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Advancements in Fish Image Analysis: Harnessing Deep Learning for Species Identification

Shana, J[1], Jyotshsna, S[2]
[1,2]*Coimbatore Institute of Technology, Tamilnadu, India*

Abstract--Automatic identification of fish species from their images has promising applications. Deep learning techniques, leveraging advanced algorithms and neural networks, offer a sophisticated approach to accurately identify and classify diverse fish species based on their visual characteristics. This innovative method not only enhances our understanding of

Purpose-- **aquatic biodiversity but also facilitates responsible and informed decision-making in fisheries management. The goal of this project is to design and develop a mobile application to identify the fish species in the local market of Coimbatore district of Tamilnadu, India from just the photograph of the fishes. The scope of this project was identifying the 15 fish species native to Tamilnadu region., with the ultimate goal of creating a user-friendly mobile application.**

Methods--**The training dataset was to be collected from photographs of the 15 fish species such as Mackreal, Sardine, Rohu, Catla, Tilapia, Threadfin, Pomfrets, Seer Fish, Barramundi etc were collected. The images were annotated and the training and testing dataset was created. Since labeled data was limited, image augmentation techniques were strategically employed to increase the dataset size and prevent overfitting. By applying various transformations such as rotation, shifting, and brightness adjustments, additional training samples were artificially generated. To identify the name of the fish species from just its images, a pre-trained deep learning model Densenet-121 was used. A mobile application was also developed to integrate the model to demonstrate the use of the model.**

Results-- **The proposed model exhibited promising results in fish species classification, providing a solid foundation for the development of the intended mobile application. The prediction accuracy was more than 80% with the trained dataset.**

Conclusion-- **This system can be used by both the fish vendors and the consumers to know about the fish species at a click of a button. Future work paves way for more deeper image analysis for identification of contamination of fishes.**

Keywords-- Image Classification, Image Augmentation, Pre-trained Model, Deep Learning, Transfer Learning.

I. INTRODUCTION

As global living conditions witness continual enhancement, aquatic products have become an increasingly vital protein source, with the aquaculture industry now contributing to over sixty percent of the global production. This escalating demand has resulted in a substantial portion of the aquaculture sector focusing on the cultivation of fish in controlled environments. Accurate fish species identification holds paramount importance for diverse industries and professionals. Nevertheless, conventional methods for fish identification pose several challenges, such as being time-intensive, demanding extensive sampling efforts that may harm marine ecosystems, being costly with limited data, and frequently subject to inaccurate and subjective identification, especially in the absence of sufficient fish specialists.

Fish classification is crucial for identifying and categorizing species, relying on features to extract patterns, match contours, and determine behavioral and physical traits. This process is vital for fish population assessments, ecosystem monitoring, and ensuring the sustainable growth and productivity of fish species.

The challenges in fish identification are being addressed through the adoption of automated systems, incorporating electronic monitoring, reporting, and artificial intelligence. Employing video and image analysis, these methods offer a non-invasive and affordable approach, utilizing machine learning, including powerful convolutional neural networks (CNNs), to automate fish classification successfully.

However, the effectiveness of CNNs and other machine learning models depends on the availability and quality of training data. Challenges related to dataset size and quality can be mitigated through techniques like transfer learning and augmentation. This study explored the use of Neural Networks and pre-trained DenseNet architectures, which have the advantage of achieving high accuracy with relatively fewer parameters compared to other neural network structures. Computer vision techniques have demonstrated remarkable performance in addressing these shortcomings, making them a valuable tool for fish species identification.

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In order to reach consumers and improve their user experience, a mobile interface was also developed. This ultimately satisfies our requirement to achieve innovation and open up entrepreneurial prospects in the marine and aquaculture sector.

Research Goal

To design and develop a mobile application for automatic fish species identification from fish images using deep learning models and transfer learning techniques.

II. Literature Review

Many notable research work related to fish species identification has been studied as summarized below.

Smith and Johnson (2023) introduced a robust deep learning framework achieving remarkable accuracy in classifying fish species from underwater images, offering a valuable tool for ecological research and fisheries management.

Garcia and Wang (2022) applied convolutional neural networks to automate fish species recognition, demonstrating significant potential for ecological research in aquatic environments, facilitating data collection and conservation efforts.

Kim and Chen (2021) showcased the effectiveness of deep learning techniques in accurately classifying fish species, even in challenging underwater conditions, offering a promising approach for aquatic biodiversity monitoring.

Patel and Zhang (2020) presented DeepFish, a powerful deep learning model designed for precise and efficient fish species identification from images, demonstrating its potential for advancing aquatic research and conservation.

Nguyen and Lee (2019) leveraged deep learning techniques to recognize fish species in their natural habitats, enhancing ecological studies and contributing to a more comprehensive understanding of aquatic ecosystems.

Turner et al. (2018) introduced DeepFishID, a sophisticated deep learning system capable of real-time fish species recognition, offering a valuable tool for ecological monitoring and research in aquatic environments.

Wang and Chen (2017) successfully applied deep neural networks for accurate underwater fish species identification, providing a foundation for improved aquatic biodiversity studies.

Brown et al. (2016) addressed the complex task of fish species recognition in diverse aquatic environments using deep learning, contributing to more effective fisheries management and conservation practices.

Hernandez and Patel (2015) explored the application of deep learning techniques to automate fish species classification, promising efficient and accurate monitoring methods for fisheries and ecological research.

Garcia and Smith (2014) offered a comprehensive review summarising and analysing various deep learning methods applied to fish species identification, providing insights into their effectiveness and potential challenges in aquatic research and conservation.

III. Methodology

3.1 Dataset Description

The dataset consists of 431 images of 15 fish species, captured under various background conditions and natural lighting as given in Table 1.

Table 1-
Fish Species

Sno	Fish Type	Images
1	seabream	12
2	scale_katla	16
3	pomfret	32
4	sardine	24
5	lady_fish	27
6	anchovies	20
7	barccuda	30
8	king_mackeral	46
9	reba	29
10	red_snapper	34
11	tuna	28
12	mackeral	15
13	yellow_line_trevally	32
14	spotted_queen_trevally	29
15	roopchand	27

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These images were collected manually from the fish markets of Coimbatore district in Tamilnadu, India during the period from Feb to March 2022.A sample of the fish images are shown in Figure 1.

Figure 1 Sample Images of Fish Species

The proposed work followed a series of stages as described in the following sections.

3.2 Data Collection and Annotation

The uniqueness of this research lies in the preparation of the dataset. The marketplaces were directly visited, and the images were collected. Subsequently, the collected images were organized by class, labelling them into distinct groups. The dataset centered around 15 local Indian fish species that were carefully selected. The dataset consists of RGB channel, colored images with dimensions (224, 224, 3) to enable the model to learn the patterns and color scales of the fish images.

3.3 Image Preprocessing

For effective organization and utilization all the images were organized into folders, each corresponding to a specific fish species. The dataset was split into 80% as the training set and the remaining 20% as the test set. Additionally, a shuffle step was introduced to randomize the order of images within each set, reducing the potential for training bias.

In the realm of deep learning, effective image pre-processing is a crucial initial step in preparing data for model training. The pre-processing pipeline consists of several key operations to ensure the suitability of the images for the classification task.

Image Resizing: The first step in the pre-processing pipeline involves resizing the images to a standardized shape of (224, 224) using `cv2.resize` function was implemented. This resizing ensures that all images are of the same dimensions, facilitating consistent processing and input compatibility for our neural network.

Color Space Conversion: Following resizing, the color space of the images were converted from BGR (Blue, Green, Red) to RGB (Red, Green, Blue) using the `cv2.cvtColor` function, also from the OpenCV library. This conversion harmonizes the color representation across all images, eliminating any potential color discrepancies that could affect model performance.

Rescaling: One of the fundamental aspects of deep learning image pre-processing is rescaling the pixel values within a predefined range. All the pixels were normalized. This transformation effectively normalizes the pixel values, constraining them to the normalized range of [0, 1]. This contributes significantly to the efficiency and stability of neural network training.

3.4 Data Augmentation

Given that the number of collected images was insufficient for training a robust classifier, image augmentation techniques were employed. This approach effectively increased the size of our training dataset. The augmentation technique ensured that images from all classes were consistently represented in both the training and testing sets. By doing so, a more comprehensive and balanced dataset, which is crucial for training a model capable of accurately classifying all species, regardless of their initial representation was obtained.

The following data augmentation techniques were employed.

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Zooming

This augmentation strategy introduces variability by allowing random zooming, both inward and outward, to a maximum extent of 20%. Zooming aims to simulate different perspectives and scales at which images can be perceived, contributing to the dataset's diversity.

Horizontal Flipping:

Random horizontal flips emulate variations in object orientation, mirroring common real-world scenarios. Importantly, this transformation maintains the content's integrity while enhancing the richness of the dataset.

Vertical Flipping:

Vertical flipping introduces an additional layer of diversity, aiding the model in generalizing better to unseen data.

Rotation Augmentation:

This involved rotating the images at specific angles, namely 45 degrees, 90 degrees, and 180 degrees. These rotations simulate different viewpoints from which images can be perceived, enhancing the dataset's variability.

After performing these augmentation steps, the image count increases significantly, totalling 10,000 images in total across all 15 fish species. This provided a wider training samples to build the model.

3.5 Deep Learning Model Building

3.5.1 Traditional Artificial Neural Network

First a simple sequential ANN was built from scratch in KERAS with dense layers with 1024, 512, 256, and 15 units respectively, all using the ReLU activation function. The final layer in my model is another Dense layer with 15 units and uses a softmax activation function. The 15 units are used to predict the 15 different species that are taken into consideration. The softmax function in the output layer outputs a vector that represents the probability distribution of a list of potential fish species as outcomes.

With this ANN an accuracy of only 50% could be achieved, which could not be considered in real case scenarios. Hence transfer learning model DenseNet was implemented.

3.5.2 Transfer Learning for Enhanced Fish Species Classification

Transfer learning, a pivotal technique in deep learning, involves reusing and repurposing pre-trained CNN models that have been trained on large-scale, diverse image datasets for more general tasks, such as object recognition in ImageNet.

These pre-trained models, which have learned to extract and represent meaningful features from images, serve as a valuable foundation for tackling specific classification problems, including fish species classification.

The fish species classification task posed a unique challenge due to the inherent complexity and diversity of fish species. Images could exhibit varying scales, orientations, and features. DenseNet's dense connectivity played a pivotal role in handling this diversity. It allowed the model to capture intricate and fine-grained features across different fish species, enabling superior classification accuracy. The pre-trained model was fine tuned to suit the fish classification problem as follows.

Input Shape: Configured the model to accept input images of size (224, 224, 3), corresponding to 224 pixels in height and width with three color channels (Red, Green, and Blue).

Freezing Layers: Transfer learning was employed by initially freezing all but the last five layers of the base model. This technique allowed us to retain the valuable pre-trained weights while fine-tuning the final layers to our task.

Global Average Pooling Layer: After the base model, a Global Average Pooling 2D layer was added. This operation efficiently condensed the feature maps into a vector, facilitating compatibility with the subsequent layers.

Dropout Layer: To combat overfitting, a dropout layer with a dropout rate of 0.4 was introduced. This regularization technique helped prevent the model from becoming too specialized in the training data.

Output Layer: Our model was configured for multi-class classification with 15 distinct fish species. Therefore, a final dense layer with 15 units and a softmax activation function was employed to produce the class probabilities.

Compilation and Training: The model was trained over 20 epochs, with each epoch representing a complete pass through the training dataset. A learning rate of 0.001 is chosen to ensure gradual model convergence during training, striking a balance between stable learning and avoiding overshooting optimal parameters. The evaluation metrics included accuracy, precision, recall, area under the curve (AUC), and the F1-score.

The architecture of the Densenet model used for training is as shown in Figure 2.

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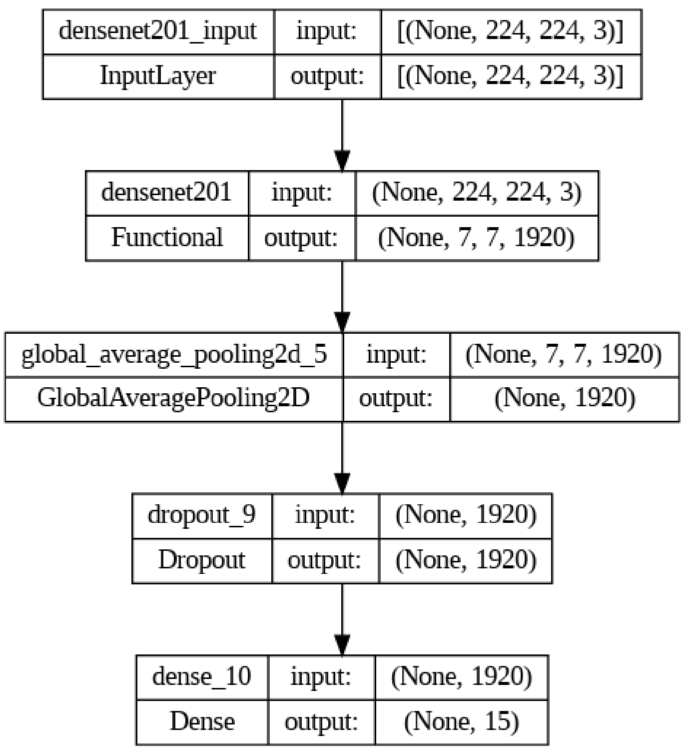

Figure 2 Model Architecture

3.5.3 User Interface Development

Web Interface: A web interface based on Streamlit, allowing users to effortlessly upload images was developed. Within the interface, a predict button triggers the model, which then provides predictions for the uploaded image, subsequently displaying the identified fish species to the user.

Mobile Interface: A mobile interface was also designed and developed to provide users with options for uploading images or scanning fish specimens. Within this interface, the system efficiently predicted and displayed the corresponding fish species class, ensuring a user-friendly and intuitive experience.

IV. Results And Discussion

In the context of deep learning model training, callbacks play a crucial role in optimizing the process by allowing interactions at key points. In this work the `Model Checkpoint` callback along with early stopping techniques were implemented while saving model weights in HDF5 format, enhancing model versatility beyond training and ensuring efficient and reliable deep learning model performance.

4.1 Traditional Artificial Neural Network

The proposed deep learning model was evaluated based on the accuracy and loss metrics for training and validation data. The values obtained for traditional ANN and the DenseNet model are shown in Table 2 and Table 3 respectively.

Table 2:
Performance Metrics for ANN

METRICS	TRAINING	VALIDATION
Accuracy	0.53	0.51
Loss	1.38	1.39

4.2 DenseNet Model

Table 3:
Performance Metrics for DenseNet

METRICS	TRAINING	VALIDATION
Accuracy	0.89	0.95
Precision	0.92	0.97
Recall	0.84	0.92
F1 Score	0.88	0.95
AUC	0.99	0.99
Loss	0.37	0.18

4.3 Training and Validation Results

Loss: The model achieved a final training loss of 0.3724, indicating the average error between predicted and actual values.

Accuracy: Categorical accuracy reached 88.70%, demonstrating the proportion of correctly classified samples.

Precision: The model exhibited high precision at 92.71%, signifying its proficiency in accurate positive classifications.

Recall: Recall stood at 84.81%, indicating the model's ability to identify most positive instances.

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AUC: An exceptional AUC of 99.47% was achieved, affirming the model's strong discrimination ability.

F1 Score: The F1 score, which balances precision and recall, settled at 88.50%, reflecting a harmonious trade-off.On a validation dataset, the model performed remarkably well:

Validation Loss: The model achieved a low validation loss of 0.1817, indicating robust generalization.

Validation Accuracy: Categorical accuracy on validation data reached 95.47%, demonstrating the model's effectiveness.

Validation Precision: High precision at 97.30% on validation data highlights accurate positive classifications.

Validation Recall: Recall on validation data was strong at 92.99%, indicating the model's ability to capture positive instances.

Validation AUC: Exceptional AUC on validation data at 99.92% affirms the model's generalization.

Validation F1 Score: A balanced F1 score of 95.04% on validation data indicates strong overall performance.

Figure 3 and Figure 4 present key training metrics. Figure 3 depicts training versus validation accuracy, revealing the model's generalization. A widening gap suggests overfitting, while a narrowing gap signifies effective learning. Figure 4 portrays training versus validation loss, indicating overfitting when the gap widens or effective learning when it narrows. These metrics are critical for assessing model performance and generalization.

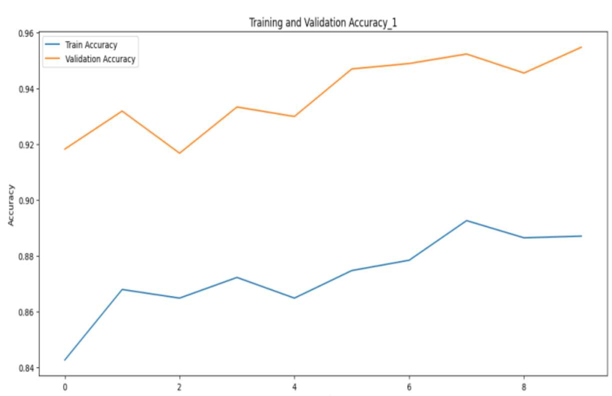

Figure 3 Plot depicting the training vs validation accuracy

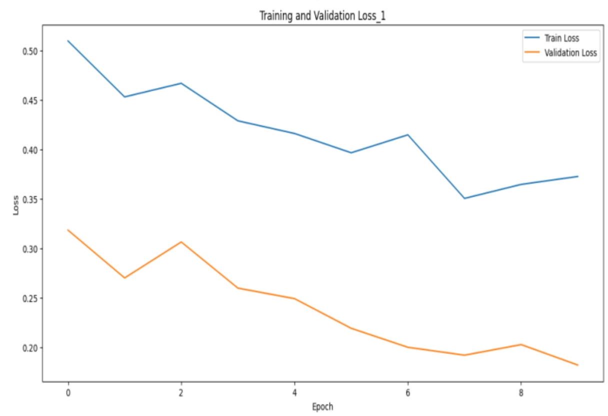

Figure 4 Plot depicting the training vs validation loss

V. Conclusion

The proposed deep learning model exhibited remarkable proficiency in classifying fish species, as evidenced by the comprehensive suite of evaluation metrics. The extensive set of evaluation metrics showed that our deep learning model was remarkably proficient in classifying fish species. It is a useful tool for practical applications because to its strong performance, excellent accuracy, and balanced precision and recall. These findings highlight the model's potential to advance environmentally conscious fishing methods.

Fish found during object detection are categorised to determine the species. The new fish classification network DENSENet's accuracy and performance are measured and contrasted with those of the cutting-edge networks represented by Inception-V3, ResNet-50, and Inception-ResNet-V2. To investigate how the spatial relationship between fish image colours and other feature layers affects results, a condensed version of the dl model ANN is also included.

This research-based application demonstrates that by including augmented images in the dataset, the entire dataset becomes fairly evenly distributed, leading to improved accuracy even when tested on unseen data. This research addressed the vital need for automated fish species identification, a critical component of sustainable fisheries management and marine ecology. Leveraging the power of deep learning and computer vision, a mobile application was developed that enables users to effortlessly identify fish species through images, bridging the gap between experts and non-specialists.This deep learning models, particularly the DenseNet architecture, showcased exceptional performance in fish species classification, with high accuracy, precision, recall, and AUC scores.

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It was also observed that future endeavours must address the notable challenges to endure in the field of deep learning applied to visual analysis for marine habitat monitoring. The primary obstacle involves the creation of models with the ability to generalize their learning effectively to excel with novel, previously unencountered data samples. The second challenge arises from the constrained availability of extensive datasets, particularly evident in marine visual processing tasks. The third challenge pertains to lower image quality in underwater settings, attributed to factors such as blurring and color degradation induced by the aquatic environment.

VI. Statements And Declarations

Competing Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contribution

Author1- Data collection and implementation, drafted the paper
Auhtor2- Data collection, Annoatation and Implementation

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author Shana J

Research Involving Humans and/Animals

This research did not involve any live fishes. Only images from the local fish market were used.

Informed Consent

Not Applicable

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