Automated Fish Species Detection

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Abstract - *Fish species detection is essential for many different uses, including managing fisheries and monitoring aquatic ecosystems. In this research, we present a deep learning-based method for precise fish species identification using MobileNetV2 architecture. The MobileNetV2 is a compact and effective convolutional neural network (CNN) model that successfully strikes a compromise between precision and computational effectiveness, making it especially ideal for contexts with limited resources. We assembled a large collection of fish photos from various species with different lighting, backdrops, and orientations in order to evaluate our method. We demonstrate the efficiency of our approach in attaining accurate fish species detection and categorization through comprehensive training and evaluation. Notably, our methodology maintains computational economy while delivering competitive performance compared to cutting-edge technologies, enabling its use in real-time scenarios. By presenting an automated system for fish species detection, our proposed application aims to streamline and enhance the efficiency of monitoring aquatic ecosystems. This, in turn, contributes significantly to the conservation of biodiversity by providing a more precise and efficient means of assessing and managing fish populations.*

Key Words: *(Fish species detection, MobileNetV2, CNN, Aquatic ecosystems.)*

1.INTRODUCTION

Fish species detection plays a crucial role in the field of aquaculture, which is the cultivation of aquatic organisms such as fish, shellfish, and aquatic plants for various purposes. The essence of aquaculture lies in its ability to meet the increasing global demand for seafood, alleviate pressure on wild fish stocks, and promote sustainable food production.

In order to effectively manage aquaculture operations and ensure optimal growth and health of fish populations, it is essential to accurately identify and monitor the different fish species present. This is particularly important in situations where multiple species coexist within the same aquatic environment, such as in fish farms or natural water bodies used for aquaculture purposes.

Accurate species detection in aquaculture has several benefits. It enables aquaculturists to maintain species-specific environmental conditions, feed formulations, and disease management strategies. It also aids in ensuring proper fish health and welfare, preventing the spread of invasive species, and facilitating the breeding and genetic improvement of specific fish species with desirable traits

Fish species detection involves the use of various techniques and technologies to identify and classify different fish species based on their physical characteristics, genetic markers, or behavioral patterns. These methods can range from traditional visual identification by experienced aquaculturists to advanced technologies like DNA analysis, computer vision, and machine learning algorithms.

This research provides an extensive examination of the latest techniques and advancements in automated fish species detection. Our focus is specifically directed toward exploring the utilization of the MobileNetV2 architecture. MobileNetV2 is an efficient and lightweight convolutional neural network (CNN) model that effectively balances accuracy and computational efficiency.

The primary objective of this paper is to provide researchers, practitioners, and enthusiasts with a comprehensive understanding of the current methodologies, challenges, and future directions in automated fish species detection using MobileNetV2. We also discuss the underlying principles, network structure, and transfer learning strategies employed in adapting MobileNetV2 for this specific application.

Through this research paper, we aim to provide researchers and practitioners with a valuable resource that can guide future developments in automated fish species detection, foster collaborations, and promote advancements in this critical field of study.

2. LITERATURE SURVEY

2.1. Research on fish identification in tropical waters under unconstrained environment based on transfer learning[2022]:

The paper focuses on fish detection in tropical waters using transfer learning in an unrestricted environment. The method begins with pre-processing of the images using affine transformation to improve the data. Then, a RestNet50 deep convolutional neural network is built using transfer learning. The effectiveness of fish detection and recognition is compared prior to and following transfer learning. The results demonstrate that using the pre-trained model from ImageNet as the network's starting weight gives better accuracy and lower loss compared to non-transfer learning approaches. After training the model for 150 epochs, the indicators start to link up, indicating that the model is able to better accomplish the identification of fish in tropical seas amid the difficult unrestricted environment.

2.2. Automated Detection, Classification, and Counting of Fish in Fish Passages With Deep Learning[2022]:

Fishes are the main part of the marine ecosystem.Most of the people in the world depend on fish for their diet. The data is collected by using acoustic devices, visual and active sonar, and optical cameras. To analyze this data to detect count and classify fish species they generated an automated system by using YOLOv3 and Mask-R CNN deep learning models which can detect and classify the fish species.Data is collected from DIDSON device to detect and classify the fishes, but this dataset have only 8 types of fish species to classify.The highest mean average precision value achieved by using YOLO is 0.73 and by using Mask-RCNN is 0.62.

2.3. Fake Hilsa Fish Detection Using Machine Vision[2022]:

Hilsa is the national fish of Bangladesh and it has more value in the market. Some businessmen started selling fake hilsa fishes for more profits. Fake hilsa cannot be detected just by looking it or by traditional methods because the they have similar features like original one with very slight differences like eyes, scales hence an automated system is required to generate identify the original and fake one, so they proposed a system that can detect original and fake hilsa fish. They collected the data which has 16,622 images. To detect the fake one they used five different types of CNN models they are Xception, VGG16, Inception V3, DenseNet201, NASANetMobile. All these five models have different accuracies where NASANetMobile show less accuracy of 86.75% whereas DenseNet201 show high accuracy of 97.02%.

2.4. A Scalable Open-Source Framework for Machine Learning-Based Image Collection, Annotation, and Classification: A Case Study for Automatic Fish Species Identification[2022]:

Non-commercial inland and coastal fisheries, which offer numerous societal benefits and have significant ecological effects, often lack sufficient data and assessments. To address this gap, this study aims to promote the widespread utilization of computer vision tools in fisheries and ecological research, encompassing tasks such as large-scale image database, efficient handling, accurate innovation, and automated classification. To achieve this objective, we employed technologies such as Tensorflow lite model maker library, transfer learning techniques, and convolutional neural network (CNN) layers. This research mainly focuses on data preprocessing, annotations, data augmentation, and model building. The best performance was achieved when the model was trained on EfficientNet-Lite0 model with batch size 32 and 20 epochs which gave an precision of 91%. This study also pointed out many problems like hectic manual annotation, low availability of public datasets, and overlapping fish images.

2.5. Fish Detection and Classification Using Convolutional Neural Networks[2020]:

For the conservation of fish species it is important to know about the size and diversity of every species. For this an automated system is required to detect and classify the captured species. To perform these tasks CNN is used. In this project they used a dataset which has 3777 images divided into 8 categories. This dataset is divided into training phase and testing phase where its validation accuracy is 90% and took about 6hrs to train the model. This project have better results compared to the traditional image processing techniques but the whole process is slow.

2.6. Fish detection and species classification in underwater environments using deep learning with temporal information [2020]:

Marine scientists need to estimate the abundance of fish species and also observe the changes in population of fishes. The data collected in the form of videos hence it has many challenges because of fish camouflage, backgrounds, shape and deformations of swimming fish and subtle variations between some fish species. To overcome these problems they proposed a model based on YOLO deep neural network. By using YOLO they combine optical flow and Gaussian mixtures. Using temporal information that is obtained from Gaussian mixture and optical flow models they detect the moving fishes. They used two types of datasets and they got F-scores as 95.64% and 91.2% and accuracies as 91.64% and 79.8% on each datasets respectively.

2.7. Underwater Fish Detection with Weak Multi-Domain Supervision [2019]:

Underwater fish detection is challenging because of low visibility, changing lights, and occlusions. Traditional computer imaginative and prescient techniques conflict on this domain. The reviewed paper introduces a novel method using susceptible multi-domain supervision. This method combines categorized and unlabeled information from a couple of domains, consisting of synthetic and real underwater pictures. This overcomes barriers of scarce actual-global classified facts. The approach includes a domain version community and a fish detection network. The domain version community aligns visual traits thru hostile schooling, facilitating know-how switch from artificial to real underwater pictures. The fish detection network employs a CNN and an RPN. The CNN extracts excessive-degree features, while the RPN localizes and classifies fish regions. Integration improves accuracy. Evaluation uses a complete dataset of actual underwater snap shots. The method outperforms present day strategies in accuracy and robustness. Weak multi-domain supervision proves effective. Significance lies in packages to underwater exploration, marine biology, and environmental tracking. Accurate fish detection aids in analyzing ecosystems, assessing biodiversity, and tracking human effect on aquatic existence. The technique offers advancements for stepped forward information and management of underwater environments.

2.8 Assessing fish abundance from underwater video using deep neural networks[2018]:

Marine biologists are an increasing number of adopting the use of underwater cameras or videos to evaluate fish diversity and abundance. However, processing videos manually for estimation through human analysts is both time-taking and labour intensive. To deal with this challenge and obtain cost and time efficiency, automated video processing strategies may be used. The primary objective is to broaden the accurate and dependable system for fish detection and recognition, that's specifically vital for autonomous robot systems. However, this challenge provides numerous challenges which includes complicated backgrounds, deformations, low decision, and the propagation of light. The recent improvements in deep neural networks have paved the manner for actual-time object detection and reputation. In this have a look at, an quit-to-stop deep studying-based totally architecture is brought, surpassing the performance of existing strategies and pioneering the field of fish evaluation. The technique combines a Region Proposal Network (RPN) from the Faster R-CNN object detector with three classification networks for detecting and recognizing fish species captured by means of Remote Underwater Video Stations (RUVS). The experiments achieved an impressive accuracy of 82.4% (Mean Average Precision), considerably surpassing the performance of formerly proposed methods.

3. METHODOLOGY

The framework developed in this study is divided into four main modules: Dataset collection and preprocessing; Model Architecture; Transfer learning and fine-tuning; and Training and Evaluation.

3.1. Dataset Collection and Preprocessing:

To assess the performance of our proposed approach, we curated a dataset of fish images encompassing multiple species, varying lighting conditions, and different orientations. The dataset was collected from Kaggle [1]. This dataset contains 9 different fish types. There are 1000 augmented images in each class, along with their paired enhanced ground facts. Each image has a resolution of 590 x 445 pixels. Care was already taken to ensure a balanced representation of different fish species to avoid biases. The collected dataset underwent preprocessing steps to enhance the performance for training the deep learning model. Data Transformation techniques were applied to increase the dataset size and improve the model's generalization ability. Moreover, manual annotation was performed to label each image with the corresponding fish species.

Fig -1: An illustration of a fish species used for testing and training models.

3.2. Model Architecture:

MobileNetV2, a lightweight and efficient convolutional neural network (CNN) model, was chosen as the backbone architecture for fish species detection. MobileNetV2 is specifically designed to achieve a stability between precision and computation effectiveness, making it well-suited for resource-constrained environments such as underwater monitoring systems. The MobileNetV2 architecture consists of 53 convolution layers, which significantly decrease the count of variables and computational complexity compared to commonly used CNN layers. This allows the model to achieve high accuracy while minimizing the computational resources required for inference.

3.3. Transfer Learning:

To leverage the representation learning capabilities of MobileNetV2, we employed transfer learning. The pre-determined weights of MobileNetV2, trained on a large-scale dataset such as ImageNet, were used as the initialization for our fish species detection task. By initializing the model with pre-trained weights, we benefited from the learned features that were effective for general image recognition tasks. After initialization, we fine-tuned the MobileNetV2 model using our curated fish species dataset. Fine-tuning involved updating the model's weights by training it on our dataset, while keeping the early layers frozen to retain the general feature extraction capabilities of the pre-trained model. This process allowed the model to alter the specific characteristics and variations present in our fish species images.

3.4. Training and Evaluation

The training process involved feeding the preprocessed and augmented fish species dataset into the MobileNetV2 model. A categorical cross-entropy loss function is used for this classification task. Adam optimizer is employed to optimize the model's parameters during training. To evaluate the performance of our approach, we employed various evaluation metrics, including accuracy, precision, recall, and F1 score. The dataset is split into training, validation, and testing sets in the ratio (70%-15%-15%), ensuring that images from the same fish species were present in multiple sets to assess the model's generalization ability. Extensive experiments were conducted to find optimal hyperparameters and assess the model's performance under different scenarios.

4. UML DIAGRAMS

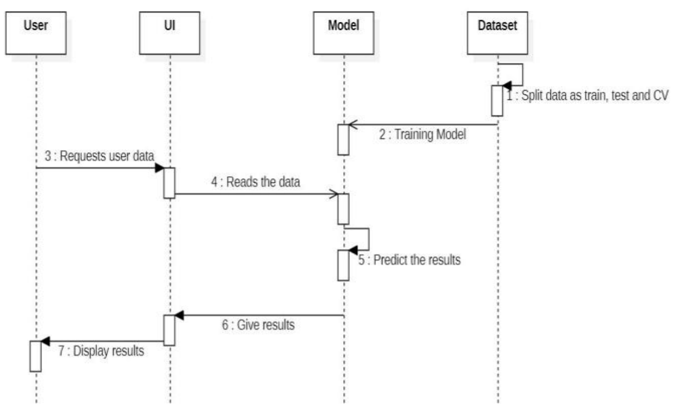

Fig -2: Use case diagram

In the use case diagram shown in Fig 2, the user is requested to upload the input fish image, the UI reads the input data and data is pre-processed while training and testing the model. The Api builds a model to detect fish species and the results are displayed in the UI.

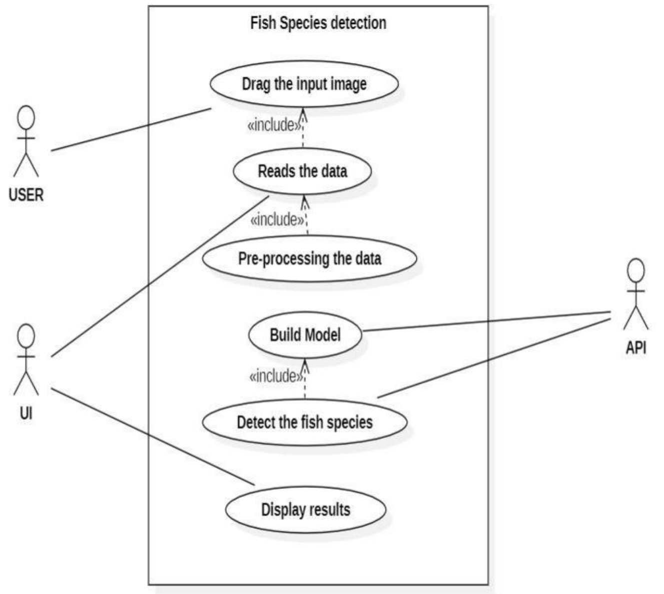

Fig -3: Sequence diagram

In the sequence diagram as shown in Fig 3, the lifelines are:

- User
- UI
- Model
- Data set

The dataset is split into three parts as train, test and cv data. Training data set is used to train the model. The user sends a request to the UI for data. The model reads the data and detects the fish species. The model predicts the results. The results are sent to UI and displayed to the user

5. RESULTS

Our experiments demonstrated the effectiveness of the MobileNetV2-based approach for fish species detection. The model achieved competitive performance compared to modern approaches while maintaining computational efficiency. The results indicated an accuracy of 99% on the test data. From the confusion matrix in Figure 4, we can observe that the precision, recall, and F1 score values of each class are surprisingly high validating the robustness and effectiveness of our proposed methodology. The class activation map in Figure 5 has highlighted the regions in the images that contribute the most to the predicted classes.

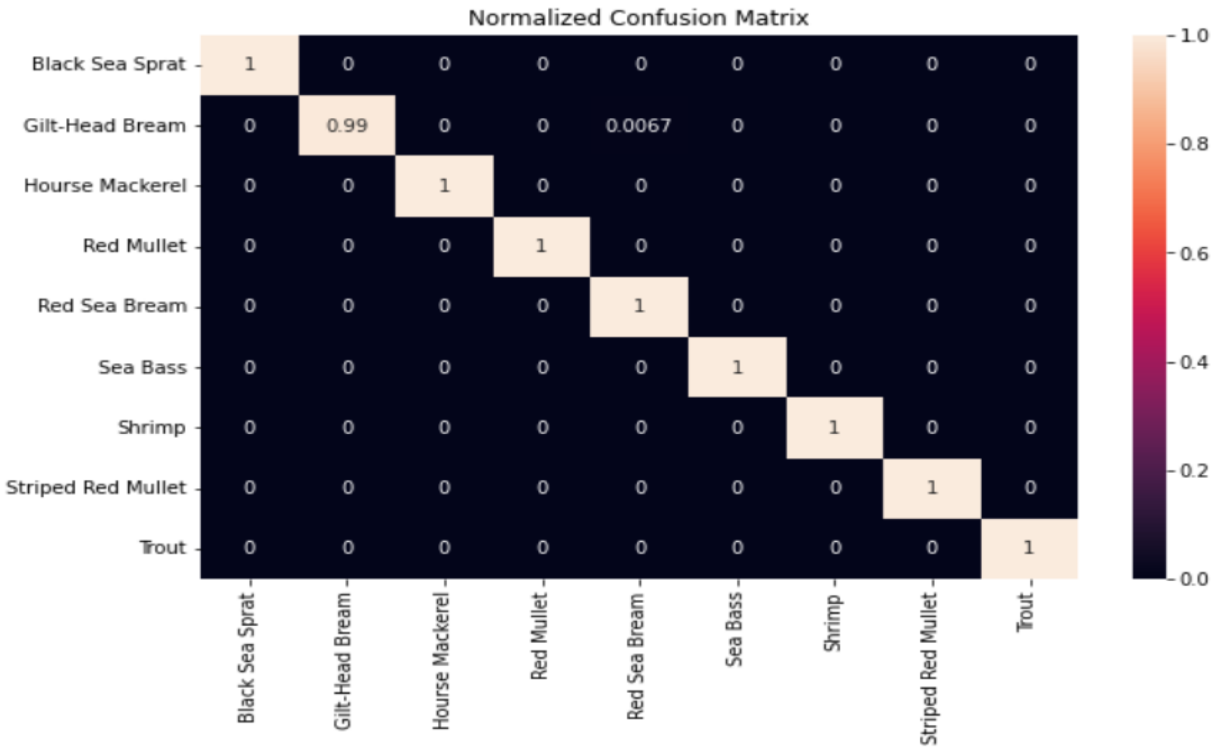

Fig -4: Normalized Confusion matrix of the fish image classification results, obtained when using MoblienetV2 model architecture, with a batch size of 32 and 5 epochs.

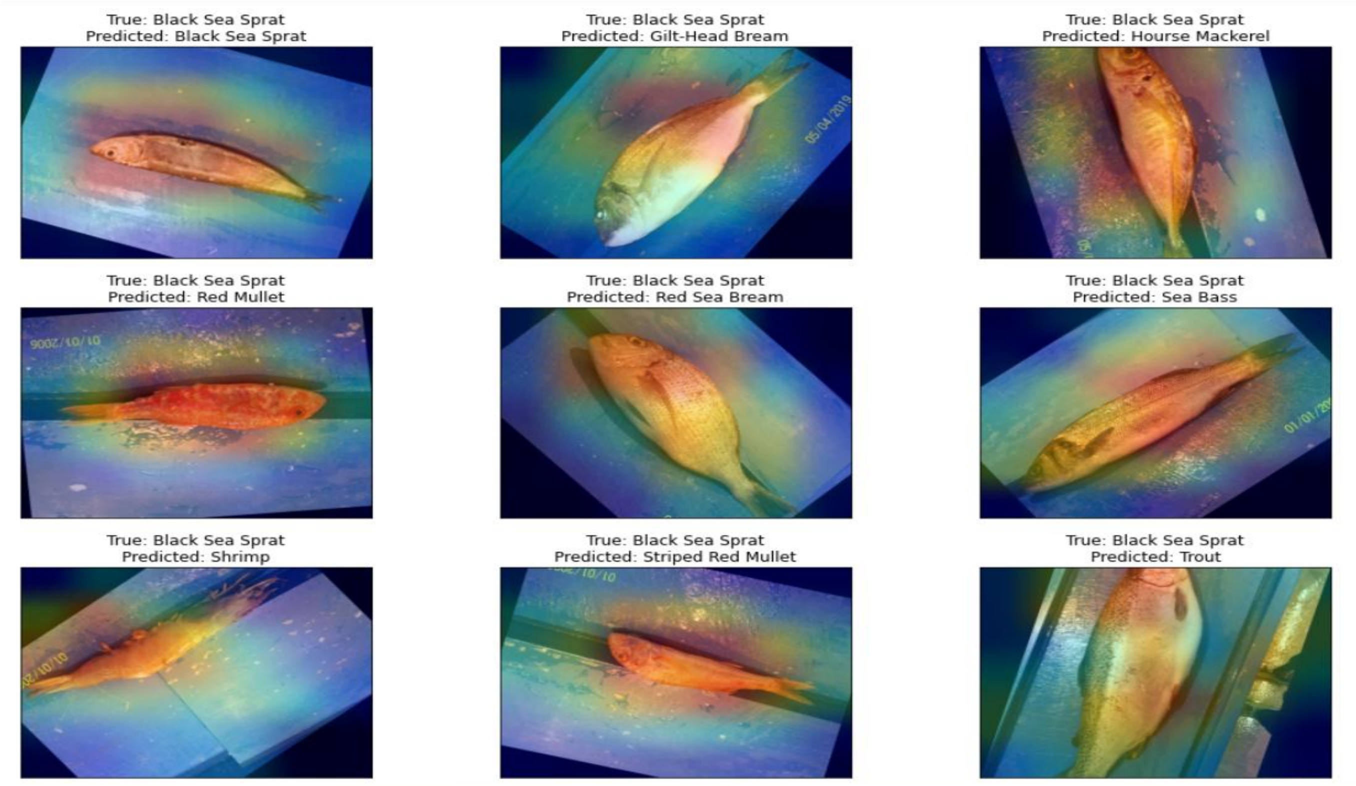

Fig -5: Class activation heatmap for fish images of 9 different classes.

6. DISCUSSIONS

The fine-tuning process with transfer learning facilitated faster convergence and improved generalization ability, enabling the model to accurately classify fish species even with limited training data. Moreover, our approach demonstrated computational efficiency, making it suitable for real-time scenarios and resource-constrained environments. The lightweight nature of the MobileNetV2 architecture enabled fast inference times without compromising accuracy, facilitating its deployment in applications where real-time fish species detection is essential.

Visualization techniques such as activation maps and class activation mapping (CAM) provided valuable information about the regions that contributed most to the model's predictions. This insight helps in understanding the model's decision-making process.

Although the model is highly accurate and efficient, the effectiveness of any machine learning model heavily relies on the quality and representativeness of the training dataset. One of the major reasons for the high accuracy results is due to the simple and clean dataset. But the real-time monitoring imposes various challenges in terms of lighting conditions and complex environments.

Based on this study, some of the future directions are discussed below to advance the aquaculture field.

- Data Collection is crucial: In extensive fish detection studies, open-source data is relatively small due to various factors like difficult environment and internal traits of fish species. Therefore, most studies have been supervised under controlled conditions. Toward real-life applications, there is a need for more realistic images in aquaculture.
- Interpreting intrinsic characteristics of the fish: A majority of studies focused on fish-counting and bio-mass estimation in high-density scenarios. A future direction would involve methods which not only used to count fish but can also present the spatial distribution of fish in the image.
- Developing Commercial applications: Implementing the usage of underwater cameras and sensors to monitor aquatic ecosystems and fisheries management.

7. CONCLUSIONS

In this research paper, we introduced a deep learning-based approach utilizing the MobileNetV2 architecture for accurate fish species detection. Our comprehensive survey examined the latest techniques and advancements in automated fish species detection, with a specific focus on the utilization of MobileNetV2.

Through extensive training and evaluation, we demonstrated the effectiveness of our approach in achieving precise fish species detection and classification. The lightweight and efficient nature of the MobileNetV2 architecture made it well-suited for resource-constrained environments, enabling real-time fish species detection applications.

By automating fish species detection, our proposed application contributes to the efficient monitoring of aquatic ecosystems, fisheries management, and biodiversity conservation. The ability to accurately identify fish species provides valuable insights into population dynamics, habitat health, and ecosystem assessments, ultimately aiding in the conservation of biodiversity.

We hope that this research paper serves as a valuable resource for researchers, practitioners, and enthusiasts in the field of automated fish species detection. The survey, methodology, and results presented here provide a foundation for further advancements in this critical area of study. By leveraging the strengths of the MobileNetV2 architecture and addressing the identified challenges, future research can continue to improve the accuracy, efficiency, and interpretability of fish species detection systems.

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