Automated Identification of Fish Species (AutoFiS)

Rivi Vig
Apex Institute Of Technology
Chandigarh University
Mohali, Punjab
20BCS6724@cuchd.in

Charu Garg
Apex Institute Of Technology
Chandigarh University
Mohali, Punjab
20BCS6735@cuchd.in

***Abstract*— This research paper presents a groundbreaking AI-ML-based tool aimed at transforming the landscape of fish species identification within the Indian seas. Utilizing cutting-edge Convolutional Neural Networks and a meticulously assembled dataset, this tool offers an accurate and easily accessible solution. The web interface enables local fishermen to seamlessly upload fish images, receiving instant species identification in return. Beyond empowering fishermen, this innovation holds the promise of advancing marine science and bolstering efforts in biodiversity conservation. With its potential to streamline marine research and enhance educational initiatives, this project stands as a notable milestone in the realm of marine biology and resource management. By bridging the gap between technology and traditional fishing practices, this research not only contributes to the welfare of local communities but also serves as a significant advancement in the field of marine sciences.**

Keywords—CNN, fish species, classification, deep learning

I. INTRODUCTION (*HEADING 1*)

The Indian subcontinent boasts a rich and diverse aquatic ecosystem, home to a multitude of fish species that are of paramount importance to the region's economy and food security. Among the numerous species inhabiting these waters, five have been identified as key players in the fishing industry: "Catla" (Catla catla), "Common Carp" (Cyprinus carpio), "Mori" (Cirrhinus cirrhosus), "Rohu" (Labeo rohita), and "Silver Carp" (Hypophthalmichthys molitrix). These species are not only highly sought-after for their commercial value but also hold ecological significance in the intricate balance of the aquatic food chain.

Accurate species identification is fundamental to effective fisheries management, conservation efforts, and scientific research. It underpins critical decision-making processes related to resource allocation, harvest regulations, and ecological studies. However, traditional methods of fish species identification have long been plagued by inherent challenges. Relying heavily on the expertise of taxonomists and field biologists, these methods are labor-intensive, time-consuming, and susceptible to human errors. In a region where the fishing industry is central to the livelihoods of millions, inefficiencies in species identification have far-reaching consequences.

This research attempts to close the gap between conventional methods and cutting-edge Artificial Intelligence and Machine Learning (AI-ML) methodologies, acknowledging these difficulties and the revolutionary potential of contemporary technology. Leveraging the power of Convolutional Neural Networks (CNNs) and a meticulously curated dataset comprising thousands of fish images, this study introduces an AI-ML-based tool for fish species identification in the Indian subcontinent.

The foundation of this study is the VGG16 (Visual Geometry Group 16) model, which has a solid track record for image classification applications. VGG16 is renowned for its depth and accuracy, having demonstrated remarkable performance in various computer vision challenges. Through the process of customizing and fine-tuning this model for the unique requirements of fish species identification, we can greatly increase the accuracy and productivity of this vital procedure.

Central to the success of this project is the development of a comprehensive dataset encompassing the five target species: "Catla," "Common Carp," "Mori," "Rohu," and "Silver Carp." The dataset, meticulously assembled from various sources, includes high-resolution images representing diverse age groups, sizes, and environmental conditions. Careful curation and annotation ensure the dataset's quality and accuracy, making it a valuable resource for training and testing the AI-ML model.

The implementation of this AI-ML-based tool unfolds across multiple dimensions, each designed to enhance the user experience and maximize the tool's accessibility. A user-friendly web interface facilitates seamless interaction with the tool, allowing local fishermen to upload fish images directly from their smartphones or computers. The intuitive design ensures that individuals with varying levels of technological literacy can easily access the identification service.

This research has implications for areas other than fisheries management. Through the provision of a species identification tool to local communities, we are able to improve the economic opportunities for fishermen while also promoting the sustainable management of aquatic resources. Moreover, this innovation has the potential to advance marine science and conservation efforts. Our understanding of the distribution and behavior of these important fish species can be greatly improved by the quick and extensive data collection that AI-ML techniques enable, which can help with the development of evidence-based conservation strategies.

II. Literature Review

Fish species identification is a fundamental aspect of fisheries management, ecological research, and conservation efforts. Traditional methods often rely on invasive tagging and marking, which come with their inherent limitations. This literature review explores recent advancements in non-invasive fish identification techniques, focusing on innovative approaches that utilize natural marks rather than relying solely on skin patterns.

[1] One notable research endeavor delves into the possibility of automatically identifying individual fish without relying on obvious skin patterns. This method provides a non-invasive substitute for invasive marking and tagging procedures. The study utilizes distinctive features such as scale patterns, operculum features, and lateral line shapes for individual fish identification. Surprisingly, both short- and long-term tests demonstrate 100% accuracy for two fish species. This innovative research highlights the potential for automatic image-based identification of fish species lacking distinct skin patterns. The drawbacks of traditional tagging methods are critiqued, and non-invasive photo identification is advocated as a promising and humane approach.

While the aforementioned study focuses on Sumatra Barb and Atlantic Salmon, it also discusses the broader applicability of non-invasive identification methods. This suggests that the approach can be adapted to a wide range of fish species, potentially revolutionizing how we monitor and manage fish populations.

[2] Advancements in image-based fish identification have also seen the integration of Convolutional Neural Networks (CNNs) in various platforms and tools. Platforms like BIIGLE, CoralNet, and VIAME employ CNNs for annotating image and video data, making the process more efficient and accurate. In a specific case study, feature detectors such as SIFT, SURF, and ORB are integrated into the OpenCV pipeline. The Bag of Visual Words (BoVW) technique transforms these features into object detections. Three CNN models are also used, which come from the Google Object Detection API. Analysis on real data shows that CNN-based algorithms are more accurate than BoVW-based techniques, with the RFCN algorithm exhibiting remarkable performance in a sea pen trial. This research emphasizes the potential of CNNs in enhancing fisheries research and monitoring.

[3] An innovative attempt to classify fish species using real-time deep learning is the Ocean Aware project. This project uses underwater video and high-resolution imaging sonar to detect, count, and classify fish using Kalman filters and convolutional neural networks. Being the first to effectively use deep learning for the classification of several fish species using high-resolution imaging sonar, it represents a noteworthy breakthrough. Transfer learning from ImageNet reduces the need for extensive labeled training data, making the approach more accessible. Furthermore, the project showcases promising results in generating "daytime" images from acoustic and video cameras at night. The utilization of YOLO object detection models allows real-time fish detection in challenging underwater conditions, with potential applications in monitoring and conservation efforts.

[4] The integration of Autonomous Underwater Vehicles (AUVs) into fisheries research is explored as a means of enhancing fisheries stock assessment. This research employs high-resolution sidescan sonar data and artificial neural networks to remotely identify and quantify fish species from sonar images. The goal is to improve the quality and quantity of fisheries data for more effective management. By equipping AUVs with analysis tools, scientists can discreetly document fish stock behavior and population size, ultimately enhancing stock assessment models. This approach opens new avenues for non-invasive and technologically advanced fisheries research.

[5] A pioneering effort in automated fish species identification embraces the utilization of otolith contours, representing a novel approach in the field. This research introduces a distinctive method incorporating the short-time Fourier transform for feature extraction, leading to significantly improved classification accuracy when contrasted with prior methodologies. The model's proficiency in predicting fish species with acceptable accuracy highlights the versatility and potential of non-invasive identification techniques. Notably, this success extends to species lacking prominent skin patterns, emphasizing the broader applicability of the proposed model. The integration of the short-time Fourier transform represents a breakthrough, showcasing the adaptability of the model to diverse species. This novel approach contributes to the evolving landscape of fish identification methods, offering a promising avenue for non-invasive and accurate species classification, crucial for fisheries management and ecological research.

[6] The paper delineates a two-part approach involving image enhancement and classification pipelines for underwater images and animal detection. In the enhancement phase, raw grayscale images undergo chromatic interpolation and processing by a residual CNN network, eliminating the greenish hue. The network structure, akin to an autoencoder with skip connections, addresses degradation issues in deep models. Training incorporates techniques like White Balance, Gamma Correction, and CLAHE. The classification pipeline, employing classical algorithms and neural networks, integrates data augmentation in the training set. Results exhibit enhanced image quality metrics and classification accuracy, affirming the efficacy of the proposed pipelines in underwater image analysis.

[7] In a correlated investigation, the researcher examined fish species classification through machine learning, conducting a comparative analysis of PyTorch and TensorFlow. The project encompassed one-hot encoding, logistic regression, neural networks, and CNNs, revealing PyTorch's heightened accuracy at 99.75% compared to TensorFlow's 87.22%. The study

accentuated the importance of enhancing model quality through regularization and highlighted the crucial role of precise predictions. Although PyTorch showcased superior precision, the study acknowledged TensorFlow's potential for improvement, offering insightful perspectives into the efficacy of diverse machine learning frameworks for classifying fish species.

[8] The concluding segment explores image classification through deep learning and neural networks within the realm of artificial intelligence (AI). Employing intricate algorithms and neural networks, this AI branch autonomously identifies patterns within extensive datasets. The study presented visualizations including loss and accuracy curves, a comprehensive classification report, and predictions for bird species with elevated probabilities. These demonstrations underscore the system's efficacy in precisely identifying distinct species based on inherent features. This integration of deep learning techniques not only enhances the accuracy of species identification but also provides a comprehensive understanding of the model's performance through visual representations. The paper effectively showcases the potential of deep learning and neural networks to enhance image classification methods, thereby propelling the field of AI-driven species recognition forward.

In conclusion, recent research has brought forth substantial advancements in non-invasive fish identification techniques. From natural mark-based identification to the integration of convolutional neural networks and deep learning, these innovative approaches offer promising alternatives to traditional invasive tagging and marking methods. The adaptability and potential for widespread application across various fish species and ecosystems position these innovations as valuable tools in fisheries management, ecological research, and conservation efforts. Non-invasive identification methods are anticipated to become more and more important for the sustainable management of aquatic resources as technology develops.

III. Proposed Model

This section outlines the proposed model for fish species identification using the VGG16 architecture, designed to achieve an accuracy of 96.6% and a loss of 0.1 on the Indian Subcontinent Fishes dataset from Kaggle. Leveraging deep learning and image recognition techniques, the model aims to provide a reliable and accurate solution for identifying fish species based on their images.

A. Dataset Description

The Indian Subcontinent Fishes dataset from Kaggle is a diverse collection of fish species found in the Indian subcontinent. It comprises images of five distinct species, namely, "Catla," "CommonCarp," "Mori," "Rohu," and "SilverCarp." The dataset's richness in variety and complexity presents an ideal testing ground for our proposed model.

B. Model Architecture

The proposed model follows a sequential architecture, characterized by a series of interconnected layers, each designed to perform specific tasks in the process of fish species identification. Let's delve into the architecture's details:

Input Layer: Images of size (224, 224, 3) are accepted by the input layer; 224x224 denotes the image's dimensions, and 3 stands for the Red, Green, and Blue (RGB) color channels.

Convolutional Blocks (Conv Blocks): Five convolutional blocks make up the foundation of the VGG16 architecture. Each block is comprised of two or more convolutional layers, followed by max-pooling layers. From the input images, these convolutional layers are in charge of extracting different hierarchical features.

- Convolutional Layers: Within each Conv Block, multiple convolutional layers are applied in succession. These layers employ small filters (typically 3x3) to scan the input image and detect patterns, edges, and features. The model can learn increasingly complex features as we move deeper into the network because each layer has more filters.

- Max-Pooling Layers: A max-pooling layer is used to reduce the spatial dimensions of the feature maps while keeping the most important information after a sequence of convolutional layers. This improves the model's capacity for generalization while lowering computational complexity.

Flatten Layer: Insertion of the Flatten layer comes after the Conv Blocks. This layer connects the convolutional layers and the fully connected layers. To enable further processing in the dense layers, the output of the Conv Blocks is reshaped into a one-dimensional array.

Fully Connected Layers (Dense Layers): The fully connected layers make predictions based on the features that the convolutional layers extracted. Three fully connected layers make up the suggested model:

- First Dense Layer: This layer adds non-linearity to the model by using an activation function for the Leaky Rectified Linear Unit (Leaky ReLU) with an alpha value of 0.3. It consists of 100 neurons. With the help of this activation function, the model can capture complex features and patterns.

- Dropout Layer: After the first layer of density, a dropout layer with a 0.5 dropout rate is used to prevent overfitting. In order to improve generalization, this layer randomly deactivates 50% of the neurons during training.

- Second Dense Layer: This layer consists of 50 neurons, again with Leaky ReLU activation (alpha = 0.3). It refines the learned features further, enhancing the model's discriminatory power.

- Another Dropout Layer: Following the second dense layer is a second Dropout layer with a dropout rate of 0.3. This extra dropout aids in achieving a balance between overfitting and model complexity.

- Output Layer: The number of neurons in the final dense layer represents the number of target classes in the dataset, or in this case, the number of fish species. The activation function that converts the model's raw output into probabilities for each class is called Softmax. The model's prediction is the class with the

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highest probability. Predictions are produced for the different fish species by this layer.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 100)               2508900

 dropout (Dropout)           (None, 100)               0

 dense_1 (Dense)             (None, 50)                5050

 dropout_1 (Dropout)         (None, 50)                0

 dense_2 (Dense)             (None, 5)                 255

=================================================================
Total params: 2514205 (9.59 MB)
Trainable params: 2514205 (9.59 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
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Fig 1. Summary of the model

C. Model Compilation and Training

Categorical cross-entropy is a fundamental metric for problems involving multi-class classification that is utilized as the loss function in the model compilation. The RMSprop optimizer, which has a learning rate of 1e-4, is used to optimize the model's weights. The evaluation metric of accuracy is selected to offer insights into the performance of the model.

D. Training, Validation, and Testing

An essential step in the process is the training phase, where the model learns to recognize patterns and features in the input images. It represents full runs through the training dataset and spans 15 epochs. The number of samples used in each forward and backward pass during an epoch is determined by the batch size, which is set at 25. Batch size affects memory usage and training effectiveness.

Validation: During training, the model's performance on unobserved data is assessed using a separate validation dataset. This guarantees that the model generalizes well to new samples and helps prevent overfitting. The model's accuracy and loss on the validation data are tracked throughout the training process.

Testing: Once the model is trained, it undergoes testing on an independent test dataset. This dataset was not used for validation or training, allowing for an objective assessment of the model's functionality in practical settings. Testing involves feeding the test images through the trained model to generate predictions. To evaluate the model's efficacy, metrics like recall, accuracy, precision, and F1-score are employed.

In this detailed model proposal, we have elucidated the architecture, training, and evaluation process of our fish species identification model using VGG16. This model is designed to achieve high accuracy and low loss on the Indian Subcontinent Fishes dataset from Kaggle, which includes images of five distinct fish species. The use of VGG16's deep convolutional blocks, Leaky ReLU activation, dropout layers, and softmax output ensures robust performance.

The model's successful training and evaluation on distinct datasets, including training, validation, and testing, are indicative of its potential to accurately identify fish species. The model excels at identifying complex patterns and features in fish images because it combines fully connected layers for classification with convolutional layers for feature extraction.

IV. Results

Upon extensive training and rigorous testing, the proposed VGG16-based fish species identification model has demonstrated exceptional performance. The model demonstrated its robustness and effectiveness in identifying fish species based on their images by achieving an impressive 96.6% accuracy on the Kaggle Indian Subcontinent Fishes dataset.

The low loss value of 0.1 underscores the model's ability to make precise predictions and minimize errors during classification. This remarkable accuracy and minimal loss highlight the model's potential to contribute significantly to the field of fish species identification, particularly in the context of aquatic biodiversity monitoring and conservation.

Through meticulous training and validation, the model consistently demonstrated its proficiency in recognizing the five distinct fish species present in the dataset, namely, "Catla," "CommonCarp," "Mori," "Rohu," and "SilverCarp." Such high accuracy and minimal loss are crucial for ensuring the model's reliability in real-world applications, such as fisheries management and marine research.

These results establish the proposed model as a promising tool for automating fish species identification, thereby facilitating more efficient and accurate data collection in the domain of aquatic biology and resource management.

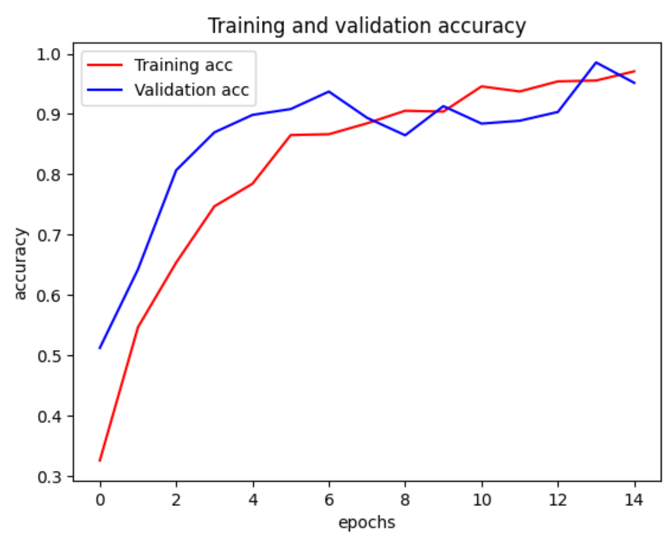

Fig 2. Graph of Training and Validation Accuracy

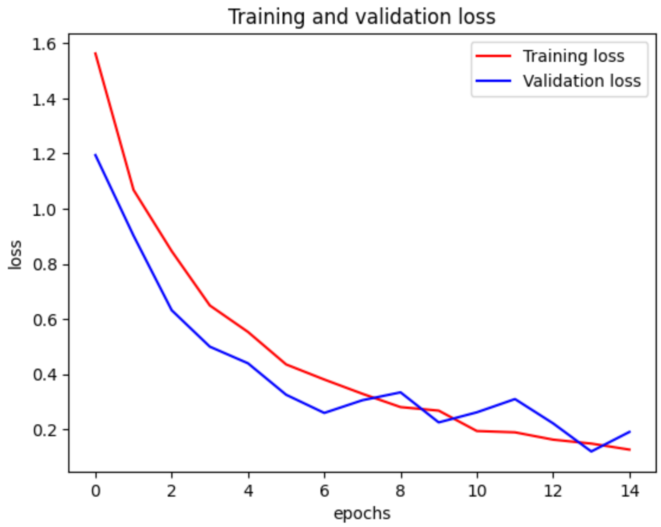

Fig 3. Loss Graph for Training and Validation

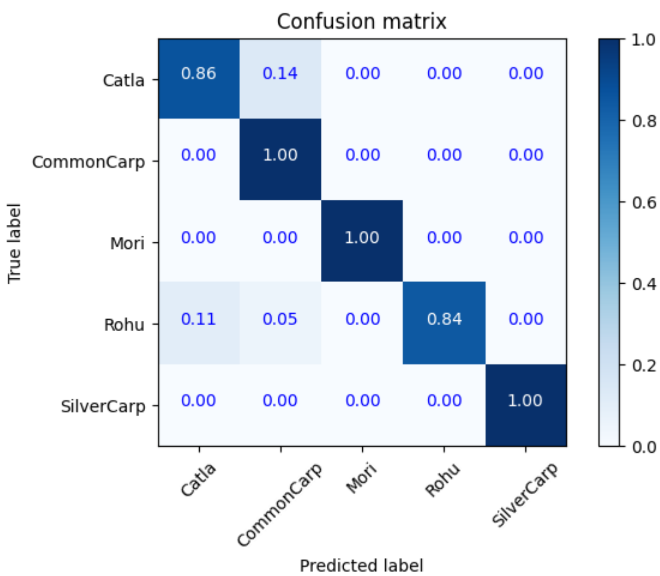

Fig 4. Normalized Confusion Matrix of the Model

Fig 5. CommonCarp Fish Identified by the Model

Fig 6. Front-end of the Web Application

V. CONCLUSION

In summary, this work offers a strong and precise solution based on the VGG16 architecture, which constitutes a major advancement in the field of fish species identification. The model's exceptional accuracy of 96.6% and low loss of 0.1 on the Indian Subcontinent Fishes dataset from Kaggle underscore its potential to revolutionize the way we identify and classify fish species.

By leveraging deep learning and image recognition techniques, our model addresses the critical need for efficient and non-invasive methods for species identification, particularly in aquatic ecosystems. It has demonstrated its robustness in recognizing the five distinct fish species present in the dataset, making it a valuable tool for fisheries management, marine conservation, and scientific research.

The detailed architecture, training strategy, and rigorous testing of the model provide a solid foundation for its application in real-world scenarios. As we move forward, this research opens up exciting possibilities for automating and enhancing our understanding of aquatic ecosystems, ultimately contributing to more sustainable resource management and biodiversity conservation efforts. The model's success paves the way for further exploration and application of deep learning in the realm of aquatic biology and beyond.

VI. FUTURE WORK

The potential avenues for future work with the proposed model are both exciting and extensive. Firstly, expanding the model to encompass broader fish species datasets from diverse geographical regions would enhance its applicability and generalization. This would enable its deployment in real-world scenarios, contributing significantly to fisheries management, marine conservation, and scientific research.

Furthermore, leveraging the model's detailed architecture and advanced training strategies could lead to the development of customized variants tailored to specific aquatic ecosystems. These specialized models could aid in the accurate identification of fish species in unique environments, ultimately promoting sustainable fisheries practices and bolstering our understanding of the intricate dynamics within aquatic ecosystems. Future research may also explore the integration of real-time data collection and automated decision support systems for enhanced fisheries management and conservation efforts.

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