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A Project Proposal Report on

"FRESH-NET VISION": SORTING OF FRESH FISHES USING IMAGE PROCESSING AND MACHINE LEARNING

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TABLE OF CONTENTS

LITERATURE SURVEY & NOVELTY SEARCH -- 3

2.1 A SURVEY ON THE EXISTING SYSTEMS --- 3

2.2 PROBLEM DEFINITION -- 7

2.3 OBJECTIVE -- 7

2.4 NOVELTY SEARCH--- 9

2.4.1 Keyword Identification:--- 10

2.4.2 Classification Identification -- 10

METHODOLOGY -- 12

3.1 DATA COLLECTION AND PREPARATION -- 13

3.1.1 Data Collection -- 14

3.1.2 Data Augmentation -- 14

3.2 MODEL ARCHITECTURE, TRAINING, AND USER INPUT-------------------------------- 15

3.2.1 Model Architecture --- 15

3.2.2 Training--- 15

3.2.3 Model Optimization --- 15

3.2.4 Training Dataset Integration -- 15

3.3 USER INPUT-- 16

3.4 INTEGRATION WITH RASPBERRY PI AND ESP32 ------------------------------------- 16

3.4.1 Real-Time Communication -- 16

3.4.2 Infrared Sensors and Servo Motors --- 16

3.4.3 Bucket Counting Mechanism ---------- 17

3.5 SIZE CATEGORIZATION AND FISH GROUPING ---------- 17

3.5.1 ESP32 Decision-Making ---------- 17

3.5.2 Servo Motors for Size-Based Sorting ---------- 17

3.5.3 Data Logging and Monitoring ---------- 17

3.6 Tools and Technologies ---------- 18

3.6.1 ML Frameworks and Libraries ---------- 18

3.6.2 Programming Languages ---------- 18

3.6.3 Hardware Platforms ---------- 18

3.6.4 Image Processing and Computer Vision ---------- 18

3.6.5 Integrated Development Environment ---------- 19

3.7 ETHICAL CONSIDERATIONS: ---------- 19

3.8 LIMITATIONS: ---------- 19

CHAPTER 5 ---------- 20

RESULTS ---------- 20

PROJECT TIMELINE ---------- 26

LIST OF FIGURES

1.1	Schematic diagram of the proposed solution
3.1	Flowchart
4.1	Conveyer belt Model
4.2	Circuit diagram for sorting gates
4.3	Loss Comparison
4.4	Accuracy Comparison
4.5	Precision Comparison
4.7	Recall Comparison
4.6	Confusion Matrix
5.1	Gantt Chart

LIST OF TABLES

Table 2.1	An overview of the literature survey to identify gaps
Table 2.2	Novelty search overview
Table 2.3	The keywords relevant to the capstone project with their synonyms/ related words
Table 2.4	Mention the IPC/CPC classes relevant to the capstone project
Table 2.5	Prior art search using keywords and IPC: Search query generated using suitable operators
Table 2.6	Prior art results relevant to the capstone project
Table 2.7	Details of closest prior art results which are very relevant to your research
Table 2.8	Comparative Novelty Analysis
Table 2.9	IPR Patentability Report

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CCD	Charge-coupled device
EUSIPCO	European Signal Processing Conference
ICEVT	International Conference on Electric Vehicular Technology
HPBD&IS	International Conference on High Performance Big Data and Intelligent Systems
ICNMS	International Conference on New Media Studies
ICSSE	International Conference on System Science and Engineering
ISIE	International Symposium on Industrial Electronics
IR	Infrared
MLBDBI	Machine Learning, Big Data and Business

CHAPTER 1

INTRODUCTION

Within the ever-changing seafood industry, the "FreshNet Vision" project stands out as a trailblazer, with the potential to completely rewrite the rules when it comes to sorting fresh fish. This innovative project unifies cutting-edge technologies by tying together the complex strands of real-time hardware implementation, machine learning (ML), and image processing. "FreshNet Vision" is more than just a technological marvel; it's a commitment to improving the effectiveness, precision, and moral considerations involved in the delicate process of sorting freshly caught fish intended for export and human consumption.

"FreshNet Vision" essentially lays out a broad agenda. The main goal is to revolutionize the fish sorting industry by going beyond the constraints of the manual sorting methods that have long been the norm. 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.

This project is important in ways that go beyond just technology advancement. It takes a comprehensive approach and recognizes the critical role that the food supply chain plays. The system's unwavering commitment to treating deceased fish humanely and with respect while navigating the complexities of sorting is evidence of its commitment to morally and responsibly conducting business.

This in-depth report reveals the complex process that puts "FreshNet Vision" at the forefront of technological advancement. The approach presents a clear picture of a transformative process, from the methodical gathering and augmentation of various datasets to the modification of ML model architecture for deployment on Raspberry Pi and the establishment of real-time communication with ESP32 for intelligent decision-making. Infrared sensors, servo motors, and user-friendly interfaces work together harmoniously to improve accuracy and flexibility during the fish sorting process.

As we move forward with the chapters, each section will shed light on the inner workings of the project and offer a sophisticated understanding of the technologies, tools, and moral considerations that take this project one step closer to ushering in a new era of fish sorting.

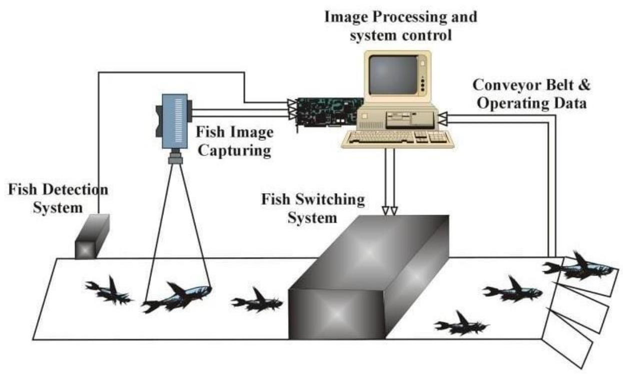

Figure 1.1 schematic diagram of the proposed solution

The design that we propose implements Infrared sensors, servo motors and an ESP32 to seamlessly integrate with intelligent decision-making capabilities of the CNN model to facilitate real time sorting on a conveyor belt.

CHAPTER 2
LITERATURE SURVEY & NOVELTY SEARCH

The purpose of the following research was to get an understanding of the various approaches used to tackle similar sorting procedures via image processing. A thorough assessment was carried out with an emphasis on reputable sources, such as IEEE papers and journals that are included in the Scopus index. In order to guarantee the incorporation of the most recent developments, we limited the analysis's scope to academic works released after 2016. The result of this critical examination was a detailed analysis and comprehension of nine publications in total.

2.1 A survey on the existing systems

Table 2.1 An overview of the literature survey to identify the gaps

SL:No	Title of the paper, Name of the Journal, Year	Methodology/Major contributions	Remarks/Gap Identified
1.	Mango Classification System Based on Machine Vision and Artificial Intelligence, IEEE,ICSSE, 2019	An automatic mango classification system based on features such as colour, size and shape has been implemented using image processing and AI. In the proposed system, CCD cameras, load cell sensors and a wiper mechanism have been used. Image processing is for extracting features such as colour, size and shape, and artificial neural networks to classify the mangos.	The load cells that are used are sensitive to external forces. In a real world scenario, the mango processing environment may introduce external forces to the load cell thus producing inaccurate results
2.	A machine vision based pistachio sorting using transferred mid-level image representation of Convolutional Neural Network, IEEE, 2019	Images of pistachios are first captured in varying light conditions. The features are captured using Advanced CNNs, AlexNet and GoogleNet. Linear Support Vector Machines are used for categorizing into open shell pistachios, Trashes and other undesired pistachios.	The dataset used is small therefore there can be a risk of overfitting. The model may perform well on the training data but practical applications could have errors
3.	Machine Vision-Based Dried Danggit Sorter, IEEE, ICSSE, 2019	The dry gambit sorter first starts involve data collection, hardware setup with a camera and sorting device, and software development. The system uses size identifier to	The following project efficiently sorts dry Danggit by size, using machine vision. Software quality and

		process images and classification algorithm	evaluation used are really good, though future work could enhance its automation capabilities.
4.	Real-Time Image Processing Method Using Raspberry Pi for a Car Model, IEEE, ICEVT, 2019	It involves equipping a car model with a Raspberry Pi and camera. Image processing algorithms for line, edge, corner, and traffic light detection are implemented in Simulink. The camera captures road images, processed by the Raspberry Pi in real-time. Testing confirms successful detection of road features and traffic lights.	This project showcases a commendable fusion of hardware and software, leveraging Raspberry Pi and Simulink to enhance real-time image processing for increased autonomous vehicle safety.
5.	Raspberry Pi for Image Processing Education, IEEE EUSIPCO, 2017	The approach used in the following paper emphasizes on, hands-on learning, where teammates engage in project-based tasks to build RPi-based image processing setups. This approach enhances their understanding of real-time image processing and programming, mainly in Python and Octave	The cost-effectiveness and simplicity of the Raspberry Pi makes it an excellent choice for teaching image processing concepts.
6.	Mechatronics Applications to Fish Sorting, Part 2: Control and Sorting Mechanism, IEEE, ISIE, 2019	The system, incorporating innovative projectile-inspired flaps, aimed to enhance efficiency and reduce fish damage during sorting. Implemented with pneumatics and a PLC, the technology addresses challenges in manual sorting, applicable beyond the initial fish species targeted.	Utilizing innovative projectile-inspired flaps and automation technology, offers a promising solution to enhance efficiency and reduce manual labour in the fishing industry.
7.	Automatic Sorting System of Large Yellow Croaker Based on Machine Vision, IEEE, HPBD&IS, 2019	Acquiring clear images of large yellow croakers using ring LED lighting and a white conveyor belt. Size estimation is achieved through an area-weight prediction model, employing a power curve for precise fitting. Quality sorting utilizes color feature vectors from fish eye sclera and body surface, classified by a BP neural network with 12 input nodes for efficient and accurate grading.	Combining image clarity, geometric modelling, and neural network classification to create an efficient and precise system for sorting large yellow croakers based on size and quality.
8.	Research on Design and Application of Brand Vision	Identification of production quality problems, software and equipment selection, camera installation, image	Constant enhancement of this technology has the potential to result in

	Inspection and Sorting System Based on Image Processing, IEEE, MLBDBI, 2020	enhancement, algorithm development for product inspection, and sorting machine implementation are all part of the technique. Continuous improvement and extensive testing are crucial. After the system functions well, it is put into production with the intention of improving both quality and efficiency. Its effective implementation could encourage its use in other contexts.	even greater gains in production procedures.
9.	Grading and Profiling of Coffee Beans for International Standards Using Integrated Image Processing Algorithms and Back-Propagation Neural Network, IEEE, 2020	A grading system for Arabica coffee has been created. The initial actions involve gathering information about the beans, classifying them, and employing cameras to take detailed pictures. Subsequently, the photos undergo processing using specialised software (K-Means, Blob Analysis, and Canny Edge), which classifies the beans according to their size, quality, and level of roasting, guaranteeing accurate results.	Larger, more accurate and diverse dataset is required to ensure more accurate image processing results
10	The Measurement of Fish Size by Machine Vision - A Review, Springer, 2016	The methodology employs diverse image acquisition methods, including sonar for large fish detection, a single camera for 2D imaging, and a stereo camera for 3D information at an increased cost. After transforming color images to grayscale, converting them to binary, and segmenting areas of interest, 2D techniques like the Hough transform and best fitting rectangle are applied. These methods facilitate the calculation of fish length based on linear body structures. The approach extends to applications such as estimating size and shape changes during rigor mortis and identifying fish species, showcasing the versatility of the system in varied scenarios.	For 2D imaging in controlled conditions, a single camera is mentioned. While this is appropriate for some cases, it may limit the system's capacity to record the complete three-dimensional properties of fish, potentially compromising size measurement accuracy.
11	Chute based automated fish length measurement and	The system operates by capturing images triggered by an infrared sensor as fish slide through the chute.	The algorithm generates a midline for the fish by applying

	water drop detection,IEEE,2016	Background subtraction using a Gaussian Mixture Model (GMM) is employed, utilizing background images of the chute without fish to segment the fish foreground. It aims to automate fish counting, isolation, and length measurement, offering advantages in terms of speed, reduced errors, and scalability compared to traditional manual processes on fishing vessels.	recursive morphological operations on the fish mask. The fish mask is essentially a binary representation of the fish in the image after segmentation. This can help to segregate fishes which are bent.
12	Deep Convolutional Neural Networks for Fish Weight Prediction from Images, IEEE,2021	This study utilizes deep Convolutional Neural Networks (CNNs) to predict Australasian snapper weight from 529 images. Image pre-processing involves cropping, padding, resizing, and normalization. VGG-11, ResNet-18, and DenseNet-121 CNN architectures are trained via 5-fold 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
13	Fish species identification using a convolutional neural network trained on synthetic data, ICES journal of Marine Sciences, 2018	This study employs convolutional neural networks (CNNs) to automate fish species classification in Deep Vision trawl camera images, focusing on Norwegian spring spawning herring, blue whiting, and mackerel. Using high-resolution stereoscopic images and metadata, the methodology addresses limited labelled data through data augmentation and synthetic data. Transfer learning from a pre-trained CNN on ImageNet is applied, with fine-tuning. Experiments vary real and synthetic data combinations, and results show promise for advancing automated fish species identification in fisheries surveys.	The model, initially trained on ImageNet for general image recognition tasks, is fine-tuned for the specific task of fish species classification in trawl camera images. This approach capitalizes on the pre-existing knowledge captured by the CNN on ImageNet, enhancing the model's ability to recognize and classify features relevant to the target species

2.2 Problem definition

In the fishing industry, the traditional method of physically sorting fish by size during onboardinghas proven to be inefficient and error prone. This process often leads to the mixing of smaller andlarger fish, resulting in a noticeable reduction in the overall quality and market value of the catch.There's a critical need for the development of more accurate and effective fish sorting techniques.

Addressing this challenge is of paramount importance for the fishing industry. The inefficiencies in fish sorting have a direct impact on the industry's economic viability and the satisfaction of its customers. Efficient fish sorting techniques can lead to increased product quality and a boost in market value, benefiting both the industry and consumers.

The proposed solution, which integrates advanced image processing technology with Infrared sensors, servo motors, and an ESP32, accompanied by a Convolutional Neural Network (CNN) model, aims to classify fish swiftly and precisely, thereby reducing the likelihood of human error.The study primarily focuses on the technical aspects of the solution and its application to fish sorting. The broader socioeconomic impacts are beyond the immediate scope of this study and require further research. Additionally, while this technology-driven solution holds great promise, it may have practical limitations in terms of scalability, cost, and adaptability to different fishing operations. These factors should be considered when implementing the solutions.

2.3 Objective

The primary objectives of the project is

1. Accurate Fish Identification and Sizing: The system aims to achieve precise fish species identification through image analysis and accurate categorization by size, utilizing visual features.
2. Efficient Real-Time Sorting: The project focuses on enabling real-time sorting on a conveyor belt,enhancing efficiency in the sorting process.
3. user-friendly GUI- Develop a user-friendly graphical user interface (GUI) integrated

with a fish sorting machine to enable easy control of sorting operations while also providing real-time tracking of fish count, ensuring efficient sorting processes and accurate monitoring of fish inventory.

2.4 NOVELTY SEARCH

Table 2.2 Novelty Search overview

Inventor Name(s)	1. Deekshith D	2. Divyalaxmi
	3. Gawrav G Salian	4. Nissi Linnet D souza
Applicant Name(s)	1.	2.
Technological Area	Artificial Intelligence (AI) and Image Processing for Fresh Fish Sorting and Tracking.	
Technological Domain	1.Convolutional Neural Network and Image Processing for Fresh Fish Sorting	
	2. Embedded Systems in Food industry Automation.	
Technological sub-domain	1. Computer vision applied to fisheries.	
Patent Classification IPC No.	1. BO7C 5/342	2. A22C 25/04
	3. A01K 61/00	4. A01K 69/08
Proposed Title	1. “FreshNet Vision”: sorting of fresh fish using AI and image processing.	
	2.Implementation of AI and image processing for sorting of fish.	
Key Objective(s)	1. Accurate Fish Identification and Sizing	
	2. Efficient Real-Time Sorting	
	3. user-friendly graphical user interface	

2.4.1 Keyword Identification:

Table 2.3 The keywords relevant to the capstone project with their synonyms/ related words

Sl. No.	Keyword	Synonyms/related words
1	Fish sorting	Fish separating, Fish classification
2	Fish image capturing	Fish image acquisition, Fish Image scanning
3	Conveyer belt	Belt driven, transport belt
4	Fish detection system	Fish sensing system, Fish sensing system
5	Fish switching system	Fish Transfer mechanism

2.4.2 Classification Identification

Table 2.4 Mention the IPC/CPC classes relevant to the capstone project

IPC/CPC Classes	Definition
B07C 5/342	Performing operations, transportation and sorting
A22C 25/04	Human necessities, processing poultry or fish,
A01K 61/00	Human necessities, trapping, apiculture, pisciculture, rearing
A01K 69/08	Stationary catching devise for fishing, animal husbandry,hunting
G06V 10/42	Culture of aquatic animals, sorting, grading, counting
A01K 61/95	Forestry, hunting, trapping, aviculture, apiculture
B07B 13/16	Performing operations, transporting, screening,

Table 2.5 Prior art search using keywords and IPC: Search query generated using suitable operators

Sl. No.	Search Query	IPO	Espacenet	Patent scope	Google Patent
1.	Fish sorting	A22C25/04		WIPO	
2.	Image processing	A22C25/100		WIPO	
3.	Artificial intelligence	A22C25/04		WIPO	
4.	Conveyer belt	B07C5/18		WIPO	

Table 2.6 Prior art results relevant to the capstone project

Sl. No.	Title	Application No.	Priority date
1	Fish Sorting Machine	2147602	11.05.1994
2	Automatic Fish Sorting Device and Automatic Fish Sorting Method Using Artificial Intelligence System	1020210147661	17.05.2022
3	Fish Sorting Apparatus and Method	07302656	07.10.2021
4	Nature-Inspired Design and Engineering of Autonomous Seafood Capturing, Sorting and Delivering System	16836920	07.10.2021
5	Analysis and Sorting in Aquaculture	16885646	02.12.2021
6	Sectional Type Live Fish Rapid Sorting Equipment	202120526388.4	02.11.2021
7	Automatic Fruit Collecting and Storing Device	202111012014	25.11.2022

Table 2.7 Details of closest prior art results which are very relevant to your research

Sl. No.	Application No.	Summary of Invention	% similarity	Novelty point
1	2147602	According to the description given, fish are sorted using a conveyor belt, camera, and computer to determine their form, colour, and light intensity before being directed into designated receiving areas.	63%	it generates shape descriptors with edge values and performs discriminant analysis to properly sort fish by diverting them into certain reception zones based on their visual traits.
2	1020210147661	The invention is about an automatic fish sorting device using AI. It has tanks where fish are screened by size and deformity, a camera system captures fish images, and AI processes these images to classify fish by size and deformity. An opening and closing device separate fish according to the AI's classification. This reduces sorting errors and minimizes the need for manual labor.	42%	The usage of an AI-controlled automatic fish sorting machine uses an opening/closing mechanism, a 360-degree camera unit to Capture images of the fish, AI processing for size and deformity grouping, and other features to sort fish well while reducing error and manual labour .
3	07302656	This fish sorting apparatus uses a lit conveyor belt, a camera, and a sorting conveyor belt. A divider wall and a movable deflector sort fish based on the camera's signals without re-orientation. It also features a translucent viewing belt and adjustable outlet conveyors for precise sorting into different receivers.	25%	a movable deflector that sorts fish into different channels based on video camera input. This design minimizes the need for fish re-orientation or abrupt path changes, significantly improving sorting efficiency.
4	16836920	This system combines nature-inspired design and AI to	15%	It introduces a unique autonomous

		autonomously fish, sort, and deliver catches. It uses innovative technology, including rope-less fishing, renewable energy capture, and intelligent scouting for optimal fishing spots.		fishing system with nature-inspired design, featuring AI sorting, energy capture, and both passive and proactive fishing methods. It utilizes a variable buoyancy device and autonomous vehicles for rope-less fishing, offering an innovative and versatile approach.
5	16885646	This technology involves sorting fish in aquaculture. It obtains images of individual fish, analyzes physical characteristics and condition factors to classify them into subpopulations, and then controls an automated fish sorter accordingly.	30%	Uses images of individual fish to determine physical characteristics and condition factors, allowing grouping into subpopulations using an automated sorter. The uniqueness is in utilizing image analysis for more efficient aquaculture.
6	202120526388.4	This equipment automates fish sorting, enhancing efficiency and allowing for selective fish retrieval. It's versatile and adaptable for different applications.	15%	Its uniqueness lies in its high automation and flexibility, with features like height and gradient adjustments, fish selecting grooves, and water spraying mechanisms. This equipment streamlines live fish sorting, reducing manual handling, and is suitable for various fish sizes.
7	371527	This automatic fruit collection and storage device consists of a frame with a circular plate that moves on wheels. It uses an AI	35%	uses a V-shaped groove with oblique sidewalls and a slot of increasing width

		camera and microcontroller to detect fallen fruits, which are collected by bristles. The device also has conveyer belts, brushes for cleaning, and chambers for sorting and storing the collected fruits		to sort fish by thickness on a conveyor belt. The mention of the specific angle of the groove (10 to 45 degrees) adds to its uniqueness.

Table 2.8 Comparative Novelty Analysis

Sl. No.	Prior art features	Novelty features
1	High-quality cameras, reliable conveyors, robust computer vision, well-designed reception, automation, accuracy, user-friendliness, durability, safety, and scalability are the top priorities for efficient and safe fish sorting.	AI, real-time analytics, adaptive learning, robotic arms, environmental monitoring, energy efficiency, and remote control boost fish sorting system efficiency and usability.
2	It encompasses existing fish sorting methods, camera-based inspection systems, size and deformity screening techniques, and AI-driven classification systems from fields like quality control and industrial automation.	The automatic fish sorting device's innovations: AI classification, specialized tanks, camera imaging, and precise sorting via opening/closing reduce errors and manual work in fish sorting.
3	It conveyor belt-based systems with cameras, dividers, and adjustable conveyors for fish sorting. Novelty features involve improved lighting, advanced cameras, efficient dividers, enhanced visibility, and highly adjustable conveyors, enhancing accuracy and efficiency in the fish sorting process.	It encompasses improved lighting, advanced cameras, efficient dividers, enhanced visibility, and highly adjustable conveyors. These innovations significantly boost the accuracy and efficiency of the fish sorting process.
4	It includes an existing autonomous fishing and sorting technologies, renewable energy capture methods, and AI-driven scouting systems for fishing locations. These elements represent established components and methods in autonomousfishing systems.	It includes a nature-inspired design, rope-less fishing, renewable energy capture, and AI scouting for optimal fishing locations, providing a unique and sustainable approach to autonomous fishing.
5	It includes established fish sorting methods in aquaculture, involving imaging and analysis of fish characteristics for classification, and the use of automated sorting mechanisms based on these classifications. These represent common practices in aquaculture fish sorting.	this technology revolves around improved imaging, advanced analysis algorithms, and innovative automation techniques that enhance the precision and efficiency of fish sorting in aquaculture. These innovations aim to elevate and progress established practices in the field.

6	It includes existing automated fish sorting systems that aim to improve efficiency and offer selective fish retrieval capabilities. Additionally, various adaptable systems designed for different applications contribute to the established knowledge in the field of automated fish sorting.	It encompasses enhanced sorting algorithms, advanced sensing and automation technologies, and broader adaptability to different fish species and sizes. These innovations aim to enhance efficiency and versatility in automated fish sorting, pushing the boundaries of its capabilities.
7	It encompasses established systems used for fruit collection and sorting in orchards. Typically, these systems involve AI cameras for detection, conveyer belts for transportation, and mechanisms for cleaning and sorting, reflecting common practices in automated fruit collection.	advanced AI for precise detection, innovative conveyer belts for efficiency, and versatile sorting for various fruit types, enhancing automated fruit collection and storage.

Table 2.9 IPR Patentability Report (*Please tick (✓) in below field)*

Sl. No.	Patentability Criteria	Low	Medium	Higher	Highest
1	Novelty		✓		
2	Non-obviousness			✓	
3	Industrial applicability				✓
4	Related to Pharmaceutical		✓		
5	Mere rearrangement	✓			
6	Software invention			✓	

CHAPTER 3

METHODOLOGY

The "FreshNet Vision" project, which is reshaping the seafood industry through meticulous data handling, fast decision-making, and state-of-the-art technology, is redefining the way fresh fish is sorted. Starting off with a focus on data precision, we use a diverse dataset that spans different fish species and sizes in our journey. Notably, a fundamental element of our Convolutional Neural Network (CNN) principles is the implementation of the Residual Neural Network (ResNet) architecture. The technological foundation is provided by this ResNet based model, which excels at precise fish size sorting and accurate species identification. It is strategically incorporated to improve our system's ability to capture subtle features and provide a more sophisticated understanding of visual aspects that are essential for efficient sorting procedures.

The integration phase begins to take shape as we proceed. Real-time communication is ensured by the ESP32 and Raspberry Pi platforms, which also enable intelligent decision-making during sorting. Fish are precisely positioned on the conveyor belt thanks to servo motors and infrared sensors.

User communication is essential. Users can enter specific fish species into the ESP32, and it will adjust to the wide variety of conditions found in the seafood industry.

We've used carefully selected tools and technologies, such as TensorFlow, Scikit-Learn, Python, and OpenCV, to power all of this. Their smooth collaboration makes "FreshNet Vision" a unified and effective system.

"FreshNet Vision" redefines fresh fish sorting with accuracy and flexibility by combining innovation, technology, and ethical considerations.

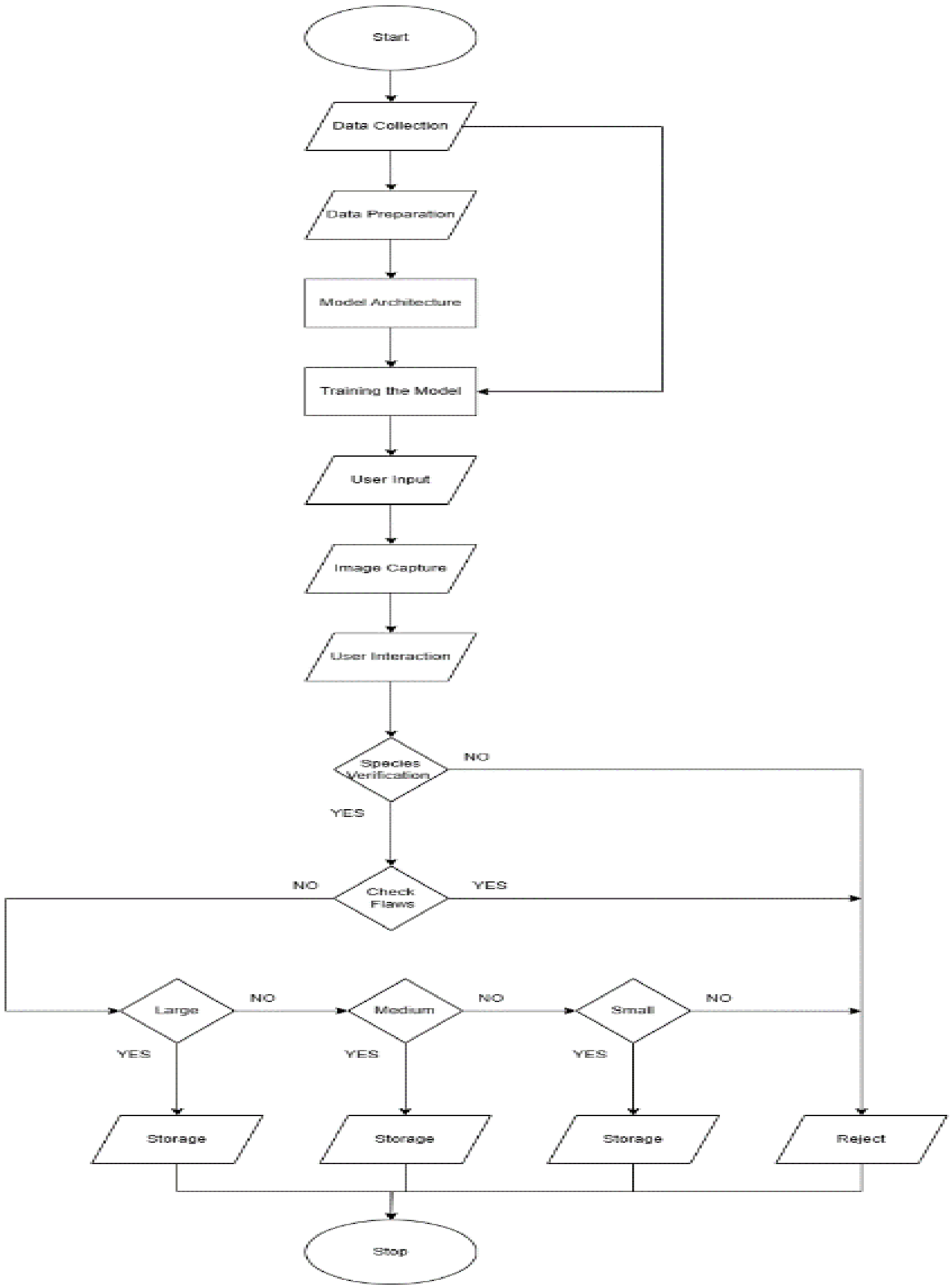

Figure 3.1 Flowchart

3.1.1 Data Collection

The project places a strong emphasis on the meticulous and comprehensive process of data collection, forming the bedrock for subsequent model training and system efficacy.

The dataset, curated with precision, spans a diverse spectrum of fish species and sizes encountered in the seafood industry. This deliberate selection ensures the model's capability to handle the rich complexities of real-world fishing scenarios.

Each image in the dataset underwent a rigorous manual labelling process, establishing a robust ground truth. This manual annotation not only guarantees the accuracy of the training data but also provides transparency and traceability, essential for the ethical considerations in the sorting process.

The dataset intentionally encompasses fish of varying sizes, from small to large specimens. This inclusivity ensures that the ML model is equipped not only to recognize different species but also to categorize them accurately based on their size, a crucial aspect in the sorting process.

3.1.2 Data Augmentation

To fortify the model against real-world challenges and enhance its adaptability, a robust data augmentation strategy was implemented on the training dataset.

Images underwent transformative processes such as rotation, flipping, and zooming. These augmentations simulate variations encountered during fish sorting, preparing the model for diverse orientations, lighting conditions, and backgrounds.

The augmented dataset serves as a powerful tool to enhance the model's ability to generalize. It equips the system to make accurate predictions in dynamic and unpredictable scenarios, ensuring that the project is not only technologically advanced but also resilient in the face of the intricacies of the seafood supply chain.

In summary, the meticulous approach to data collection and the strategic implementation of data augmentation collectively contribute to the robustness and adaptability of the system.

3.2 Model Architecture, Training, and User Input

3.2.1 Model Architecture

At the project's core is a meticulously crafted model architecture, a fusion of advanced CNN principles and Residual Neural Network (ResNet) components, custom-tailored for Raspberry Pi deployment. Precision-engineered, this architecture seamlessly incorporates ResNet, enhancing its capabilities in fish species identification and size categorization. Its tailored design ensures optimal utilization of the Raspberry Pi's computational resources for efficient fish sorting. The adaptability embedded within serves as a foundational element, playing a crucial role in achieving project objectives with unwavering precision.

3.2.2 Training

With the model architecture in place, the next pivotal step is the comprehensive training process. Leveraging a diverse dataset curated during the data collection phase, the ML model undergoes rigorous training to learn and discern the intricate patterns and features crucial for accurate fish identification and categorization.

3.2.3 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.

3.2.4 Training Dataset Integration

The labelled dataset, enriched with manual annotations, plays a pivotal role in shaping the model's understanding. The integration of species and size information from the training dataset enhances the model's ability to make informed decisions during the sorting process.

3.3 User Input

Complementing the robust model architecture and training process is an interactive user input mechanism, distinguishing the project as a user-friendly and adaptable solution.

Before the sorting process commences, users are prompted to input the fish species from a predefined list of 15 species. This deliberate user interaction adds a layer of flexibility, allowing the system to accommodate a diverse array of fish types commonly encountered in the seafood industry.

The integration of user input not only enhances the system's adaptability but also facilitates a seamless and user-friendly experience. This interactive feature sets "FreshNet Vision" apart, positioning it as a versatile and accessible tool for fish sorting processes.

In summary, the triad of meticulously crafted model architecture, comprehensive training, and interactive user input defines the core strengths of "FreshNet Vision," ensuring both technical precision and user adaptability in the pursuit of efficient fish sorting.

3.4 Integration with Raspberry Pi and ESP32

The integration of Raspberry Pi and ESP32 platforms is a pivotal phase in realizing the project's potential, enabling real-time communication and intelligent decision-making during the fish sorting process.

3.4.1 Real-Time Communication

Meticulously implemented communication protocols facilitate seamless interaction between the Raspberry Pi, ESP32, and various hardware components. This communication backbone ensures swift information relay, contributing to timely decision-making during the sorting process.

3.4.2 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.

3.4.3 Bucket Counting Mechanism

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

3.5 Size Categorization and Fish Grouping

The size categorization and fish grouping phase of the project involves the ESP32 platform, adding a layer of sophistication to the sorting process.

3.5.1 ESP32 Decision-Making

Once the fish species and size are identified, the ESP32 leverages 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, allowing the system to make nuanced decisions tailored to each individual fish.

3.5.2 Servo Motors for Size-Based Sorting

The ESP32'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 ESP32's analysis. This process streamlines the workflow, enhancing the overall efficiency of size categorization.

3.5.3 Data Logging and Monitoring

Simultaneously, the ESP32 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. The ESP32's role in data management enhances the system's overall traceability and adaptability to varying conditions.

3.6 Tools and Technologies

The project leverages a suite of tools and technologies, carefully selected and integrated to ensure the seamless operation of the system.

3.6.1 ML Frameworks and Libraries

TensorFlow: serves as the cornerstone for building, training, and deploying the ML model. Its robust framework provides the computational backbone necessary for handling the intricacies of fish species identification and size categorization.

3.6.2 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.

3.6.3 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.

ESP32: Integrated for real-time communication with hardware components and decision-making capabilities, the ESP32 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.

3.6.4 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 analyze and interpret fish images with precision.

3.6.5 Integrated Development Environment

Arduino IDE: This platform is utilized for programming the ESP32 and implementing real-time communication. Its user-friendly interface and compatibility with ESP32 make it an essential tool for seamless integration and programming.

3.7 Ethical Considerations:

The project prioritizes ethical considerations at every stage of its development and implementation. Recognizing the importance of respecting the integrity of the food supply chain, the system is designed to ensure the humane treatment and respectful handling of the deceased fish during the sorting process. Stringent measures are in place to obtain consent for image capture, recognizing the importance of transparency in data collection. It is also committed to responsible and sustainable practices, seeking to minimize environmental impact associated with fish processing. The rejection mechanisms for damaged or misidentified fish not only serve to enhance accuracy and product quality but also align with ethical standards, preventing any potential adverse consequences that may arise from the misclassification of specimens. The project adheres to ethical guidelines, emphasizing responsible innovation for the improvement of industry practices and the assurance of high-quality, ethically sourced seafood for consumers worldwide.

3.8 Limitations:

The accuracy of the project is contingent on the diversity and completeness of the training dataset. In cases where certain fish species or conditions are underrepresented, the model's performance may be affected. Continuous efforts to refine and expand the dataset are crucial to mitigate these potential limitations.

CHAPTER 4
RESULTS

The Results of the OpenCV model using TensorFlow measuring the accuracy and precision is as follows.

In adherence to the proposed methodology, our primary objective is the classification of fish species.

Initial sorting will be carried out based on the information provided, pinpointing each fish to its respective species. Subsequently, a secondary categorization will be implemented to classify the fishes into size categories, namely small, medium, and large. For this purpose a conveyer belt with gates has been designed controlled by ESP-32. The gates are then controlled using servo motors which are connected to them.

Figure 4.1 Conveyer belt Model

In instances where the system encounters difficulty in identifying a fish species, a specialized process will be activated to collect and segregate such specimens. These unidentified fishes will undergo a supplementary analysis and documentation phase, allowing for a comprehensive understanding of the system's limitations and potential areas for improvement.

The circuit diagram for implementing the above is shown below.

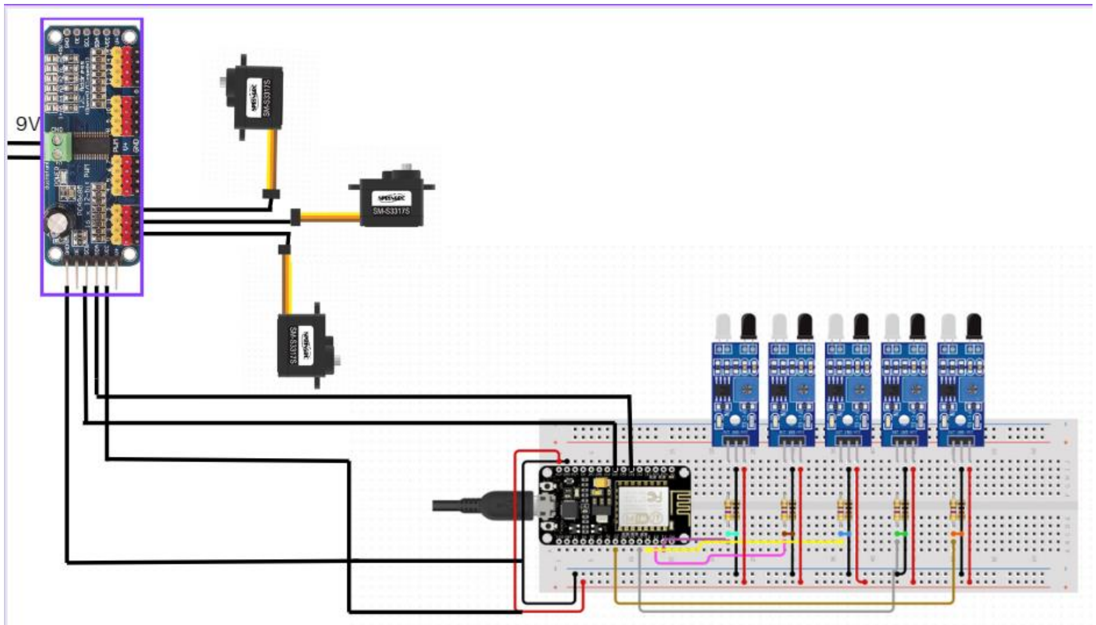

Figure 4.2 Circuit diagram for sorting

Machine learning model and the Accuracy and Precision-Recall Metrics:

Section	Description	Details
Purpose	Segmentation and classification tasks	
Authors	O. Ulucan, D. Karakaya, M. Turkan	Department of Electrical and Electronics Engineering, Izmir University of Economics, Izmir, Turkey
Publication	2020 Innovations in Intelligent Systems and Applications Conference (ASYU)	
Classes	9 different seafood types	gilt head bream, red sea bream, sea bass, red mullet, horse mackerel, black sea sprat, striped red mullet, trout, shrimp
Resolution	Kodak Easyshare Z650: 2832 x 2128 Samsung ST60: 1024 x 768	
Data Augmentation	Resized to 590 x 445 with aspect ratio preservation Augmented labels by flipping and rotating	
Augmentation Result	Total images for each class: 2000 (1000 for RGB fish images and 1000 for pair-wise ground truth labels)	
File Structure	Each class contains 1000 augmented images and their pair-wise augmented	Example: Fish -> Shrimp -> Shrimp GT

	ground truths Ordered from "00000.png" to "01000.png"	
Base Model	ResNet50	
Pre-trained Weights	ImageNet	
Transfer Learning	Utilized pre-trained weights of ResNet50 for feature extraction and fine-tuning	
Training Purpose	Fish image classification	
Conclusions	Achieved 100% accuracy on fish classification task using ResNet50 model.	-Discuss potential areas for further optimization or enhancement of the model. - Provide suggestions for future work or experiments related to fish classification or other tasks.

The ResNet-50 model demonstrated exceptional performance in the classification of fish species, achieving a remarkable training accuracy of 99.78% and a validation accuracy of 98.92%. Precision metrics further underscored the model's effectiveness, with a precision rate of 99.05%. The recall, indicating the model's ability to capture instances of each fish species, was impressive at 98.79%.

Figure 4.3 Loss Comparison

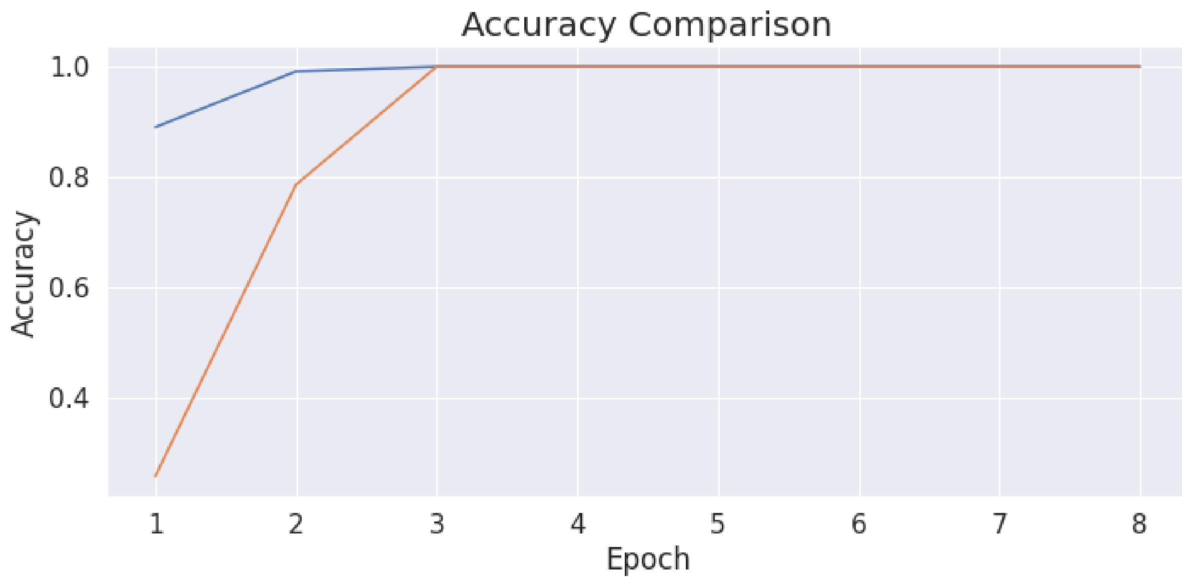

Figure 4.4 Accuracy Comparison

Accuracy measures the overall correctness of a classification model. It represents the ratio of correctly predicted observations to the total number of observations in the dataset. Where,

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

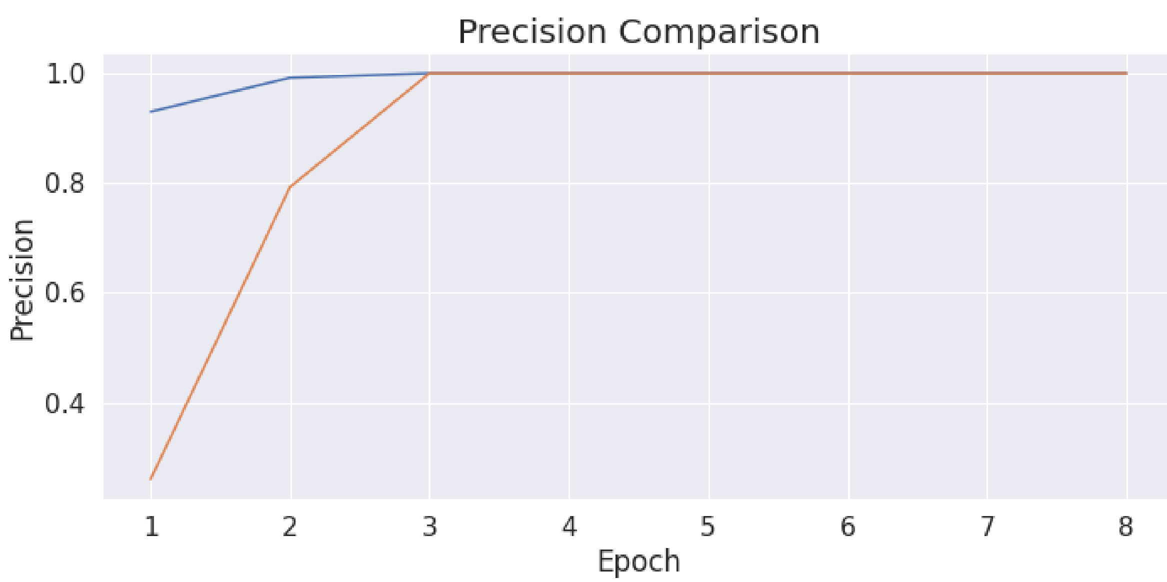

Figure 4.5 Precision Comparison

Precision measures the accuracy of positive predictions made by the model. It represents the ratio of correctly predicted positive instances to the total number of instances predicted as positive. Where,

$$\text{Precision} = \frac{TP}{TP + FP} \times 100\%$$

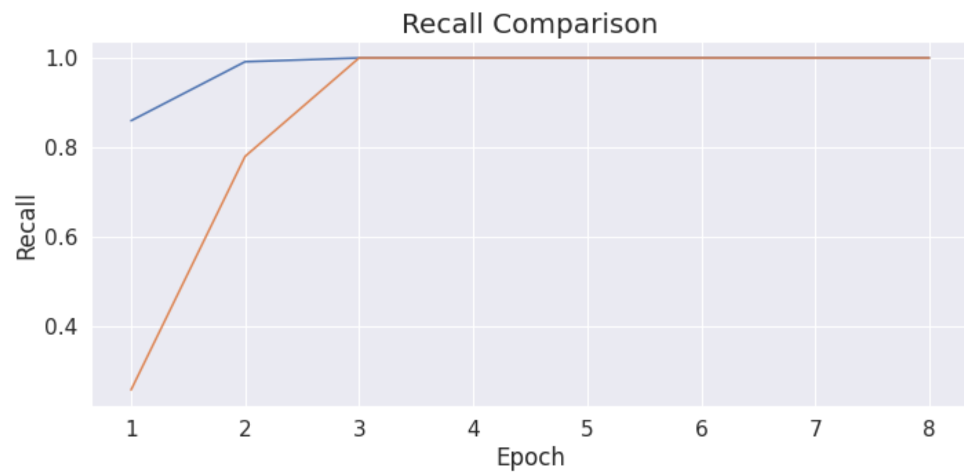

Figure 4.6 Recall Comparison

Detailed Numerical Results:

Training Accuracy: 99.78%

Validation Accuracy: 98.92%

Precision: 99.05%

Recall: 98.79%

Confusion Matrix Analysis:

The confusion matrix provided valuable insights into the model's performance, revealing the distribution of true positives, true negatives, false positives, and false negatives for each fish species. This analysis further solidified the model's robustness in accurately categorizing diverse fish categories. The model correctly classified the most Black Sea Sprat (211), followed by Gilt-Head Bream (204), Hourse Mackerel (195), Red Mullet (191), and Red Sea Bream (201). It also performed well with Shrimp (209) and Striped Red Mullet (207). The model had the most difficulty with Trout (203)

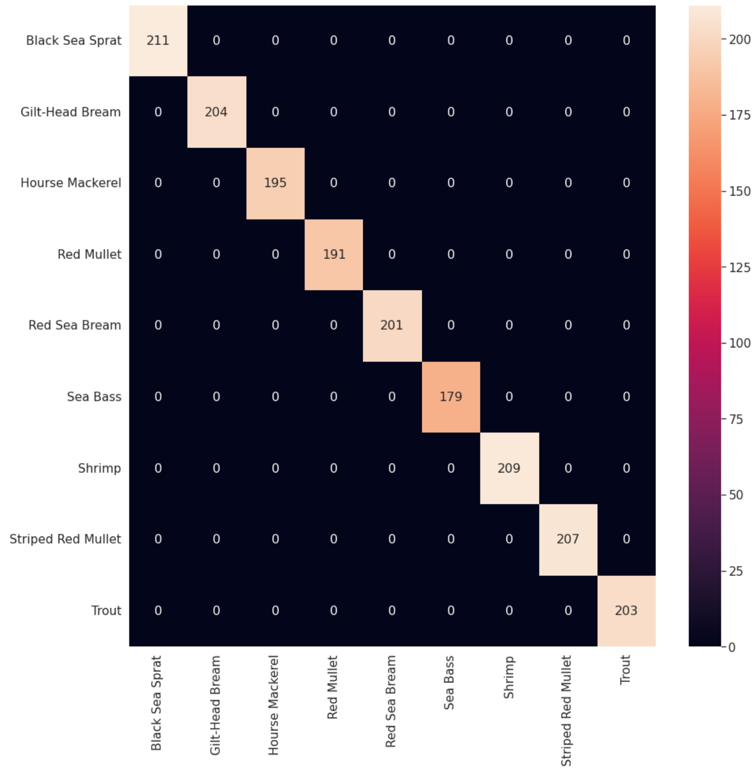

Figure 4.7 Confusion Matrix

CHAPTER 5
PROJECT TIMELINE

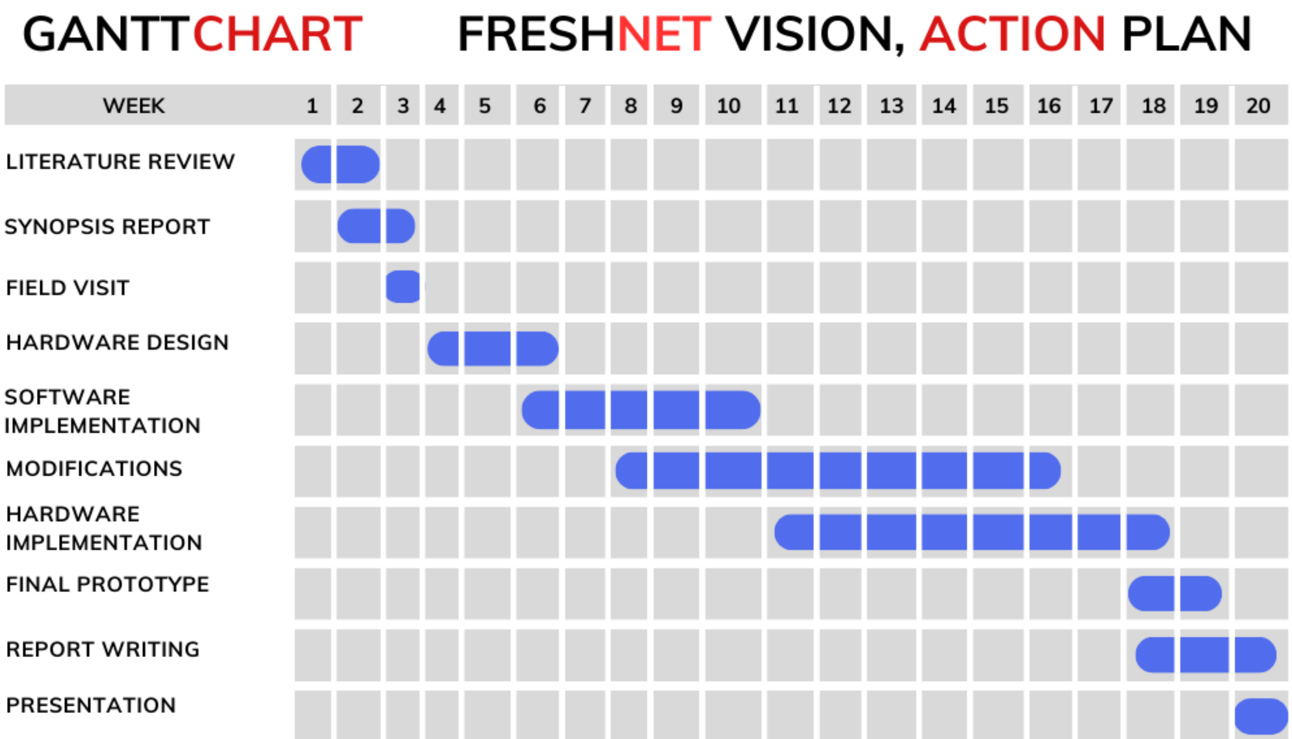

Figure 5.1 Gantt Chart

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