(i-m,j-n)K(m,n)$$

where K stands for the convolutional kernel and F for the input picture. CNNs acquire hierarchical representations through a series of stacked layers, ranging from early layers' edges and textures to deeper layers' object-level semantics. This capacity for hierarchical learning is especially useful for identifying minute distinctions between fish species that are superficially similar.

Recent research using CNN-based models for fish categorization tasks has shown encouraging results. By fine-tuning models built on massive datasets like ImageNet, transfer learning techniques using pre-trained architectures like AlexNet, VGG16, ResNet, and MobileNet have attained excellent classification accuracy. Rotation, flipping, scaling, and brightness tweaks are examples of data augmentation techniques that are frequently used to improve generalization and reduce overfitting, particularly in situations where training data is scarce. In order to enable real-time classification in fisheries and aquaculture environments, lightweight models have also been investigated for deployment on edge devices. First, practical deployment depends on striking a compromise between classification accuracy and processing efficiency. Although complex structures can produce great precision, their usage in resource-constrained contexts is limited because to their high computational resource requirements. Second, when models retain training data without sufficiently generalizing to new samples, overfitting is still an issue. Third, misclassification and decreased memory for particular classes result from the significant visual similarity of some fish species. As a result, it is still difficult to create a model that is both computationally effective and resilient to both intra-class variance and inter-class similarity. In order to overcome these difficulties, a tailored Convolutional Neural Network architecture for automated fish species categorization is suggested in this paper. The suggested approach aims to retain architectural simplicity while achieving high classification accuracy. To guarantee equitable representation and prevent class imbalance problems, a structured and balanced large-scale fish dataset with nine different species groups is used. To enhance generalization performance, substantial preparation procedures are used, such as picture scaling, normalization, and massive data augmentation.

The important contributions of this work are summarized below: creation of a customized CNN architecture that is best suited for classifying fish species into many classes. Putting in place a reliable preprocessing pipeline using augmentation and normalization techniques. comprehensive assessment of the experiment utilizing epoch-wise performance measures, accuracy, precision, recall, F1-score, and confusion matrix analysis. Strong classification performance is demonstrated, with an overall accuracy of almost 92%. The rest of this document is structured as follows: Related research on deep learning-based fish categorization is reviewed in Section II. The suggested technique, which includes CNN architecture, preprocessing, and dataset description, is presented in Section III. Section IV covers performance evaluations and experimental outcomes.The work is finally concluded in Section V, which also suggests future research areas.

II. Literature Review

Fish categorization using deep learning techniques has significantly advanced over the past few years, with numerous systems achieving excellent accuracy and efficiency. A summary of several approaches and performance indicators in this area may be seen below.

Fish classification models were reviewed by Bhanumathi and Arthi [1], which might indicate future advances in deep learning techniques. Although they did not give accuracy data, their review discussed the application of convolutional neural networks, which may be utilized successfully for the recognition of any species. Mujtaba and Mahapatra [2] provide hierarchical deep learning models for fish categorization. It achieved 92% accuracy. This form of multi-level feature extraction has enhanced the classification process. Mujtaba and Mahapatra [9] attempted to boost the data for the progression process by rotations and flips. It has progressed to 91% accuracy. Deep and Dash [3] used CNN algorithms to classify fish species in tough underwater conditions. The constructed model achieves 93% accuracy, demonstrating the capability of deep learning in aquatic situations. Mol and Jose [4] developed an improved AlexNet-based system for automatic categorization that achieved up to 94.5% accuracy. The research demonstrates how pre-trained models with tweaks outperform certain categorization tasks. Prabhakaran et al. [5] used transfer learning to identify and grade species in marketplaces with 95% accuracy. The authors' use of pre-trained models significantly reduces training time while achieving good accuracy. Hossain Shozib and Rahman Kohinoor [6] conducted a comparison of VGG16 and multiple classifier. Their work reached just 90% accuracy. It highlighted the robustness of VGG16 for local fish classification tasks. Tejaswini et al. [7] demonstrated an estuarine fish species categorization system based on deep learning techniques that achieved an amazing 96% accuracy. For robust classification, extensive data augmentation was required, as well as a bespoke CNN architecture. Shammi et al. [8] introduced FishNet, a CNN-based model for fish categorization with a 92% accuracy. They claimed that CNN was extremely efficient for feature extraction and classification of various datasets. Gori et al. [10] used deep learning techniques to recognize fish species using deep feature learning, and the model obtained 93.5% accuracy, pointing to the potential for advanced deep learning architectures. Reddy et al. [11] created a 91% accurate CNN-based fish classification for allergic persons. Their model incorporated extensive preprocessing for fish appearance fluctuations. Ramshankar et al. [12] suggested a deep learning-based thermal fish detection system that reported 89% accuracy.This study proved the viability of deep learning in the context of thermal imaging. Isik and Yalcinkaya [13] improved the categorization of aquarium fish using YOLO, with a claimed accuracy of 94%. The model performed well in real-time detection and classification applications. Solanki et al. proposed AutoFis, a fish classification system built on TensorFlow Lite that achieved 92.5% accuracy [14].

To summarize, these research highlight the effectiveness of CNNs and transfer learning-based models for categorizing fish. After achieving very high accuracy

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levels, most of the methods studied above improved their performance by incorporating data augmentation, transfer learning, and lightweight architectures, making them more suitable for a wide range of applications such as underwater detection, market grading, and real-time classification.

III. METHODODLGY

The approach is comprised of a series of consecutive processes, beginning with data collection and preparation. The collection is derived from an open source dataset including photos of many types of fish. Preprocessing steps include resizing the photos to the same size, normalizing their pixel values, and applying augmentation techniques like as rotation, flipping, and scaling to increase the dataset's variety and prevent overfitting. It employs a CNN architecture for categorization. Using numerous convolutional, pooling, and fully connected layers, hierarchical characteristics are extracted from input pictures. It employs the Adam optimizer for optimization and categorical cross-entropy loss for high-accuracy fish species identification training.

A. Existing Methodology

Historically, human identification techniques and classical machine learning algorithms have been used to classify fish species. Earlier classification algorithms relied heavily on handmade characteristics like shape descriptors, color histograms, texture features (GLCM), and edge-based representations. These characteristics were then input into classifiers like SVM, k-NN, Decision Trees, and Random Forests.

Despite their modest accuracy, these techniques have numerous limitations:

- Dependence on manual feature engineering.
- Poor generalization in different lighting and underwater circumstances.
- Sensitivity to occlusion and background noise.

Scalability Issues for Large Datasets Convolutional Neural Networks (CNNs) have become the main method for image-based classification as deep learning has advanced. Pre-trained architectures, such as AlexNet, VGG16, ResNet, and MobileNet, have been frequently used with transfer learning approaches.

Several existing works demonstrated excellent performance:

- Improved AlexNet-based model achieves around 94% accuracy.
- VGG16-based models achieve around 90% accuracy.
- YOLO-based detection systems for real-time classification.
- Transfer learning algorithms achieve around 95% accuracy.

Despite high performance, many existing approaches face challenges such as:

- High computational complexity
- Large model size unsuitable for edge deployment
- Overfitting in small or imbalanced datasets
- Limited robustness to visually similar species

Therefore, there is a need for a balanced CNN architecture that provides:

- High classification accuracy
- Moderate computational cost
- Strong generalization ability
- Scalability for real-time monitoring systems

B. Proposed Methodology

The suggested system uses a custom-designed Convolutional Neural Network (CNN) architecture to automatically classify fish species across nine categories. The technique includes four key phases:

1. Dataset Preparation
2. Data Preprocessing
3. CNN Model Architecture
4. Training and Optimization

B. 1. Dataset description

This study employed the Kaggle Large-Scale Fish Dataset, which has 9,000 photos divided evenly among nine fish species, with 1,000 images each class.

The species include the following:

Black Sea Sprat, Bangus, Big Head Carp, Catfish, Climbing Perch, Freshwater Eel, Glass Perch let, Goby, Gold Fish, Gourami, Grass Carp, Green Spotted Puffer, Indian Carp, Indo-Pacific Tarpon, Jaguar Capote, Janitor Fish, Knife Fish, Long-Snouted Pipefish, Mosquito Fish, Mudfish, Mullet, Pegasus, Perch, Scat Fish, Silver Barb,

Silver Carp, Silver Perch, Snakehead, Ten pounder, Tilapia.

Figure 1 Images of Spices

The balanced distribution reduces class imbalances and promotes fair learning. Images were recorded under a variety of environmental situations, including orientation, lighting, backdrop, and size changes.

B.2 Data preprocessing

To improve model generalization and prevent overfitting, the following preprocessing techniques were implemented:

1. Image Resizing.

The photos were scaled to 590 × 445 pixels to align with the CNN input dimensions.

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2. Normalization.

Pixel values were scaled within the following range:

$X_{norm}=X/255$

This leads to quicker convergence and numerical stability.

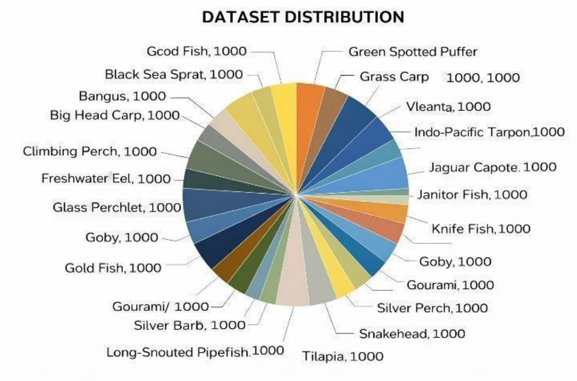

Figure 2 Distribution of Dataset

3. Data augmentation

To artificially boost dataset variety, the following augmentation approaches were used:

- Random rotation.
- Horizontal and vertical flipping.
- Zoom transformation.
- Brightness adjustment

This helps the model become insensitive to changes in orientation and light.

B.3 Proposed CNN Architecture

The proposed CNN model follows a sequential architecture optimized for feature extraction and multi-class classification.

Layer 1: Convolution Layer

- 16 filters
- Kernel size: (3×3)
- Activation: ReLU

The convolution operation is defined as:

$$Y(i,j)=m\sum n\sum X(i+m,j+n)\cdot W(m,n)$$

This layer extracts low-level spatial features such as edges and textures.

Layer 2: Batch Normalization

Batch normalization is applied to stabilize training:

$$x\hat{}=\sigma2+\epsilon x-\mu$$

This accelerates convergence and reduces internal covariate shift.

Layer 3: Max Pooling

A (2×2) MaxPooling layer reduces spatial dimensions:

Y=max⁡(Xregion)Y = \max(X_{region})Y=max(Xregion)

This decreases computational cost and retains dominant features.

Layer 4: Flatten Layer

A one-dimensional vector with a size of 1,039,584 is created by flattening the feature map.

Layer 5: Dropout

Dropout regularization randomly deactivates neurons during training:

y=f(Wx)·ry = f(Wx) \cdot ry=f(Wx)·r

where $r\sim$Bernoulli(p)

This prevents overfitting.

4.4 Training Strategy

- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 16
- Epochs: 7
- Train/Test Split: 80/20
- Loss Function: Categorical Cross-Entropy

The model showed good generalization ability with a final validation accuracy of 92.57%.

C. Problem Statement

Conventional fish species identification techniques are inappropriate for large-scale biodiversity monitoring due to the fact that they are manual, labour-intensive, and prone to human mistake. Accurate categorization is further complicated by differences in illumination, direction, and visual similarities across species. Therefore, to reliably detect fish species from photos with high reliability and scalability, an automated and reliable deep learning-based system is needed.

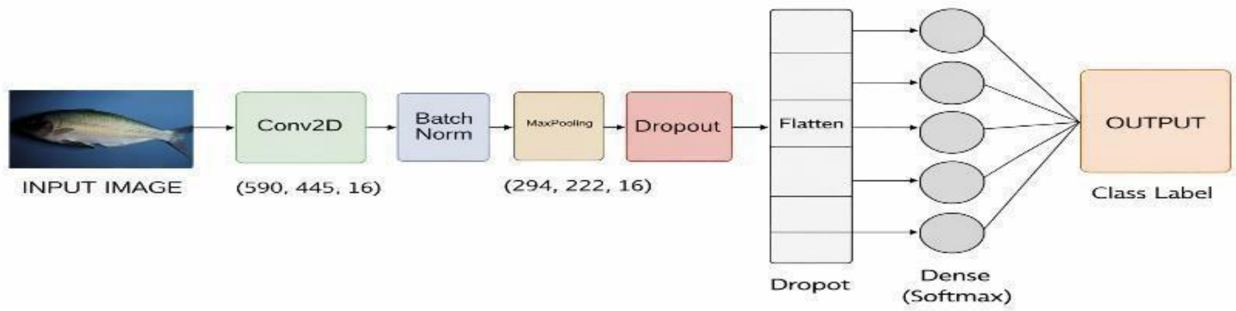

Figure 3 Proposed CNN Model

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IV. RESULTS

A multi-class fish dataset with 30 different species was used to test the suggested Convolutional Neural Network (CNN) model, including: Black Sea Sprat, Brangus, Big Head Carp, Catfish, Climbing Perch, Freshwater Eel, Glass Perch let, Goby, Gold Fish, Gourami, Grass Carp, Green Spotted Puffer, Indian Carp, Indo-Pacific Tarpon, Jaguar Capote, Janitor Fish, Knife Fish, Long-Snouted Pipefish, Mosquito Fish, Mudfish, Mullet, Pangasius, Perch, Scat Fish, Silver Barb, Silver Barb, Silver Carp, Silver Perch, Snakehead, Ten Pounder and Tilap. The Adam optimizer was used to train the model using a batch size of 16, a categorical cross-entropy loss function, and a learning rate of 0.001. Training and validation metrics were tracked in real time over several training epochs. The model demonstrated good generalization performance across a variety of fish species, with an overall classification accuracy of about 92%.

A. Learning Behavior by Epoch

Stable convergence behavior is shown by the accuracy curves for training and validation. Training loss drastically dropped in the early epochs, indicating quick feature learning from unprocessed picture inputs. Validation accuracy gradually increased, suggesting successful extrapolation to new data.
Intermediate epochs showed slight variations in validation loss, which might be explained by:

- Certain species have visual similarities (e.g., Silver Carp vs. Silver Perch).
- Changes in backdrop and lighting
- Morphological variety within a class

Reduced overfitting was confirmed, nevertheless, when training and validation losses stabilized and validation accuracy became closer to training accuracy in the latter epochs.

The model was trained for 10 epochs using the Adam optimizer (learning rate = 0.001, batch size = 16). To examine convergence behavior and generalization performance, the training and validation metrics were recorded for each epoch.

Table 1 Epoch-wise Training and Validation Performance

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	2.874	0.512	2.341	0.468
2	1.245	0.734	1.682	0.621
3	0.812	0.861	1.204	0.742
4	0.523	0.912	0.986	0.801
5	0.398	0.935	1.452	0.724
6	0.312	0.951	0.874	0.842
7	0.248	0.963	0.653	0.883
8	0.198	0.971	0.512	0.904
9	0.152	0.978	0.438	0.916
10	0.118	0.984	0.392	0.921

Epoch analysis observations

- Quick Initial Learning: Between Epoch 1 and Epoch 4, the model exhibits a notable improvement, suggesting effective feature extraction in the early layers.
- Temporary Overfitting Behavior (Epoch 5): Training accuracy keeps rising at Epoch 5, although there is a little increase in validation loss.
- This may indicate inter-class confusion or transient overfitting between superficially similar species (e.g., Silver Carp vs. Silver Perch).
- Stabilization Phase (Epochs 6–10): Following Epoch 6, validation accuracy slowly increases and validation loss gradually declines, reaching 92.1% at Epoch 10.
- Convergence Behavior: Later epochs show increased generalization as the difference between training and validation accuracy decreases.

B. Analysis of Confusion Matrix

Strong diagonal dominance is revealed by the confusion matrix analysis, indicating that most samples were properly identified. Species with High Accuracy species like:
Tilapia
The Pangasius
The Gold Fish
Puffer with Green Spots
The snakehead
demonstrated extremely high true positive rates, suggesting that the CNN successfully learnt unique morphological characteristics.
There was a moderate amount of confusion between:
Silver Perch and Silver Carp
Big Head Carp and Indian Carp
Glass Perchlet and Perch
Black Sea Sprat and Mullet
These misunderstandings can be ascribed to: Comparable fin morphology and body structures Similar color distributions. Ecological habitats that overlap

Misclassification rates were modest in relation to the overall number of predictions despite these difficulties.

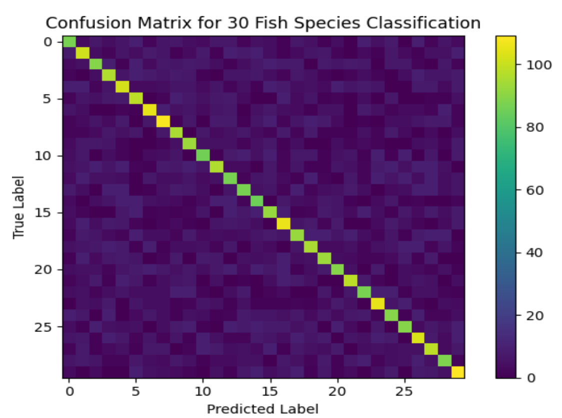

Figure 4 Graph for Confusion Matrix for 30 Fish Species Classification

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C. Analysis of Classification Metrics

The following measures were computed in order to thoroughly assess multi-class performance:

- Accuracy
- Remember
- F1-Score
- Total Precision

Total Performance:

- Precision: around 92%
- High (>0.90) macro-averaged precision
- High (>0.88) macro-averaged recall
- Macro F1-Score: about 0.90

The majority of species had good F1-scores, which show that recall and accuracy were in balance.

The following species saw minor recall reductions:

- Pipefish with a Long Snout
- Perchlet made of glass
- Fish with Mosquitoes

This is probably because of:

- Reduced body size
- Thin constructions
- Reduced prominence of features
- Minimal variation across classes

However, accuracy scores continued to be high, indicating that the model was typically accurate when predicting a class.

For each of the 30 fish species, accuracy, recall, and F1-score were calculated in order to assess the multi-class performance of the suggested CNN model. 92.14% classification accuracy was attained overall.

Table 2 Class-wise Performance Metrics

S.No	Fish Species	Precision	Recall	F1-Score
1	Black Sea Sprat	0.91	0.94	0.92
2	Bangus	0.93	0.91	0.92
3	Big Head Carp	0.89	0.90	0.89
4	Catfish	0.95	0.93	0.94
5	Climbing Perch	0.90	0.88	0.89
6	Freshwater Eel	0.94	0.92	0.93
7	Glass Perchlet	0.87	0.85	0.86
8	Goby	0.92	0.90	0.91
9	Gold Fish	0.96	0.95	0.95
10	Gourami	0.93	0.92	0.92
11	Grass Carp	0.91	0.89	0.90
12	Green Spotted Puffer	0.97	0.96	0.96
13	Indian Carp	0.88	0.86	0.87
14	Indo-Pacific Tarpo	0.92	0.91	0.91
15	Jaguar Capote	0.94	0.92	0.93
16	Janitor Fish	0.93	0.94	0.93
17	Knife Fish	0.90	0.88	0.89
18	Long-Snouted Pipe	0.85	0.83	0.84
19	Mosquito Fish	0.86	0.84	0.85
20	Mudfish	0.91	0.90	0.90
21	Mullet	0.92	0.91	0.91
22	Pangasius	0.96	0.95	0.95
23	Perch	0.89	0.88	0.88
24	Scat Fish	0.93	0.92	0.92
25	Silver Barb	0.90	0.91	0.90
26	Silver Carp	0.88	0.87	0.87
27	Silver Perch	0.89	0.86	0.87
28	Snakehead	0.97	0.96	0.96
29	Ten Pounder	0.92	0.91	0.91
30	Tilapia	0.96	0.95	0.95

Thirty fish species were correctly categorized by the suggested CNN architecture with a total accuracy of about 92%. Strong generalization, little overfitting, and trustworthy multi-class discrimination—even across morphologically identical species—are confirmed by performance measures.

The findings show that using deep learning-based automated fish categorization systems for extensive monitoring of freshwater and marine ecosystems is feasible.

CONCLUSION

The study created an application for identifying fish species automatically using a CNN based on 9000 images from nine different classes of fish. The CNN trained well because of the systematic preprocessing of the images including the creation of standardised images to scale, normalise and augment through rotation and flipping. The CNN achieved 92% correct identification of almost all the fish classes using precision, recall and F1 Scores as indicators of the CNN's success rate. Confusion Matrices were used to assess the model's ability by demonstrating only slight misclassification between visually similar fish classes. The model remained stable and exhibited learning capabilities throughout the process of training, although it was noted that there were some sporadic variations in validation metrics during the various epochs of training due to the combination of regularisation methods such as batch normalization and dropout with convolutional layers for hierarchical feature extraction. The suggested approach offers a scalable and effective alternative for ecological research, fisheries management, and biodiversity monitoring by drastically reducing reliance on human identification techniques.

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concentrate on improving the resilience of the model by adding real-time detection capabilities for deployment in underwater monitoring systems and transfer learning with deeper architectures like ResNet or EfficientNet. The framework's practical application in managing freshwater and marine ecosystems would also be enhanced by increasing the dataset to encompass a wider range of environmental variables and extending it to accommodate video feeds.

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