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Fish Classification with Machine Learning: Enhancing Accuracy and Efficiency

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Abstract: Fishery sector is regarded as a sunrise sector and is expected to play a significant role in the near future. This paper emphasizes the need for a comprehensive aquaculture supervisory system that prioritizes fish identification and classification in order to effectively monitor and control a variety of aquaculture operations. In order to automatically identify and classify fish species from a variety of data sources and do away with manual identification, the suggested approach integrates Artificial Intelligence and Machine Learning technologies, including CNN, MobileNetV2, ResNet152, and YOLOv8 models. Fish image analysis using deep learning and other cutting-edge methods improves accuracy by identifying complex patterns. This approach is meant to be adaptive and flexible; it can be changed in response to new facts and circumstances. A fruitful implementation would boost fish identification and classification for effective management, as well as aquaculture's sustainability, profitability, and efficiency. With a minimum loss function of 0.02 and an accuracy of 94.8%, YOLOv8 stood out for its exceptional performance, demonstrating its potential for high-accuracy testing and training in the context of fish identification and classification techniques. However, to fully realize the benefits of AI and ML in aquaculture, issues like the scarcity of high-quality training data and the requirement for specialized knowledge in these fields must be resolved.

Keywords: Aquaculture, Machine Learning, Convolutional Neural Network, YOLOv8, MobileNetV2, ResNet152.

1. INTRODUCTION

Aquaculture, the controlled cultivation of aquatic organisms such as fish, mollusks, and crustaceans, plays a crucial role in meeting the escalating global demand for seafood. In order to achieve sustainability, overfishing must be avoided. As a result, it is crucial to keep developing new methods for tracking the fishing process. In order to prevent overfishing and the depletion of wild fisheries, tracking species fishing quotas requires knowledge about a fishing ship's intake. Every sweep of the fishing nets may contain a varied number and quantity of fish species due to the nature of the fishing techniques. Currently, the two processes of species separation and quantity measurement are mostly carried out by simple manual labor [1]. This industry has experienced rapid growth, diversification, and technological advancements in recent years, aiming to enhance production efficiency and environmental sustainability. A major factor in increasing the productivity of the fish industry through automation is the use of deep learning and computer or machine vision for automatic fish recognition. The challenges of rising food demand and the possibility of food scarcity in the future brought on by the world's population growth, the effects of climate change, and global warming can be addressed with the aid of an automatic sorting system [3]. In the realm of aquaculture management, fish identification and classification are pivotal aspects that directly influence operational efficiency, environmental impact, and overall success. Traditionally, these tasks have been performed manually, requiring labor-intensive efforts and often leading to inaccuracies. However, the integration of artificial intelligence (AI) and machine learning (ML) technologies has revolutionized fish identification and classification processes. The necessity for advanced AI and ML techniques in fish identification arises from the complex aquaculture operations. An extensive system that efficiently monitors and manages various facets of aquaculture must include precise fish identification and classification capabilities. These technologies enable the automatic identification and categorization of different fish species from diverse data sources, such as photographs,

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without the need for manual intervention. Deep learning methods, like those employed in models such as CNN, MobileNetV2, ResNet152, and YOLOv8, analyze intricate patterns and features in fish images, significantly improving the precision of species identification. The importance of employing AI and ML in fish identification and classification lies in its potential to enhance efficiency, profitability, and sustainability within the aquaculture industry. Accurate identification facilitates targeted and optimized management practices, ensuring appropriate care for each species and minimizing environmental impact. By adhering to ethical and sustainable practices, these technologies contribute to the overall success of aquaculture, addressing challenges posed by fluctuating conditions and evolving information. The necessity for their application is underscored by the potential benefits of increased accuracy, reduced manual effort, and streamlined management processes, ultimately promoting responsible and efficient aquaculture practices in a rapidly evolving global industry.

2. RELATED WORK

The subject of classifying fish has been extensively researched in the fields of information retrieval, pattern recognition, and segmentation, hence there are several works carried out in this field, where author Filipe Monteiro, et al. pushes the boundaries by introducing multispectral data and tackling the challenge of partial visibility where it pioneers the use of multispectral data in fish classification, presenting a custom-made camera (MultiCam) capturing 12 spectral bands capturing twelve distinct wavelengths between 390 nm and 970 nm for improved species identification. To address partial fish visibility, they introduce a novel approach of classifying "small fish neighborhoods" using three machine learning algorithms (kNN, MLP, SVM). Notably, SVM achieved the highest accuracy of 63.8% for three common Portuguese species, marking a significant advancement in challenging underwater environments. Recognizing the limitations of existing fish classification methods like low accuracy, small datasets, and complex backgrounds, author Md. Asif Ahmed, et al. proposed a comprehensive solution with two key components: the first one is deep learning-powered dataset creation, model analysis, and system architecture; and second is an IoT-based smart container design with sensors. It introduces a novel dataset of 800 images representing eight local fish species and rigorously evaluates seven pre-trained deep learning models, ultimately demonstrating the superiority of a combined Convolutional Neural Network and Long short-term memory architecture achieving a remarkable 97% accuracy. Additionally, they introduced a smart fish monitoring method utilizing an Android application, showcasing the practical implementation of their deep learning solution [2]. To overcome the challenges of fish detection in dynamic situations, Ari Kuswantori, et al. proposed a novel approach utilizing the YOLOv4 model with a custom dataset of high-speed fish motion on conveyor belts under varying backgrounds. Their unique contribution lies in introducing a landmarking labeling technique, which, when compared to conventional methods and different training or testing schemes, significantly improves accuracy. Notably, the combination of extracted images, landmarking labels, and the full YOLOv4 model achieved an impressive 98.96% accuracy on test videos, highlighting the effectiveness of their combined approach for robust fish detection in complex environments [3,4]. The foundation for comprehending machine vision in fish categorization is established by Daoliang Li, et al. in their papers, which also thoroughly examines image gathering methods such as underwater cameras and drones and explores popular public datasets. They further propose innovative methods to enhance dataset quality and quantity, employing image generation, synthetic data, and transfer learning. The paper meticulously details various fish classification methods, encompassing both traditional machine learning algorithms and cutting-edge deep learning techniques. Notably, they offered perceptive contrasts between the benefits of different architectures and model performance, but they also raise relevant questions regarding the field's future obstacles, such as the great diversity of fish species, the dynamic nature of underwater environments, and the dearth of large-scale, high-quality datasets. Additionally, they highlighted the promising potential of integrating multiple modalities and domains for further advancements [5]. Building upon the foundational understanding of machine vision in fish classification established by previous papers, subsequent works have explored and addressed specific challenges within this domain. For instance, Vishnu Kandimalla, et al. have taken a decisive step forward by applying cutting-edge deep learning models to a public dataset, effectively demonstrating the potential for non-invasive fish monitoring, and taking a decisive step forward by applying cutting-edge deep learning models, YOLOv3 and Mask-RCNN, to a public DIDSON dataset of eight fish species. They demonstrate the models' efficacy in accurately detecting and classifying fish using high-resolution imaging sonar data, paving the way for a future where traditional tagging methods are replaced by this non-invasive approach. This novel system holds immense potential for in-depth scientific research, enhanced regulatory monitoring of at-risk fish species, and broader applications in fish passages and marine energy sites [6]. C.G. Raghavendra et al. reviewed an automatic fish counting system based on reliable technology. It assists farmers in real-time, accurate, and non-disruptive fish population counts. Additionally, they focused on aquaculture and explored water quality assessment using

ICT to enhance productivity and ecological balance [7,8]. Furthermore, Smitha Raveendran et al. conducted a comprehensive review of underwater image enhancement techniques, covering challenges and recent trends [9]. In a separate study, Mathur et al. introduced an automatic fish classification method for underwater images, addressing challenges posed by light scattering and absorption in ocean water [10]. Ajay et al. proposed a methodology for integrated production models in aquaculture, considering socioeconomic and environmental effects. Their aim was to enhance sustainable and efficient aquaculture production [11]. and Ashkan Banan et al. focused on using deep learning to extract appearance features for automated carp species identification. They addressed challenges in underwater videos, achieving high accuracy [12]. similarly, Irina M. Benson et al. explored using near-infrared spectroscopy to differentiate fish species from different ecosystems based on otoliths. Their study provided insights into spatial variability and interactions [13], by considering all this Ahsan Jalal et al. combined optical flow, Gaussian mixture models, and YOLO deep neural network to detect and classify fish in unconstrained underwater videos. Their approach achieved impressive accuracy on underwater datasets [14]. Whereas Jayasundara D et al. investigated on multispectral imaging for automated fish quality grading. They explored techniques to assess fish quality in an industrial context [15]. Similarly, Saliha Zahoora proposed an automated system for identifying and classifying fish species based on visual features. they utilized a modified Alex Net model with fewer layers, achieving a testing accuracy of 90.48% on a benchmark fish dataset [16], but a different approach was adopted by Eko Prasetyo et al. and they focused on classifying milkfish freshness based on eye segmentation and they introduced the Cosine KNN (CosKNN) method, which provides soft values representing class membership levels. Precision and recall evaluation show promising results [17]. In contrast to previous research efforts, our study addresses several critical challenges in fish classification. Firstly, we tackle the issue of limited dataset availability and the complexity of underwater environments by curating a sizable dataset comprising nearly 8,000 fish images across nine distinct species. Additionally, we employ advanced deep learning techniques coupled with innovative preprocessing methods such as data augmentation, noise removal, and image annotation to enhance model robustness and accuracy. Furthermore, our investigation provides insights into the efficacy of different deep learning architectures. Moreover, our study contributes to the field by providing comprehensive analyses of model performance metrics such as loss functions and mean average precision (mAP), shedding light on the effectiveness of our approach in addressing challenges related to object detection and segmentation in complex underwater environments.

3. METHODOLOGY

This paper investigates the use of deep learning for classifying different species of fish from images. The prescribed methodology utilizes a dataset of nearly 8,000 fish images captured from markets and online sources, encompassing nine distinct categories. To enhance model performance, various techniques are employed, including data augmentation, noise removal, and different model architectures.

A. Dataset Description

The dataset utilized in this research was sourced from local food and fish markets, as well as from Kaggle. Several fish species are represented in the dataset: Oreochromis niloticus (Tilapia), Catla catla (Catla), Labeo rohita (Rohu), Mugilidae (Mullet), Chanos chanos (bangus), Cirrhinus mrigala (Mori), and Hypophthalmichthys molitrix (Silver carp). A total of 7928 images were used, and these were divided into nine different categories.: Rohu (1394), Silver carp (1240), Catla (1255), Mori (1050), Bangus (855), Negative images (735), Tilapia (1510), Mullet (870), Snakehead (1160).

B. Image Augmentation

Data augmentation is a machine learning approach that involves applying different changes to preexisting data without adding new data points, hence increasing the quantity

(a) (b) (c)

Figure 1. (a)Ready Dataset, (b)Dataset collected from fish market, (c) Underwater Fish Images collected from Go-pro hero 9 black underwater camera.

of training data. Data augmentation is based on the notion that by exposing machine learning models to a wider variety of data, it might help them become more broadly applicable. For instance, data augmentation methods for picture classification tasks might involve manipulating

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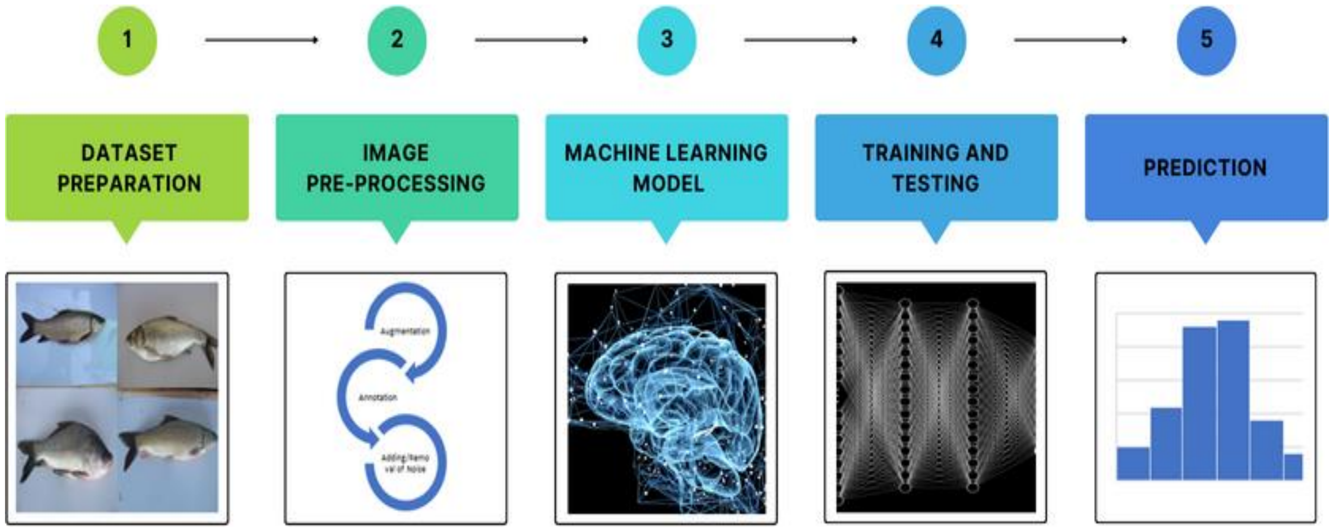
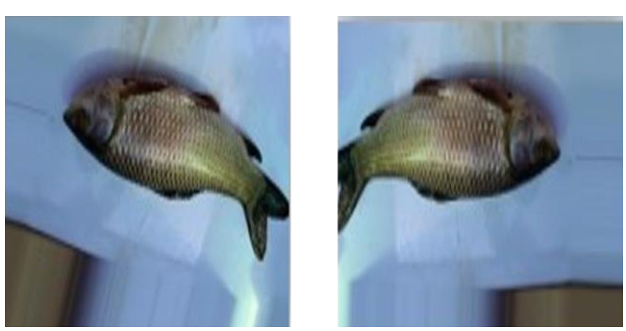


Figure 2. Methodology Block Diagram

photos by flipping, rotating, zooming, or cropping them, altering their contrast or brightness, or introducing noise or distortions. The model may be trained to identify items or patterns that could appear differently in real-world circumstances and become more resilient to changes in lighting, orientation, or other conditions by applying these modifications to the available data. Overall, data augmentation is a powerful tool that can help improve the accuracy and performance of machine learning models, particularly in situations where the amount of training data is limited or imbalanced.



(a) (b)

Figure 3. (a) Original Image, (b) Augmented Image.

C. *Image Annotation:*

Image annotation is the process of labeling, categorizing, or annotating images. It is typically carried out for computer vision or machine learning applications. As it allows one to correlate certain visual aspects or objects in an image with descriptive labels or tags, image annotation is a crucial activity for training and assessing machine learning models. Depending on the particular needs of the application, a variety of picture annotation techniques can be applied. Among the most often used methods for picture annotation are *Bounding box annotation* this involves drawing a rectangular box around objects in an image to indicate their location and size. *Semantic segmentation* this involves labelling each pixel in an image with a corresponding class or category, such as object or background. Instance segmentation this involves labelling each individual instance of an object in an image with a unique identifier, such as a different color or shape. *Landmark annotation* this involves identifying and labelling specific features or landmarks in an image, such as facial features or key points on an object

Figure 4. Annotated Images.

D. *Adding Noise:*

One common technique in machine learning to enhance and increase the variability of data is to add Gaussian noise to the dataset. Random noise with a normal distribution, where values are more likely to be around the

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mean and less likely to be farther from it, is known as Gaussian noise. Each data point in the dataset is given a random value from a normal distribution as part of the Gaussian noise addition procedure. By varying the distribution's standard deviation, one may regulate the amount of noise introduced; larger numbers indicate more substantial noise.

(a) (b)

Figure 5. (a) Original Image, (b) Noisy Image

E. Removal of Noise:

Removing noise from an image is a common image processing task that involves removing unwanted variations or distortions in the image that are not part of the underlying structure or content. Image noise can be caused by various factors, such as sensor noise in the camera, compression artifacts, or interference from other sources. There are various techniques that can be used to remove noise from an image, depending on the type and level of noise present. Some common techniques include: Median filtering, Gaussian filtering, Wavelet denoising, non-local means filtering.

(a) (b)

Figure 6. (a) Noisy Image, (b) Image after removing Noise

F. Classifier Model:

For the purpose of classification, we used 4 different model architectures namely CNN, Resnet152, MobilenetV2 and YOLOV8 etc. following is the information regarding these architectures.

CNN:

Using the TensorFlow Keras API, a basic Convolutional neural network (CNN) model was constructed. It is made up of several fully linked, pooling, and convolutional layers. A max pooling layer with a pool size of 2x2 is placed after the convolutional layer, which has 32 filters and a kernel size of 5x5. Two further pairs of convolutional and max pooling layers, each with 32 filters and a 3x3 kernel size, are then added to this. The last two layers take the feature maps' spatial dimensions down to 1x1, and then they are flattened into a vector. After being flattened, the vector is sent through a dropout layer to lessen overfitting, then a fully connected layer with 512 units and a ReLU activation function. With nine units and a softmax activation function, the final layer is dense and produces a probability distribution across the nine potential classes. In general, this model has nine potential classes and is intended for use in image classification tasks on RGB images with 224 x 224 pixels.

Resnet 152:

A convolutional neural network built on top of the ResNet152 architecture. The base model is loaded with pre-trained ImageNet weights and all its layers are set to be untrainable. A global average pooling layer, two fully linked layers, and a new input layer are defined and coupled to the basic model. The last layer is a softmax activation layer with 9 output classes. The model's optimizer, loss function, and evaluation metric are set using the compile() method. The model is then trained using the fit() function with early halting as a callback to avoid overfitting on the training set. The history object is used to store the training history of the model, which is then used to plot the training and validation loss and accuracy over epochs. Overall, this classification model using transfer learning with the ResNet152 architecture for image recognition tasks with 9 output classes.

Mobilenet V2:

Using the MobileNetV2 architecture as the convolutional base, a convolutional neural network (CNN) model was constructed. The ImageNet dataset, which comprises millions of photos with thousands of classifications, was used to train the pre-trained CNN model known as MobileNetV2. The first line of code imports the MobileNetV2 model with pre-trained weights from the ImageNet dataset, but with the top layer removed. The trainable parameter is set to False to freeze the weights of the convolutional base, preventing them from being updated during training. The next few lines define the input and output layers of the model, as well as the intermediate layers. The 240x240 RGB image that makes up the input layer's form specification. A global average pooling layer is then applied to the MobileNetV2 convolutional base output in order to compress the spatial dimensions of the feature mappings to a single vector. After that, this vector is sent through a dropout layer to lessen overfitting, then a fully connected layer with 512 units and a ReLU activation function. Ultimately, a probability distribution across the nine potential classes is produced by the dense layer with nine units and a softmax activation function that makes up the output layer. The optimizer, loss function, and model metrics are specified using the compile method. The model's performance is assessed using the accuracy metric, the categorical cross-entropy loss function is employed for multi-class classification, and the Adam optimizer with a learning rate of 0.0001 is employed in this instance. Next, the model is trained using the training data by invoking the fit function. To guarantee that the complete dataset is used for training and validation, the steps_per_epoch and validation_steps parameters are set to the lengths of the training and validation data generators, respectively. If the validation loss does not improve after four epochs, training is stopped early using the EarlyStopping callback, and the best weights from the training process are restored by setting the restore_best_weights argument to True. Lastly, using the history object that the fit method returned, the training and validation loss and accuracy are shown over the training process.

YOLOv8:

The most recent state-of-the-art YOLO model, YOLOv8, is distinguished by its ability to perform a wide range of tasks, including object identification, image categorization, and instance segmentation. The article uses Roboflow platform to harness the potential of YOLOv8. This all-inclusive solution not only made it easier to implement the YOLOv8 model for particular goals, but it also made crucial chores like augmentation and annotation much more efficient. The overall research was more efficient since the augmentation and annotation processes ran well in the Roboflow environment.

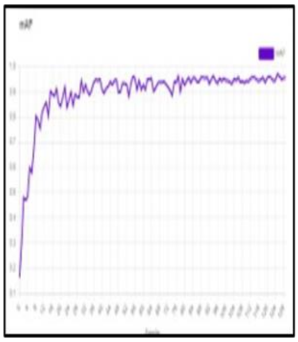
After all the models were ready, they were deployed in a web application using Flask. The deployment of a machine learning model using TensorFlow and Flask involves a meticulous process. TensorFlow, renowned for its capabilities in model development and training, is paired with Flask, a lightweight Python web framework, to serve predictions from the trained model. Upon the completion of training, the TensorFlow model is saved in HDF5 format, recognized by the ".h5" extension, facilitating seamless storage and retrieval of TensorFlow models. In the Flask application setup, careful attention is given to the integration of the trained TensorFlow model. Specifically, code is crafted to initialize the Flask app, ensuring the timely loading of the TensorFlow model from the ".h5" file into the application's memory upon startup. This preparatory step guarantees that the model stands ready to execute predictions as soon as the Flask app becomes operational. Furthermore, the Flask application architecture is meticulously designed to accommodate diverse incoming requests. Through the definition of routes within the Flask app, a structured approach is established to manage various types of requests effectively. For instance, a dedicated route may be allocated to handle POST requests containing input data awaiting prediction. Upon receipt of such requests, the data undergoes preprocessing tailored to the model's requirements, encompassing tasks such as scaling or formatting. Subsequently, the preprocessed data is seamlessly relayed to the loaded TensorFlow model for prediction. Upon completion of the prediction process, the resulting output is meticulously formatted and encapsulated within an appropriate response. This response, often presented in JSON format or a similarly structured representation, is then dispatched to fulfill the original client request. In summary, the orchestrated deployment of a TensorFlow model within a Flask application exemplifies a meticulous endeavor, characterized by seamless model integration, structured request handling, and comprehensive testing protocols. Such endeavors pave the path towards the realization of efficient and scalable machine learning-powered solutions in real-world applications.

4. Results

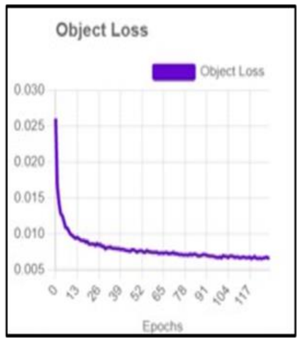
TABLE I. COMPARISION OF MODELS

Model Architecture	Performance Metrics	
	Accuracy	*Loss*
CNN	55.96 %	0.36
ResNet152	73.23%	0.54
MobileNetV2	77.51%	0.64
YOLOv8	94.8%	0.02

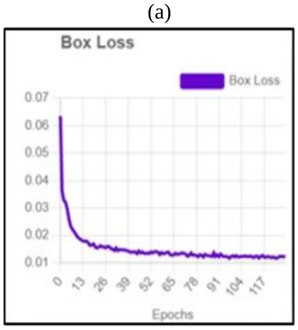
It is evident from the above table that the CNN model is the least accurate. Regarding predicting, CNN and Resnet152 provided some inaccurate estimates. Out of all the models, YOLOV8 had the best accuracy (94.8%), along with a good prediction. Systems for object detection and segmentation are frequently evaluated for performance using Mean Average Precision (mAP). The YOLOV8 curve in Figure 8a) makes it clear that the model has been properly trained. The remaining three plots different forms of losses: object, class, and box losses. Box loss is a measure of how successfully the algorithm locates an object's center and how well an object is covered by the projected bounding box. The sum of the squared errors between the expected and ground truth bounding boxes and class probabilities is the basis for object loss.



(a)



(b)



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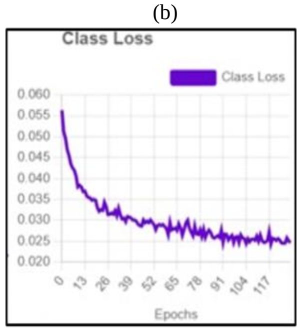
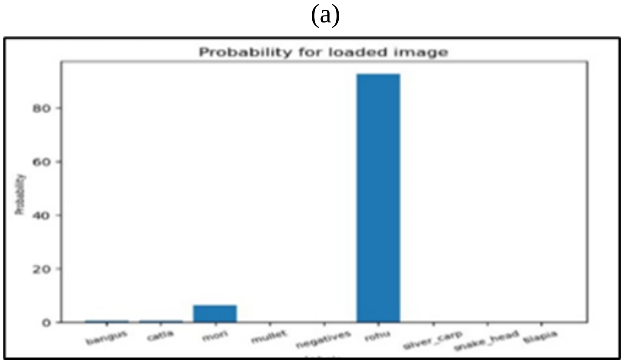


(d)

Figure 8. (a) mAP curve (b) Object loss (c) Box Loss (d) Class Loss for YOLO V8 Model

Figure 8 shows that there are very few losses, which means that YOLOV8 has outperformed all other models with respect to predictions as well as accuracy.

(a)



(b)

FIGURE 9: (a) Rohu (b) Prediction Plot

Figure 9 shows an underwater photo of Rohu taken with a GoPro camera, and a bar graph for the MobilenetV2 model with predictions of 92.56% for Rohu. The results make it evident that YOLOV8 and MobilenetV2 have excellent prediction accuracy. For the same image Figure-9(a) the Resnet 152 even though is a deeper model gave wrong prediction as mullet. Even though Yolo v8 and Mobilenetv2 are well trained there is a possibility that these models can provide wrong prediction.

(a)


```
{
"predictions":[
  {
    "x": 255,
    "y": 133,
    "width": 508,
    "height": 266,
    "confidence": 0.566,
    "class": "tilapia"
  }
 ]
}
```


(b)

FIGURE 10: (a)Tilapia (b) Prediction Plot

Figure 10 illustrates the prediction of the YOLOV8 model. The picture of the fish, which was taken from the GoPro Hero 9 Black underwater camera, was used as the input for the prediction. The picture next to it indicates that the model correctly identified the fish as tilapia 56.6% of the time, despite the fact that it is hard to see. This indicates how successfully the model has been trained.

5. Conclusion

This study has determined the accuracy and loss function for each model. CNN produced an accuracy of 55.6% and a loss function of 0.3581, mobileNetV2 produced the second-highest accuracy of 77.51% but a higher loss function of 0.6400, Resnet152 produced an accuracy of roughly 73.23% and a loss function of roughly 0.5430, and YoloV8 produced the highest accuracy of 94.8% with a lower loss function of 0.02 in comparison to all other models. Thus, it can be concluded from the comparison above that the YoloV8 model produced the best accuracy and lowest error. The model stands out with its 94.8% accuracy, exceeding the next best by 0.7% which was implemented. Additionally, its advantages in architecture, dataset size, and noise handling position it as a robust and generalizable solution for diverse underwater environments and fish species. Beyond fish species classification, the system's potential extends to environmental monitoring by integrating with applications measuring temperature, water quality, and other factors affecting fish populations. This integration allows for the identification of potential hazards and targeted conservation measures. The system's utility further extends to estimating biomass and counting fish, offering insights into the health and abundance of fish populations, enabling sustainable harvesting practices, and informing fisheries management strategies. In order to improve efficiency, this paper recommends implementing an automated fish sorting system that sorts fish according to species or other characteristics. By reducing personnel expenses related to manual sorting, this integration enhances commercial fishing operations. Overall, the fish species classification system's value is increased by its connectivity with other applications, which helps conservation efforts, encourages sustainable fishing methods, and advances our knowledge of fish species.

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