VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

Department of Computer Engineering

Project Report on

Masa Daily: A Fisherman's Guide

In partial fulfillment of the Fourth Year, Bachelor of Engineering (B.E.) Degree in Computer Engineering at the University of Mumbai

Academic Year 2022-23

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(2023-24)

VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

Department of Computer Engineering

Certificate

This is to certify that **Denzil Nelson (D17B, 57), Omkar Mahajan (D17B, 39), Divyang Patel (D17B, 53), Sanket Jaiswal (D17B, 56***)* of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on "**Masa Daily: A Fisherman's Guide** " as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor **Dr. Dashrath Mane** in the year 2023-24.

This project report entitled **Masa Daily: A Fisherman's Guide** by ***Denzil Nelson, Omkar Mahajan, Divyang Patel, and Sanket Jaiswal*** is approved for the degree of **B.E. Computer Engineering.**

Programme Outcomes	Grade
PO1,PO2,PO3,PO4,PO5,PO6,PO7, PO8, PO9, PO10, PO11, PO12 PSO1, PSO2	

Date:

Project Guide:

Project Report Approval

For

B. E (Computer Engineering)

This project report entitled **Masa Daily: A Fisherman's Guide** by **Denzil Nelson, Omkar Mahajan,** ***Divyang Patel, and*** **Sanket Jaiswal** is approved for the degree of **B.E. Computer Engineering.**

Internal Examiner

External Examiner

Head of the Department

Principal

Date:

Place: Mumbai

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Date:

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We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement several times

Computer Engineering Department

COURSE OUTCOMES FOR B.E PROJECT

Learners will be able to,

Course Outcome	**Description of the Course Outcome**
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilised.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one's competency.
CO 11	Able to develop a professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

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Abstract

The "Masa Daily" initiative stands at the forefront of leveraging cutting-edge technology to propel marine fishing practices into a new era of efficiency and sustainability. Through the integration of Machine Learning and Computer Vision technologies, this groundbreaking project endeavors to equip fishermen with sophisticated tools that revolutionize the way they operate on the open waters.

At the heart of "Masa Daily" lies a multifaceted approach aimed at addressing the intricate challenges inherent in marine fisheries. Central to its mission is the provision of Potential Fishing Zone (PFZ) data to fishermen, arming them with invaluable insights into the most optimal locations for their endeavors. By harnessing real-time data and predictive analytics, fishermen can now make informed decisions regarding where to cast their nets, significantly enhancing their chances of a fruitful catch while minimizing unnecessary resource depletion.

Furthermore, "Masa Daily" recognizes the critical role that weather conditions play in the success and safety of fishing expeditions. To this end, the initiative delivers comprehensive weather data directly to fishermen, enabling them to navigate volatile marine environments with confidence and foresight. By empowering fishermen with up-to-the-minute weather forecasts and insights, the project mitigates risks and ensures safer operations at sea.

In its relentless pursuit of innovation, "Masa Daily" has embarked on ambitious research endeavors aimed at automating fish detection on fishing vessels. By leveraging advanced image recognition model like YOLOv8, the project seeks to streamline the laborious process of identifying and sorting through various fish species. This automated approach not only accelerates the fishing process but also facilitates more accurate catch selection, reducing bycatch and minimizing the ecological impact of fishing activities.

Moreover, "Masa Daily" recognizes the imperative of sustainability in modern fishing practices. By promoting the adoption of advanced technologies and data-driven strategies, the initiative aims to foster a more harmonious relationship between fishermen and marine ecosystems. Through optimized catch selection and navigation, as well as the reduction of manual monitoring and reporting, "Masa Daily" paves the way for a future where sustainable fishing practices are not just a lofty ideal but a tangible reality.

In essence, "Masa Daily" represents a paradigm shift in the fishing industry, where technology serves as a catalyst for positive change. By empowering fishermen with advanced tools and insights, the initiative not only enhances their livelihoods but also contributes to the preservation of marine biodiversity for generations to come. In the vast expanse of the open waters, "Masa Daily" shines as a beacon of innovation, guiding the way towards a more sustainable and prosperous future for all stakeholders involved.

Chapter 1: Introduction

1.1. Introduction:

Fishing has been an integral part of India's cultural and economic fabric for centuries, providing sustenance and livelihoods to millions of coastal communities. The nation's vast coastline offers abundant marine resources, yet the journey of Indian fishermen is fraught with challenges. These challenges include unpredictable weather conditions, navigating vast expanses of the sea, and, more importantly, the absence of adequate technological support to optimize their catch selection and reporting mechanisms.

In this academic research report, we embark on a journey into the world of marine fishing in India, with a primary focus on addressing the pressing need for a guiding application for fishermen and the modernization of data collection and reporting methods.

1.2. Motivation:

The motivation behind this research lies in recognizing the potential to enhance the lives of Indian fishermen and improve the sustainability of marine resources through technological intervention. The aspiration to build a guiding application that empowers fishermen with real-time data and predictive analytics stems from the understanding that such a tool can revolutionize the fishing industry. Moreover, there is an intrinsic motivation to alleviate the challenges posed by outdated data collection and reporting mechanisms, ultimately leading to more informed decision-making and sustainable fishing practices.

1.3. Problem Definition:

The primary problem addressed by this research report is two-fold:

1. Outdated Data Collection and Reporting:

The marine fishing industry in India continues to rely on archaic manual methods for logging and reporting fishing activities. These methods result in limited sample sizes, errors, and outdated datasets. Furthermore, the absence of a centralized system for fish detection and prediction hampers efficiency and sustainability.

2. Need for a Guiding Application:

There is a glaring need for a guiding application tailored to the specific needs of Indian fishermen. The absence of proper guidance, even when technological solutions are available, hinders the adaptation of modern tools by rural fishermen.

3. Electronic monitoring systems:

Modern fishing vessels are equipped with state-of-the-art electronic monitoring systems, featuring video
cameras meticulously positioned to document the bustling deck where fish are landed. Initially designed for security and safety, these camera systems hold untapped potential for identifying fish species and precisely tracking and counting the marine harvest. The urgency to automate these tasks drives our research, emphasizing the need for a real-time image processing system to ensure swift and accurate fish
identification and counting.

1.4. Existing Systems:

1. Fish verify

Fish Verify is a mobile application designed for amateur fishermen as well as small-scale commercial fishermen. The functionality of this application includes:

- Fishing trip and catch log: Fishermen can count and weigh their catch and record it in the app. It records catch along with trip metrics like path followed, time taken, times net deployed, etc.
- Wallet for storing licenses and permits: Fishing in many countries often requires a permit often for multiple authorities, which is a hassle that this feature solves.
- Optical identification of fish: Amature fishermen often don't know about the species of the fish, automated identification helps with this.
- Blogs: The fishermen community can share their experiences, best practices, tips, and tricks with other fishermen using this feature.

Limitations of this application include:

- Paid subscription

- No PFZ detection
- It is not designed for the Indian environment.

2. Fishing Points

This is a mobile application primarily designed for amateur fishermen in a marine environment. The functionality of this application includes

- Weather forecasting: This is especially useful for amateur fishermen who may cancel their fishing trip even in slightly bad weather.
- Manual catch logging: Fishermen can count and weigh their catch and record it in the app.
- Nautical maps: provide a draft map of oceans, swell direction, wind direction, shipping lanes, maritime borders, etc
- Tide: may influence fish migrating patterns, when boats can move out of harbor, etc

Limitations of this application include:

- Paid subscription
- No PFZ detection
- It is not designed for the Indian environment.

1.5. Lacuna of the Existing System:

Although existing systems have PFZ prediction, catch reporting, etc. None of them is a one-stop solution that is also available in the local language which is a prime requirement for fishermen in India. Most of the existing systems are designed for people to fish as a leisure and not as a living. Hence, commercialization of this app is necessary. The project we are developing would result in an app where both commercial and amateur fishermen can have all the features like fish identification, potential fishing zone identification, catch reporting, and blogs in one easy-to-use app.

1.6. Relevance of the Project:

This research project holds immense relevance due to its potential to transform the fishing industry in India. By addressing the challenges of outdated data collection and reporting methods and introducing a guiding application, the project aims to empower fishermen with real-time insights, bridge gaps in data collection, reduce errors, and promote sustainable fishing practices. This endeavor is not just about technological advancement but also about enhancing the livelihoods of fishermen and preserving marine ecosystems.

Chapter 2: Literature Survey

2.1. Research Papers :

1) Automated Freshwater Fish Species Classification using Deep CNN

Year of Publication: 2023

Inference Drawn: The study reports remarkable results in terms of classification accuracy, precision, and recall rate. Achieving a 100% accuracy rate at a learning rate of 0.001 is a significant accomplishment. This suggests that deep CNN models like AlexNet and ResNet-50 are highly effective in automating the classification of freshwater fish species. The success of these deep CNN models can be indicative of the quality and representativeness of the custom dataset created for the research.

2) The Fishnet Open Images Database: A Dataset for Fish Detection and Fine-Grained Categorization in Fisheries

Year of Publication: 2021

Inference Drawn: This paper introduces the Fishnet Open Images Database, a substantial dataset comprising 86,029 electron microscopy (EM) images, specifically designed for fish detection and fine-grained categorization on commercial fishing vessels. The dataset serves as a benchmark for evaluating the performance of computer vision algorithms in the context of fisheries management.

3) Mobile-based Fish Quality Detection System Using K-Nearest Neighbors Method

Year of Publication: 2020

Inference Drawn: The paper introduces a novel approach for fish quality detection by employing the K-Nearest Neighbors (KNN) algorithm. KNN is known for its simplicity and effectiveness in classification tasks, making it a suitable choice for this application. The reported results indicate that the KNN-based fish quality detection system achieved the highest accuracy of 82.6% and a precision of 84.1%.

4) Forecasts for Fish Migration and Fishing Time under Marine Environment Changes based on the ARIMA Model

Year of Publication: Nov 2020

Inference Drawn: The paper utilizes the ARIMA model to investigate the impact of marine environmental changes on fish migration patterns and fishing time. This method allows for the generation of multiple scenarios, helping to assess the robustness and variability of the forecasts. One of the key findings of this study is the projected reduction in the future migration amount of fish. This result suggests that marine environmental changes are expected to have a significant impact on fish behavior, potentially leading to altered migration patterns or decreased migration altogether.

5) Analyzing and Forecasting Fisheries Time Series: Purse Seine in Indian Ocean as a Case Study

Year of Publication: 2016

Inference Drawn: The primary objective of this research is to analyze and forecast fisheries time series data. Fisheries time series data typically include records of catch levels over time, which are crucial for understanding fish population dynamics and supporting sustainable fisheries management. Purse seine fishing involves the use of large nets to encircle schools of fish, making it particularly relevant to the study of catch patterns in this region.

6) Participatory GIS in Trawl Fisheries along Mumbai Coast, Maharashtra

Year of Publication: 2016

Inference Drawn: The primary focus of this research is the utilization of Geographic Information System (GIS) technology. GIS is a powerful tool for collecting, analyzing, and visualizing spatial data, making it well-suited for studying and managing fisheries in coastal regions. The study is specifically centered around the Mumbai coast in the state of Maharashtra, India. This coastal region is known for its active fisheries, and Mumbai is a major metropolitan city on the western coast.

7) Fish-Pak: Fish species dataset from Pakistan for visual features based classification

Year of Publication: 2019

Inference Drawn: The Fish-Pak dataset serves as a valuable resource for research in fish species classification using computer vision and machine learning techniques. By providing images of six distinct fish species captured under controlled conditions, this dataset facilitates the evaluation of classification algorithms, offering insights into factors like learning rate and momentum. Researchers can leverage this dataset to enhance the performance of Convolutional Neural Networks (CNNs) for visual fish species identification.

8) Exploring Spatiotemporal Trends in Commercial Fishing Effort of an Abalone Fishing Zone: A GIS-Based Hotspot Model

Year of Publication: 2015

Inference Drawn: The research presented in the paper on exploring spatiotemporal trends in commercial fishing effort of an abalone fishing zone highlights the importance of utilizing Geographic Information System (GIS) technology and spatio-statistical models for assessing patterns of fisheries activity. Focusing on the blacklip abalone (Haliotis rubra) stocks along the south-west coast of Victoria, Australia, from 2008 to 2011, the study demonstrates that catch per unit of fishing effort (CPUE) is not uniformly distributed in space and time.

9) Developing a GIS-Based Decision Rule for Sustainable Marine Aquaculture Site Selection: An Application of the Ordered Weighted Average Procedure

Year of Publication: 2021

Inference Drawn: This study on developing a GIS-based decision rule for sustainable marine aquaculture site selection using the Ordered Weighted Averaging (OWA) procedure underscores the significance of incorporating environmental, economic, and social factors into the decision-making process for aquaculture site allocation. By employing the OWA methodology in the Caspian Sea (Iran), the research aims to generate marine aquaculture suitability maps with various strategies, taking into account multiple criteria and constraints.

10) Counting Fish: Testing Shipboard Video Monitoring - Coastwatch

Year of Publication: 2015

Inference Drawn: The study on shipboard video monitoring for fish counting drew several important inferences. It demonstrated that Electronic Monitoring (EM) systems, when compared to records from independent observers, provide a reliable and consistent method for overall fish count, supporting their potential as valuable tools for fisheries management. However, the varying levels of accuracy among fishermen in recording fish counts emphasize the importance of proper training and standardization when implementing EM systems in the fishing industry. The study also highlighted the capacity of EM systems to provide information on species identification and the length of discarded fish, though challenges arise when distinguishing visually similar species.

Chapter 3: Requirement Gathering for the Proposed System

In this chapter, we are going to discuss the resources we have used and how we analyzed what the fishermen actually need and what we can provide. We will also discuss the functional and non-functional requirements and finally the software and hardware used.

3.1. Introduction to Requirement Gathering and Use cases:

Requirement Gathering is a process of requirements discovery or generating list of requirements or collecting as many requirements as possible by end users. It is also called as requirements elicitation or requirement capture.

USE CASE	Description
Register and Login	Fishermen can register and log in the MASA mobile app
Potential Fishing Zone	Fishermen can view the potential fishing zone along the Indian coastline
Waves	Fishermen can get live state of waves in the sea
Sea surface temperature	Fishermen can get live sea surface temperature which is an important factor in estimating catch location
Winds	Fishermen can get live wind direction and speed updates that help to decide the course of their fishing trip
Species identification	Fishermen can use to the MASA app to click an image of a fish and identify its species.
Catch log	Fishermen can maintain a log of their catch
Catch analysis	Fishermen can view previous catches anytime

Table 3.1: Use cases

3.2. Functional Requirements:

- **User Registration and Authentication:**

Users will be able to register and log in securely to access the app's features.

- **Fish Catch Identification:**

Users will be able to identify various fish species using images or descriptions.

- **Catch Log:**

Users will be able to log their fishing activities, including date, time, location, and type of fish caught.

- **Fishing Zone Locator:**

The app will use GPS or map integration to help users locate fishing zones.

- **Catch Count Estimation:**

The app will use statistical algorithms or user-provided data to make estimates.

3.3.Non-Functional Requirements:

- **Performance:**

Response times for fish identification and catch logging should be minimal.

- **Security:**

User data, including login credentials and personal information, should be securely stored

- **Scalability:**

The app will be designed to handle a growing user base and an increasing amount of data.

- **Usability and Accessibility:**

The user interface will be intuitive and user-friendly.

- **Compatibility:**

The app will be compatible with a wide range of Android devices and screen sizes.

3.4.Hardware, Software, Technology and Tools Utilised:

Hardware Used:

- **User:**
  - Smartphones with Android 9+
  - 4GB+ Ram
  - 2GB of free space
- **Developer:**
  - A system with 7th gen i7 or better processor
  - 8GB or more memory
  - 10 GB of free space

Software Used:

- Programming Language: Python 3+, React native / Flutter
- Machine Learning Frameworks: Libraries such as TensorFlow, Keras, PyTorch
- Image Processing Libraries: OpenCV
- Integrated Development Environment (IDE): PyCharm, Jupyter Notebook
- Android Studio version: v3.2-8.2

Tools Used:

- Google collab
- Kaggle
- Roboflow

TECHNOLOGY USED

- **IDE:** Android Studio, PyCharm/VSCode
- **Language:** Python, JAVA, XML
- **Database:** Firebase(Realtime Database & Storage

Tools:-

- **Roboflow:-** Roboflow is a comprehensive platform tailored to facilitate the creation and deployment of computer vision models. It offers a suite of tools encompassing data annotation, preprocessing, and model training, empowering users to develop custom object detection and image classification models with ease. By centralizing these crucial components in a user-friendly interface, Roboflow simplifies the complexities inherent in computer vision workflows, making them accessible to developers of varying expertise levels. With its emphasis on efficiency and scalability, Roboflow accelerates the development cycle, enabling teams to rapidly iterate and deploy high-quality models for diverse applications ranging from autonomous vehicles to medical imaging and beyond.

- **Vscode:-**Visual Studio Code is a streamlined code editor with support for development operations like debugging, task running, and version control. It aims to provide just the tools a developer needs for a quick code-build-debug cycle and leaves more complex workflows to fuller featured IDEs, such as Visual Studio IDE.
- **Google Colab:-** Collaboratory, or "Colab" for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary Python code through the browser and is especially well suited to machine learning, data analysis, and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing access free of charge to computing resources including GPUs.

3.5. Constraints:

- Internet Access is required.
- Fishermen need basic skills to operate a mobile phone.
- Fishermen should have some vocational training to fully utilize MASA app
- Automated counting cannot be implemented in research due to absence of video dataset.

Chapter 4: Proposed Design

4.1. Block Diagram of the proposed system:

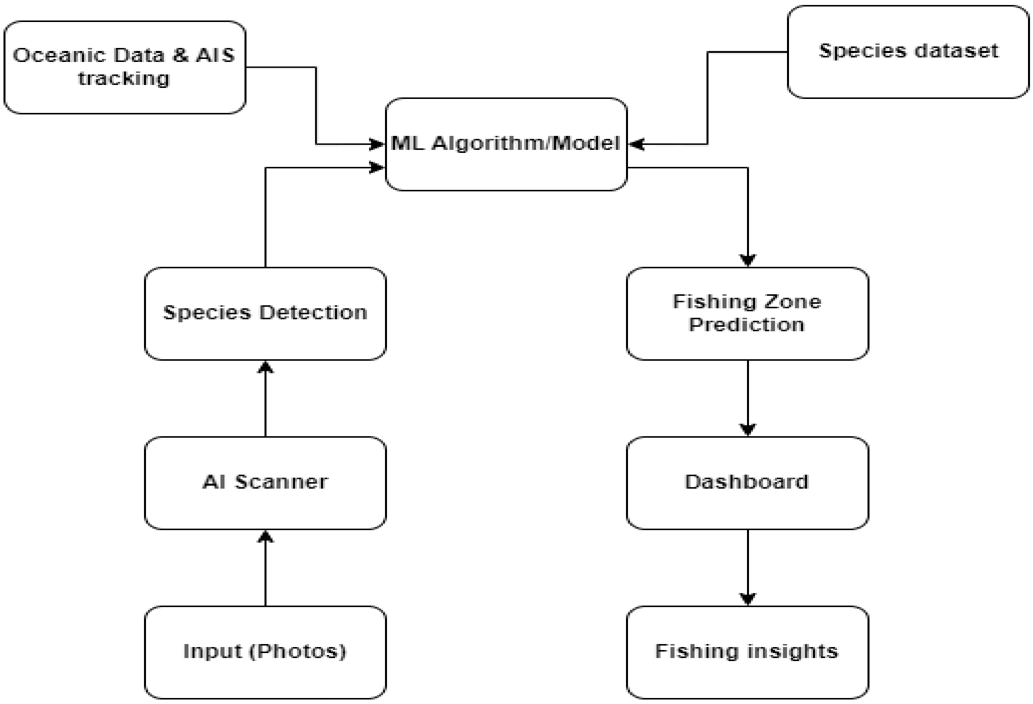

Fig 4.1: Block Diagram

Oceanic Data & AIS Data: Real-time updates from oceanic data and AIS sources enable the model to pinpoint potential fishing zones.

AI Scanner: The AI scanner automates catch reporting by identifying species and quantifying them in uploaded images.

Fishing Zone Prediction: Utilizing machine learning algorithms, historical data, and pertinent factors, the system forecasts optimal fishing zones.

Dashboard: The user-friendly dashboard provides real-time access to a wealth of data, including fishing zone predictions and actionable insights, supporting informed decision-making.

4.2. Project Scheduling & Tracking using Time line/Gantt Chart:

The Gantt chart of our project where we worked for the whole semester to create this model is shown in a timeline pattern. It is the most important part to think and design the planning of your topic and so we planned our work like the gantt chart shown.

	Task	Assigned To	Start	End	Dur	%	2023 Jul	Aug	Sep	Oct
	Masa Daily: A Fisherman's Guide		7/24/23	10/14/23	59					
1	Deciding Project topic and domain		7/24/23	7/26/23	3					
2	Discussing the topic with mentor		7/29/23	8/1/23	2					
3	Research on various papers		8/1/23	8/14/23	10					
4	Working on the Model		8/15/23	8/29/23	11					
5	Meeting with the mentor for discussion		8/30/23	8/31/23	2					
6	Working on the changes		9/1/23	9/4/23	2					
7	Started drafting the Presentation		9/5/23	9/6/23	2					
8	Review 1		9/7/23	9/7/23	1					
9	Worked upon suggestions, and doing more research		9/8/23	9/18/23	7					
10	Started implementation of Android app		9/19/23	10/1/23	9					
11	Meet with mentor		10/2/23	10/2/23	1					
12	Started working on Integration		10/3/23	10/10/23	5					
13	Started drafting the Report		10/11/23	10/12/23	2					
14	Meet with mentor for final suggestions		10/13/23	10/13/23	1					
15	Final Review	Project Chart	10/14/23	10/14/23						

	Task	Assigned To	Start	End	Dur	%	2024 Jan	Feb	Mar	Apr
	Masa Daily - A Fisherman's Guide		1/17/24	4/12/24	63					
1	Started working on changes for new semester		1/17/24	1/17/24	1					
2	Research on new papers		1/18/24	1/25/24	6					
3	Meeting with mentor		1/26/24	1/27/24	1					
4	Improving App UI		1/28/24	1/31/24	3					
5	Improving App functionality for classification of fish		2/1/24	2/6/24	4					
6	Created a draft of Research Paper		2/6/24	2/8/24	3					
7	Meeting with mentor for discussion		2/8/24	2/9/24	2					
8	Review 1		2/9/24	2/10/24	1					
9	Working on Research paper and formatting		2/11/24	2/22/24	9					
10	Added Weather map functionality in app		2/23/24	3/4/24	7					
11	Making suggested changes in Research paper		3/5/24	3/8/24	4					
12	Meeting with mentor for discussion		3/8/24	3/9/24	1					
13	Review 2		3/10/24	3/11/24	1					
14	Improving the research paper		3/12/24	3/21/24	8					
15	Adding PFZ functionality in app		3/22/24	3/28/24	5					
16	Searching for conference/journal for paper publishing		3/29/24	4/6/24	6					
17	Creating Black book and updating the presentation		4/7/24	4/11/24	4					
18	Meeting with mentor for final discussion		4/11/24	4/11/24	1					
19	Final BE project Review		4/12/24	4/12/24	1					

Fig. 4.2: Gantt chart

Chapter 5: Implementation of the Proposed System

5.1.Methodology employed for development:

First, we state the methodology employed for the research module of our project. In the expansive realm of maritime activities, modern fishing vessels are equipped with state-of-the-art electronic monitoring systems, featuring video cameras meticulously positioned to document the bustling deck where fish are landed. Initially designed for security and safety, these camera systems hold untapped potential for identifying fish species and precisely tracking and counting the marine harvest. The urgency to automate these tasks drives our research, emphasizing the need for a real-time image processing system to ensure swift and accurate fish identification and counting. The integration of automated systems, such as real-time image processing technology, offers a robust solution for enforcing fishing catch quotas. By employing advanced algorithms capable of swiftly and accurately identifying fish species and quantities onboard fishing vessels, authorities can efficiently monitor compliance with catch limits. This automated approach reduces reliance on manual inspections, minimizes the risk of errors, and promotes transparency within the fishing industry, ultimately contributing to sustainable fisheries management and the preservation of marine ecosystems.

This automation is achieved through use of YOLO. You Only Look Once (YOLO) operates on the principle of unified object detection through a grid-based approach, exhibiting notable efficacy in real-time computer vision applications. YOLO's core mechanism involves dividing input images into a grid, and each grid cell is responsible for predicting bounding boxes and class probabilities concurrently. This unique design facilitates the expeditious and comprehensive identification of multiple objects within the image. Within each grid cell, YOLO predicts bounding box coordinates relative to the cell's spatial dimensions, along with associated class probabilities. The model employs a single convolutional neural network (CNN) to process the entire image, enabling end-to-end predictions. This streamlined architecture significantly accelerates inference speed while maintaining competitive accuracy, addressing the imperative of real-time applications.

YOLO integrates non-maximum suppression to refine the output by eliminating redundant bounding boxes and enhancing localization precision. The model is trained through a comprehensive loss function, encompassing localization, confidence scores, and class predictions, optimizing parameters through backpropagation. The YOLOv8 model is the latest version of the YOLO model developed by ultralytics company.

Keys features of YOLOv8:

1. Anchor-Free Detection - YOLOv8 diverges significantly from earlier models by adopting an anchor-free approach in object detection. This entails direct prediction of the object's center, eliminating the need for offsets from predefined anchor boxes. Anchor boxes, a historical challenge in earlier YOLO models, often did not align with the distribution of custom datasets. The shift to anchor-free detection in
YOLOv8 addresses the complexities associated with anchor boxes, reducing computational load and enhancing adaptability to custom datasets. This modification significantly impacts the number of box predictions, consequently expediting Non-Maximum Suppression (NMS), a critical post-processing step that refines candidate detections post-inference. This streamlined approach improves the model's efficiency without compromising its real-world applicability.

2. Closing the Mosaic Augmentation - In deep learning research, while model architecture often takes the spotlight, the training routine is crucial for the success of models like YOLOv5 and YOLOv8. YOLOv8 employs online image augmentation during training, exposing the model to slightly varied images in each epoch. A significant technique is mosaic augmentation, where four images are stitched together to challenge the model with new object locations, partial occlusion, and different surroundings. However, empirical evidence suggests that continuous use of mosaic augmentation throughout training can degrade performance. To address this, it is beneficial to disable it for the final ten training epochs.

5.2.Algorithms and Flowcharts for the respective modules developed:

1. ARIMA

ARIMA stands for AutoRegressive Integrated Moving Average and is a widely used time series forecasting method in statistics and data analysis. It is a powerful tool for modeling and predicting time-dependent data, such as stock prices, temperature trends, or sales figures. In the case of this project, it can be used to predict the catch volumes in a particular part of the ocean, which leads to the identification of potential fishing zones.

2. XGBoost Regression

It stands for Extreme Gradient Boosting Regression and is a highly effective machine learning algorithm for solving regression problems. It is part of the gradient-boosting family, known for its remarkable predictive accuracy and versatility.

XGBoost builds an ensemble of decision trees iteratively, where each new tree corrects the errors made by the previous ones. It combines the predictions of multiple weak learners (individual decision trees) to create a strong predictive model. The "gradient" in XGBoost refers to the optimization technique used to minimize the loss function, making it highly efficient and capable of handling large datasets.

3. Convolutional neural networks

Convolutional Neural Networks (CNNs) are a specialized type of artificial neural network designed for processing and analyzing visual data, particularly images and videos. CNNs are inspired by the human visual system, which is proficient at recognizing patterns, edges, and shapes.

CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers are responsible for extracting features from the input data through a process called convolution, which involves sliding small filters (kernels) over the image to detect patterns like edges and textures. Pooling layers reduce the spatial dimensions of the feature maps, which helps reduce computational complexity.

5.3.Datasets source and utilization:

Image Fish classification (Fish Pak Dataset)

This is a demonstration of the classification and species identification of fish using an image dataset. The image would be provided by the user by clicking a picture with the camera interface provided in the app.

We have used MobileNetV2 which is a lightweight convolutional neural network architecture designed for efficient deep learning on mobile devices and embedded systems, offering impressive performance while minimizing computational resources. The dataset had only 36 images per class and had 6 classes in total.

Fishnet Dataset Characteristics

The fishnet data set consists of images from longline tuna vessels in the western and central Pacific are included in the fishnet dataset. Four visually similar tuna species (albacore, yellowfin, skipjack, and bigeye) are represented by almost 85% of the included fish annotations. The "L1" label collection comprises 25 more species from which the other fish annotations are derived. The FAO ASFIS List of Species for Fishery Statistics Purposes is another source of 12 coarser classes that group related species and create the "L2" label set. "Unknown" L1 classes and those with fewer than 1000 labels are included in the L2 "OTH" (other) class; sharks are excluded for conservation purposes. Indicators of fishing activity include annotations made by humans. Due to uneven catch among boats and skewed species distribution, both the L1 and L2 class distributions are long-tailed, as shown in the dataset.

The training, validation, and testing sets are designed to emulate real-world operating situations for EM algorithms. Mimicking both visible (current EM program members) and invisible (new EM program members) vessels is critical. The Fishnet validation and test sets include equal amounts of imagery from "seen" and "unseen" cameras, which is consistent with datasets that originate photographs from many distinct places. The final split included 59,497 training images, 13,648 validation images, and 12,891 test images. Figure 1 depicts the class distribution. Class Frequency Distribution

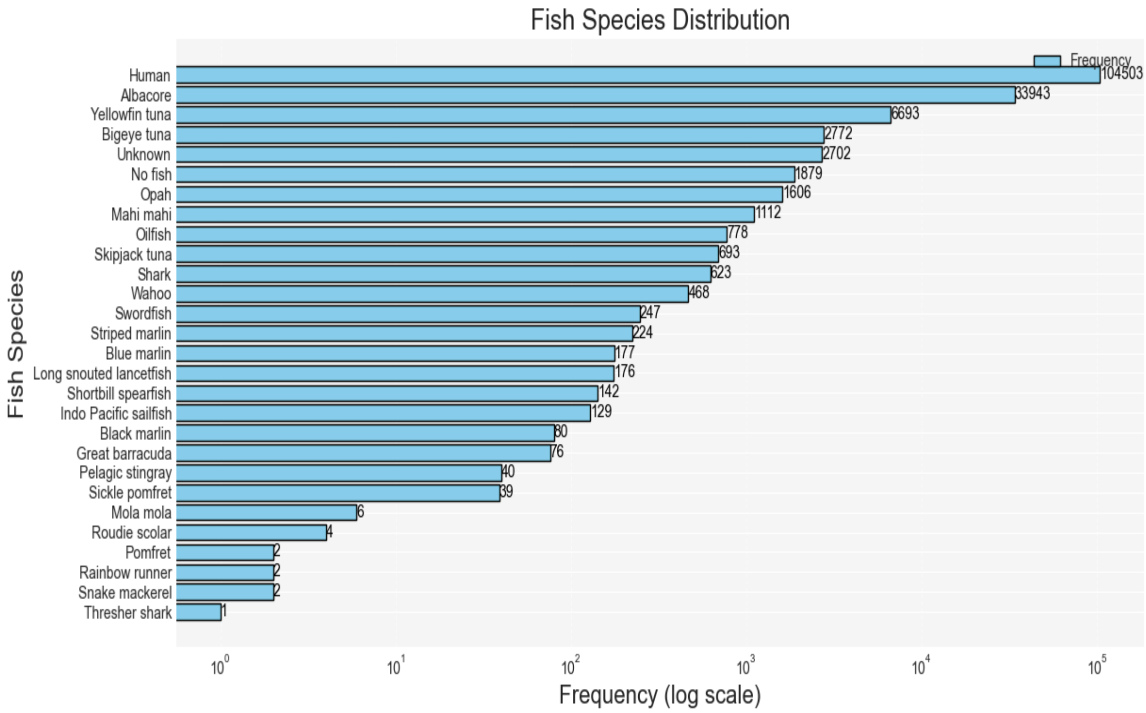

Fig. 5.1. Class Frequency Distribution

The dataset is highly unbalanced as some classes have little representation, which is unsuitable for a good result. As a result, only the most common classes were chosen for training: "Albacore", "Bigeye tuna", "Yellowfin tuna", and "Unknown". A subset of the dataset was isolated such that each class would have 2700 instances spread across 6618 images.

Chapter 6: Results and Discussions

6.1.Screenshot of Use Interface(UI) for the system:

App Screenshots

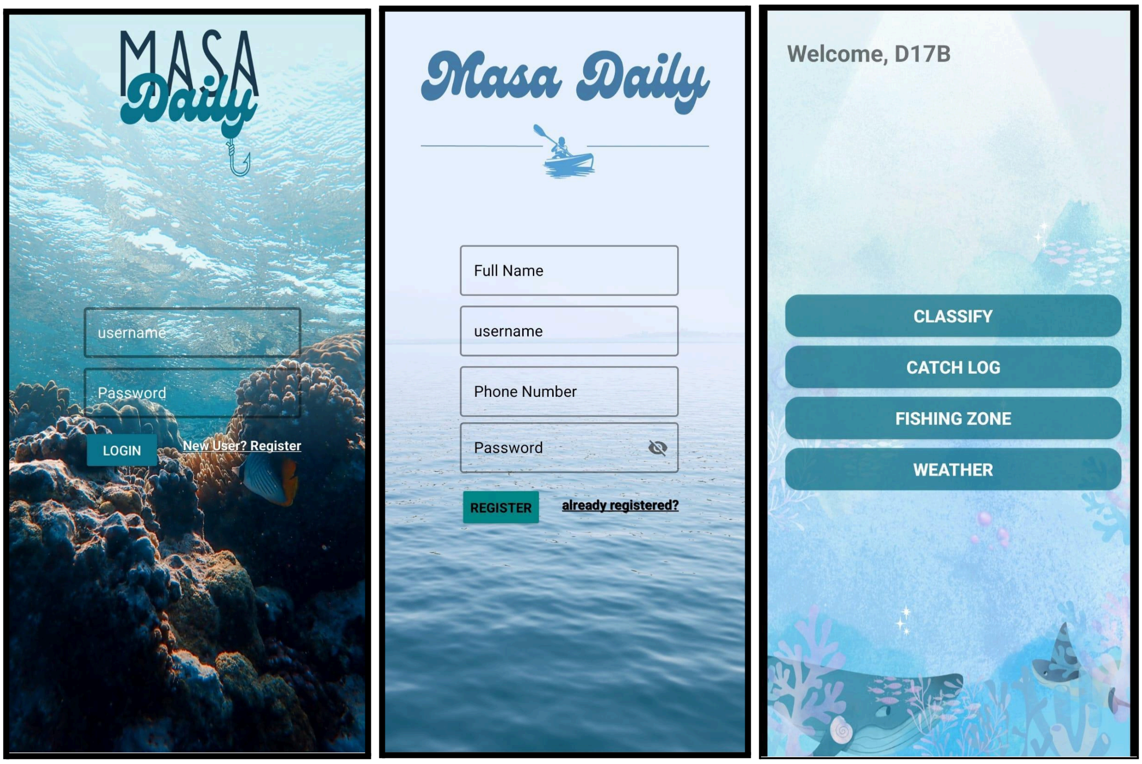

Fig: 6.1.1 Login, Registration, Home page

- The login and registration pages are seamlessly integrated with Firebase real-time database functionality, facilitating efficient data registration and verification processes.
- Each field within both pages is equipped with validation mechanisms tailored to the specific field types. This implementation ensures data integrity and accuracy by enforcing validation rules corresponding to the respective data input requirements.

- The Menu Page provides three functionalities:
    - Classify - For Catch Identification
    - Catch Log - To Keep track of their catches
    - Fishing Zone - To locate the nearby Preferable Fishing Zones
    - Weather - view the current Weather and Ocean Conditions

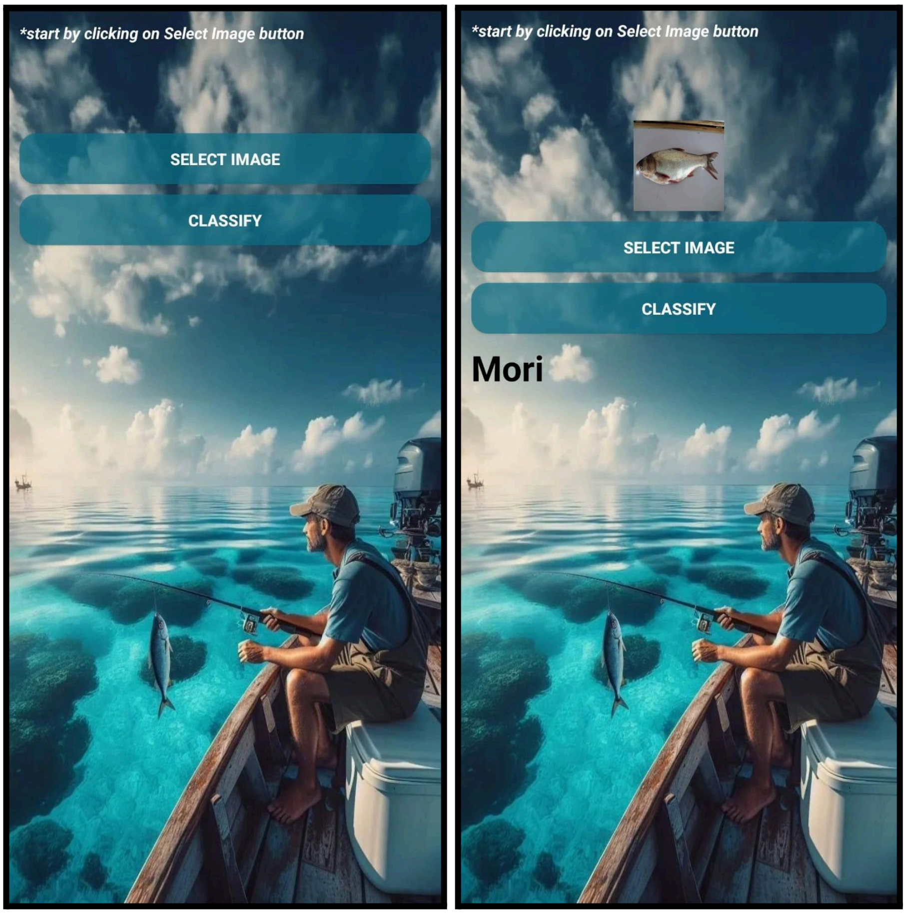

Fig: 6.1.2 Fish identification in app

- The Classification feature facilitates user interaction whereby the selection of an image is enabled through the utilization of the select button, followed by the initiation of the classification process via the classify button. This mechanism empowers users to input images for analysis and promptly obtain corresponding classification results, thereby enhancing the functionality and usability of the system.
- TFLite model integrated into our app, users can enjoy offline functionality, eliminating the need for constant internet connectivity for fish classification. This ensures reliable performance even in remote locations or areas with limited network coverage.
- Our app provides real-time classification capabilities, allowing users to capture fish images on the spot and receive instant identification results.The selected image can be previewed on top and the result can be seen below.

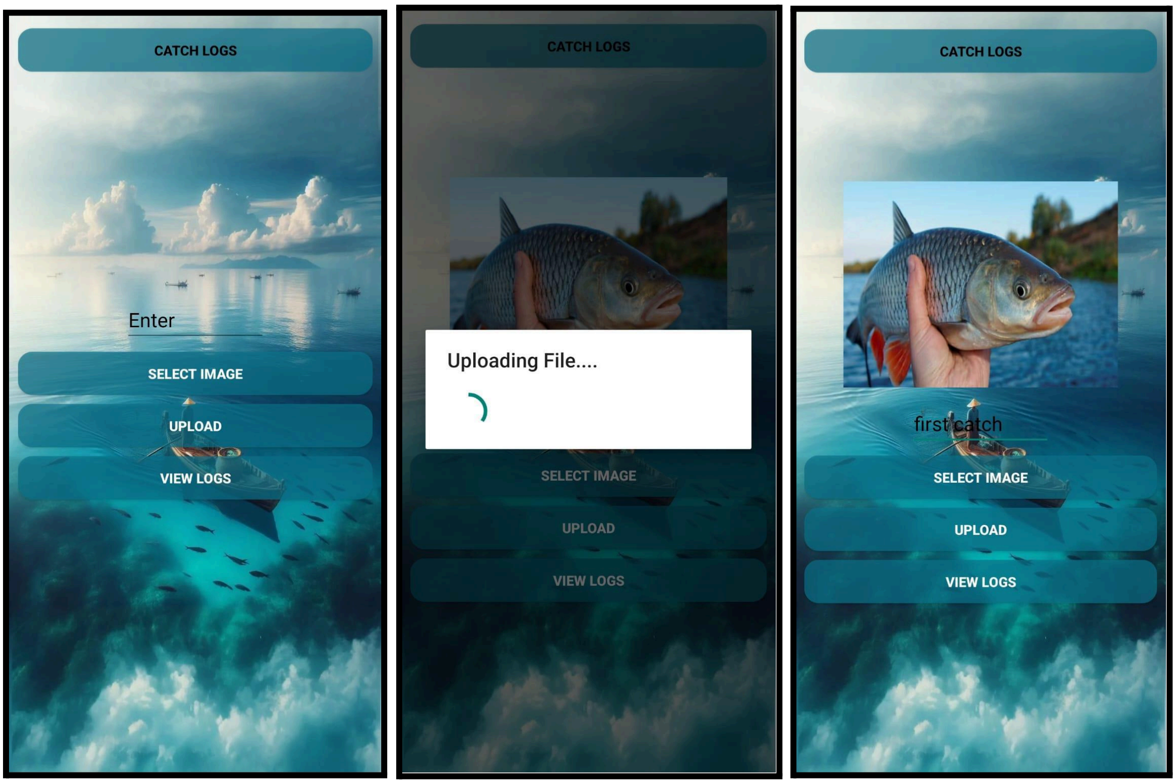

Fig: 6.1.3 Catch Log in app

- Our Android Java app simplifies the process of logging catches with an intuitive upload page. Users can effortlessly select an image of their catch, name it for reference, and proceed to upload it to Firebase Storage with just a few clicks.
- In the event of an error arising during the loading procedure, the user is promptly apprised through the utilization of a toast message mechanism. This notification method serves to enhance user experience by providing expedient recognition of encountered failures, thus facilitating efficient error resolution and enabling seamless reporting procedures.
- Our app ensures secure and reliable storage for users' catch images. The seamless integration enables quick and hassle-free uploading, providing users with peace of mind knowing that their valuable catch data is safely stored in the cloud.

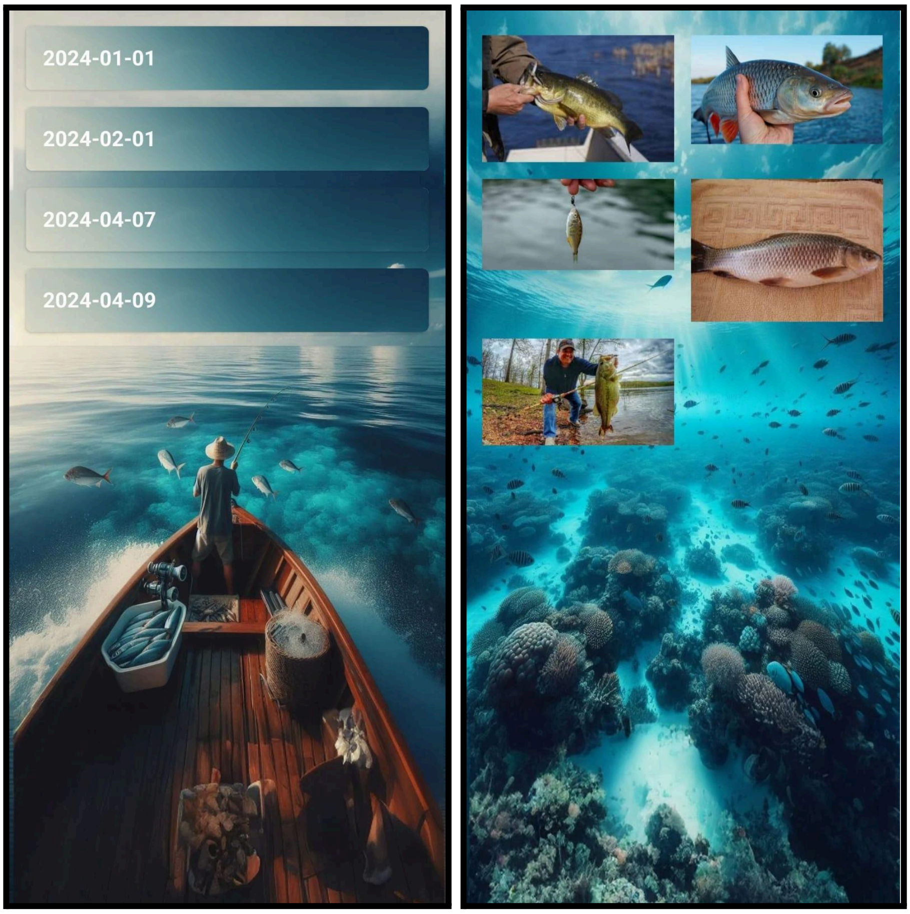

Fig: 6.1.4 View Log in app

- View Logs feature, presenting logs categorized by the date they were added. Each date functions as a folder, allowing users to easily navigate through their past fishing sessions and associated catch logs.
- Upon selecting a specific date folder, users are presented with all the catch images uploaded on that particular day. This streamlined display ensures efficient browsing, enabling users to quickly review their catch logs and associated images without unnecessary navigation.
- This user-friendly interface promotes engagement and satisfaction among fishing enthusiasts seeking to revisit their memorable catches.

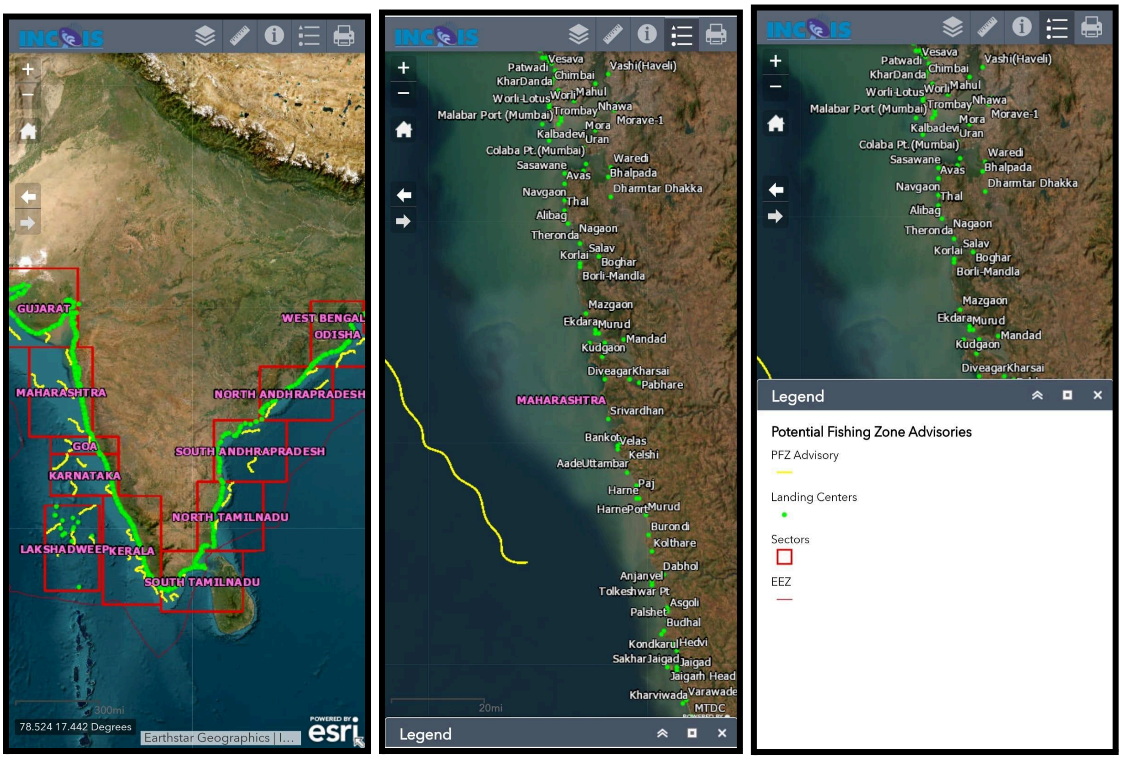

Fig: 6.1.5 Potential Fishing Zone Advisory

- The presented figure depicts real-time status updates of Potential Fishing Zones (PFZs) along the entirety of the Indian coastline. PFZ announcements are delineated according to designated sectors, each denoted by a distinct red bounding box.
- Users can seamlessly obtain coordinates of any desired point by simply clicking on the corresponding area of interest. Subsequently, the updated coordinates are dynamically displayed at the bottom left corner of the screen. This intuitive functionality enhances user interaction, providing a straightforward method for acquiring precise location data within the application interface.
- The illustration offers an enlarged perspective specifically focusing on the Maharashtra sector. Within this sector, green markers denote port locations, while yellow lines serve to demarcate PFZ advisory areas.

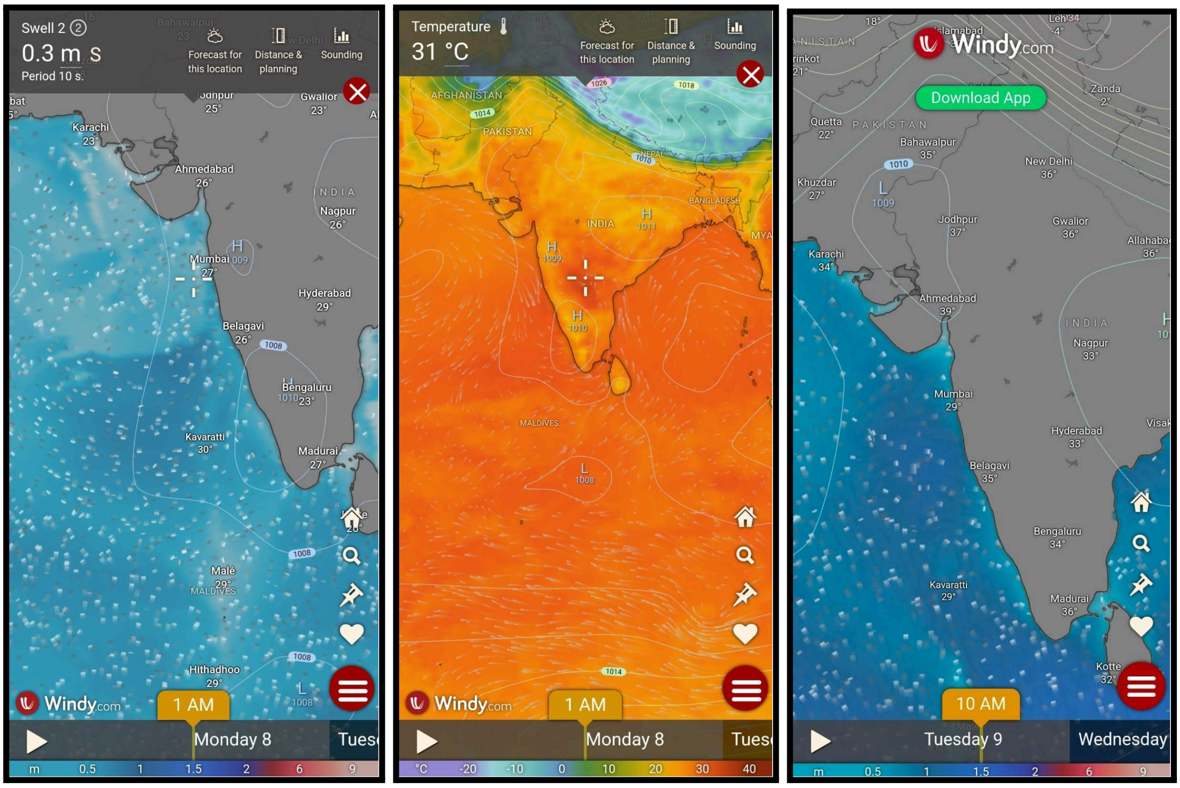

Fig: 6.1.5 Weather Map

- The depicted figure conveys real-time observations pertaining to swell dynamics. Swell, characterized by elongated, undulating waves originating from distant meteorological phenomena, exerts significant influence on maritime activities. Its manifestation poses substantial challenges to fishing vessels, introducing instability and potential hazards such as capsizing or navigational complexities. The monitoring of swell patterns assumes paramount importance for fishing fleets, facilitating preemptive measures to navigate adverse sea states, optimize routes, and mitigate risks to both crew and vessel integrity.

- The figure also provides insights into the live assessment of sea surface temperature (SST). Serving as a crucial determinant of oceanic conditions, SST delineates the thermal profile of the uppermost ocean layer. Its fluctuations profoundly impact fish behavior and distribution patterns, thereby directly influencing fishing endeavors. The ability to monitor SST enables fishermen to discern optimal habitats, refine navigation routes, and adapt operational strategies, thereby augmenting catch efficiency through informed decision-making processes.

6.2. Performance Evaluation Measures:

For the YOLOv8 model based on fishnet dataset, the following performance evaluation measures were considered:

1. **mAP** - Mean Average Precision (mAP) is the primary performance measure of computer vision models. mAP is equal to the average of the Average Precision metric across all classes in a model. You can use mAP to compare both different models on the same task and different versions of the same model. mAP is measured between 0 and 1

2. **Precision** - Precision is a metric in a confusion matrix measuring the accuracy of positive predictions. It is calculated as the ratio of true positives to the sum of true positives and false positives.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

3. **Recall** - Recall, also known as sensitivity or true positive rate, is a metric in a confusion matrix measuring the model's ability to correctly identify all positive instances.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

6.3. Input Parameters/Features considered:

Experimental Environment

CPU: Intel(R) Xeon(R) CPU @ 2.00GHz

GPU: Tesla P100-PCIE-16GB

Driver Version: 535.129.03

CUDA Version: 12.2

Python version” 3.10.12

Hyperparameters

Model type: yolov8s

Epochs: 100

Image Size: 640x640

Batch Size: 16

Optimizer: SGD

IOU: 0.7

Momentum: 0.937

Weight_decay: 0.001

6.4. Graphical and statistical output

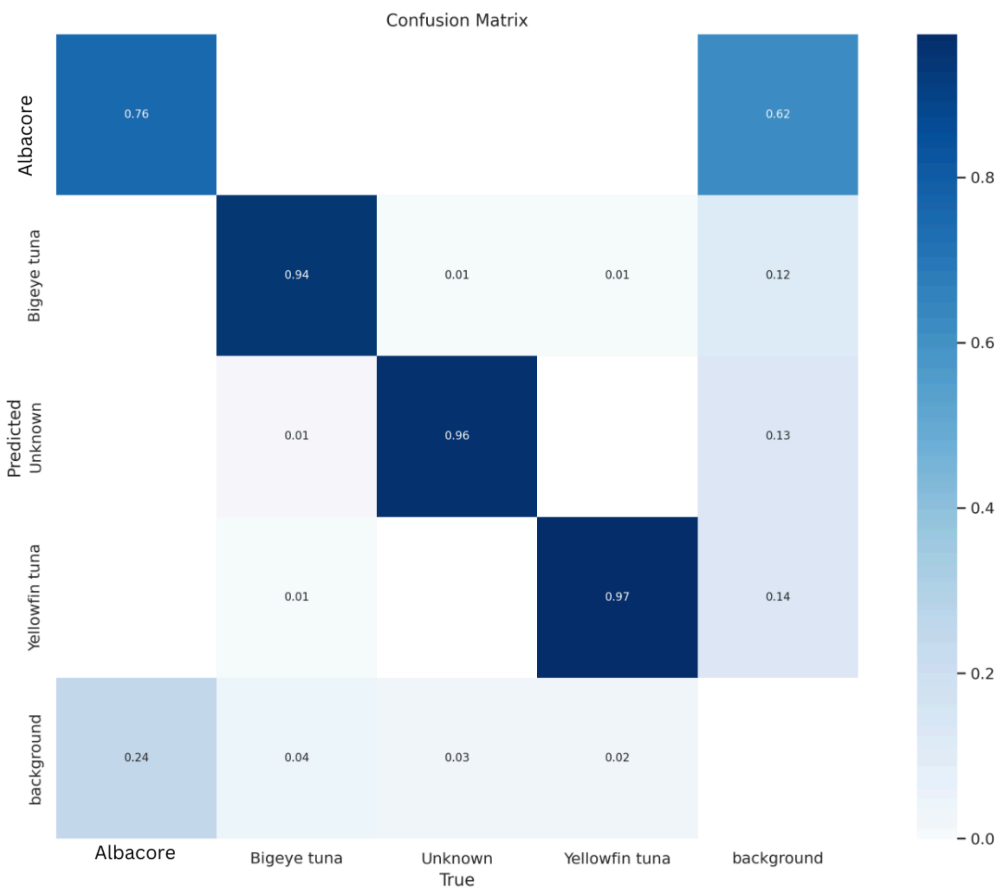

Fig. 6.4.1. Confusion Matrix

The exhaustive training regimen of the model yielded impressive results, showcasing a mean Average Precision at IoU (Intersection over Union) 50 (mAP50) of 0.90351 and a mAP50-95 of 0.69167. These metrics serve as robust indicators of the model's proficiency in accurately detecting and localizing fish in the dataset.

The precision-recall curve for the You Only Look Once (YOLO) model is vital as it assesses the trade-off between precision and recall, providing insights into the model's ability to accurately detect objects while minimizing false positives, crucial for evaluating its performance comprehensively. The Precision-Recall curve shown in Fig offers a granular depiction of the mean Average Precision for each specific class.

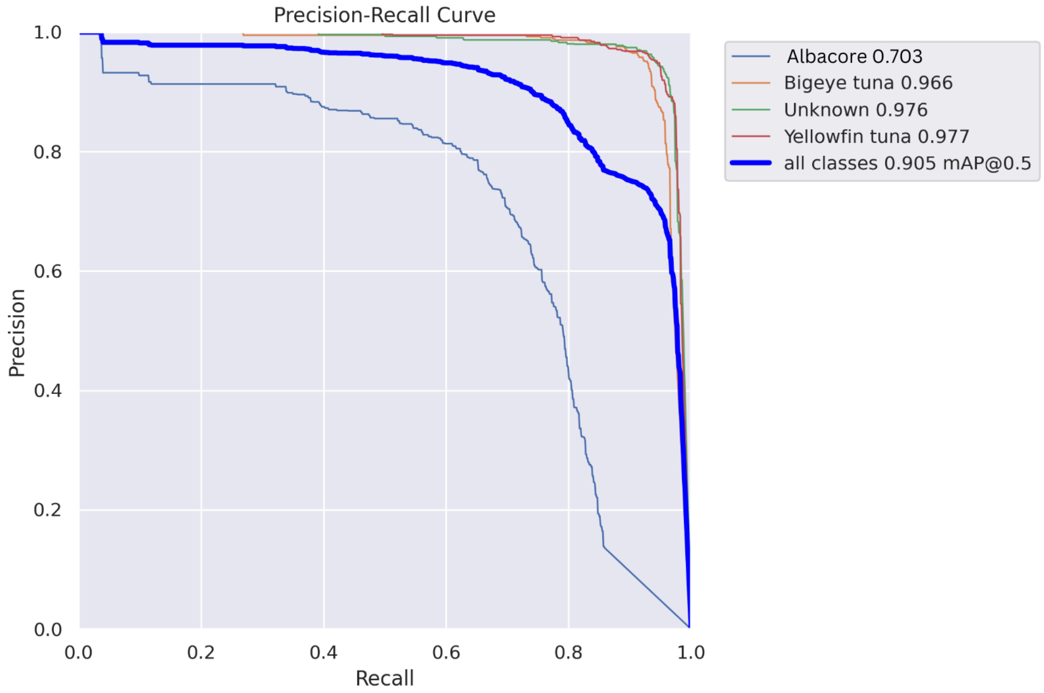

Fig. 6.4.2. Precision-Recall Curve

The Mean Average Precision (mAP) - Epochs curve serves as a pivotal metric in evaluating the performance of object detection models over training epochs. It offers insights into the model's learning progress and convergence, guiding adjustments for optimal performance enhancement throughout the training process.

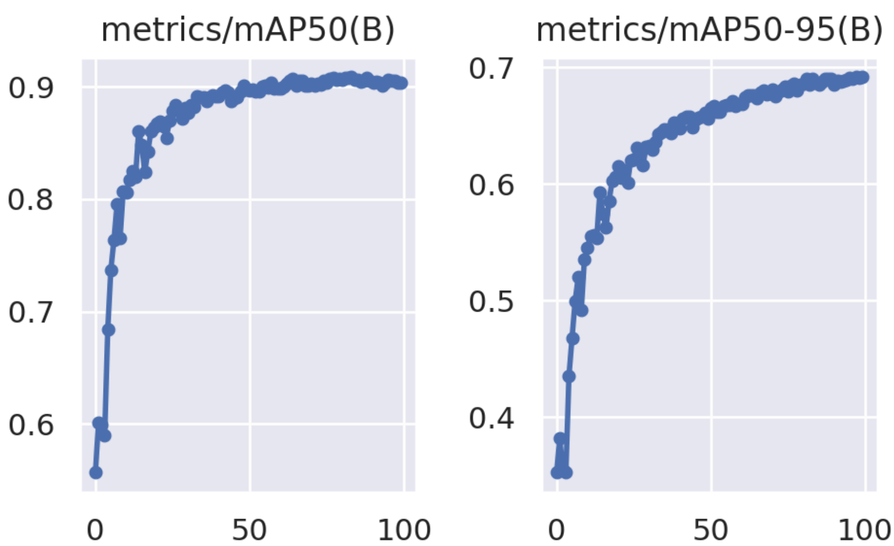

Fig. 6.4.3. mAP through epochs

The loss-epochs curve is essential for monitoring the training progress of object detection models. It illustrates the evolution of loss values over training epochs, indicating the model's convergence and providing crucial feedback for fine-tuning hyperparameters to optimize performance and ensure efficient learning.

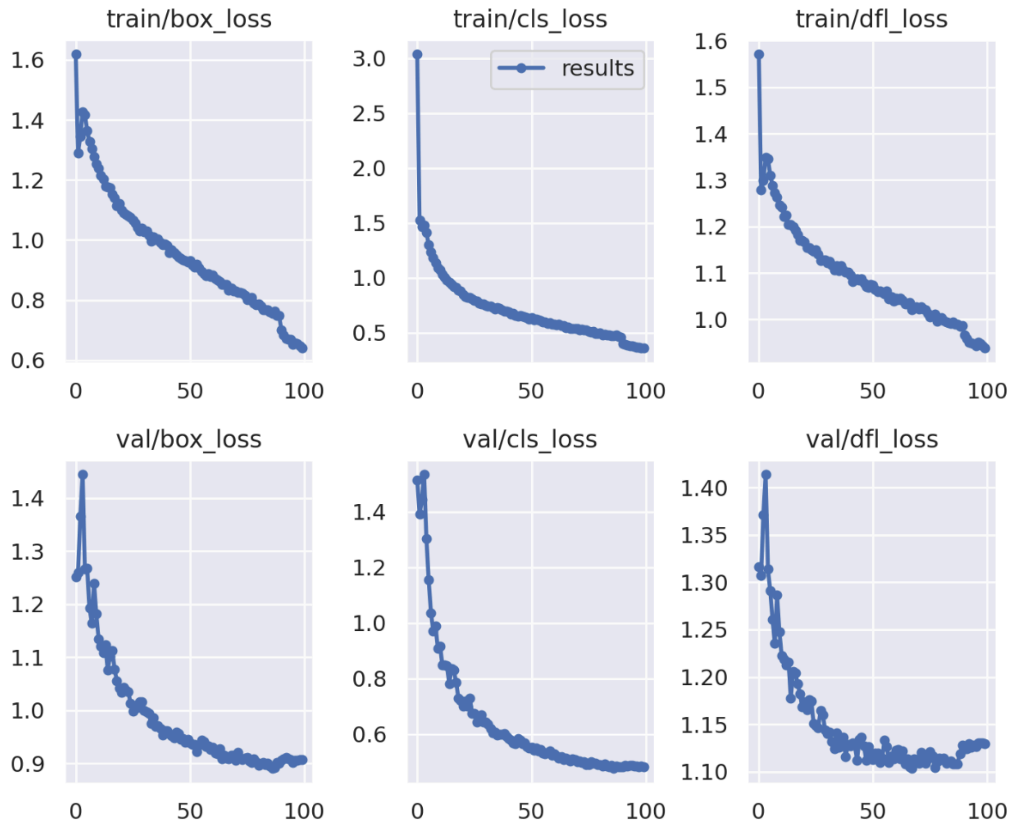

Fig. 6.4.4 Loss Metrics during training

A sample prediction result from the model showcases its ability to accurately identify fish within an image, providing bounding box coordinates and corresponding class labels. This demonstrates the model's effectiveness in real-world object detection tasks.

Fig. 6.4.5. Prediction Results

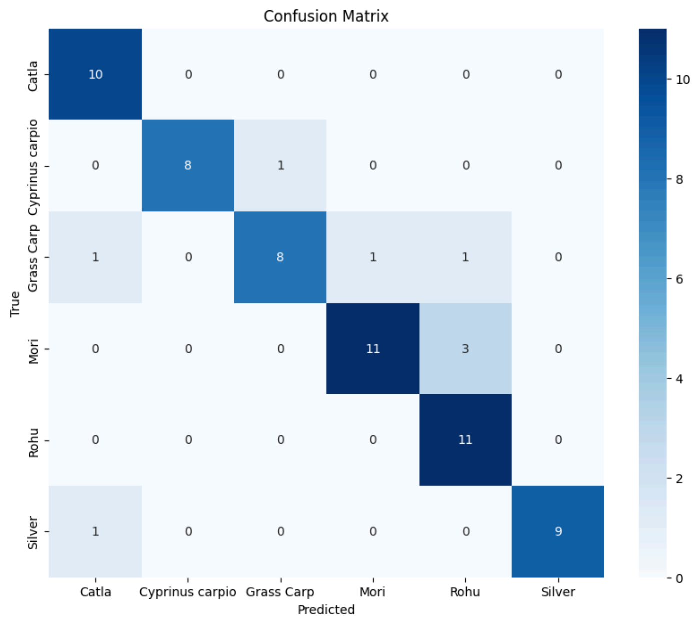

Fig: 6.4.6 Confusion matrix Fish pak

6.5. Inference Drawn:

The MASA app has undertaken a bold initiative to address the gaps prevalent in the market of fishing apps. MASA app promises to revolutionize the landscape of fisheries management practices. The research has demonstrated the use of the latest technological advancements in the field of object detection promising outcomes that carry significant implications for fisheries management practices. Through rigorous testing and validation, the research has underscored the efficacy and potential of these advancements, paving the way for transformative outcomes in the realm of marine resource management

Chapter 7: Conclusion

7.1.Limitations:

- In research automated counting could not be implemented due to the absence of a video-based dataset.
- Identification of rare fishes is difficult, as the rarity also reduces the frequency of such fishes in datasets.

7.2.Conclusion:

The project presents a comprehensive solution to enhance fishing practices through the integration of AI/ML, and image recognition. By leveraging real-time oceanic data, and ML-powered fish species identification, the system aims to provide fishermen with valuable insights and tools for optimized fishing. The proposed evaluation measures will help assess the accuracy, speed, usability, and impact of the system, ensuring its effectiveness in improving catch efficiency and sustainable marine resource management. As this innovative solution addresses the challenges faced by fishermen in identifying fishing zones and species, it holds the potential to revolutionize traditional fishing practices and contribute to the preservation of marine ecosystems.

7.3.Future Scope:

- Availability of video-based datasets would allow automated counting of fishes.
- Automated systems to process the data collected by electronic monitoring systems can be used to enforce fishing quotas, which would prevent overfishing.

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Appendix

1] Paper I details :-

a.Paper I :-

YOLOv8 based fish detection and classification on fishnet dataset

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Abstract— **The research examines the marine fishing sector and highlights the urgent need for an electronic monitoring system designed to meet the unique needs of fishermen. The initiative's motive is emphasized in the paper, which highlights how cutting-edge technology like object detection and tracking could revolutionize the fishing industry when integrated into an electronic monitoring framework. The research proposes an electronic monitoring system based on YOLOv8 (You Only Look Once) as a comprehensive solution to address current issues, such as out-of-date data collection methods and a lack of guiding applications. The review of the literature, which highlights gaps in the current fishing applications, is an important component of the paper. The research is geared towards training an object detection model on the fishnet dataset. The focus is on data processing created by an electronic monitoring system to rectify the current state of the fishing industry's deficiencies.**

I. INTRODUCTION

In the expansive realm of maritime activities, modern fishing vessels are equipped with state-of-the-art electronic monitoring systems, featuring video cameras meticulously positioned to document the bustling deck where fish are landed. Initially designed for security and safety, these camera systems hold untapped potential for identifying fish species and precisely tracking and counting the marine harvest. The urgency to automate these tasks drives our research, emphasizing the need for a real-time image processing system to ensure swift and accurate fish identification and counting.

Our research is fueled by a dual commitment—to advance technological frontiers and to foster an economically and environmentally sustainable ecosystem within the fishing industry. At its core, our primary goal is to lay the groundwork for the seamless implementation of automated counting and species identification of the fish catch. This ambition extends beyond individual fishing operations, aiming to elevate the sustainability and efficiency of marine fishing methods globally.

The fishnet dataset, a repository of annotated images extracted from video frames, serves as the backbone of our exploration. Leveraging the YOLOv8 model, a robust object detection algorithm, we delve into the intricacies of the dataset, paving the way for automation of catch reporting. While our current focus is on static images, the YOLOv8 model is poised for a dynamic transition to video feeds, contingent upon the availability of an appropriate dataset. Furthermore, our research contemplates the model's and application of live video streams captured by electronic monitoring systems' cameras.

In essence, our research signifies the convergence of technological prowess and environmental stewardship. By tapping into the potential of electronic monitoring systems, annotated datasets, and advanced object detection algorithms, we aspire to redefine the trajectory of marine fishing practices. The future beckons towards a realm where sustainability and efficiency harmoniously coexist, driven by the innovative solutions that emerge from our dedicated exploration of the seas.

II. Overview

A. Related Work

1) Early lessons in deploying cameras and artificial intelligence technology for fisheries catch monitoring: where machine learning meets commercial fishing[1]

MLAI-based approaches for automating fishery catch and bycatch monitoring face challenges related to data quantity and operational complexity. When it comes to improving the efficiency and accuracy of data gathering in the demanding and ever-changing environment of fishing vessels, MLAI-based systems for automating fishery catch and bycatch monitoring offer an appealing answer. Obtaining annotated training datasets is a major difficulty, particularly in fisheries with changeable conditions and various catch compositions. The diversity and quality of the training data are essential for building strong models that can handle the intricacies of many species, climates, and lighting changes. In order to implement MLAI effectively, the study highlights the significance of prioritizing species according to their ecological, economic, or vulnerability status. This is because imbalanced data may result in insufficient training for specific species.To combat this bias and guarantee a more fair representation of species in training data, techniques like undersampling or creating synthetic images are recommended. Furthermore, the work highlights the significance of taxonomic categorization and suggests a multi-label, hierarchical method for MLAI models to concurrently classify captures at various taxonomic levels.

2) Research on target detection of Engraulis japonicus purse seine based on improved model of YOLOv5 [2]

The study focuses on improving the YOLOv5 model for the detection and analysis of Engraulis japonicus fishing vessel operations. To improve feature extraction and detection accuracy, the Squeeze-and-Excitation Network (SENet), a fusion attention mechanism, is incorporated into the proposed YOLOv5 model. The model performs better than the baseline YOLOv5 and other modified versions when measured by mean average precision (mAP), precision, recall, and loss functions.To track and count the number of fishing baskets, fishing nets, and processing vessels, the research incorporates a target identification approach that uses Kalman filtering and the Hungarian matching algorithm. In comparison to human counting, the study's automated statistical analysis of fishing vessel activity is expected to be more precise and efficient. The results show that when compared to previous models, the enhanced YOLOv5_SE model obtains a higher mAP (99.4%) as well as better precision and recall. The suggested strategy also addresses issues with statistical accuracy, including the use of threshold techniques for processing vessels and fishing nets. The report does, however, point out areas that still need work, such as the size and complexity of the model, and it makes recommendations for possible future improvements including automatic labeling and the application of sophisticated feature extraction techniques.

3) The Fishnet Open Images Database: A Dataset for Fish Detection and Fine-Grained Categorization in Fisheries[3]

The dearth of publicly accessible data regarding camera-based electronic monitoring (EM) systems on commercial fishing vessels is addressed by the Fishnet Open Images Database. It is the largest and most varied dataset for fish detection and classification in the context of fisheries EM, with over 86,000 photos containing 34 object classifications. The dataset comes from the increasing number of ships that have EM systems installed to apply computer vision to automate the assessment process in light of the anticipated increase in data volume. Fishnet provides a difficult benchmark for creating computer vision algorithms suited to the particular difficulties of EM images taken above water, in contrast to other datasets like ImageNet and COCO, which lack data specific to fishing.In order to obtain raw video and capture annotations, the dataset collection process entails agreements with authorities and EM service providers. Privacy is protected by means of facial blurring and the removal of identifiable vessel information. The dataset presents issues such as visual resemblance between species, skewed class distributions, and unfavorable weather circumstances. It focuses on longline tuna vessels in the western and central Pacific Ocean. It replicates real-world situations and is divided into training, validation, and test sets. This makes it an essential tool for developing computer vision applications in fisheries electronic monitoring.

4) Deep learning methods applied to electronic monitoring data: automated catch event detection for longline fishing [4]

This work presents a unique method for automating the detection of capture events in electronic monitoring (EM) video footage from fishing vessels using deep learning. The system uses a two-step process: it first uses frame-by-frame identification of fish and fishermen, and then it applies a temporal filter to identify catch events. Convolutional neural networks (CNNs) were the basis of the object detection framework that showed encouraging results; TensorBox, which used the ResNet 152 architecture, worked well. The catch event detection system demonstrated its potential for precise and quick analysis of massive amounts of EM data by achieving excellent recall and precision.Even with the accomplishment, there are still issues to be resolved, like the requirement for bigger and more varied training datasets to improve the model's ability to generalize across various vessels and circumstances. The suggested approach offers an alternative to the time-consuming and prone to mistake human video analysis process, addressing the growing significance of EM in fisheries management. Deep learning techniques have the potential to be widely used in fisheries monitoring as long as they continue to progress, leading to more sustainable and knowledgeable management strategies.

5) Increasing the functionalities and accuracy of fisheries electronic monitoring systems [5]

Together with the use of novel techniques such as a multi-scale fusion feature pyramid network, large-scale depthwise separable convolutions, and a cross-stage partial DWNeck backbone, the research presents CMS-YOLO, a road scene recognition method that improves real-time performance and detection accuracy. With noteworthy gains in mAP@0.5 on the BDD100K and Udacity Self-Driving datasets, CMS-YOLO shows amazing improvements over YOLOv5, and in autonomous driving scenarios, it reaches an impressive real-time detection speed of 34.5 frames per second. Turning its attention to fisheries management, the report emphasizes how EM systems—which include sensors, cameras, GPS, and data loggers—are being used more and more to address issues that human observers encounter.Situated as a cost-effective and expandable substitute, EM systems surpass traditional observer initiatives by utilizing real-time data transfer via satellite, Automatic Identification Systems (AIS), Video Monitoring Systems (VMS), and sophisticated sensors.

6) YOLO-ACN: Focusing on Small Target and Occluded Object Detection [6]

Inspired by YOLOv3, YOLO-ACN is a novel object recognition method that improves speed and accuracy, especially for small and occluded objects, by introducing innovations including an attention mechanism, CIoU loss function, Soft-NMS, and depthwise separable convolution. On the MS COCO and KAIST datasets, experimental results show that YOLO-ACN has an AP of 18.2%, a single-class mAP of over 80%, and a real-time mAP50 of 53.8%. The architecture has been improved to solve problems with small targets and occlusions. It does this by incorporating attention methods, depthwise separable convolution, and improved CIoU and Soft-NMS loss functions for accurate bounding box regression and better handling of occlusions.YOLO-ACN outperforms YOLOv3 with noticeable minor target identification improvements and is quicker and more accurate than SSD513. It also matches faster R-CNN precision. The important effect of the attention mechanism on accuracy is demonstrated by ablation studies. To sum up, YOLO-ACN provides a workable way to identify small, obscured objects in real-time.

7) Digital camera monitoring of recreational fishing effort: Applications and challenges

The underuse of digital cameras for tracking recreational fishing efforts is highlighted in the literature, which draws on early adopter research conducted in Germany, Australia, and New Zealand. Conventional approaches, characterized by their labor-intensive and irregular nature, impede a thorough comprehension of dynamic recreational fisheries. The writers support affordable digital camera monitoring systems, highlighting their capacity to track trends of fishing efforts over time. Different jurisdictions have different ethical standards, including privacy rights. It is advised to follow privacy regulations and use low-resolution photographs. For monitoring to be effective, representative monitoring locations, infrastructure requirements, and technological factors like lens selection and data storage are essential. Over time, the program's cost-effectiveness and efficacy are influenced by strategic choices on monitoring methodologies, ongoing attention to system components, and resolution of possible problems.

III. THEORY

A. Limitations and Research Gap

Electronic monitoring (EM) technologies for fisheries management have made significant strides, but there are still several restrictions and knowledge gaps. Although improving recall and precision, the suggested YOLOv5-based method for Engraulis japonicus fishing recognition might not be scalable or universal. It has successfully cut down on storage and review time, but the automated catch event detection framework still needs more validation to be more flexible. Though useful, the Fishnet Open Images Database might not accurately depict EM difficulties in the real world. Although the approach for automatic species identification utilizing optical tracking and convolutional neural networks shows promise, issues with species variety and environmental variability require more research. For EM systems to be fully and successfully used in fisheries management, several deficiencies must be filled.

IV. METHODOLOGY

A. Dataset Characteristics

Images from longline tuna vessels in the western and central Pacific are included in the fishnet dataset. Four visually similar tuna species (albacore, yellowfin, skipjack, and bigeye) are represented by almost 85% of the included fish annotations. The "L1" label collection comprises 25 more species from which the other fish annotations are derived. The FAO ASFIS List of Species for Fishery Statistics Purposes is another source of 12 coarser classes that group related species and create the "L2" label set. "Unknown" L1 classes and those with fewer than 1000 labels are included in the L2 "OTH" (other) class; sharks are excluded for conservation purposes.

Indicators of fishing activity include annotations made by humans. Due to uneven catch among boats and skewed species distribution, both the L1 and L2 class distributions are long-tailed, as shown in the dataset.

B. Data Split

The training, validation, and testing sets are designed to emulate real-world operating situations for EM algorithms. Mimicking both visible (current EM program members) and invisible (new EM program members) vessels is critical. The Fishnet validation and test sets include equal amounts of imagery from "seen" and "unseen" cameras, which is consistent with datasets that originate photographs from many distinct places. The final split included 59,497 training images, 13,648 validation images, and 12,891 test images. Figure 1 depicts the class distribution. Class Frequency Distribution

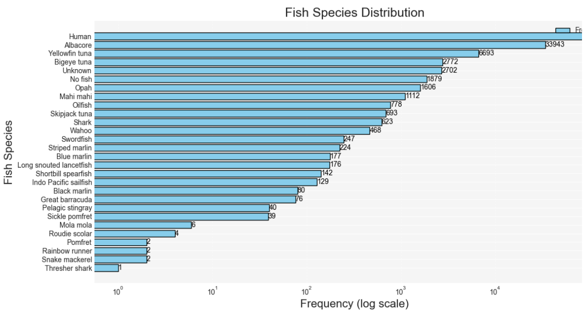


Fig. 1. Class Frequency Distribution

The dataset is highly unbalanced as some classes have little representation, which is unsuitable for a good result. As a result, only the most common classes were chosen for training: "Albacore", "Bigeye tuna", "Yellowfin tuna", and "Unknown". A subset of the dataset was isolated such that each class would have 2700 instances spread across 6618 images.

C. YOLO

You Only Look Once (YOLO) operates on the principle of unified object detection through a grid-based approach, exhibiting notable efficacy in real-time computer vision applications. YOLO's core mechanism involves dividing input images into a grid, and each grid cell is responsible for predicting bounding boxes and class probabilities concurrently. This unique design facilitates the expeditious and comprehensive identification of multiple objects within the image. Within each grid cell, YOLO predicts bounding box coordinates relative to the cell's spatial dimensions, along with associated class probabilities. The model employs a single convolutional neural network (CNN) to process the entire image, enabling end-to-end predictions. This streamlined architecture significantly accelerates inference speed while maintaining competitive accuracy, addressing the imperative of real-time applications.

YOLO integrates non-maximum suppression to refine the output by eliminating redundant bounding boxes and enhancing localization precision. The model is trained through a comprehensive loss function, encompassing localization, confidence scores, and class predictions, optimizing parameters through backpropagation. The YOLOv8 model is the latest version of the YOLO model developed by ultralytics company.

Keys features of YOLOv8:

1. Anchor-Free Detection - YOLOv8 diverges significantly from earlier models by adopting an anchor-free approach in object detection. This entails direct prediction of the object's center, eliminating the need for offsets from predefined anchor boxes. Anchor boxes, a historical challenge in earlier YOLO models, often did not align with the distribution of custom datasets. The shift to anchor-free detection in YOLOv8 addresses the complexities associated with anchor boxes, reducing computational load and enhancing adaptability to custom datasets. This modification significantly impacts the number of box predictions, consequently expediting Non-Maximum Suppression (NMS), a critical post-processing step that refines candidate detections post-inference. This streamlined approach improves the model's efficiency without compromising its real-world applicability.
2. Closing the Mosaic Augmentation - In deep learning research, while model architecture often takes the spotlight, the training routine is crucial for the success of models like YOLOv5 and YOLOv8. YOLOv8 employs online image augmentation during training, exposing the model to slightly varied images in each epoch. A significant technique is mosaic augmentation, where four images are stitched together to challenge the model with new object locations, partial occlusion, and different surroundings. However, empirical evidence suggests that continuous use of mosaic augmentation throughout training can degrade performance. To address this, it is beneficial to disable it for the final ten training epochs. This strategic adjustment exemplifies the meticulous attention given to refining YOLO modeling, evident in the YOLOv5 repository and ongoing YOLOv8 research.

D. Evaluation Metrics

The following metrics are used to evaluate the model performance[9]:

1. **mAP** - Mean Average Precision (mAP) is the primary performance measure of

computer vision models. mAP is equal to the average of the Average Precision metric across all classes in a model. You can use mAP to compare both different models on the same task and different versions of the same model. mAP is measured between 0 and 1

2. **Precision** - Precision is a metric in a confusion matrix measuring the accuracy of positive predictions. It is calculated as the ratio of true positives to the sum of true positives and false positives.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

3. **Recall** - Recall, also known as sensitivity or true positive rate, is a metric in a confusion matrix measuring the model's ability to correctly identify all positive instances.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

B. Experimental Environment

CPU: Intel(R) Xeon(R) CPU @ 2.00GHz
GPU: Tesla P100-PCIE-16GB
Driver Version: 535.129.03
CUDA Version: 12.2
Python version" 3.10.12

Hyper parameters

Model type: yolov8s
Epochs: 100
Image Size: 640x640
Batch Size: 16
Optimizer: SGD
IOU: 0.7
Momentum: 0.937
Weight_decay: 0.001

V. RESULTS AND EVALUATIONS

The training of the model yielded mAP50 of 0.90351 and mAP50-95 of 0.69167. The mAP of individual classes is further illustrated through the following Precision-Recall curve.

The exhaustive training regimen of the model yielded impressive results, showcasing a mean Average Precision at IoU (Intersection over Union) 50 (mAP50) of 0.90351 and a mAP50-95 of 0.69167. These metrics serve as robust indicators of the model's proficiency in accurately detecting and localizing fish in the dataset. The Precision-Recall curve shown in Fig 2 offers a granular depiction of the mean Average Precision for each specific class.

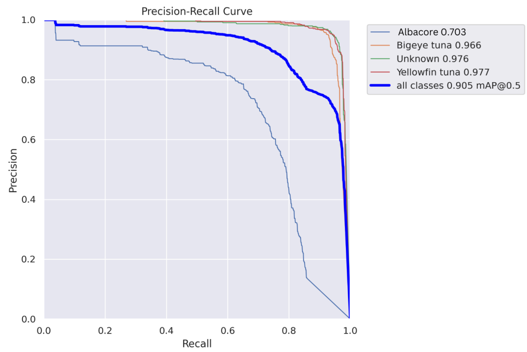


Fig. 2. Precision-Recall Curve

Figure 3 visually depicts the progressive increase in mean Average Precision (mAP) across the training epochs, highlighting a notable upward trend. Notably, the mAP50-95 begins to plateau around the 90-epoch mark, suggesting diminishing returns in performance improvement. This observation guided the decision to cap the training duration at 100 epochs, striking a balance between optimizing the model's accuracy and mitigating the diminishing returns associated with prolonged training.

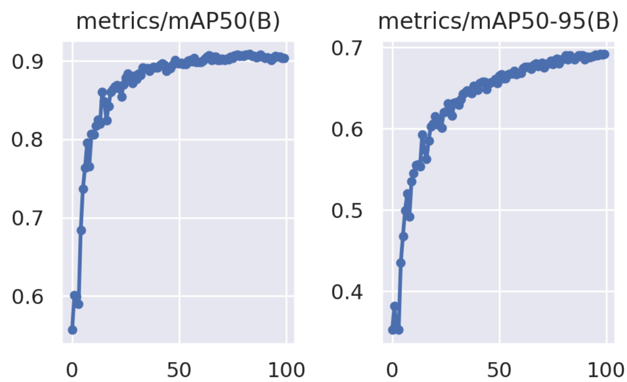
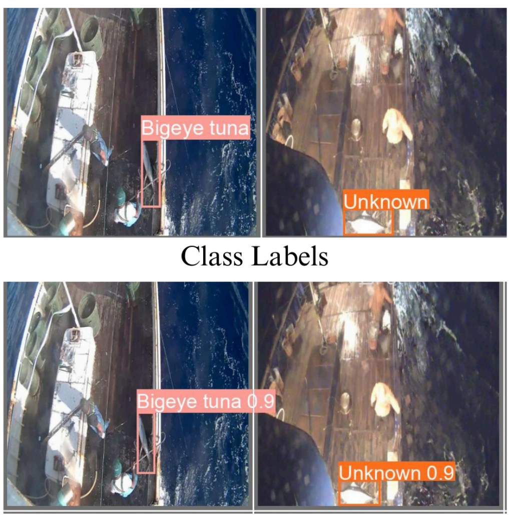


Fig. 3. mAP through epochs

The generated confusion matrix provides a comprehensive visualization of the prediction outcomes for the four distinct classes, along with the background category. This matrix serves as a valuable tool for assessing the model's performance in terms of classification accuracy and potential areas for improvement.

Fig. 4. Confusion Matrix

Figure 5 presents a concrete illustration of model predictions. In the upper images, class labels are clearly denoted, providing a visual reference for the ground truth. Meanwhile, the lower images showcase the model's predictions, presented in the form of class names accompanied by their corresponding confidence scores. The confidence scores range between 0 and 1, offering a quantitative measure of the model's certainty in its predictions. This visual representation provides a clear insight into the model's ability to accurately classify objects while quantifying the level of confidence associated with each prediction.



Predicted Outputs

Fig. 5. Prediction Results

Figure 6 displays a spectrum of loss metrics, where a lower value is indicative of better model performance. Notably, at the 90th epoch, there is a discernible absence of substantial differences in most of the loss metrics. This observation aligns with the notion of diminishing returns, suggesting that further training beyond this point may yield marginal improvements in performance. The nuanced analysis of these loss metrics provides valuable insights into the training dynamics and aids in determining an optimal training duration to balance model refinement and computational efficiency.

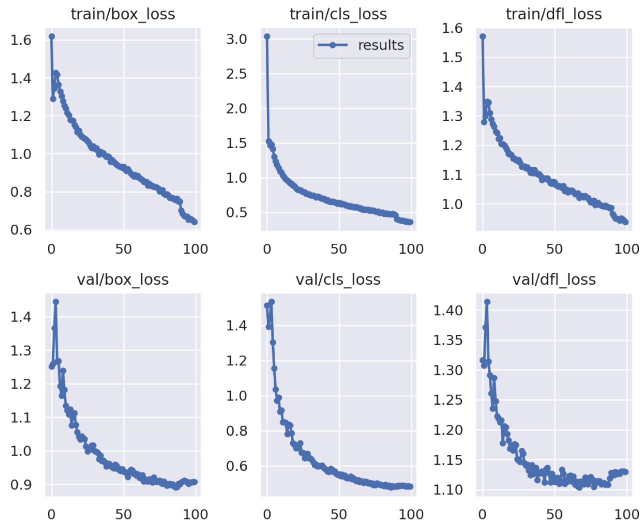


Fig. 6. Loss Metrics during training

VI. Conclusion

To conclude, our study presents a thorough examination of an upgraded YOLO (You Only Look Once) model applied to the fishnet dataset, revealing promising outcomes that carry significant implications for fisheries management practices. As we navigate the dynamic waters of technological innovation, our findings illuminate a promising path toward a more refined and efficient system for monitoring fisheries activities.

Looking ahead, there exists ample room for future research to enhance the YOLO model's practical impact by integrating advanced features like fish tracking and automated counting. This expansion into real-time video feeds not only bolsters accuracy but also holds the potential to revolutionize the enforcement of fishing quotas, addressing challenges associated with manual reporting and mitigating the risks of underreporting.

In essence, the proposed enhancements position the YOLO model as a transformative tool for sustainable fisheries practices, elevating its technical capabilities beyond its current scope. This research not only lays the foundation for future investigations into automated fish tracking but also presents innovative solutions with far-reaching implications for global fisheries conservation and management. As we continue to navigate the confluence of technology and environmental stewardship, our study envisions a future where automated systems contribute significantly to the preservation and sustainable management of our marine resources.

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b.Plagiarism Report

YOLOv8 based fish detection and classification on fishnet dataset

ORIGINALITY REPORT

14%	13%	13%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

c.Project review sheet ;

Project review sheet 1:

Inhouse/ Industry_Innovation/Research:

Sustainable Goal: Industry - Innovation

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C

Group No.: 23

Title of Project: MASA DAILY : Electronic Monitoring System fisherman's Guide

Group Members: Denzil Nelson (57) OMKAR MAHAJAN (39) Divyang Patel (53) Sanket Jaiswal (29) Absent

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environ ment Friendly (2)	Ethics (2)	Team work (2)	Presentati on Skills (2)	Applied Engg&M gmt principles (3)	Life - long learning (3)	Profess ional Skills (3)	Innov ative Appr oach (3)	Resear ch Paper (5)	Total Marks (50)
03	03	03	03	03	02	02	02	02	02	02	03	02	3	03	38

Comments: quality research paper based on results expediting before next review

Dr. D. G. Ma[illegible]

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environ ment Friendly (2)	Ethics (2)	Team work (2)	Presentati on Skills (2)	Applied Engg&M gmt principles (3)	Life - long learning (3)	Profess ional Skills (3)	Innov ative Appr oach (3)	Resear ch Paper (5)	Total Marks (50)
03	03	03	03	03	02	02	02	02	02	02	03	02	03	03	38

Comments:

Date: 10th february, 2024

10/2/24 Dr. Rohini Temkar

Name & Signature Reviewer 2

Project review sheet 2:

Project Evaluation Sheet 2023 - 24

23

Title of Project: Masa Daily- A Fisherman's guide

Group Members: Denzil Purvathingal, Omkar Mahajan (39) Divyang Patel (53) Sanket Jaiswal (29)

D17B 57 D17B D17B D17B

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	**Research Paper** (5)	**Total Marks** **(50)**
04	04	04	03	04	02	02	02	02	02	03	03	02	02	03	42

Comments: publication awaited

Dr. D. G. M
Name & Signature Reviewer1

Inhouse/ Industry _Innovation/Research:

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	**Research Paper** (5)	**Total Marks** **(50)**
04	04	04	03	04	02	02	02	02	02	02	03	02	02	03	40

Comments:

Date: 9th March, 2024

9/3/24
Name & Signature Reviewer 2
Dr. Rohini Temkar