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Fish Species Classification Using Deep Learning

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***Abstract**: Fish represent one of the most diverse groups of vertebrates inhabiting aquatic environments, including freshwater and marine ecosystems. They play a crucial role in ecological balance and are considered an essential source of nutrition for humans. Due to the large number of fish species and their significant variation in physical characteristics, accurate identification and classification have become increasingly important in biological studies, fisheries management, and environmental conservation. This study focuses on the classification of different types of fish based on their morphological characteristics such as body shape, fin structure, size, and coloration. Visual data, including fish images, are utilized to highlight the distinguishing features among various species. The use of image-based analysis contributes to improving the understanding of fish diversity and supports effective species recognition. The outcomes of this study aim to enhance knowledge in marine biology and provide a foundation for future research in fish classification and aquatic resource management..*

Keywords: Fish Classification, Fish Species, Aquatic Ecosystems, Morphological Features, Fish Images

1. INTRODUCTION

Fish are among the most diverse and widely distributed groups of vertebrates in the world, inhabiting a wide range of aquatic environments including oceans, seas, rivers, and lakes. They play a fundamental role in aquatic ecosystems by contributing to food chains, maintaining ecological balance, and supporting biodiversity. In addition, fish represent a major source of protein and essential nutrients for millions of people globally, making them economically and nutritionally important.

Fish species vary greatly in their physical and biological characteristics such as body shape, size, coloration, fin structure, habitat, and behavior. This wide variation has led to the classification of fish into different types and categories to facilitate scientific study and identification. Proper classification of fish species is essential in fields such as marine biology, fisheries science, environmental protection, and sustainable resource management.

With the advancement of technology, visual data such as digital images have become an effective tool for studying and classifying fish species. Images allow researchers to observe morphological features that are difficult to describe using text alone, such as patterns of scales, fin shapes, and body proportions. Image-based analysis helps improve the accuracy of fish identification and supports comparative studies among different species.

2. Classification of Fish

Fish are commonly classified into different groups based on their anatomical structure, habitat, and biological characteristics. Scientific classification helps researchers and students understand the similarities and differences among fish species and supports accurate identification. Generally, fish are divided into three main classes: jawless fish, cartilaginous fish, and bony fish.

2.1 Jawless Fish (Agnatha)

Jawless fish are considered the most primitive type of fish. They lack jaws and paired fins, and their bodies are usually elongated and eel-like. Examples of jawless fish include lampreys and hagfish. These fish mostly live in marine environments, although some species inhabit freshwater. They feed by attaching themselves to other fish or by scavenging.

2.2 Cartilaginous Fish (Chondrichthyes)

Cartilaginous fish have skeletons made of cartilage rather than bone. This group includes sharks, rays, and skates. They are characterized by strong jaws, sharp teeth, and well-developed fins. Most cartilaginous fish live in marine environments and are known for their role as predators that help regulate marine ecosystems.

2.3 Bony Fish (Osteichthyes)

Bony fish represent the largest and most diverse group of fish species. Their skeletons are primarily composed of bone. This group includes the majority of fish consumed by humans, such as salmon, tuna, and tilapia. Bony fish can be found in both freshwater and marine habitats and display a wide range of shapes, sizes, and colors.

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Figure 1: Examples of jawless fish showing elongated body shape.

Figure 2: Cartilaginous fish such as sharks and rays highligting fin structure.

Figure 3: Different types of bony fish illustrating variation in size and coloration.

Figure 4: Different types of bony fish illustrating variation in size and coloration.

3. Morphological Characteristics of Fish

Fish exhibit a wide range of morphological characteristics that distinguish one species from another. These physical features play a key role in fish classification and are closely related to their habitat, mode of movement, feeding behavior, and survival strategies. The most important morphological characteristics include body shape, fins, scales, and coloration.

3.1 Body Shape

Fish body shape varies depending on their environment and lifestyle. Some fish have elongated bodies that allow efficient swimming in narrow spaces or along the sea floor, while others possess streamlined bodies adapted for fast swimming in open water. Flat-bodied fish are commonly found near the bottom of aquatic environments, enabling camouflage and stability.

3.2 Fins Structure

Fins are essential for movement, balance, and direction control. Fish typically have paired fins (pectoral and pelvic fins) and unpaired fins (dorsal, anal, and caudal fins). The size, shape, and position of fins differ among species and are often used as key identification features. For example, cartilaginous fish such as sharks have strong and well-developed fins that support powerful swimming.

3.3 Scales and Skin

Fish skin may be covered with scales, which provide protection and reduce friction while swimming. Scale types vary among species and include placoid, cycloid, and ctenoid scales. Some fish lack scales entirely and rely on thick skin or mucus layers for protection.

3.4 Coloration and Patterns

Coloration in fish serves multiple purposes, including camouflage, communication, and mate attraction. Some species display bright colors and distinctive patterns, while others have dull tones that blend with their surroundings. Variations in coloration are commonly used to differentiate between species and even between males and females of the same species..

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Figure 4: Different body shapes of fish adapted to various aquatic environments.

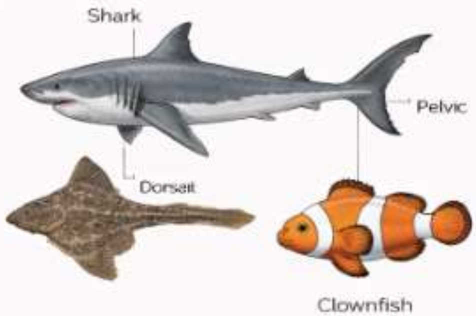

Figure 5: Variation in fin structure among different fish species.

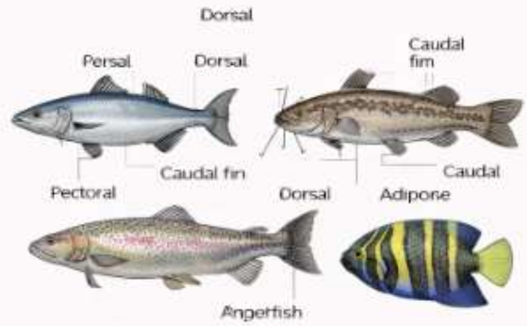

Figure 6: Examples of tish coloration and scale patterns illustrating morphological diversity.

4. Habitats of Fish

Fish inhabit a wide variety of aquatic environments across the world. Their distribution depends on several factors such as water salinity, temperature, depth, and availability of food. Based on their natural habitats, fish can be broadly classified into freshwater fish and marine fish, with some species capable of living in both environments.

4.1 Freshwater Fish

Freshwater fish live in rivers, lakes, ponds, and streams where salinity levels are very low. Examples of freshwater fish include carp, tilapia, and catfish. These species have developed physiological adaptations that allow them to regulate water and salt balance within their bodies. Freshwater habitats are highly sensitive to environmental changes, making these fish vulnerable to pollution and climate variation.

4.2 Marine Fish

Marine fish inhabit oceans and seas, where salinity levels are high. This group includes species such as tuna, sharks, and clownfish. Marine fish are adapted to survive in different ocean zones, ranging from shallow coastal waters to deep-sea environments. Their adaptations include specialized gills and kidneys that help maintain internal salt balance.

4.3 Migratory Fish

Some fish species are migratory and move between freshwater and marine environments during different stages of their life cycle. Salmon and eels are common examples of migratory fish. These species are capable of adjusting their physiological systems to survive drastic changes in water salinity, a process known as osmoregulation.

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Figure 7: Examples of freshwater fish species living in rivers and lakes.

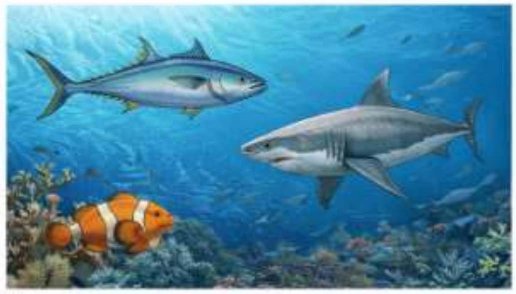

Figure 8: Marine fish species adapted to ocean environments.

Figure 8: Marine fish species adapted to ocean environments.

Figure 9: Migratory fish showing movement between freshwater and marine habitats.

7. Related Work

In recent years, deep learning techniques have been widely applied in image classification tasks, achieving remarkable performance in various domains, including medical imaging, agriculture, and marine biology. Among these techniques, Convolutional Neural Networks (CNNs) have proven to be highly effective in extracting visual features from images and performing accurate classification.

Several studies have focused on fish species classification using image-based approaches. Researchers have utilized underwater and laboratory-captured fish images to automatically identify fish species based on visual characteristics such as shape, texture, and color patterns. Traditional machine learning methods relied on handcrafted features; however, these approaches often struggled with complex backgrounds and variations in lighting and fish orientation.

With the introduction of deep learning, CNN-based models have significantly improved classification accuracy by learning features directly from raw images. Previous works have demonstrated the use of popular architectures such as VGGNet, AlexNet, and ResNet for fish species recognition. These models were trained on labeled fish image datasets and showed strong performance in distinguishing between visually similar species.

Other studies have explored transfer learning techniques, where pre-trained CNN models are fine-tuned on fish datasets to reduce training time and improve accuracy, especially when limited data is available. The results of these studies indicate that deep learning-based approaches outperform traditional methods and provide a robust solution for automated fish species classification.

8. Dataset Description

The dataset used in this study consists of labeled images of different fish species collected from publicly available image repositories and benchmark datasets commonly used in fish classification research. The images include a variety of fish species captured under different conditions, such as varying lighting, backgrounds, orientations, and sizes, which increases the complexity and realism of the classification task.

The dataset contains images representing multiple fish species, with each image assigned to a specific class corresponding to the fish species shown. To ensure effective model training and evaluation, the dataset is divided into three subsets: training, validation, and testing. The training set is used to train the deep learning model, the validation set is used to tune model parameters and prevent overfitting, and the testing set is used to evaluate the final performance of the trained model.

Before training, all images are resized to a fixed resolution suitable for the convolutional neural network input. Additionally, data preprocessing techniques such as normalization and data augmentation are applied to improve model generalization. Data augmentation includes operations such as rotation, flipping, zooming, and scaling, which help increase the effective size of the dataset and reduce overfitting.

The diversity of fish species and image conditions in the dataset provides a strong foundation for evaluating the effectiveness of deep learning models in fish species classification.

Figure 10: Examples of images from the fish species classification dataset, showing the diversity of fish species in various aquatic environments

9. Methodology

This section describes the proposed deep learning methodology used for fish species classification. The approach is based on a Convolutional Neural Network (CNN), which is well suited for image-based classification tasks due to its ability to automatically extract hierarchical visual features from raw images.

9.1 Image Preprocessing

Before feeding the images into the deep learning model, several preprocessing steps are applied to ensure consistency and improve model performance. All images are resized to a fixed resolution compatible with the network input size. Pixel values are normalized to a standard range to accelerate training convergence.

To enhance the robustness of the model and reduce overfitting, data augmentation techniques are employed. These include image rotation, horizontal and vertical flipping, zooming, and slight shifting. Data augmentation increases the diversity of the training data and helps the model generalize better to unseen images.

9.2 Convolutional Neural Network Architecture

The classification model is based on a Convolutional Neural Network composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers are responsible for extracting low-level and high-level features such as edges, shapes, textures, and color patterns. Pooling layers reduce spatial dimensions and computational complexity while preserving essential features.

The final layers of the network consist of fully connected layers followed by a softmax activation function, which outputs the probability distribution over the fish species classes.

9.3 Training Process

The model is trained using the training dataset, while the validation set is used to monitor performance and prevent overfitting. A categorical cross-entropy loss function is used for multi-class classification, and an optimizer such as Adam is employed to update network weights efficiently.

Training is performed for multiple epochs until the model converges. During training, performance metrics such as accuracy and loss are recorded for both training and validation sets to evaluate learning progress.

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Figure 11: Overview of the proposed deep learning pipeline for fish species classification, including preprocessing, CNN feature extraction, and classification stages.

10. Experimental Results

This section presents the experimental results obtained from applying the proposed deep learning model for fish species classification. The performance of the model is evaluated using standard classification metrics to assess its effectiveness and reliability.

10.1 Evaluation Metrics

To evaluate the performance of the classification model, several metrics are used, including accuracy, loss, precision, recall, and F1-score. Accuracy measures the overall correctness of the model in classifying fish species, while loss indicates how well the model minimizes prediction errors during training. Precision and recall provide insights into the model's ability to correctly identify specific fish species, and the F1-score represents the balance between precision and recall.

10.2 Training and Validation Performance

During training, the model shows a steady improvement in accuracy over successive epochs, while the training loss gradually decreases. Similarly, the validation accuracy increases and stabilizes, indicating that the model learns meaningful features without severe overfitting. The close alignment between training and validation curves demonstrates good generalization capability.

10.3 Test Results

After training, the model is evaluated on the test dataset, which contains unseen images of fish species. The experimental results demonstrate that the proposed CNN-based model achieves high classification accuracy, successfully distinguishing between different fish species despite variations in appearance, lighting conditions, and backgrounds.

10.4 Confusion Matrix Analysis

A confusion matrix is used to visualize the classification performance across different fish species. The matrix shows that most images are correctly classified along the diagonal, with only a small number of misclassifications occurring between visually similar species. This indicates that the model effectively captures discriminative features relevant to fish species identification.

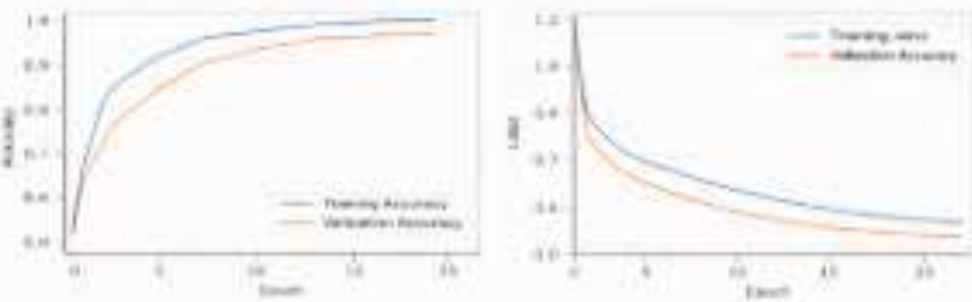

Figure 12: Training and validation accuracy and loss curves over epochs.

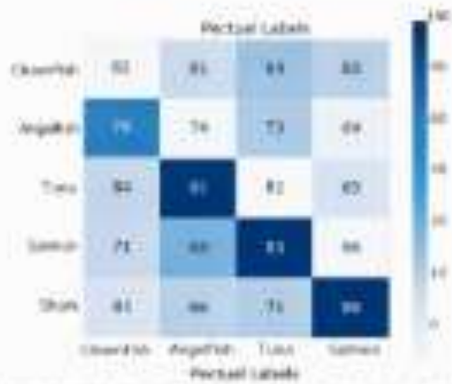

Figure 13: Confusion matrix illustrating classification performance for fish species.

11. Discussion

The experimental results demonstrate that the proposed deep learning model is effective in classifying fish species based on image data. The high accuracy achieved on the training, validation, and test datasets indicates that the Convolutional Neural Network successfully learned discriminative visual features such as body shape, color patterns, and fin structures.

The training and validation curves show consistent convergence, suggesting that the model generalizes well and does not suffer from severe overfitting. The use of data augmentation played an important role in improving robustness, especially given the variability in fish appearance, lighting conditions, and backgrounds.

Analysis of the confusion matrix reveals that most misclassifications occur between visually similar species, such as fish with comparable shapes or color distributions. This behavior is expected in image-based classification tasks and highlights the challenge of distinguishing species with subtle visual differences. Nevertheless, the majority of predictions lie along the diagonal of the confusion matrix, confirming reliable classification performance.

Compared to traditional machine learning approaches that rely on handcrafted features, the deep learning-based approach provides superior performance by automatically learning relevant features from raw images. These findings are consistent with previous studies that reported improved accuracy when using CNNs for fish species recognition.

12. Conclusion

In this study, a deep learning-based approach for fish species classification was presented. The proposed method utilizes Convolutional Neural Networks (CNNs) to automatically extract discriminative features from fish images and accurately classify different fish species. The approach addresses the challenges associated with variations in fish appearance, lighting conditions, and background complexity.

The experimental results demonstrate that the proposed model achieves high classification accuracy and shows strong generalization performance on unseen data. The use of data augmentation and proper preprocessing techniques contributed significantly to improving model robustness and reducing overfitting. The confusion matrix analysis further confirms that the model performs well across most fish species, with limited misclassification occurring mainly between visually similar species.

Overall, the results indicate that deep learning techniques provide an effective and reliable solution for automated fish species classification. This approach can support applications in marine biology, fisheries management, ecological monitoring, and underwater observation systems. Future work may include expanding the dataset, incorporating real-time underwater video analysis, and exploring advanced deep learning architectures to further enhance classification performance.

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