**Automatic Fish Species Identification System From Fish Images Using Deep Learning Techniques**

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**Abstract**

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. Many people are unaware of the type of fish they are consuming and such knowledge would be helpful to know the ecosystem. This can be later used for deeper analysis of fishes.

The scope of this project was identifying the 15 fish species native to Tamilnadu region. In order to identify the name of the fish species from just its images, a pre-trained deep learning model Densenet-121 was used. There are no datasets available currently in the public domain and hence the photographs of the 15 fish species such as Mackreal, Sardine, Rohu, Catla, Tilapia, Threadfin, Pomfrets, Seer Fish, Barramundi etc were collected, with the ultimate goal of creating a user-friendly mobile application. The images were collected and 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. The Densenet model were implemented successfully on the training dataset. The interface for the mobile application was built to demonstrate the use of the model.

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. 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 and Mobile Application.

**1. INTRODUCTION**

As living conditions continue to improve worldwide, aquatic goods have emerged as an increasingly essential source of protein, with the aquaculture industry now accounting for over sixty percent of global production. This surge in demand has led to a significant portion of the aquaculture sector being dedicated to raising fish in captivity. Accurate identification of fish species is crucial for various industries and personnel. However, manual methods for fish identification present various challenges, including being time-consuming, requiring extensive sampling efforts that can harm the marine environment, being expensive with limited data, and often prone to incorrect and subjective identification, especially when fish specialists are scarce.

Automated systems have gained momentum as a solution to these challenges, with the integration of electronic monitoring, electronic reporting, and artificial intelligence into fish identification processes. The utilization of video and images of fish has become increasingly common, offering effective, portable, non-invasive, and non-destructive methods that provide high-quality, affordable, high-resolution images. Machine learning techniques, including deep learning methods, have shown promise in automating fish classification, with convolutional neural networks (CNNs) emerging as particularly successful tools.

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. In this study, we explore the use of Simple Neural Networks and 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.

Fish classification plays a pivotal role in identifying and categorizing fish species based on their features, aiding in the extraction of important patterns, contour matching, and the determination of behavioral and physical traits. It has significant implications for fish population assessments, ecosystem monitoring, and the management of fish species to ensure their sustainable growth and productivity.

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

***1.1 Research Goal***

This work aims to develop a mobile application to identify the fish species automatically using the images. The users have to just click the image of the fish and it would display the name of the species just like an expert. For this deep learning models have been implemented using transfer learning techniques. In our proposed method, we utilize a cost-effective image acquisition device, specifically a smartphone, to capture images from various fish markets in Coimbatore during the period from August 2022 to September 2022.

This application paves way for further deeper analysis of fish images for contamination prediction taken up as future work.

**2. LITERATURE REVIEW**

Many work related to fish species identification has been studied for this work 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 summarizing and analyzing various deep learning methods applied to fish species identification, providing insights into their effectiveness and potential challenges in aquatic research and conservation.

**3. 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 the 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 |

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.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| anchovies | barccuda | barramundi | king\_mackeral | lady\_fish |
| pomfret | reba | red\_snapper | roopchand | sardine |
| scale\_katla | seabream | spotted\_queen trevally | yellow\_linetrevally | tuna |

**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 our research lies in the preparation of our dataset. Given that our research focuses on classifying fish images from local marketplaces, we took a hands-on approach. The marketplaces were directly visited, and the images were collected. Subsequently, we meticulously organized these collected images by class, labelling them into distinct groups. The dataset centers around 15 local Indian fish species that we carefully selected for our research. 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 of our dataset, we organized all the images into folders, each corresponding to a specific fish species. To ensure a balanced and representative split between the training and test datasets, we developed a Python script. This script randomly selected 80% of the images 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. Our pre-processing pipeline consists of several key operations to ensure the suitability of the images for our 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. This standardization operation holds paramount importance for several reasons. To achieve rescaling, we meticulously divide all pixel values by 255. This transformation effectively normalizes the pixel values, constraining them to the normalized range of [0, 1]. This harmonization 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, we employed image augmentation techniques. This augmentation process involved creating duplicate images from the originals while preserving their essential features. 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.

The following data augmentation techniques were employed.

***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 our dataset.

***Vertical Flipping:***

This augmentation expands our dataset by including vertical flips, akin to viewing images from an inverted perspective. Vertical flipping introduces an additional layer of diversity, aiding the model in generalizing better to unseen data.

***Rotation Augmentation:***

Rotational transformations are pivotal augmentation techniques in our research. These transformations involve 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, totaling 10,000 images in total across all 15 fish species. This augmented dataset is essential for improving our model's performance in fish image classification tasks, as it provides a wider range of training examples and reduces the risk of overfitting to the original data distribution.

***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 is used to predict the 15 different species that is 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 is a key technique in the realm of deep learning that has revolutionized the way we approach such classification tasks. It 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.

In this paper, we delve into the significance of transfer learning in the context of fish species classification. Specifically, we focus on our utilization of the DenseNet121 architecture. DenseNet121 is a powerful CNN model that has been pre-trained on extensive datasets, making it adept at feature extraction and representation.

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 given in Figure 2.

Architecture of the model


**Figure 2 Architecture of model**

***3.6 User Interface:***

***3.6.1 Web Interface:***

We created a web interface utilizing Streamlit, allowing users to effortlessly upload images. 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.

***3.6.2 Mobile Interface:***

Our mobile interface was designed to provide users with options for uploading images or scanning fish specimens. Within this interface, the system efficiently predicts and displays the corresponding fish species class, ensuring a user-friendly and intuitive experience.

**4. RESULTS:**

In the context of deep learning model training, callbacks play a crucial role in optimizing the process by allowing interactions at key points. One notable callback, `ModelCheckpoint`, is particularly vital as it periodically saves the model's weights, safeguarding against overfitting and preserving the best model version. Additionally, early stopping is employed, triggered when monitored metrics like validation loss or accuracy cease to improve, ensuring the model retains its generalization capability and preventing excessive optimization for the training dataset. In our project, we utilized the `ModelCheckpoint` callback along with early stopping techniques, all 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:***

|  |  |  |
| --- | --- | --- |
| *METRICS* | *TRAINING METRICS* | *VALIDATION METRICS* |
| Accuracy | 0.53 | 0.51 |
| Loss | 1.38 | 1.39 |

***4.2 DENSENET:***

|  |  |  |
| --- | --- | --- |
| *METRICS* | *TRAINING METRICS* | *VALIDATION METRICS* |
| 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 *Key training results are summarized below:***

***4.3.1 Training 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.

**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.

***4.3.2 Validation Results:***

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.

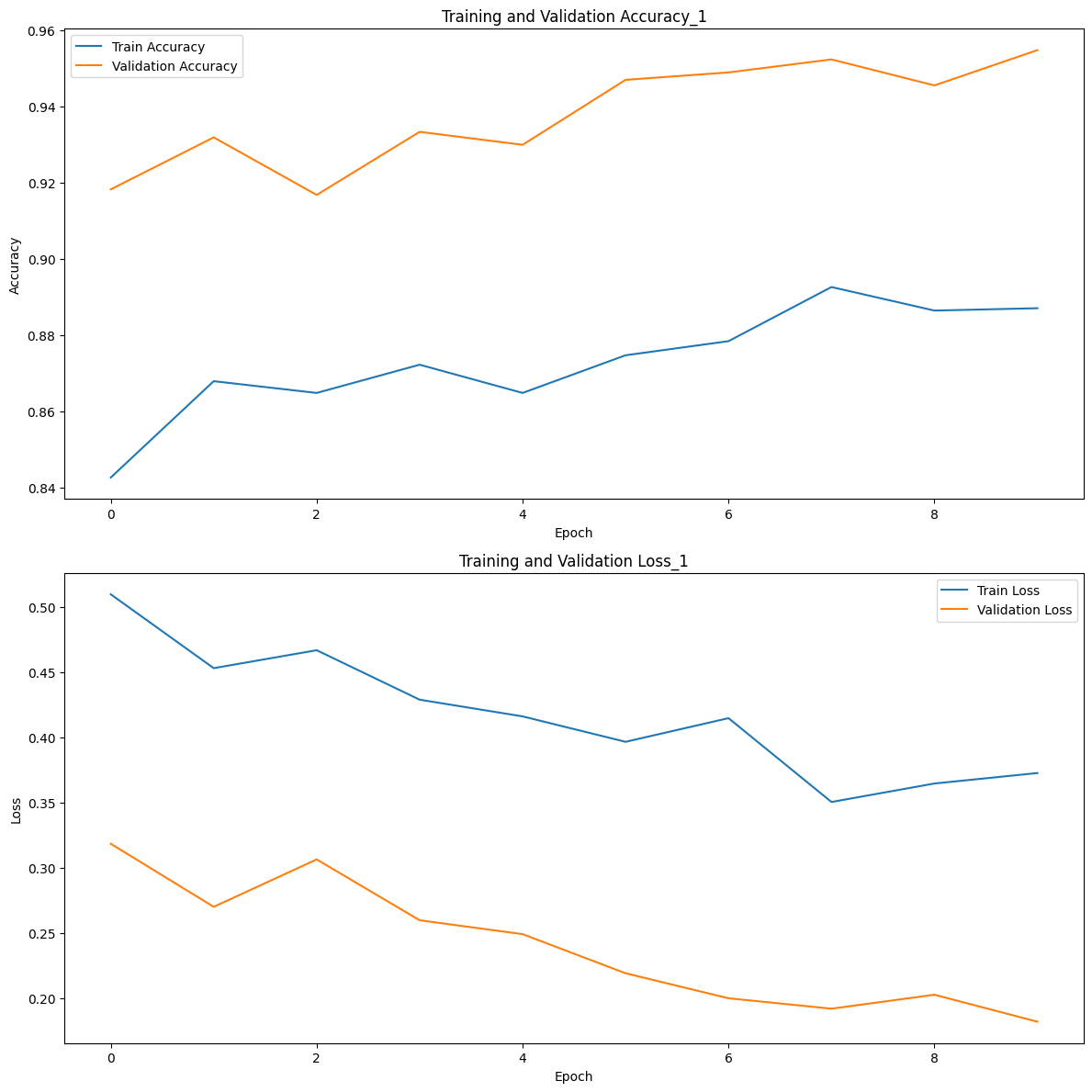
**Validation Recall:** Recall on validation data was strong at 92.99%, indicating the model's ability to capture positive instances.

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

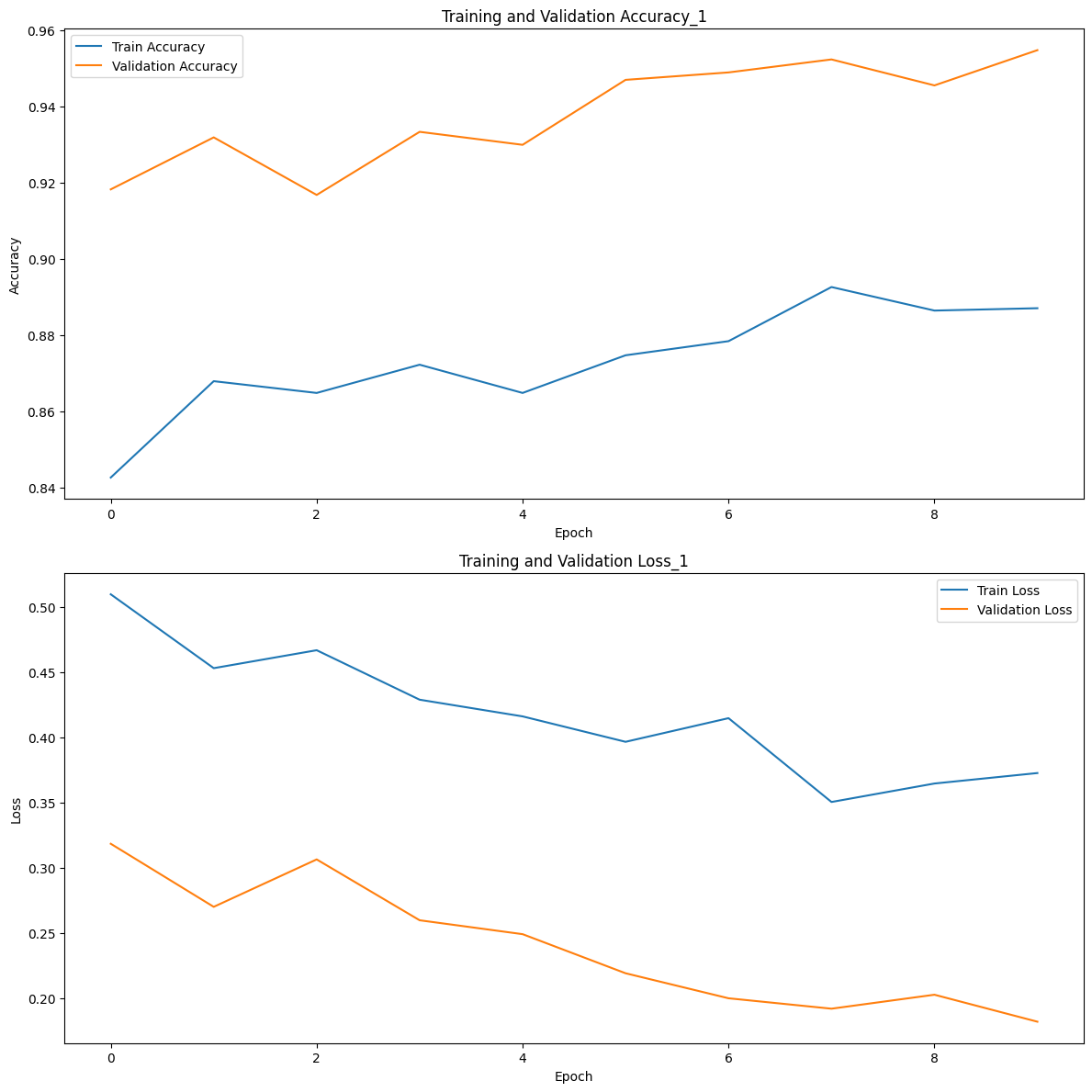
**Validation F1 Score:** A balanced F1 score of 95.04% on validation data indicates strong overall performance.

Our deep learning model exhibited remarkable proficiency in classifying fish species, as evidenced by the comprehensive suite of evaluation metrics. Its robust performance, high accuracy, and balanced precision and recall make it a valuable tool for real-world applications. These results underscore the model's potential for promoting sustainable fishing practices and environmental awareness.

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**

**5. DISCUSSION AND CONCLUSION:**

***5.1 Discussion:***

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.

Prior to the development of deep neural networks, it was challenging to consistently identify fish and other important aquatic species. The effectiveness of the deep neural network technique in deep oceans is demonstrated in this research using fish species analysis and extensive data collecting.

Our research 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—and more trustworthy metrics. Our research demonstrates that our model can be used with actual datasets, including those provided by the Nature Conservancy, even though they may not be noiseless, evenly distributed, or robust. Additionally, we have demonstrated that an effective method for correctly classifying fish images by species is a convolutional neural network. These networks are easily adaptable and scalable. Due to its accessibility, affordability, and dependability as a method of fish classification, it is the best option for the entire fishing and fisheries community.

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.

***5.2 Challenges And Approaches To Address Them***

In the domain of deep learning for marine habitat monitoring through visual analysis, several significant challenges persist. The foremost challenge is developing models capable of generalizing their learning to perform well on new, previously unseen data samples. Limited availability of comprehensive datasets, particularly in marine visual processing tasks, presents the second challenge. Lower image quality in underwater scenarios constitutes the third challenge, stemming from factors like blurring and color deterioration due to the aquatic environment. Additionally, bridging the gap between deep learning and ecological understanding poses a fourth challenge. Various algorithms and techniques have been devised to address these issues, including regularization methods, transfer learning, data augmentation, hybrid feature usage, weakly supervised learning, and active learning. These approaches aim to enhance model generalization, mitigate data set limitations, and contend with the unique challenges posed by underwater image quality, ultimately advancing the application of deep learning in marine ecology and habitat monitoring.

***5.3 Conclusion:***

In this research, we addressed the vital need for automated fish species identification, a critical component of sustainable fisheries management and marine ecology. As the demand for aquatic goods continues to rise, the aquaculture industry has become a dominant source of protein production, necessitating efficient and accurate means of identifying fish species. Manual methods present several challenges, including time-consuming processes, environmental harm, costliness, and potential for errors. Leveraging the power of deep learning and computer vision, we developed a mobile application that enables users to effortlessly identify fish species through images, bridging the gap between experts and non-specialists.

Our deep learning models, particularly the DenseNet architecture, showcased exceptional performance in fish species classification, with high accuracy, precision, recall, and AUC scores. The integration of callback techniques such as ModelCheckpoint and early stopping further ensured robust model performance and generalization. These results not only demonstrate the effectiveness of deep learning in automating fish identification but also hold promise for broader applications in marine habitat monitoring and ecological research.

This research work represents a significant step towards promoting sustainable fishing practices, fostering environmental awareness, and offering accessible, cost-effective, and reliable tools for fish species identification. Future work may explore contamination prediction and deeper analysis of fish images, extending the impact of this research on marine ecology and fisheries management.

***5.4 Future Works:***

In our future works, we aim to elevate our mobile application to encompass even more advanced functionalities. One pivotal aspect is the incorporation of contamination prediction, which will enable users to assess the safety of the fish they encounter. By expanding our dataset with a greater number of images and including a broader spectrum of fish species, we intend to enhance the model's versatility and accuracy. This evolution represents a significant step towards not only aiding in fish species identification but also contributing to food safety and environmental health, aligning with our mission of fostering sustainable practices in the aquaculture industry and marine ecology.

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