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Fish Species Detection and Recognition Using MobileNet v2 Architecture: A Transfer Learning Approach

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Abstract—The classification of fish is essential for aquatic research and the preservation of biodiversity. This article suggests a fish detection model combining transfer and deep learning methods. Our method extracts hierarchical features from fish photos using the MobileNetV2 architecture, which has been trained on the Image dataset. We obtain precise fish species classification by adjusting the pre-trained model and adding extra dense layers. Performance criteria, including accuracy, precision, recall, and F1-score, are used to measure the model's efficacy, and it is trained and tested using a dataset of fish photos. The results show the dependability and durability of our fish detection model, with a test set accuracy of 99.94%. Additionally, a thorough evaluation of the model's precision, recall, and F1score highlights its capability to categorize fish species while validating its performance accurately. The proposed model has a lot of promise for use in various applications, such as ecological study, fish population monitoring, and conservation initiatives, which will further our knowledge of and help protect aquatic environments.

Index Terms—classification, transfer learning, CNN, mobile Net

I. INTRODUCTION

Mystery and intrigue can be found in rivers, ponds, lakes, and oceans, especially in the fascinating world beneath the water's surface.The water has a significant geographical presence covering about 75% or two-thirds of the Earth's surface [1] [61]. Many fish species are dispersed within these vast marine ecosystems, playing a crucial role in maintaining the delicate balance of nature. With over 30,000 different fish species around the globe, it is practically impossible to recognize every one of them visually [2].One of the most active research areas is underwater object recognition. Identifying fish species is crucial in various sectors, including fisheries management, ecological research, and conservation initiatives. The conservation of fish species has profoundly impacted maintaining the delicate balance of natural ecosystems [3]. Traditional fish species identification techniques rely on skilled manual observation, which can be labor-intensive, time-consuming, and subject to human mistakes. Farmers face a considerable problem when it comes to controlling fish ponds and monitoring an ornamental fish farm. The traditional method necessitates farmers' actual presence on the farm and manual labor, which costs time, effort, and money. But there is an increasing need for chores to be completed quickly and effortlessly in today's technologically savvy environment [4]. The classification of fish species relies on distinct features such as fish color, shape, and texture. These features are crucial in accurately distinguishing and categorizing different fish species [1]. Fish species may also be visually classified, which makes it possible to track their movements and spot patterns and trends in their behavior. This better comprehension widens the knowledge of the species [5]. Observing and researching ecological processes in this ecosystem is difficult since it is dynamic and complicated [6]. High-resolution underwater camera [7] technology has lately made it possible to acquire enormous volumes of observations from remote locations and allow for better capturing of the species' cryptic behavior and environmental changes [8]. Although comprehensive picture and video data can be gathered, processing image data in an ecological environment is primarily manual and, thus, quite labor-intensive [9]. Furthermore, the characteristics of the undersea environment and taxonomic competence in data interpretation significantly impact how accurate human-based visual judgments are. Artificial intelligence (AI) has already made dramatic strides in several industries, including weather forecasting [10], responding to wildfire disasters [11], providing healthcare [12], and the transportation industry [13]. In addition, AI and computer vision applications have enormous potential to revolutionize recreational fisheries management [14]. Recreational fisheries management can gain from more streamlined and practical data analysis and species identification procedures, enhancing monitoring and conservation activities. A considerable amount of research has been done on fish recognition using a variety of methodologies, including image processing, hand-crafted feature-based [15], machine learning techniques [16], and deep learning methods [17].Fish species recognition presents a compelling research field within machine learning and computer vision, involving the challenging task of multi-class classification. State-of-the-art algorithms in this domain focus on individual input images and employ shape and texture feature extraction techniques for classification purposes. These algorithms aim to capture and analyze the distinctive characteristics of fish species, utilizing advanced matching methods to achieve accurate recognition results. The fusion of machine learning and computer vision approaches in fish species recognition holds great potential for advancing our understanding of aquatic ecosystems and supporting various fisheries management and conservation applications [18].However, recent developments in deep learning methods have completely changed the field of computer vision, making it possible to automatically and accurately identify different species of fish from pictures or videos; researchers have recently turned to image recognition and classification methods. The Deep Learning approach was used in the most recent research on fish species classification. An example of a deep learning architecture is convolutional neural networks (CNNs), which have achieved outstanding results in tasks requiring object recognition, such as fish species identification. Researchers have created compelling and dependable fish species detection and recognition techniques by utilizing CNNs' capacity to extract pertinent information from photos.The classification methods described in the research references employ a preprocessing technique called background removal to recognize fish species within images accurately [3] [53] [54]. The essential advantage of deep learning systems is their capacity to learn discriminative features directly from unprocessed picture data, obviating the need for custom features or in-depth domain expertise. As a result, complex patterns and differences in fish appearance, such as coloration, shape, and texture, which are essential for identifying species, may be automatically captured and generalized by the models. Applying deep learning in fish species detection and recognition significantly impacts various domains [55] [56]. In fisheries management, automated identification procedures can assist in monitoring fish populations, tracking migration patterns, and executing fishing regulations. Ecological deconstructions can benefit from automated species identification to evaluate biodiversity, habitat quality, and ecological interchanges. Preservation efforts can be maintained by accurately identifying threatened or invasive species [57][58]. With further advancements in computer vision and machine learning, these methods can revolutionize how we study, manage, and conserve fish populations and habitats [57] [58]. The remaining portions of the paper are organized as follows:

- Section II provides a comprehensive review of fish species and recognization.

- Section III presents the Methodology of our work
- Section IV presents an Experimental evaluation of our proposed model

The results are typically presented as visualizations. By following this structured approach, the paper ensures a logical flow of information, from reviewing existing research to presenting the proposed algorithm, experimental results, future works, and concluding remarks.

II. RELATED WORK

Due to various issues like environmental variations, underwater environment [19], fish camouflage, dynamic environments, unclear water, lower resolution, body deformations, and nuanced variations between fish species, automated fish detection and species classification in underwater videos is a challenging task for marine scientists and conservationists. To solve these issues, authors [17] proposed a hybrid method integrating the YOLO [20] [21] [22] [23] deep neural network with optical flow and Gaussian mixture models. The approach circumvents YOLO's drawbacks using temporal data from Gaussian mixture models and optical flow. It enables the recognition of fish instances that are both freely moving and disguised. High fish detection F-scores and accurate species classifications are attained in evaluating two underwater video datasets, which shows promising findings. These results demonstrate the potency of the suggested strategy.

A recent study [3] investigated deep learning-based object detection techniques, particularly Faster R-CNN, to recognize different fish species in photos without laborious preprocessing. Using the QUT FISH Dataset as a benchmark, they sought to compare the effectiveness of Faster R-CNN to other object identification techniques, such as SSD, in detecting fish species. The outcomes demonstrated that Faster R-CNN outperformed the Single Shot Detector (SSD) model's accuracy, which stood at 49.2%, with an astounding accuracy of 80.4%. Authors [24] focused on detecting and recognizing fish species in underwater images using Fast R-CNN (Regions with Convolutional Neural Networks) features. Building upon CNNs success in generic datasets like VOC and ImageNet, they applied these deep ConvNets to the more complex underwater environment. They utilized a new dataset comprising 24,277 ImageCLEF fish images across 12 classes. Fast R-CNN outperforms the Deformable Parts Model (DPM) baseline by achieving an 11.2% improvement in mean average precision (mAP) with an mAP of 81.4%.

Additionally, it achieves detection speeds 80 times faster than the previous R-CNN on a single fish image [2].

Scholars [25] proposed and compared two supervised machine learning [26] methods for automatically detecting and recognizing coral reef fishes [8] in underwater HD videos [27] [28] [29]. The first method follows a traditional two-step approach involving the extraction of a Histogram of Oriented gradient (HOG) features and using a Support Vector Machine (SVM) classifier. The second method is based on Deep Learning techniques, and they evaluated and compared the performance of both methods on accurate data, discussing their respective strengths and weaknesses. Their research contributed to fish detection and recognition in underwater environments, providing insights into the effectiveness and limitations of traditional machine learning approaches versus Deep Learning methods.

Eight family fish species and 191 subspecies are included in the system for identifying family fish species introduced by the authors [30], and this work demonstrated the efficacy of the proposed deep CNN [1] architecture for precise and effective family fish species identification in aquarium settings. The system uses deep CNNs [31] with two convolutional layers and two fully linked layers. Based on various parameters, comparative results are shown, contrasting the proposed system with alternative CNN designs, including AlexNet [32] and VggNet. On an untrained benchmark dataset, the suggested system outperforms AlexNet with a testing accuracy of 85.59% compared to AlexNet's 85.41%.

Biosafety precautions are essential for preventing the spread of infectious diseases to animals and crops. Using an advanced, intelligent Machine Hearing Framework (MHF), this study [33] offered a novel method for identifying marine species [34]. The main goal is to recognize invasive alien species (IAS) by their noises. The suggested method used the innovative Deep Learning algorithm (DELE) created explicitly for this task, the Online Sequential Multilayer Graph Regularized Extreme Learning Machine Autoencoder (MIGRATE ELM), for sound recognition. A unique method known as the" Geo Location Country Based Service" is also used to determine whether a particular location belongs to the associated class (native or invasive).

Scholars [1] presented a novel fish recognition method utilizing deep CNNs [5] [35], specifically VGG16, which was pre-trained on the ImageNet dataset using transfer learning. The fish dataset consisted of 50 species, with 15 images per species for training and testing. They explored four distinct kinds of datasets:

- RGB color space image
- Canny filter image
- Blending image
- Blending image mixed with RGB image, The outcomes indicated that the blending image combined with the RGB image trained model acquires the highest acceptance rate (GAR) of 96.4%. This is followed by the RGB color space image-trained model with a GAR of 92.4%, the smart filter image-trained model with a GAR of 80.4%, and the blending image-trained model with a lower GAR value of 75.6%.

Changing the problem's definition from a specific classification network problem to an object detection task reduces the challenge of detecting many fish species in a single image. A model containing a MobileNetv3-large, VGG16, and SSD detection head was put forth by researchers [36]. The dataset's class imbalance problem is further addressed by introducing a novel class-aware loss function. This loss function gives species with fewer instances larger weights to address the imbalance issue. The SEAMAPD21 large-scale reef fish dataset experimental findings showed that the model's performance could be improved by up to 79.7% compared to the original loss. Additionally, the model outperforms the initial SSD object detection model on the Pascal VOC dataset.

The researchers [37] proposed a transfer learning [15] approach using a pre-trained Google Inception-v3 model trained on underwater fish images. By leveraging the learned features from the pre-trained model, the proposed method achieves a high accuracy of 95.37% on the Fish4knowledge (F4K) dataset. This research contributed to identifying and quantifying fish species, providing valuable insights for marine biologists to understand the underwater ecosystem, promote preservation efforts, and study the behavior of marine animals. Using transfer learning techniques in marine species recognition demonstrates the potential for overcoming limited data availability and advancing conservation efforts in marine biology.

The authors [38] contrasted the supervised and unsupervised approaches to fish feature extraction—the supervised method located particular anatomical regions of fish to create feature descriptors. In contrast, using a scale-invariant object part learning algorithm, The unsupervised approach extracted each part's appearance, location, and size information. These techniques are used using a hierarchical partial classification framework. According to experimental findings, the unsupervised strategy performs better than the supervised approach at identifying live fish in images taken by trawl-based cameras. The accuracy and effectiveness of camera-based fisheries surveys are improved due to this research's contribution to developing efficient methods for fish species identification in aquatic environments.

Underwater video surveillance databases have become available, providing opportunities to develop algorithms for fish identification, and these datasets present challenges such as low video resolution, environmental factors like murky water and seaweed movement, and the vast amount of data to be processed. In this study [29], the researchers proposed a processing chain that involved background segmentation, adaptive scale keypoint selection, OpponentSift-based description, and binary linear Support Vector Machines for species classification. Their algorithm was evaluated in the Fish task of the LifeCLEF2014 challenge and showed improved precision but lower recall than the baseline. While their bounding boxes tended to be larger, their species recognition performance was comparable to the baseline.

Underwater Wireless Sensor Networks (UWSNs) have appeared as powerful tool for monitoring environmental conditions using vehicles and sensors. Scholars [39] introduced an Intelligent Deep Learning, based Automated Fish Detection model for UWSNs, called IDLAFD-UWSN. The proposed model utilizes Mask Region Convolutional Neural Network (Mask RCNN) with Capsule Network as the baseline model for fish detection. Additionally, a Gaussian Mixture Model (GMM) is applied for background subtraction to train the Mask RCNN, capturing motion details of fishes in videos and integrating them with actual images to generate fish-dependent candidate regions. The model also employs Wavelet Kernel Extreme Learning Machine (WKELM) as the classifier. Experimental results on benchmark underwater video datasets demonstrate the promising performance of the IDLAFD-UWSN model, achieving high accuracy rates of 98% and 97% on blurred and crowded datasets, respectively, outperforming other state-of-the-art methods in various aspects.

To assess the distribution of marine animals [34] [33], automatic recognition of species' presence in specific locations can be achieved through passive acoustics monitoring using underwater audio recordings. This study focused [40] on comparing the performance of classical computer vision algorithms with modern deep learning methods for identifying the characteristic sound produced by the meager brown species in spectrograms. A deep CNN, partially trained, based on contemporary architecture, was employed and achieved an impressive accuracy of 95%. This outperformed classical computer vision algorithms, highlighting the potential of deep learning in improving species identification and contributing to practical environmental conservation efforts.

III. METHODOLOGY

Figure 1 Streamlined Research Workflow: From Discovery to Breakthroughs. It has four major steps:

- Data Collection
- Data Preprocessing
- Feature Selection • Model Building

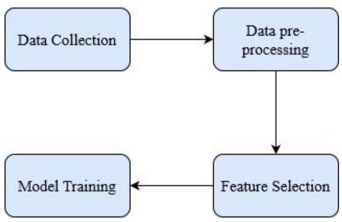

Fig. 1. Streamlined Research Workflow

A. Dataset Description

The interpretation of data effectively impacts the accuracy of human-based visual judgments, making it even more essential. The dataset employed was obtained from [41] for this particular study. This dataset was exclusively gathered from a supermarket in Izmir, Turkey, for a university-industry cooperation project at the Izmir University of Economics. It comprises nine distinct types of seafood: gilt-head bream, red sea bream, sea bass, red mullet, horse mackerel, black sea sprat, striped red mullet, trout, and shrimp image samples. Each seafood variety has its file in the" Fish _Dataset" accompanied by ground truth labels. This dataset is extensive and comprehensive, with 1000 augmented images per class and corresponding pair-wise augmented ground truths. The images are numbered from" 00000.png" to" 01000.png" for each class.

Furthermore, the work based on this dataset has been published in ASYU 2020. This dataset was collected specifically for performing segmentation, feature extraction, and classification tasks and for approximating various common algorithms in these domains, such as Semantic Segmentation, CNNs, and Bag of Features. The images were acquired using two cameras, Kodak Easyshare Z650, and Samsung ST60, resulting in resolutions of 2832 x 2128 and 1024 x 768, respectively. Before performing the segmentation, feature extraction, and classification processes, the dataset was resized to 590 x 445 while maintaining the aspect ratio. Following the image resizing, all labels in the dataset were augmented through flipping and rotating strategies. As a result of the augmentation procedure, the whole number of images for apiece class reached 2000, with 1000 images defining the RGB fish images and the remaining 1000 interconnected to their pair-wise basis truth labels.

B. Data Preprocessing

After collecting the dataset, the next step implicates image generation and preprocessing. The training generator is utilized for the training and validation parts, and the test generator is engaged for testing. The images are resized to 224x224 pixels and converted to RGB color mode. The data is rearranged with a random state of 42, and a batch size of 32 is picked for generating batches of images. The pretrained model is loaded, and additional layers are counted to create the final model. The added layers contain a global average pooling 2D, dense, and final classification layers. The pre-trained layers are usually frozen to retain their learned features. The model is assembled with an optimizer, a loss function, and a metric for evaluation. The model is then trained using the training dataset for several epochs. The data set is split into training and testing sets, and the split is performed haphazardly, with 80% of the data assigned for training and 20% for testing. The training data frame includes 7200 rows with two columns: one for the image path and one for the respective label. The testing data frame holds 1800 rows with the same two columns.

Fig. 2. Raw, unprocessed images that capture the authentic scenes are unaltered and awaiting preprocessing for further betterment.

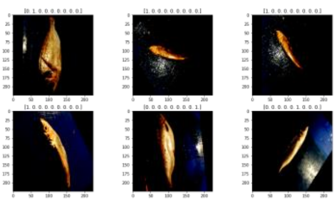

Fig. 3. After preprocessing, images reveal enhanced clarity and refined details.

C. Model

For classifying the fish, we employed MobileNetV2 [42]. A convolutional neural network design named MobileNetV2 seeks to function well on mobile devices. It is constructed on an inverted residual structure where residual relations connect the bottleneck layers. Lightweight depthwise convolutions are employed in the intermediate expansion layer as an origin of non-linearity to filter features. The architecture of MobileNetV2 contains a 32-filter initial fully convolution layer and 19 additional bottleneck layers. The summary of our model architecture, data flow, and configuration: MobileNetV2, a convolutional neural network (CNN) created for image classification tasks, is the foundational architecture [43]. Pre-trained weights from the ImageNet dataset are used to initialize the MobileNetV2 model. By setting include top=False, the top (completely linked) layers of MobileNetV2 are disregarded. The output of MobileNetV2 is subjected to global average pooling to produce a fixed-size output tensor.MobileNetV2 is layered with additional layers for additional processing and classification. The model receives input photos during either training or inference. The input images are three-channel images with a width and height of 224 pixels and a shape of (224, 224, 3). MobileNetV2 layers process the input tensor to extract hierarchical characteristics from the photos. After that, two dense layers with 128 units each and ReLU activation functions are applied to MobileNetV2's output. To create a probability distribution over nine output classes, the output of the second dense layer is processed through a third dense layer with nine units and a softmax activation function. The pre-trained weights of MobileNetV2 are frozen during training since the pretrained model is set to be untrainable (pre-trained _model.trainable = False). The model's construction uses the accuracy metric, categorical cross-entropy loss function, and Adam optimizer [44]. The train images dataset trains the model using the fit() technique. During training, the validation data is taken from the val images dataset. The training process involves iterating over the training data for 50 epochs. A summary of the model is shown in Table I

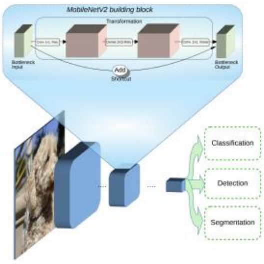

Fig. 4. Architecture of the Proposed MobileNet v2

IV. EXPERIMENTAL EVALUATION

A. Implementation

We used a dataset from a recent study [41], a large-scale fish dataset containing nine separate seafood to bring out segmentation, feature extraction, and classification tasks on seafood widely consumed in the Aegean Region of Turkey. The dataset

TABLE I

Architecture	MobileNetV2
Pre-trained Weights	ImageNet
Top Layers	Excluded (include top=False)
Input Shape	(224, 224, 3)
Additional Layers	Two dense layers with 128 units and ReLU activation
Output Layer	Dense layer with nine units and softmax activation
Pre-trained Weights	Frozen (pretrained model. trainable = False)

Metric	Accuracy
Loss Function	Categorical cross-entropy
Optimizer	Adam
Training Epochs	50

MODEL ARCHITECTURE AND PARAMETERS OF THE MODEL

consisted of underwater images and seafood that are generally not consumed. We use transfer learning to construct a training and testing data frame for a machine learning model for image classification. The main data frame was split randomly, with 80% moving into the training data frame and 20% forming the testing data frame. The preprocessing of this dataset was done similarly to the MobileNet V2 architecture, which is the architecture used in this model. Fish detection and identification are essential to observing fish behavior [45]. The main objective of this study is to identify threatened or invasive species accurately, ensure preservation efforts can be maintained, and evaluate how well the suggested model works. We used an Intel (R) Core (TM) i5-6500CPU computer with 12GB of RAM to set up our research. Due to our system not having a powerful GPU, training the model took longer. This study combined deep learning methods and transfer learning to construct a fish detection model. For data manipulation,

The solution used several libraries for model construction, visualization, and performance analysis. The pandas and numpy [46] libraries handled and manipulated data. The TensorFlow [47] and Keras [48] libraries gave the tools required for model creation and training. Data and model performance might be visualized thanks to the matplotlib [49] and seaborn [50]libraries. The computation of metrics like the classification report and confusion matrix was made easier by the scikit-learn [51] module. The OS library also supported file and directory operations. The fish detection model was effectively constructed using these potent libraries, exhibiting great accuracy and minimal loss in recognizing fish species. We have built our model using the Google colab [52], which offers a cloud-based environment for running and developing machine-learning models

B. Evaluation

Precision, recall, f-score, and accuracy are four evaluation measures we consider when assessing the model. Precision measures how many positive cases (fish) were accurately predicted out of all the positive instances. Precision in fish categorization refers to the model's capacity to identify fish species correctly. With a precision value of 98.10%, it accurately distinguishes between different fish species without misclassifying photos of objects further than fish as fish. Recall quantifies the percentage of positive occurrences (fish) that were perfectly predicted out of all the positive cases in the dataset. Recall in fish classification refers to how well the model recognizes every fish species in the dataset. In our instance, the recall value is 97.50%, indicating that it can successfully identify most fish species. The harmonic mean of recall and precision is the F-score or F1 score. Considering both precision and recall, it offers a fair assessment of the model's performance. When there is an imbalance between the classes or when both accuracy and recall are equally significant, the F-score, which combines precision and recall into one metric, is helpful. In classifying fish, the F-score offers a general evaluation of the model's capacity to identify fish species accurately while reducing false positives and negatives. Figure 5 shows the precision, recall, and f-score value graphically. In our fish

Fig. 5. Releasing the Power of Performance: Our Model's Impressive Precision, Recall, and F-score.

Classification study, we achieved remarkable results with a test loss of 0.00398, demonstrating the effectiveness of our model. Our model achieved an engaging test accuracy of 99.94%, showcasing its ability to classify fish species accurately. These outcomes underscore the success of our classification approach and highlight the model's high precision and recall rates. By minimizing false positives and negatives, our model demonstrates a robust capability to distinguish fish species accurately. These findings validate the efficacy of our fish classification model and its potential for various applications in aquatic research, fisheries management, and biodiversity conservation. Table III shows the accuracy of our model and the loss value during training time. On the test dataset, predictions were produced after the fish detection model had been trained. Based on the recognized patterns and features, the model predicted the classes for each test sample. These predicted labels represent the fish species the model recognized in the test photos.

Additionally, the test dataset's real labels, which listed the actual fish species that could be seen in each photograph, were available. We may gauge the model's predictions' accuracy and measure the model's performance by contrasting anticipated labels with actual labels. The comparison of the anticipated output and the actual results sheds light on the model's capacity to generalize to new data. It shows how well it can correctly identify fish species. The confusion matrix is shown in Figure 6.

TABLE II

REVEALING THE ACCURACY AND TRAINING LOSS OF OUR MODEL.

Metric	Value
Test Loss	0.00398
Test Accuracy	99.94%

TABLE III ACTUAL VALUE AND PREDICTED VALUE

Input	Predicted	Actual
Fish Gilt-Head Bream	Gilt-Head Bream	Gilt-Head Bream
Fish Black Sea Sprat	Black Sea Sprat	Black Sea Sprat
Fish Gilt-Trout	Trout	Trout
Fish Red Sea Bream	Red Sea Bream	Red Sea Bream
Fish Striped Red Mullet	Shrimp	Striped Red Mullet

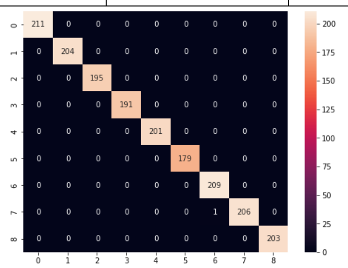

Fig. 6. The Confusion Matrix: A Comprehensive View of Label Accuracy.

V. CONCLUSION

This paper presents a highly effective and potent fish detection model that connects transfer learning and deep learning techniques. Utilizing the power of the MobileNetV2 architecture, pre-trained on the extensive ImageNet dataset, we successfully extract hierarchical features from fish photos, enabling exact species classification. We have gained remarkable performance across different performance criteria via careful adjustments to the pre-trained model and adding extra dense layers. Our model's effectiveness is estimated through rigorous evaluation using a comprehensive dataset of fish photos, and the results demonstrate its dependability and durability. With an outstanding test set accuracy of 99.94%, our fish detection model showcases its extraordinary ability to categorize fish species accurately. This high level of accuracy is further supported by an in-depth inspection of precision, recall, and F1-score, which establishes the model's capability to classify fish. The suggested fish detection model contains the following:

- An enormous promise for various applications
- Making it a useful tool in underwater research
- Biodiversity protection
- Preservation initiatives

Its deployment in ecological investigations allows researchers to acquire more profound insights into fish inhabitants and their habitats and resource management. By providing trustworthy and efficient standards of fish species classification, our model contributes immensely to preserving and protecting marine environments. Accurately identifying and observing fish species are important for maintaining biodiversity and protecting the delicate equilibrium of ecosystems. With its heightened performance and reliability, the suggested fish detection model is a worthwhile asset for scholars, environmentalists, and policymakers devoted to studying and conserving ocean life. Additional research and development can guide its integration into a comprehensive application scope, including fisheries management, ecosystem modeling, and actual national science initiatives. By continually advancing our proficiency and utilizing the power of artificial intelligence, we can persist in analyzing and protecting the wonderments of oceanic environments, assuring their Sustainability for future epochs.

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