"Fresh-Net Vision": Sorting of Fresh Fishes using Machine Learning and Image Processing

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***Abstract*- "Fresh-Net Vision" simplifies the sorting of seafood through image processing and machine learning, prioritizing efficiency, accuracy, and ethical practices. This initiative employs ML algorithms to intelligently categorize fish by species and size, surpassing manual sorting standards. The project's approach emphasizes humane treatment, acknowledging the food supply chain's role. The report outlines the methodology, ML model customization for Raspberry Pi, and real-time communication with ESP32. User-friendly interfaces, infrared sensors, and servo motors enhance precision. Subsequent sections delve into tools, technologies, and ethical considerations, illuminating the project's workings.**

Keywords— Real-time communication, ESP32, Servo motors, infrared sensors, YOLOv8

I. Introduction

Within the ever-changing seafood industry, the "Fresh-Net Vision" project stands out with the potential to completely decrease the effort when it comes to sorting freshly caught fish. This innovative project unifies real-time hardware implementation, machine learning (ML), and image processing.

The main goal of the project is to revolutionize the fish sorting industry by going beyond the constraints of the manual sorting methods that have long been the norm, especially in India. The project intends to develop an intelligent system that can classify fish according to species and size by utilizing machine learning algorithms. This will enable a smooth and effective transition from the point of catch to the international market.

Moving forward through the chapters, each section will shed light on the inner workings of the project and offer a detailed understanding of the technologies, tools, and moral considerations that take this project one step closer to a new era of fish sorting.

II. Related Works

The sorting of dried Danggits using machine vision [1] as proposed by Dennis M. Barrios, Ramil G Lumauag and Jolitte A. Villaruz first starts involves data collection, hardware setup with a camera and sorting device, and software development. The system uses size identifier to process images and classification algorithm, though future work could enhance its automation capabilities. M. Yousef Ibrahim and J Wang have designed a system [2] using innovative projectile inspired flaps. This offers a promising solution to enhance efficiency and reduce manual labor in the fishing industry. The size estimation of Yellow Croakers [3], a type of fish was achieved through an area-weight prediction model by Yuanhong Wu, Rui Zhuang, Zhendong Cui, employing a power curve for precise fitting. The quality of the fish is evaluated using various color features from the fisheye sclera. Yunhan Yang et al used deep Convolutional Neural Networks (CNNs) to predict Australasian snapper weight from 529 images in [4]. Image pre-processing involves cropping, padding, resizing, and normalization. VGG-11, ResNet-18, and DenseNet-121 CNN architectures are trained via 5fold cross-validation in PyTorch. Evaluation metrics include R2, Mean Squared Error, and Root Mean Squared Error. Results, analyzed quantitatively and visually, elucidate the efficacy of CNNs in predicting fish weight. The inclusion of VGG-16, known for its simplicity and effectiveness, provides a solid baseline for comparison. DenseNet's dense connectivity patterns foster feature reuse, potentially enhancing model efficiency. ResNet-18, with its residual blocks, tackles the vanishing gradient problem, aiding the training of deep networks.

III. Methodology

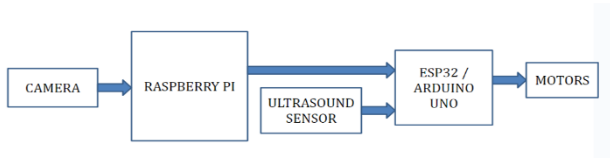

Figure. 1 Block Diagram of Hardware Design

To ensure accurate detection and identification, a diverse dataset that spans different fish species and sizes is included. This project considers 10 common fishes found in the waters of South India. Notably, a fundamental element of CNN principles is the implementation of YOLOv8.

Real-time communication is ensured by Arduino UNO and Raspberry Pi platforms, which also enables intelligent decision-making during sorting. Fish are precisely positioned on the conveyer belt and then sorted based on the decision made.
User communication is essential. Users can enter specific fish species through the GUI created. Tools such as TensorFlow, OpenCV, Python is selected to power the process.

1. Data Collection and Preparation

Flow of project starts with data collection where 10 common fishes found in the waters of south India have been considered. These include Catla, Croaker, Horse Mackerel, Mackerel, Milkfish, Rohu, Sardine, Sea Bass, Threadfin, Tilapia. Images were captured using a smartphone camera of 2600x4624 pixels. And were later resized.

For the preparation of data, images were augmented and resized to the size of 640x640. This was done with the help of Kernel Bulk Image Resizer Software. And image labelling was done using Roboflow. Each image in the dataset was manually labelled which guaranteed accuracy for training the data. Augmentation helps the model generalize between different images that are present and provides a much diverse dataset in the real-world scenario. This ensures accurate detection during the actual process of identification.

2. Model Architecture, Training

For the model the YOLOv8n has been used. It is known for its fast and accurate detection. The model follows the Single-Stage detection approach that is the whole image is processed in a single pass. This ensures that the fish is detected and identified accurately at a high speed. It is also relatively easy to use.

The training of the model using the dataset was done on Kaggle. Kaggle offers GPUs with high computational power which accelerated the training process of YOLOv8n. Its tailored design ensures optimal utilization of the Raspberry Pi's computational resources for efficient fish sorting, the ML model undergoes rigorous training to learn and discern the intricate patterns and features crucial for accurate fish identification and categorization.

3. Model Optimization

During training, the model undergoes iterative optimization, fine-tuning its parameters to enhance accuracy and generalize effectively across various conditions. This iterative process ensures that the ML model becomes adept at recognizing diverse fish species and sizes encountered in real-world scenarios.

4. User Input

A GUI has been designed using Figma and Tkinter. This platform can be used to choose the fish which is to be sorted. This interface will also give a count of Small, Medium and Large Fishes as well as a count of the rejected fishes.

A live camera feed is connected to the GUI to observe the flow of fish if needed. A motor control switch is present. This switch can be used to either turn the conveyer belt ON or OFF.

5. Infrared Sensors and Servo Motors

Strategically placed infrared sensors play a key role in enhancing the precision of fish sorting. Paired with servo motors, these sensors contribute to accurate decision-making and physical sorting mechanisms on the conveyor belt. This synchronized integration ensures the efficient placement of identified fish, optimizing the overall sorting process.

6. Bucket Counting Mechanism

A dedicated mechanism involving infrared sensors is implemented for accurate counting of fish in each designated bucket. The count is updated in the GUI for each designated class of fish. This mechanism enables the system to keep track of the sorted fish, contributing to efficient data collection and process monitoring.

7. Size Categorization and Fish Grouping

The size categorization and fish grouping phase of the project involves the Raspberry Pi platform, adding a layer of sophistication to the sorting process. The Arduino UNO is then used to control the respective gates and the corresponding IR sensors.

8. Decision making using Arduino UNO

Once the fish species and size are identified, the Arduino authorizes its decision-making capabilities to categorize the fish into three groups: small, medium, and large. This intelligent categorization is based on the visual information obtained during the sorting process from the raspberry pi allowing the system to make decisions tailored to each individual fish. Fishes which do not fall into any of these categories, are considered as rejected fishes.

9. Servo Motors for Size-Based Sorting

The Arduino UNO's decisions trigger the activation of servo motors, essential components for guiding the fish to the appropriate size buckets. The seamless integration of servo motors ensures a precise and controlled sorting mechanism, directing each fish to its designated category based on the Arduino UNO's analysis. This process streamlines the workflow, enhancing the overall efficiency of size categorization.

10. Data Logging and Monitoring

Simultaneously, the Arduino UNO facilitates data logging and monitoring, keeping a record of the categorized fish in each size group. This information contributes to process optimization and provides valuable insights for future improvements. Arduino UNO's role in data management enhances the system's overall traceability and adaptability to varying conditions.

11. Programming Languages

Python stands as the primary programming language for implementing the ML model, data preprocessing, and system integration. Its versatility and extensive libraries make it an ideal choice for orchestrating the various components of this project.

12. Hardware Platforms

Raspberry Pi: The Raspberry Pi serves as the core computing platform, responsible for running the ML model, coordinating the sorting process, and capturing fish images using the Raspberry Pi Camera with LED light. Its compact design and computational capabilities make it an efficient and practical choice for on-the-ground implementation.

Arduino UNO: Integrated for real-time communication with hardware components and decision-making capabilities, the Arduino UNO enhances the system's intelligence. Its role in categorizing fish based on size and facilitating data logging adds a layer of sophistication to the sorting process.

13. Image Processing and Computer Vision

OpenCV: A fundamental library used for image processing and computer vision tasks. Its extensive set of tools contributes to the system's ability to analyse and interpret fish images with precision. The Images of Fishes are captured through this platform and then resized accordingly.

Figure 2 shows the CAD model designed to implement the project.

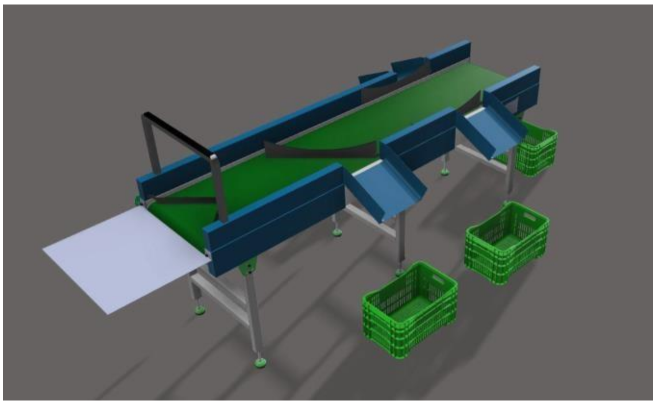

Figure. 2 CAD design of fish sorting machine

IV. IMPLEMENTATION

The hardware setup in Figure 3, consists of a conveyer belt supported by two rollers on either side to aid in the movement of the belt and simultaneously in the movement of the fishes to the corresponding hoppers that are made to guide the fishes to the respective baskets.

Simultaneously, the hardware setup is configured to enable real-time communication and decision-making during the sorting process. The Raspberry pi along with the camera is placed on a stand facing the input stream.

Figure. 3 Implemented Hardware

An Arduino UNO serves as the central control unit, orchestrating the movement of the conveyor belt DC motor based on user inputs from the GUI. Additionally, a gate mechanism, comprising of servo motors and an IR sensor is integrated with the Arduino Uno. This mechanism ensures precise sorting by opening the appropriate gate upon detection of the selected fish species, while diverting undesired or unknown species away from the sorting process. Figure 4 shows the circuit control for the gates integrated with IR sensors and servo motors.

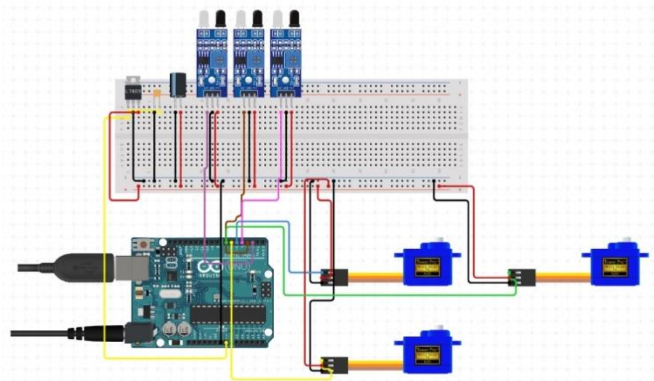

Figure. 4 Circuit Control for gates

V. RESULTS

With each fish detected as small medium and large for the corresponding fish species the slot in the GUI is updated. Fish selected is displayed along with the Live Feed from the camera as seen on figure 5.

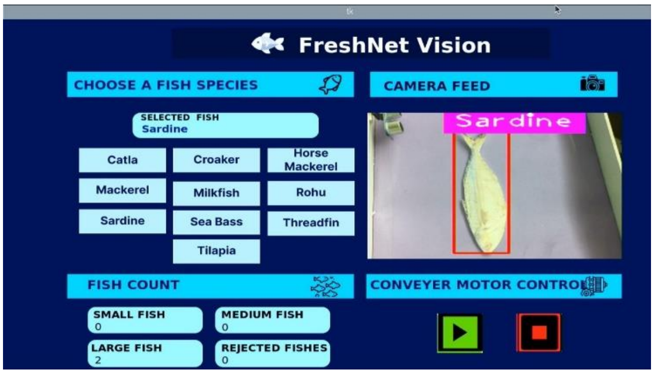

Figure. 5 GUI with results

YOLOv8n is the ML model used for the training process. Following are the results of the model. This model will output bounding boxes. These bounding boxes will include the labels of the detected fish as well as the accuracy of the detected fish. The model has successfully detected the fish. These bounding boxes as seen on Figure 6, can be used to localize the fish in the images or videos. They are also used to approximate the size of fish using a calibrated constant value.

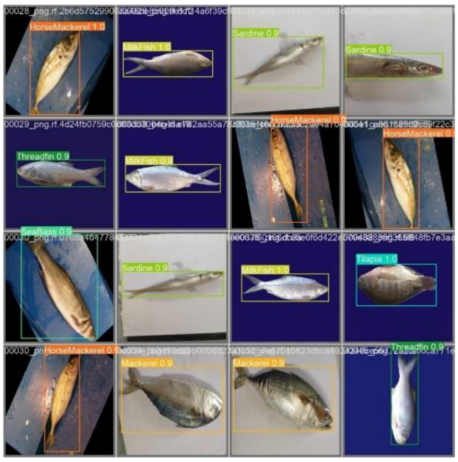

Figure. 6 Fish Detection using YOLOv8n.

The confusion matrix as seen on Figure 7, is a table layout that allows the visualization of the performance of an algorithm. It helps in evaluating the performance of a classification model. Especially in our case due to an unbalanced dataset. The diagonal of the confusion matrix represents the true positives (TP) for each class (fish species), meaning the instances where the model correctly predicted that class. This matrix provides a detailed view of the model's performance for each class and can be used to calculate various evaluation metrics such as accuracy, precision, recall, and F1 score for each class.

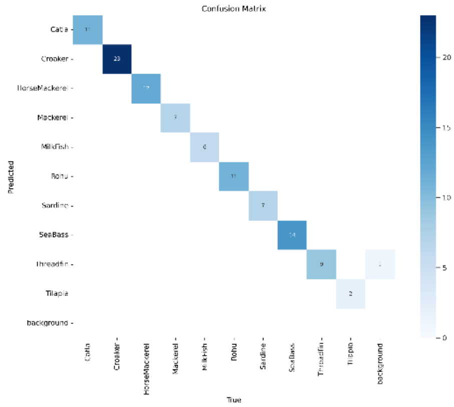

Figure. 7 Confusion Matrix

The Recall-Confidence Curve shows how the precision of the model changes with respect to different levels of recall. It plots the recall against different confident thresholds. This pattern in Figure 8 indicates that as the model becomes more lenient in its detections (lowering the confidence threshold), it starts detecting more instances, including many false positives. This behavior can be seen in models that prioritize recall over precision, possibly due to a high threshold for what is considered fish detection.

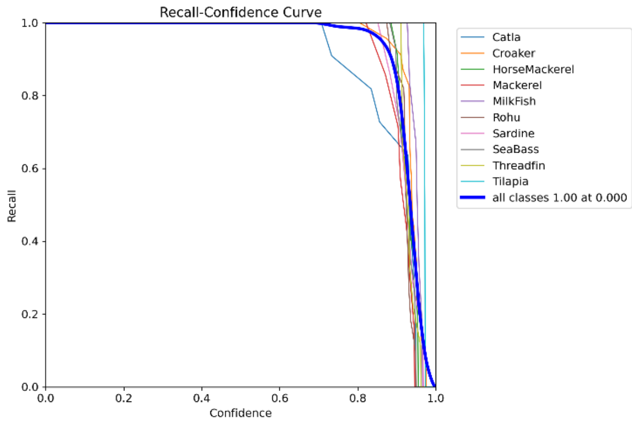

Figure. 8 Recall-Confidence Curve

The Precision-Recall curve obtained is almost a perfect curve, indicating that the model achieves 100% precision for all levels of recall. This means that every positive prediction made by the model is correct. In Figure 9, at high confidence thresholds, the model makes very confident predictions. Since it only predicts instances with high confidence, these predictions are likely to be correct, leading to high precision. As the confidence threshold decreases, the model starts making more predictions, including instances that it is less certain about. This leads to an increase in recall.

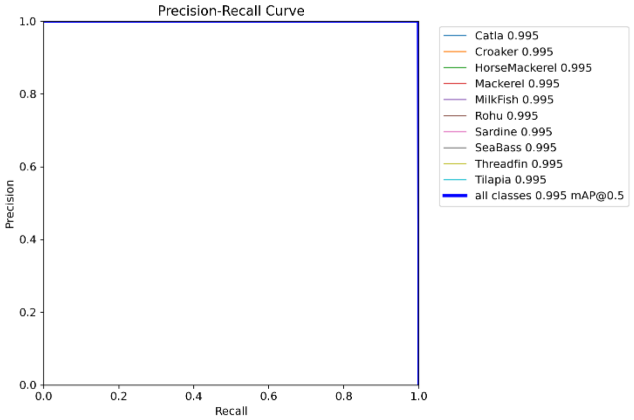

Figure. 9 Precision-Recall Curve

The F1-score in Figure 10, indicates a good balance between precision and recall. The x-axis represents the confidence threshold, and the y axis represents the corresponding F1 score.

F1 score evaluates model's performance changes with different confidence thresholds. A higher F1 score indicates better performance, and the confidence threshold at which the F1 score is maximized is often considered the optimal threshold for making predictions.

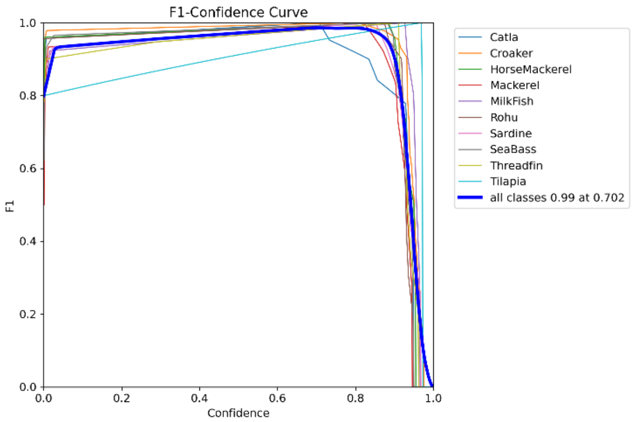

Figure. 10 F1-Confidence Curve

VI. REFERENCES

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