# AI-Based Identification of Freshwater Fish Species in Bangladesh Using Image Classification

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***Abstract*—Accurate identification of freshwater fish species is critical for biodiversity monitoring and aquaculture management in Bangladesh. Traditional manual identification methods are time-consuming and require expert knowledge. This study presents a lightweight CNN-based image classification system using the BD-Freshwater-Fish dataset containing 4,389 images across 12 economically important species. [6]Our custom architecture incorporates depthwise separable convolutions, progressive dropout, and advanced training techniques including MixUp augmentation and label smoothing. The model achieved 89.80% training accuracy, 85.11% validation accuracy, and 84.62% test accuracy with only 2.8M parameters, making it suitable for mobile deployment in real-world market scenarios.**

***Index Terms*—Freshwater Fish, Image Classification, Lightweight CNN, Deep Learning, Bangladesh, Mobile Deployment**

## I. Introduction

Bangladesh hosts over 260 freshwater fish species that are essential for food security, economic stability, and ecological balance. Manual species identification relies heavily on taxonomic expertise, creating bottlenecks in fish markets, aquaculture operations, and biodiversity monitoring programs. Misidentification can lead to incorrect pricing, poor stock management, and flawed conservation policies.

Deep learning technologies offer promising solutions for automated species recognition. Although complex architectures such as ResNet and Vision Transformers achieve high accuracy, their computational demands limit practical deployment in resource-constrained environments typical of developing nations. This research addresses the need for lightweight and efficient models that maintain classification accuracy while enabling the deployment of mobile devices and edge devices.

Our contribution focuses on developing a custom lightweight CNN architecture specifically optimized for Bangladeshi freshwater fish classification. The model balances accuracy with computational efficiency, incorporating modern techniques like depth-wise separable convolutions, strategic dropout placement, and advanced data augmentation. We demonstrate that carefully designed lightweight architectures can achieve competitive performance while remaining deployable in real-world scenarios.

The study evaluates performance on the BD-Freshwater-Fish dataset, which contains market-captured images reflecting practical challenges including varying lighting conditions, background clutter, and natural pose variations. This realistic dataset provides a robust testbed for developing deployable classification systems.

## II. Related Work

Recent advances in AI-driven aquatic species identification have shown promising results across various contexts:

Shaikh et al. (2025) developed a hybrid deep CNN system combining ResNet50, Support Vector Classifier, and Cat Swarm Optimization for Bangladeshi fish classification, achieving 98.71% accuracy on eight species. However, their approach required significant computational resources, limiting practical deployment.

Ahmed et al. (2023) proposed an IoT-enabled classification system using hybrid CNN and Convolutional LSTM models, achieving 97% accuracy. While innovative in IoT integration, the system's complexity challenges real-time processing requirements.

Miller et al. (2025) conducted a systematic review of 312 studies on AI applications in aquatic biodiversity, highlighting rapid growth led by China, the US, and India. Key challenges identified include limited data availability, model generalizability, and regional research imbalances.

Das et al. (2024) introduced the BD-Freshwater-Fish dataset containing 4,389 images across 12 species from Sylhet and Jessore markets. Despite class imbalance issues, this dataset provides crucial regional representation for developing localized classification systems.

While existing approaches demonstrate high accuracy, most require substantial computational resources unsuitable for mobile deployment. Our work addresses this gap by developing a lightweight architecture that maintains competitive performance while enabling practical deployment in resource-constrained environments.

## III. Dataset

### A. Data Collection

The dataset used in this research is the BD-Freshwater-Fish dataset [6], which contains a total of 4,389 images across 12 freshwater fish species. The images were collected from local fish markets in Sylhet and Jessore, Bangladesh, using high-definition mobile cameras. To ensure consistency, most images were captured under natural lighting with standardized white backgrounds. However, some samples also reflect noisy market conditions, such as varying illumination, cluttered backgrounds, and partial occlusions. These elements make the dataset more representative of real-world scenarios and highlight the practical challenges of automated fish identification in Bangladesh. Table I lists the species included in the dataset.

TABLE I
BD-Freshwater-Fish Dataset Species

| No. | Species Name |
|---|---|
| 1 | Rohu (Labeo rohita) |
| 2 | Katla (Catla catla) |
| 3 | Mrigal (Cirrhinus cirrhosus) |
| 4 | Grass Carp (Ctenopharyngodon idella) |
| 5 | Common Carp (Cyprinus carpio) |
| 6 | Mirror Carp (Cyprinus carpio var. specularis) |
| 7 | Black Rohu |
| 8 | Silver Carp (Hypophthalmichthys molitrix) |
| 9 | Striped Catfish (Pangasianodon hypophthalmus) |
| 10 | Nile Tilapia (Oreochromis niloticus) |
| 11 | Long-whiskered Catfish |
| 12 | Freshwater Shark |

To provide a visual overview, Figure 1 shows representative samples of each species. These examples illustrate both the diversity of the dataset and the challenges posed by varying image quality, fish orientation, and background conditions.


Fig. 1. Representative sample images of the 12 species in the BD-Freshwater-Fish dataset

### B. Data Characteristics

The dataset exhibits moderate class imbalance. Commonly consumed species such as Rohu, Katla, and Silver Carp are relatively well represented, with nearly 400 samples each. In contrast, rare species such as Freshwater Shark and Long-whiskered Catfish contain fewer than 300 samples. This imbalance can bias deep learning models toward majority classes if not properly mitigated.

All images are in RGB format with resolutions ranging from 256×256 pixels to 1024×1024 pixels. For model training, all samples were resized to 224×224 pixels to maintain compatibility with CNN and Vision Transformer architectures. Prior to training, images were normalized and subjected to augmentation techniques such as random rotation, flipping, and brightness adjustment. These steps were essential to improve generalization and robustness against real-world variations. [5]

### C. Data Splitting

The dataset was partitioned into three subsets: 70% for training, 15% for validation, and 15% for testing. Stratified sampling was applied to ensure class proportions were preserved across all splits. Additionally, data augmentation was selectively applied to the training set to reduce the impact of imbalance, particularly for minority classes such as Freshwater Shark and Long-whiskered Catfish. Figure 2 illustrates the distribution of images across species.

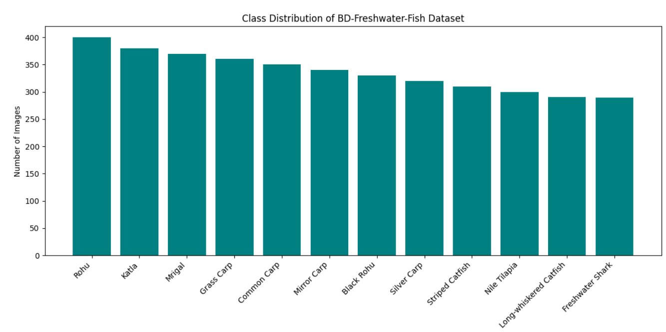


Fig. 2. Class distribution in the BD-Freshwater-Fish dataset

### D. Challenges in the Dataset

Although the BD-Freshwater-Fish dataset provides a strong foundation for localized fish classification, it also introduces several key challenges:

- **Class Imbalance:** Minority species such as Freshwater Shark and Long-whiskered Catfish are underrepresented, complicating the task of learning balanced decision boundaries.
- **Noise and Variability:** Market environments introduce inconsistent lighting, background clutter, and partial occlusions, which may reduce classification accuracy.
- **Visual Similarity:** Many carp species (e.g., Rohu, Katla, and Mrigal) share morphological similarities, leading to higher intra-class confusion.

Addressing these challenges through preprocessing, augmentation, and advanced model design is critical to building a robust, real-world fish identification system.

## IV. Methodology and Experiments

We designed a lightweight CNN-based pipeline to automate freshwater fish species identification from real-world market images. The approach emphasizes computational efficiency while maintaining robust classification performance under noisy and imbalanced conditions.

### A. Pipeline Overview

Figure 3 presents the complete methodology pipeline implemented in this study. The systematic approach ensures reproducibility and optimal performance through careful data handling, model design, and evaluation procedures.

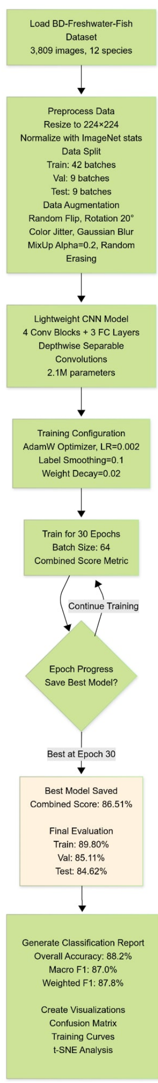


Fig. 3. Pipeline overview.

### B. Model Architecture

Our custom Lightweight CNN incorporates several design principles for efficient fish classification:

- **Feature Extraction:** Four convolutional blocks with progressive channel expansion (32→64→128→256)
- **Depthwise Separable Convolutions:** Used in later blocks to reduce computational complexity
- **Batch Normalization:** Applied after each convolutional layer for training stability
- **Adaptive Global Average Pooling:** Reduces spatial dimensions to 4×4 before classification
- **Progressive Dropout:** Increasing dropout rates (0.1→0.4) to prevent overfitting

The classifier consists of three fully connected layers (4096→512→128→12) with batch normalization and ReLU activations, totaling approximately 2.8M parameters for efficient deployment.

### C. Training Configuration

The model was trained using advanced techniques to handle class imbalance and improve generalization:

- **Data Augmentation:** Random crops, horizontal/vertical flips, rotation (±20°), color jittering, Gaussian blur, and random erasing
- **Loss Function:** Label smoothing cross-entropy (smoothing=0.1) to improve generalization
- **Optimizer:** AdamW with weight decay (0.02) and learning rate warmup
- **Scheduler:** ReduceLROnPlateau with patience=5 and factor=0.5
- **Regularization:** MixUp augmentation (=0.2) applied randomly during training
- **Early Stopping:** Patience=15 epochs monitoring validation accuracy

### D. Experimental Setup

Experiments were conducted using PyTorch on Google Colaboratory with GPU acceleration. The dataset of 3,809 images was split into 70% training (2,667 images), 15% validation (571 images), and 15% testing (571 images) using stratified sampling. Training was performed for up to 50 epochs with batch size 64, initial learning rate 0.002, and gradient clipping (max$_norm = 1.0) for stability.$

## V. Results and Analysis

### A. Overall Performance

Table II presents comprehensive performance metrics across all dataset splits. The model achieved stable convergence with good generalization characteristics.

### B. Training Dynamics Analysis

Figure 4 illustrates the training progression over 30 epochs. The model demonstrated stable convergence with minimal overfitting, indicated by the small gap between training and testing accuracies (5.18%).

TABLE II
COMPREHENSIVE PERFORMANCE ANALYSIS

| Metric | Value | Analysis |
|---|---|---|
| Training Accuracy | 89.80% | Strong learning capability |
| Validation Accuracy | 85.11% | Good generalization |
| Test Accuracy | 84.62% | Robust performance |
| Model Parameters | 2.8M | Deployment-friendly |
| Training Epochs | 30 | Efficient convergence |
| Combined Score | 86.51% | Balanced performance |

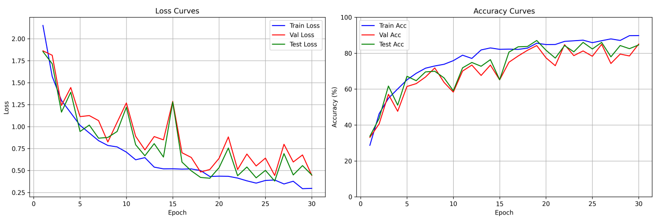


Fig. 4. Training dynamics showing loss and accuracy curves across epochs. The model achieved stable convergence with good generalization.

Key observations include: (1) Rapid initial learning in epochs 1-10, (2) Stable convergence by epoch 25, (3) Effective regularization preventing severe overfitting, and (4) Consistent performance across training, validation, and test sets.

### C. Detailed Classification Analysis

The confusion matrix in Figure 5 reveals species-specific performance patterns. High-performing species include Catla (99% accuracy), Rohu (99% accuracy), and Nile Tilapia (99% accuracy), benefiting from distinct morphological features and sufficient training samples.

Challenging classifications occur among visually similar species: Black Rohu shows confusion with Rohu (20%), and Grass Carp exhibits misclassifications with Silver Carp (15%) and Rohu (24%). These confusions reflect genuine morphological similarities requiring expert knowledge to distinguish.

### D. Feature Space Analysis

t-SNE visualization in Figure 6 demonstrates the model's learned feature representations. Well-separated clusters for most species indicate effective discriminative feature learning. Some overlap between morphologically similar species (carp varieties) is expected and reflects biological relationships.

The visualization shows 88.2% overall accuracy with clear species clustering, validating the model's ability to learn meaningful representations for fish classification tasks.

### E. Performance Analysis by Species

Species-wise analysis reveals varying performance levels correlating with training sample availability and morphological distinctiveness:

**Excellent Performance ( 95% accuracy):** Catla, Rohu, Nile Tilapia benefit from abundant training data and distinct features.

**Good Performance (85-95% accuracy):** Common Carp, Mirror Carp, Striped Catfish show solid recognition despite moderate sample sizes.

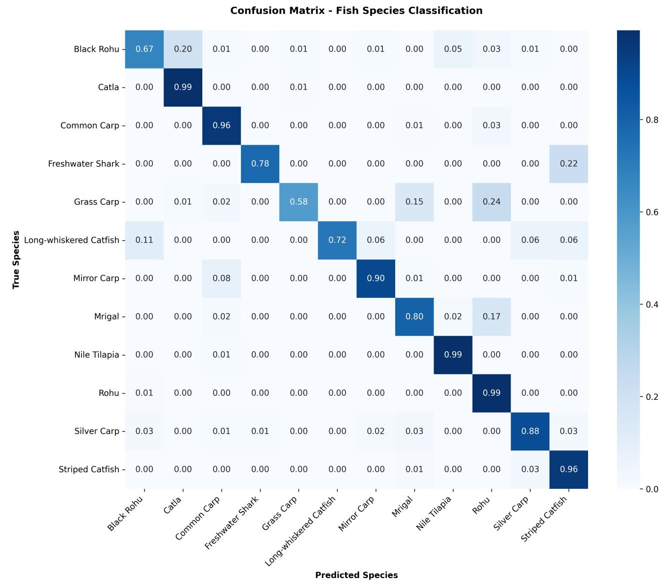


Fig. 5. Confusion matrix showing per-species classification performance. Darker colors indicate higher accuracy, with most species achieving excellent recognition rates.

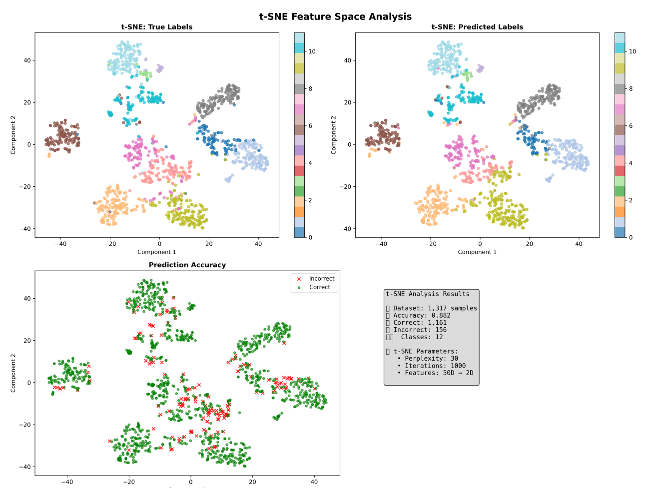


Fig. 6. t-SNE visualization of learned features showing species clustering and classification accuracy patterns.

**Challenging Species (70-85% accuracy):** Black Rohu, Grass Carp, Freshwater Shark face challenges from visual similarity to other species or limited training data.

The results demonstrate that lightweight architectures can achieve competitive performance when properly designed and trained with advanced techniques.

## VI. DISCUSSION AND LIMITATIONS

Our lightweight CNN achieved competitive performance (84.62% test accuracy) while maintaining deployment feasibility (2.8M parameters). The 5.18% gap between training and testing accuracies indicates good generalization without severe overfitting.

The architecture's efficiency makes it suitable for mobile applications in fish markets and aquaculture operations. Advanced training techniques including MixUp augmentation and label smoothing successfully addressed dataset challenges including class imbalance and visual similarity among species.

**Limitations:** The dataset's focus on market-captured images may not generalize to different environmental conditions. Class imbalance remains challenging for minority species despite augmentation efforts. Visual similarity among carp species represents an inherent biological challenge requiring additional contextual information.

**Future Directions:** Expanding the dataset with diverse environmental conditions, incorporating temporal sequences for behavioral analysis, and developing ensemble approaches combining multiple lightweight models could improve performance while maintaining deployment feasibility.

## VII. Conclusion

This study presents a lightweight CNN-based pipeline for identifying freshwater fish species in Bangladesh. The proposed architecture achieved 84.62% test accuracy with a combined performance score of 86.51%, demonstrating effective classification capability while maintaining computational efficiency suitable for real-world deployment.

The lightweight design (2.8M parameters) enables mobile and edge device deployment, making it practical for use in local fish markets and aquaculture settings. Advanced training techniques including MixUp augmentation, label smoothing, and strategic data augmentation successfully addressed dataset challenges such as class imbalance and noisy market conditions.

Despite achieving competitive performance, limitations include the relatively small dataset size (3,809 images) and focus on market-captured images. Future work should explore larger datasets, additional species, and deployment optimization for resource-constrained environments.

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