PROJECT PHASE 2 REPORT

ON

Autonomous Wheeled Robot For Intelligent Supermarket Restocking

Submitted by

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to

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of

Bachelor of Technology

in

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Department of Artificial Intelligence and Data Science

St. Joseph's College of Engineering and Technology, Palai

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Declaration

We undersigned hereby declare that the project phase 1 report on **"Autonomous Wheeled Robot For Intelligent Supermarket Restocking"**, submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala, is a bonafide work done by us under supervision of **Assistant Prof.Lakshmi G**. This submission represents our ideas in our own words and where ideas or words of others have been included. We have adequately and accurately cited and referenced the original sources. We also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in our submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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CERTIFICATE

This is to certify that the report entitled "**Autonomous Wheeled Robot For Intelligent Supermarket Restocking** " submitted by **ALAN ANTO (SJC20AD006) , ABDUL JALEEL(SJC20AD001),ABHIJITH P R (SJC20AD002) and HARI KRISHNAN A(SJC20AD035)** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Artificial Intelligence and Data Science is a bonafide record of the project work carried out by them under my guidance and supervision.

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Abstract

In response to the ongoing challenges in efficient supermarket inventory management, this research introduces an autonomous wheeled robot equipped with advanced image detection and line-following capabilities. Leveraging state-of-the-art technologies in robotics, computer vision, and artificial intelligence, the system optimizes product storage within supermarkets. Real-time shelf scanning and analysis, powered by image detection algorithms, enable the robot to identify low-stock or empty shelves promptly. Deep learning models further enhance its ability to categorize products and determine optimal shelf placements, while line-following mechanisms ensure efficient navigation through aisles.

The control system integrates a dynamic decision-making algorithm that allows the robot to adapt its path based on real-time demand data, prioritizing restocking activities accordingly. By analyzing customer purchasing patterns and inventory levels, the robot optimizes its route to replenish critical products promptly. This innovative wheeled robot system offers significant benefits, including reduced labor costs, minimized errors, and enhanced operational efficiency. Ultimately, this research demonstrates the feasibility and effectiveness of autonomous robots in automating supermarket restocking processes, paving the way for intelligent retail automation and redefining the future of retail.

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List of Abbreviations

CNN Convolution Neural Network

YOLO You Only Look Once

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Chapter 1

Introduction

In the ever-evolving realm of retail, the efficient management of supermarket inventory stands as a paramount challenge. Recognizing the need for innovation, this research introduces a pioneering solution—a self-propelled, autonomous wheeled robot equipped with state-of-the-art capabilities in image detection and line-following. As supermarkets grapple with the complexities of inventory maintenance, this system emerges as a technological beacon, seamlessly integrating robotics, computer vision, and artificial intelligence to revolutionize the restocking process.

At its core, the autonomous wheeled robot employs cutting-edge image detection algorithms, processing real-time shelf images with precision to identify and address empty or low-stock shelves. This system transcends traditional inventory management by incorporating deep learning models that not only recognize products but also categorize them, strategically determining their optimal positions on the shelves.

Efficiency takes center stage as the robot navigates supermarket aisles with agility, leveraging advanced line-following mechanisms. This ensures not only swift and obstacle-free movement but also a meticulous approach to restocking that minimizes disruption to the shopping experience. The intelligent integration of these technologies forms a cohesive solution that adapts dynamically to the store's needs in real-time, thanks to a sophisticated decision-making algorithm.

Beyond the promise of operational efficiency, this wheeled robot system signifies a paradigm shift in supermarket management. By significantly reducing labor costs and minimizing errors associated with inventory tracking, it offers a tangible pathway to a more streamlined and cost-effective retail landscape. As this research unfolds, it not only showcases the feasibility of autonomous robots in supermarket operations but also heralds a new era of intelligent retail automation, marking a transformative step towards the future of retail management.

1.1 Background

The imperative transition from conventional to contemporary methodologies in supermarket inventory management has been driven by the imperative to overcome the inherent challenges entrenched in traditional retail practices. In the traditional paradigm, supermarkets grappled with issues such as inefficient inventory tracking, labor-intensive restocking processes, and a dearth of real-time data availability, resulting in suboptimal store operations. Moreover, the unpredictability of consumer demand and stock levels exacerbated the difficulties faced by retailers, making it challenging to streamline operations effectively.

To address these challenges head-on, our project introduces a transformative solution—an autonomous wheeled robot fortified with cutting-edge technologies in robotics, computer vision, and artificial intelligence. This innovative system aims to revolutionize supermarket inventory management by seamlessly integrating advanced image detection and line-following capabilities. Unlike traditional methods, this autonomous robot dynamically responds to real-time demand data, optimizing the restocking process and mitigating challenges associated with manual inventory tracking.

The inefficiencies inherent in traditional supermarket management are addressed through the incorporation of image detection algorithms that enable the robot to accurately identify and rectify empty or low-stock shelves. Deep learning models further enhance the robot's capabilities, allowing it to recognize and categorize products, ensuring optimal shelf placements. Simultaneously, the integration of line-following mechanisms facilitates agile and obstacle-free navigation through supermarket aisles.

The intelligence of the system is underscored by a dynamic decision-making algorithm, enabling the robot to adapt its path based on real-time demand, prioritize restocking tasks, and optimize its route efficiently. This not only reduces labor costs but also minimizes errors, promising a significant enhancement in operational efficiency.

In essence, our project not only acknowledges the challenges inherent in traditional supermarket inventory management but endeavors to redefine the future of retail automation. By showcasing the feasibility and effectiveness of autonomous robots, our research paves the way for a paradigm shift in supermarket operations, offering a glimpse into an intelligent and automated future for the retail sector.

1.2 Objective and Scope

The envisioned project on autonomous wheeled robot integration into supermarket inventory management aspires to revolutionize traditional retail practices by introducing a comprehensive and intelligent solution. The primary objective is to address and overcome the challenges inherent in conventional supermarket operations, such as inefficient inventory tracking, labor-intensive restocking processes, and a lack of real-time data availability.

Our project focuses on the development and implementation of an autonomous wheeled robot equipped with advanced image detection and line-following capabilities. The key objective is to streamline the restocking process by leveraging cutting-edge technologies in robotics, computer vision, and artificial intelligence. The robot will dynamically respond to real-time demand data, accurately identifying and rectifying empty or low-stock shelves through image detection algorithms.

Simultaneously, our project aims to enhance the efficiency of supermarket inventory management by incorporating deep learning models into the robot's functionality. These models will enable the robot to recognize and categorize products, ensuring optimal shelf placements and minimizing errors in restocking.

The scope of the project extends to the integration of a dynamic decision-making algorithm that adapts the robot's path based on real-time demand. This algorithm will prioritize restocking tasks, optimizing the robot's route efficiently and further reducing labor costs. The project will also explore the feasibility and effectiveness of cloud-based platforms, providing remote accessibility for farmers and facilitating seamless communication between the robot and supermarket systems.

In essence, our project's objective is to showcase the transformative potential of autonomous robots in supermarket inventory management. By addressing the challenges faced in traditional practices, we aim to set the stage for intelligent and automated solutions that redefine the future of retail operations. The scope encompasses the development, testing, and validation of the autonomous wheeled robot system, with a keen focus on its practical applicability and scalability within diverse supermarket environments.

Chapter 2

Literature Review

1. **Automation of Library Management System using Autonomous Robot**
   This paper [4] Existing library management systems are labor-intensive and time-consuming. While line-following robots offer basic solutions, researchers propose a more comprehensive autonomous robot integrating book retrieval, delivery, and re-shelving. This user-friendly system utilizes RFID tags and sensor fusion for efficient navigation and integrates a pick-and-place arm for diverse book handling. While areas like obstacle avoidance, error handling, and security need further exploration, this paper contributes significantly by proposing a scalable and potentially cost-effective solution to revolutionize library automation.

2. **You Only Look Once: Unified, Real-Time Object Detection**
   This paper [11] revolutionizes object detection by introducing YOLO, a unified neural network that predicts bounding boxes and class probabilities in one lightning-fast pass. Unlike slow, multi-stage methods, YOLO learns directly from the entire image, achieving real-time speeds and surpassing prior accuracy, even on unconventional domains like artwork. This paradigm shift paves the way for exciting possibilities beyond detection, making YOLO a landmark in computer vision.

3. **Material Delivering Robot using Line Guided Vehicle**
   This paper [6] investigates the human pursuit of comfort and the ongoing search for innovative solutions in daily tasks and professional settings. Focusing on the

pick-and-place concept, it introduces a robot designed for executing instructions and overcoming obstacles. The study emphasizes the potential of such technology to reduce pollution by addressing labor costs through automation. In the current industrial landscape, manipulator robots, comprising metal arms with flexible structures, are gaining prominence. Integrating a mechanical arm with a line-following robot enhances capabilities, allowing the selection and transportation of items along predefined paths. The use of servos adds adaptability for obstacle clearance, particularly when encountering vehicles on the designated route. This literature survey highlights the evolving role of automation in industries and the transformative impact of robotic solutions on efficiency and environmental considerations.

4. **Image Recognition of Supermarket Shopping Robot Based on CNN**
   This paper [15] delves into the realm of autonomous retail systems, specifically focusing on the development of supermarket shopping robots designed to assist shop assistants in replenishing goods and relieving them of monotonous tasks. Guided by the criteria set forth in the "Innovation Robot Design and Production Competition-Supermarket Robot Challenge Competition," the study proposes a novel Convolutional Neural Network (CNN) image recognition algorithm. The algorithm aims to address the challenges of low recognition accuracy and sluggish processing speed in image recognition, thereby enhancing the operational efficiency of supermarket robots. Through comprehensive experimentation, the paper validates the effectiveness of the proposed image recognition algorithm, showcasing its applicability in meeting the requirements of the competition and contributing to the evolution of intelligent retail systems.

5. **Vision Based Intelligent Shelf-Management System**
   In the realm of supermarket management, the paper [10] stands out as a pioneering contribution to the pressing challenges faced by modern retailers. The paper delves into the prevalent issues of identifying empty shelves, ensuring on-shelf availability, and accurately predicting future sales in the context of contemporary supermarkets. Acknowledging the diminishing competition faced by local stores, the authors recognize the imperative for an efficient system to manage the abundant and diverse

product inventories lining supermarket shelves. The core innovation lies in the integration of machine learning techniques to automate and optimize these processes. By leveraging real-time image capture through cameras and employing sophisticated algorithms, the system detects threshold percentages or empty shelves, promptly alerting laborers for timely intervention. Furthermore, the paper extends its focus to the realm of predictive analytics, employing time series analysis and diverse machine learning algorithms to forecast future supply and demand dynamics. Through a comprehensive exploration of customer behavior, product group preferences, and seasonal variations, the authors propose a robust framework that enhances inventory management in supermarkets, especially crucial during dynamic scenarios like seasonal peaks or unexpected disruptions such as pandemics. The insights gleaned from this paper underscore the transformative potential of machine learning in revolutionizing supermarket operations for enhanced efficiency and adaptability.

6. **Design and Development of Pick and Place Arm Robot**

   The paper [12] involves designing and fabricating a pick-and-place arm-type robot for handling parts in various production processes, such as machining, sheet metal operations, and assembly. The specific design objective is to pick objects weighing approximately 100 grams, such as plastic caps and glass blanks, and transfer them between workstations. The interdisciplinary approach integrates Mechanical, Pneumatic, and Electrical disciplines.The systematic design process includes a literature review, conceptualization using CAD tools, and the development of a 3D model and 2D drawings. The robot arm employs pneumatic cylinders and suction grippers for component transformation. The electro-pneumatic circuit is designed using Festo-Fluidsim software.The implemented robot successfully reduces the time required for part transfer and increases the number of pieces transferred, despite a higher initial cost compared to the manual system. The results indicate a significant reduction in transfer time and a substantial increase in the number of pieces transferred, demonstrating the efficiency of the robotic system in production processes.

7. **Pick and Place Robotic ARM using PLC**

   This comprehensive paper [2] delves into the intricate operational stages of a pick-and-place robotic arm system, particularly emphasizing its role as an automated material handling solution synchronized with the movements of objects on a conveyor belt. While contemporary industries employ various advanced robotic technologies, the control mechanisms often rely on manual intervention or utilize processors such as Arduino and microcontrollers. Recognizing the limitations and disadvantages associated with microprocessors, this paper advocates for the adoption of Programmable Logic Controllers (PLCs) as a superior alternative for controlling and operating robotic arms.

The thorough analysis of the pick-and-place process reveals a spectrum of challenges and intricacies, all of which have been meticulously considered during the programming and design phases of the robotic arm. By leveraging the capabilities of PLCs, the paper proposes a paradigm shift towards enhanced control and operational efficiency. This transition from conventional microprocessors to PLCs is motivated by the goal of overcoming limitations and ensuring a more robust and reliable solution for automated material handling in industrial settings. Through strategic programming and design considerations, the proposed pick-and-place robotic arm system aims to provide a streamlined and efficient approach to address the complexities inherent in the material handling process.

8. **4-DOF Robot Arm for Pick and Place Process**

   This paper [3] addresses the growing need for labor in developing countries' industries by advocating the adoption of advanced robot arms. The constructed robot arm features four joints and links, each powered by a dedicated DC motor controlled through an Arduino Microcontroller. A PID-based kinematic control system is implemented to execute precise robotic manipulation tasks within the arm's workspace. Forward kinematics is computed using the Standard DH parameter convention, while an analytical method is employed to solve the inverse kinematics, determining the unknown joint angles necessary for autonomous positioning. Real-time testing demonstrates the system's effectiveness, showcasing its precise control and overall performance. Additionally, a MATLAB GUI facilitates user-friendly interaction with the Arduino controller, enhancing interface control and usability for pick-and-place operations in industrial settings.

The overarching goal of this research is to contribute to the increased efficiency of manufacturing processes by leveraging advanced robotic technology. By successfully implementing the proposed control system, the study seeks to optimize manufacturing capacity, reduce labor costs, and streamline pick-and-place operations. The combination of PID-based control, kinematic calculations, and a user-friendly interface through MATLAB GUI contributes to a robust and efficient solution for autonomous robot arm manipulation in real-world industrial applications.

9. **An Approach for Plant Leaf Image Segmentation Based on YOLOV8 and the Improved DEEPLABV3+**

   In this paper [13], the authors present an innovative approach for accurate plant leaf image segmentation, crucial for applications such as automatic leaf area estimation, species identification, and plant disease/pest monitoring. Their method combines YOLOv8 for leaf object detection with an improved DeepLabv3+ for precise leaf segmentation. YOLOv8 is employed initially to reduce background interference, followed by the enhanced DeepLabv3+ method, incorporating DenseASPP and strip pooling strategies for efficient capture of bar leaves and slender petioles. Experimental results on a publicly available leaf dataset demonstrate a significant achievement, with a mean intersection over the union (mIoU) value of 90.8%. When compared to several other popular segmentation methods, including FCN, LR-ASPP, PSPnet, U-Net, DeepLabv3, and DeepLabv3+, the proposed approach consistently outperforms them, improving mIoU by notable percentage points. The study concludes that the method's enhanced performance supports the development of smart agroforestry, showcasing its potential for advancing agricultural technologies.

10. **Object Detection with Convolutional Neural Networks**

    The paper [8] provides a thorough review of the significant growth observed in computer vision research, particularly in the realm of object detection. Object detection involves the classification and localization of objects in images, and its applications span various domains such as human-computer interaction, video surveillance, satellite imagery, transportation systems, and activity recognition. The focus of the paper is on the use of Convolutional Neural Networks (CNNs), a subset of deep learning architectures, for object detection tasks.

The paper highlights the remarkable success of deep CNN architectures in achieving impressive results for object detection in digital images. It discusses the different types of object detection models within the CNN framework, shedding light on their architectures and functionalities. Additionally, the paper provides insights into benchmark datasets commonly used for evaluating object detection models.

Moreover, the review encompasses a comprehensive overview of the diverse applications of object detection models, showcasing their versatility in addressing real-world challenges. The applications include but are not limited to human-computer interaction, video surveillance, satellite imagery analysis, transportation systems optimization, and activity recognition.

Overall, the paper serves as a valuable resource for understanding the recent developments in object detection using CNNs, offering insights into the types of models, benchmark datasets, and the extensive research conducted for various practical applications.

11. **Plant Detection and Counting: Enhancing Precision Agriculture in UAV and General Scenes**

    This study [5] introduces Yolov8 technology, a state-of-the-art machine learning model, into plant science for plant detection and counting in agriculture. The authors enhance Yolov8 with the integration of shallow-level information into the Path Aggregation Network (PANet) to address resolution loss. They also improve upsampled features using the Content-Aware ReAssembly of Features (CARAFE) and Multi-Efficient Channel Attention (Mlt-ECA) techniques, creating Yolov8-UAV. The evaluation on datasets featuring four plant species demonstrates the competitiveness of their method compared to advanced counting techniques. Additionally, the researchers release a new cotton boll dataset and update wheat ear datasets. Yolov8-UAV is recommended for UAV scenarios, while Yolov8-N is suitable for general scenes. The study contributes a powerful solution for real-world plant science challenges and provides valuable datasets, promoting cross-disciplinary research in computer vision and plant science.

12. **Towards Intelligent Retail: Automated on-Shelf Availability Estimation Using a Depth Camera**
    The paper [7] introduces an innovative framework for automated shelf monitoring to enhance on-shelf availability and inventory management. Traditional store audits are labor-intensive and unreliable, prompting the development of a low-cost embedded system using a consumer-grade depth sensor. The system employs 3D point cloud reconstruction and modeling techniques, such as surface fitting and occupancy grids, to assess product availability by comparing the current shelf status to a reference model. No prior knowledge of the product is necessary, as the system automatically learns the shelf reference model during an initial training stage. The output includes alerts for store managers and real-time updates for automated stock ordering, replenishment, and e-commerce apps. Experimental tests in a retail environment demonstrate the system's ability to estimate on-shelf availability with a maximum average discrepancy of about 5.0% for various fresh products. This approach offers an efficient and cost-effective solution for early detection of out-of-stock situations, contributing to customer satisfaction and minimizing profit loss for retailers and manufacturers.

13. **Foreign Objects Identification of Transmission Line Based on Improved YOLOv7** In this paper [14], the increasing frequency of foreign object invasions causing grid failures is addressed through a proposed deep learning-based algorithm for unmanned inspection of transmission lines. The algorithm utilizes the YOLOv7 model, enhanced by hyperparameter optimization using genetic algorithms and space-to-depth convolution for efficient foreign object recognition in UAV images. The method demonstrates prompt and accurate determination and localization of targets in aerial images. Comparative analysis with other YOLO series algorithms reveals that the improved YOLOv7 achieves the highest Mean Average Precision (mAP) at 92.2% and a competitive Frames Per Second (FPS) of 19, surpassed only by Centernet. Notably, the algorithm exhibits a significant 11.9% increase in accuracy for tower crane recognition compared to the unimproved YOLOv7, outperforming other detection targets. Additionally, the genetic algorithm-based hyperparameter optimization contributes to faster model convergence. Overall, the proposed

method proves effective in enhancing transmission line inspection and foreign object recognition, offering promising results in terms of accuracy and efficiency.

14. **Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images**

    In this paper [9], the authors address the critical need for accurate and efficient segmentation of gliomas, the most common and aggressive brain tumors, to enhance treatment planning and improve the quality of life for oncological patients. They propose an automatic segmentation method based on Convolutional Neural Networks (CNN) using small 3×3 kernels. This design choice enables a deeper architecture, mitigates overfitting, and reduces the number of network weights. The authors also explore the effectiveness of intensity normalization as a pre-processing step, combined with data augmentation, for improved segmentation in MRI images.

    The proposed method was validated on the BRATS 2013 database, achieving first place in the Brain Tumor Segmentation Challenge. It demonstrated high performance in segmentation accuracy, with Dice Similarity Coefficient metrics of 0.88, 0.83, and 0.77 for the complete, core, and enhancing regions, respectively. Additionally, the model obtained the overall first position in the online evaluation platform. The authors further participated in the on-site BRATS 2015 Challenge, securing the second place with Dice Similarity Coefficient metrics of 0.78, 0.65, and 0.75 for the complete, core, and enhancing regions. This work highlights the efficacy of their CNN-based segmentation method in addressing the challenges of glioma segmentation in MRI images.

15. **An Improved Faster R-CNN for Small Object Detection**

    The paper [1] introduces an enhanced approach to address the challenges of small object detection within the realm of convolutional neural networks (CNNs), particularly focusing on the widely used Faster R-CNN algorithm. The proposed method employs a two-stage detection process. In the positioning stage, a refined loss function based on intersection over Union (IoU) is introduced for bounding box regression, and bilinear interpolation is utilized to enhance the regions of interest (RoI) pooling operation, addressing issues related to positioning deviation. In the recognition stage, multi-scale convolution feature fusion is implemented to enrich the feature map with more information. Additionally, an improved non-maximum suppression (NMS) algorithm is incorporated to prevent the loss of overlapping objects. Experimental results indicate that the proposed algorithm demonstrates superior performance in detecting small objects, particularly showcasing effectiveness in the context of traffic signs with resolutions ranging from 0 to 32. The algorithm achieves a commendable 90% recall rate and an 87% accuracy rate, outperforming the baseline Faster R-CNN significantly. Overall, the proposed algorithm stands out as an effective and robust solution for small object detection in complex scenarios.

2.1 Survey Summary

In the survey of fifteen papers related to Autonomous Wheeled Robot for Intelligent Supermarket Restocking, various innovative approaches and technologies were explored to enhance automation and efficiency in supermarket restocking processes. One paper focused on the automation of library management systems, proposing a comprehensive autonomous robot for book retrieval and re-shelving, utilizing RFID tags and sensor fusion. Another paper introduced YOLO, a real-time object detection system, revolutionizing computer vision applications, including artwork detection and potentially transforming supermarket restocking.

A paper on material delivering robots highlighted the potential of automation in reducing pollution and labor costs, especially in industries. Image recognition in a supermarket setting was addressed with a novel Convolutional Neural Network (CNN) algorithm, aiming to improve the accuracy and speed of recognizing items for restocking. Additionally, a vision-based intelligent shelf-management system integrated machine learning techniques to automate on-shelf availability estimation and predict future sales, contributing to efficient supermarket operations.

The design and development of pick-and-place arm robots, using both traditional robotic arms and PLC-based systems, showcased advancements in manufacturing processes, reducing transfer time and increasing efficiency. Another paper introduced a 4-DOF robot arm for pick-and-place processes, emphasizing its role in optimizing manufacturing capacity and reducing labor costs.

Furthermore, a paper on plant detection and counting introduced Yolov8 technology, enhancing it for UAV scenarios and general scenes, providing a powerful solution for real-world plant science challenges. The application of depth cameras for automated on-shelf availability estimation was discussed in a paper, offering a cost-effective solution for early detection of out-of-stock situations in retail environments.

In addressing the challenges of foreign object identification in transmission lines, a deep learning-based algorithm using an improved YOLOv7 demonstrated high accuracy and efficiency. Lastly, a paper on brain tumor segmentation using CNNs emphasized the significance of accurate and efficient segmentation for enhancing treatment planning.

Overall, the surveyed papers collectively contribute to the advancement of autonomous wheeled robots for intelligent supermarket restocking, incorporating diverse technologies and methodologies to address specific challenges in the field. These findings hold promise for creating more efficient, accurate, and adaptive solutions for modern supermarkets.

Chapter 3

Proposed Methodology

3.1 Introduction

The landscape of supermarket restocking is currently marked by manual and labor-intensive methods that can impede efficiency and hinder the optimization of inventory management. Traditional approaches rely heavily on periodic manual observations and human experience, leading to potential inefficiencies and suboptimal utilization of resources. While some supermarkets have begun to integrate basic automation technologies, these systems often operate in isolation, lacking the real-time data acquisition and intelligent decision-making capabilities crucial for optimizing restocking operations.

The adoption of standalone automation solutions represents a step towards modernization, yet they fall short of providing the necessary sophistication required for precision restocking in a dynamic retail environment. The absence of real-time data acquisition and intelligent decision-making mechanisms can lead to delayed responses to changing inventory demands, affecting the overall efficiency and customer satisfaction. Moreover, scalability remains a challenge, particularly for larger retail establishments with diverse product offerings and multiple locations.

Acknowledging the limitations of current supermarket restocking systems, there is a pressing need for the development and implementation of an advanced solution. Enter the Autonomous Wheeled Robot for Intelligent Supermarket Restocking, a cutting-edge approach that leverages robotics, computer vision, and artificial intelligence to revolutionize the restocking process. This innovative system aims to seamlessly integrate into supermarket operations, providing a scalable, interconnected, and technologically advanced framework that empowers retailers to optimize inventory, streamline restocking processes, and enhance the overall shopping experience for customers.

3.2 Proposed Methodology

In the evolving landscape of retail, efficient inventory management is crucial for maintaining a seamless shopping experience and optimizing operational processes. This project delves into cutting-edge technologies to address this challenge, focusing on the integration of the YOLO algorithm for accurate product detection. The overarching goal is to develop an autonomous retail inventory management system that not only identifies products running low on the shelf but also autonomously restocks them.

3.2.1 Block Diagram

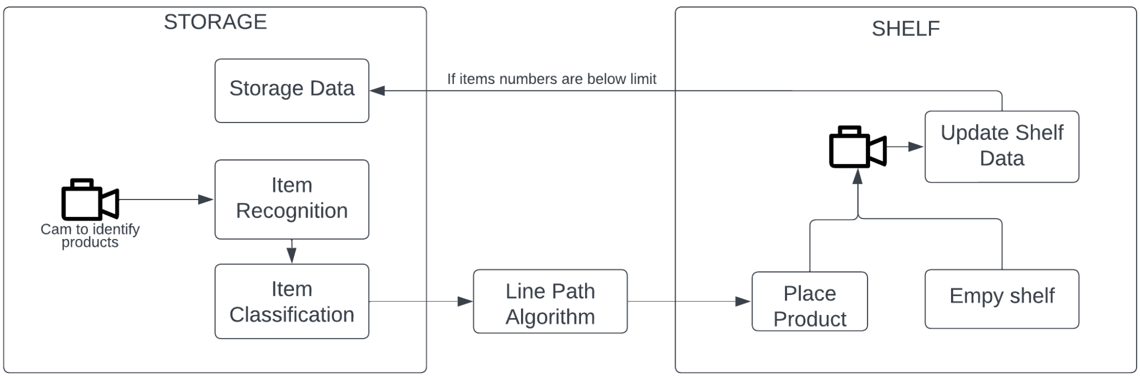

Figure 3.1: Block Diagram of System

The Figure 3.1 Provides a detailed understanding of the proposed working of the system. The System occurs majorly in two separate locations. a) Storage, Where the goods are stored in bulk amount and b) Shelf where the products are placed for display for the customer.

- In Storage we have a dedicated camera to provide video input feed to detect what item is in front. Once detected the system automatically classifies the object into it's corresponding category/class. Once the category is determined we can understand which aisle the item corresponds to and which shelf it belongs to.
- Once the necessary details are received, the pick-n-place robot picks up the item and navigates to the shelf using Line-Following Algorithm, where each aisles will have their own corresponding lines which they have to follow. On reaching correct the shelf the robot places the item into their corresponding shelf.
- In Shelf we have another camera mounted facing the shelf. These cameras are responsible for identifying the empty spaces within the shelf and also update the value once a new item is added. Once the number of items in one shelf goes bellow a set value the system updates the shelf data and sents a message to storage for re-stocking.

3.2.2 Data Collection

In the context of mobile photography for product documentation, the proposed setup involves utilizing smartphones equipped with high-resolution cameras to capture images of various products. The emphasis is on visiting multiple supermarkets and employing smartphone cameras to create a comprehensive dataset. This dataset aims to include diverse images of product shelves, taken from various angles, distances, and lighting conditions.

During supermarket visits, the focus is on capturing a wide range of products, encompassing different categories, sizes, and packaging types. The goal is to compile a rich collection that reflects the diversity of products available in supermarkets.

Ethical considerations are an integral part of this process. Adherence to ethical guidelines and respect for privacy are emphasized, particularly when capturing images in public spaces. Obtaining necessary permissions from supermarket owners or managers before capturing images within their stores is essential to ensure compliance with ethical standards.

In essence, the mobile photography setup is designed to leverage the capabilities of smartphones for comprehensive product documentation. The supermarket visits are aimed at gathering diverse and representative images, while ethical considerations underscore the importance of respecting privacy and obtaining permissions in the process. This approach ensures a well-rounded and responsible methodology for creating a valuable data-set of product images.

Some of the captured images are shown in the Figure 3.1:

Figure 3.2: Sample Data1

3.2.3 Annotation

- Annotation with Roboflow: - You used Roboflow to annotate the 5000 supermarket product images. This involved drawing segmented borders around the products, indicating their segmentation. Each annotation includes class labels specifying the type of product and segmentation coordinates describing the location of the product in the image.

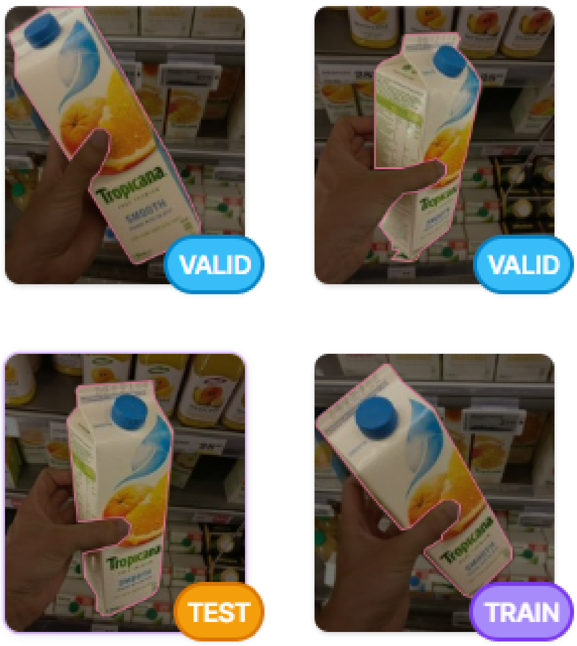

Figure 3.3: Annotation

- Class Labels: - Class labels are important because they tell the model what type of product is present in each annotated region. For example, if a bounding box is drawn around a cereal box, the class label might be "cereal."

- Segmentation Coordinates: - Segmentation coordinates define the boundaries of the annotated regions. They provide information on where the product is located in the image. This information is crucial for the model to learn how different products are positioned.

- Data Augmentation: - Data augmentation techniques have been applied to increase the diversity of your dataset. This involves creating variations of the original images by applying transformations such as flipping, rotating, or adjusting brightness. Augmenting the data helps the model generalize better to different scenarios and variations it might encounter during real-world use.

  By following these steps, you've prepared a well-annotated and augmented dataset that can be used to train a machine learning model. This model should be more robust and capable of handling various situations in a supermarket environment. If you proceed to train your model using this dataset, it's likely to perform well in recognizing and segmenting different types of supermarket products.

3.2.4 Technology Selection:

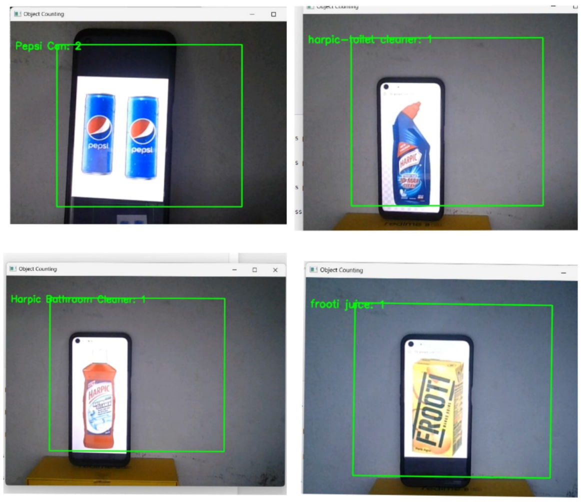

Figure 3.4: Annotation

The foundation of this project lies in the careful selection of cutting-edge technologies. The YOLO algorithm is at the forefront, known for its real-time object detection capabilities. By leveraging YOLO, we aim to enhance the accuracy and speed of product detection in a retail setting, ensuring timely restocking and reducing instances of out-of-stock items.

Figure 3.5: Annotation

3.2.5 Algorithm Integration:

A significant component of this project involves the development and integration of YOLO algorithms tailored for product detection. The algorithms are designed to accurately recognize products that are low in stock on the store shelves. This integration involves training the YOLO model on a diverse dataset to enhance its ability to identify a wide range of products across various categories.

3.2.6 Autonomous Restocking System:

Beyond detection, the project extends its focus to the creation of an autonomous restocking system. Once a low-stock product is identified, the system is engineered to autonomously navigate the store environment, locate the corresponding product, and place it accurately on the designated shelf location. This automation not only improves operational efficiency but also reduces the need for manual intervention.

3.2.7 Testing and Validation:

A crucial phase of the project involves extensive testing in a controlled environment. The YOLO-based product detection system undergoes rigorous testing to ensure its accuracy and efficiency in real-world scenarios. This includes simulations of varying shelf layouts, lighting conditions, and product arrangements to validate the robustness of the algorithm.

3.2.8 Robot Design and Construction:

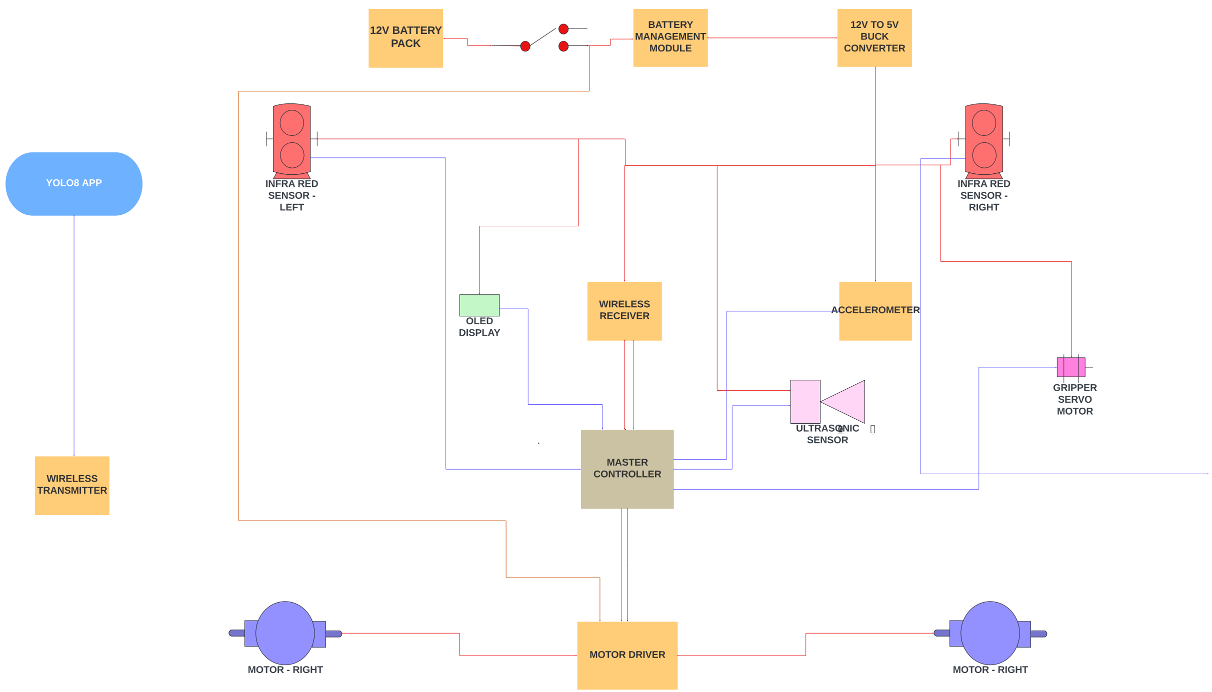

Figure 3.6: circuit diagram

To implement the autonomous restocking system, a specialized robot is designed and constructed. This wheeled robot is equipped with the necessary sensors.Line-following capabilities are integrated to ensure precise navigation through the store aisles.
The required hardware components for the robot hardware based on our research is listed below. The list may be subject to change along the building phase.

- Arduino Mega:

The brain of the robot, responsible for processing data and controlling various components. Arduino Mega is chosen for its ample number of digital and analog pins, suitable for interfacing with sensors, actuators, and other peripherals.

- Motor Drivers:

  Dual Motor Driver Module (e.g., L298N or L293D) to control the movement of the robot's wheels. Motor drivers are essential for interfacing with the motors that drive the robot, enabling precise control of speed and direction.

- DC Motors:

  Geared DC motors to drive the wheels of the robot. Encoders on the motors for precise control of movement and feedback on wheel rotation.

- Chassis:

  Robot chassis to provide structural support and house the various components. The chassis should be designed to accommodate the size and weight of the robot and provide space for sensors, actuators, and the power source.

- Wheels and Casters:

  Robust wheels suitable for the terrain of the supermarket. Swivel casters for stability and ease of movement.

- Infrared (IR) Sensors:

  To detect obstacles and prevent collisions with other objects in the supermarket.

- Power Supply:

  Lithium-ion or LiPo batteries with sufficient capacity to power the motors, Arduino Mega, and sensors. Voltage regulators to ensure stable power supply to the components.

- Grippers:

  Mechanism with grippers for picking up and placing items on shelves. Servo motors or stepper motors for controlling the gripper movement.

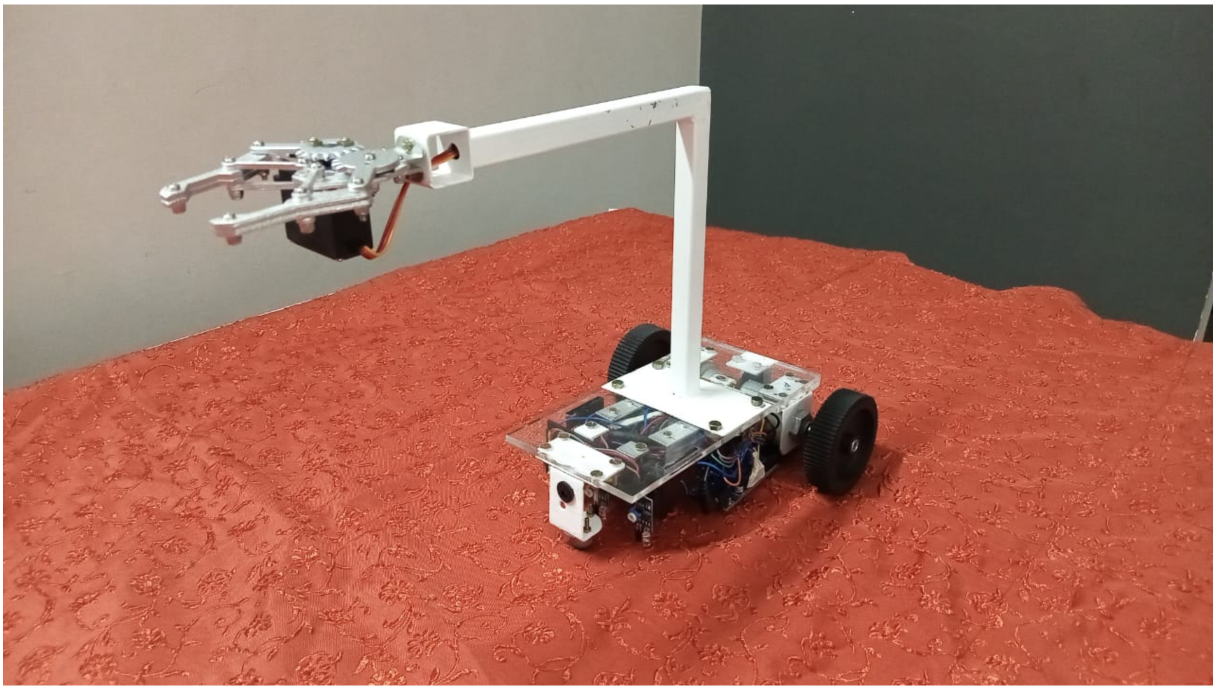

Figure 3.7: Robotic System

- Wireless Communication Module:

  Wi-Fi or Bluetooth module for communication with a central server or remote control. Enables the robot to receive restocking instructions and send status updates.

- Microcontroller for Gripper Control:

  Another Arduino or microcontroller dedicated to controlling the gripper mechanism. Communicates with the main Arduino Mega for coordinated actions.

- LEDs and Indicators:

  LEDs for indicating the robot's status or any issues. Indicators for displaying the current operation (e.g., restocking, moving, idle).

- Enclosures and Mounts:

  Protective enclosures for sensitive components. Mounts for securing sensors and cameras in optimal positions.

In conclusion, this project represents a holistic approach to revolutionizing retail inventory management. By integrating the YOLO algorithm for precise product detection and developing an autonomous restocking system, the aim is to streamline operations, enhance accuracy, and ultimately provide a more seamless shopping experience for customers. This intersection of advanced computer vision and robotics showcases the potential for innovation in the retail sector, paving the way for future advancements in autonomous systems.

Chapter 4

Results and Discussions

4.1 Performance Analysis

4.1.1 Confusion matrix

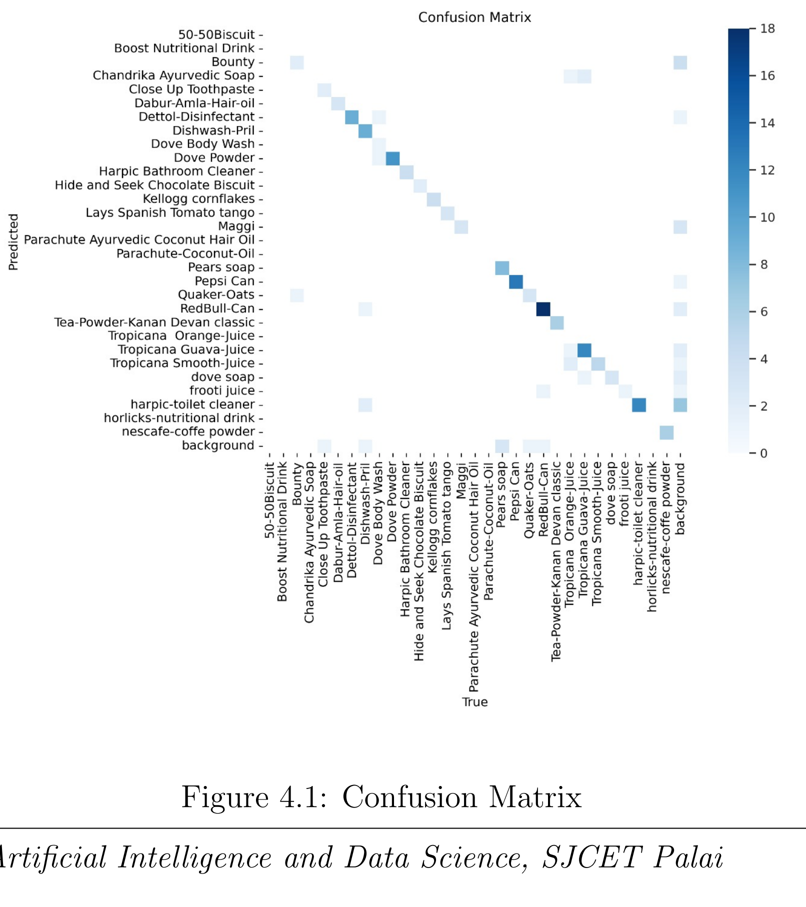

Figure 4.1: Confusion Matrix

- Diagonal Dominance: The main diagonal, where the predicted class matches the true class, shows varying degrees of blue shades, indicating different levels of correct predictions for each class. Darker shades on the diagonal suggest a higher number of correct predictions. For most products, the matrix shows moderate to high correct classification rates (darker shades), implying that the model is generally effective at identifying these items correctly.

- Misclassifications: Lighter or no shades off the diagonal indicate few or no misclassifications between classes. However, some classes show light blue shades off the diagonal, suggesting occasional confusion between certain products. For instance, some confusion might be seen between closely related products or those with similar packaging.

- Scale and Distribution: The color scale ranges from 0 to 18, where these numbers represent the normalized count of predictions. It shows the frequency of each predicted class for a true class, normalized possibly by the number of instances in each true class or total predictions. The distribution of colors across the matrix helps identify which classes are most accurately predicted and which are most commonly confused.

- High Accuracy: Classes with very dark blue squares on the diagonal generally indicate a high accuracy rate for those particular items.

- Areas for Improvement: Light blue squares off the diagonal, where confusion between classes occurs, highlight areas where model training could be enhanced. It might be beneficial to further analyze why these misclassifications occur—this could be due to similarities in product appearance, packaging, or insufficient examples in the training set.

- Overall Model Strengths and Weaknesses: The strengths of the model lie in its ability to accurately classify a majority of the products, as indicated by the darker squares along the diagonal. The weaknesses, albeit fewer, are evidenced by the lighter squares where the model confuses one product for another.

In summary, while the model performs well for most classes, identifying specific products accurately, there are notable discrepancies where performance could be enhanced, either through training on more diverse data sets or by refining the model's architecture and parameters to better distinguish between similar products.It highlights both the robustness of the model in accurately identifying most products and the specific areas where the model might be improved through additional training, feature engineering, or data augmentation to reduce confusion between similar items. This information is crucial for refining the model and improving its practical application in scenarios like automated supermarket checkout systems or inventory management.

4.1.2 Precision,Recall - confidence Curve

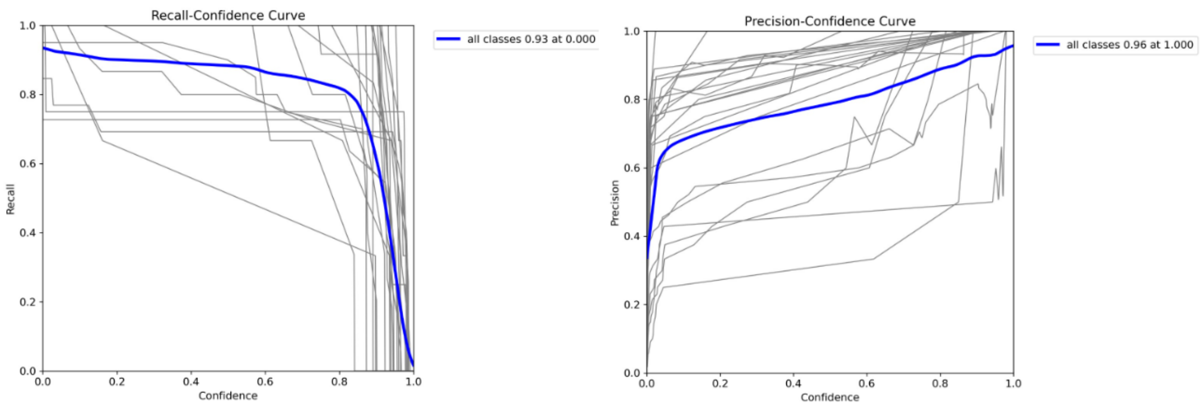

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Figure 4.2: Recall,Precision - confidence curve

Recall-Confidence Curve

- Description: This graph plots recall against confidence levels for the classification predictions. Each line represents the recall for a different class at varying confidence thresholds.
- Key Observations: The bold blue line representing the average recall across all classes shows that recall is very high (near 1.0) at low confidence thresholds but

decreases as the confidence threshold increases. This trend is typical because, at lower thresholds, the model captures more true positives but also allows more false positives. Individual lines for each class (grey lines) suggest variability in recall among different products. Some lines drop sharply, indicating a significant reduction in recall with a minor increase in confidence threshold for those classes. The recall value of approximately 0.93 at a confidence threshold of 0 indicates a high ability to identify relevant items but with less strict confidence criteria.

Precision-Confidence Curve

- Description: This graph shows the precision of the model's predictions across different confidence levels. Similar to the recall graph, each line represents precision for each class at varying confidence levels.
- Key Observations: The bold blue line representing average precision across all classes reveals that precision starts low at lower confidence thresholds but increases and stabilizes as the confidence threshold approaches 1. This is indicative of the model's increasing selectivity, where higher thresholds yield more precise but fewer predictions. As with the recall, there is variability among classes (grey lines), with some demonstrating steep improvements in precision as confidence increases, while others are more stable across thresholds. Notably, the precision at the highest confidence threshold is approximately 0.96, which is excellent, suggesting that when the model is confident, its predictions are highly reliable.

Recall-Confidence Curve

- Curve Interpretation: The curve shows the trade-off between precision and recall for different threshold settings. A perfect classifier would create a curve that goes to the top-right corner of the plot. The bold blue line represents the average precision-recall performance across all 35 classes. Each grey line likely represents the precision-recall performance for an individual class.

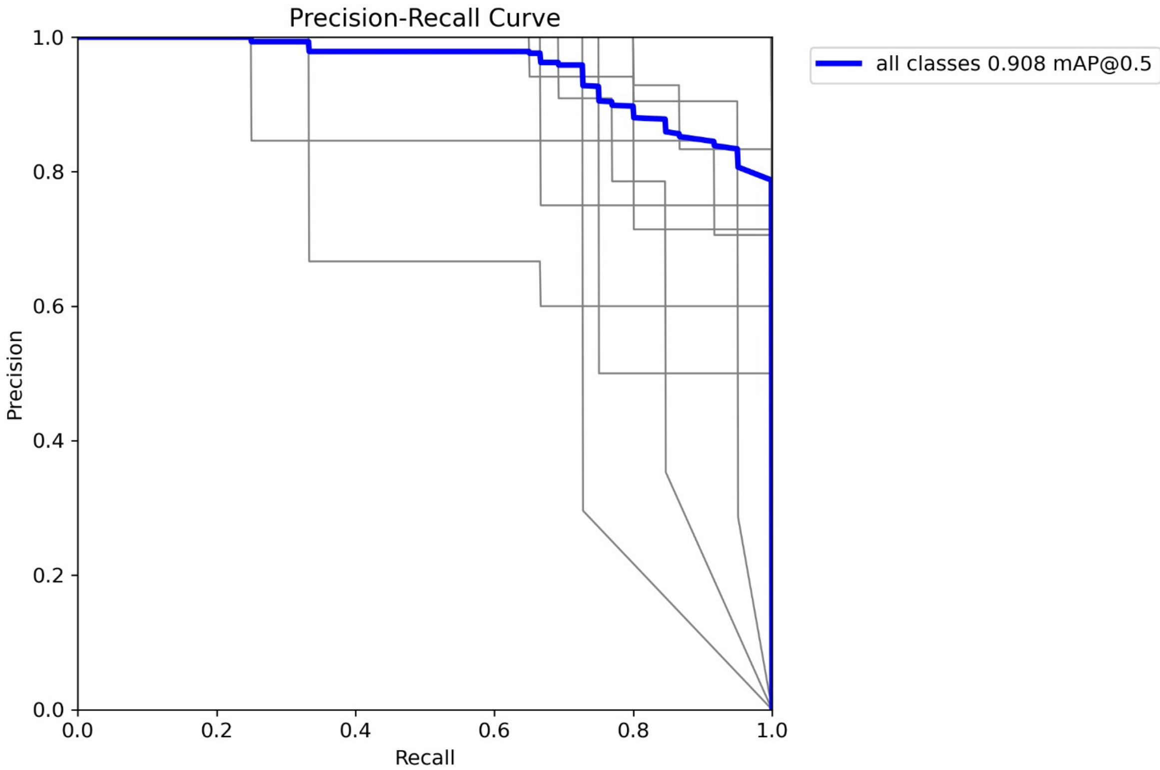

Figure 4.3: Recall-Precision curve

- mAP (Mean Average Precision) at IoU=0.5: The notation “0.908 mAP@0.5” indicates a mean average precision (mAP) of 0.908 when the Intersection over Union (IoU) threshold is set to 0.5. mAP is a single figure that summarises the precision across all recall levels and is a common metric in evaluating models like YOLO for object detection tasks. An IoU of 0.5 means that the overlap between the predicted bounding box and the ground truth bounding box needs to be at least 50 percent for a prediction to be considered correct.

Overall Review Model Performance: The model exhibits high precision and recall at different levels of confidence, indicating robustness. However, the trade-off between recall and precision across different confidence thresholds is evident, highlighting typical challenges in balancing the two metrics. Utility for Practical Use: In practical applications, choosing the optimal confidence threshold will depend on whether it is more critical to avoid false positives or to ensure no item is missed. For example, a higher threshold might be appropriate for scenarios where precision is crucial to avoid costly errors, while a lower threshold might be suitable in cases where missing an item could be detrimental.

4.1.3 Loss Distribution

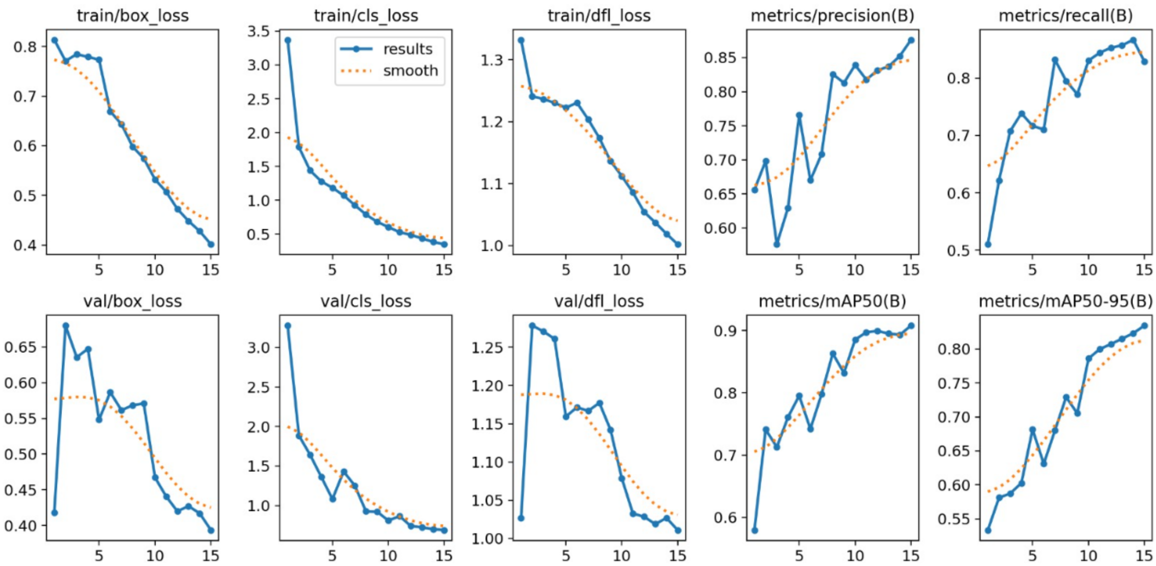

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Figure 4.4: Precision- Recall curve

The Fig 4.3 is a compilation of graphs related to YOLO v8 training and validation process. Each graph shows a different metric tracked over epochs, which are iterations of the entire training dataset. Let's discuss each graph individually:

- train/box-loss: This graph indicates the loss associated with bounding box prediction in an object detection model during training. The loss is decreasing, which is good—it means YOLO is getting better at predicting the location of objects over time
- train/cls-loss: This graph represents the classification loss during training. It tracks how well the model is doing at classifying objects. The downward trend is positive, showing improved performance over epochs.
- train/dfl-loss: This is likely the loss associated with a specific component of YOLO (possibly related to landmark or pose estimation). It also shows a decline, which

indicates learning progress.

- metrics/precision(B): Precision is a metric used to evaluate the performance of YOLO. This graph shows the precision of the model in detecting class "B" objects, and it's trending upwards, meaning the model is correctly identifying more true positives over time.

- metrics/recall(B): This graph shows the recall for class "B". Recall measures the model's ability to find all the relevant cases within a dataset. An upward trend is visible, implying that the model is missing fewer true positives as training progresses.

- val/boxloss: This is the validation loss for the bounding box predictions. It's vital this mirrors the training loss's downward trend, indicating that YOLO is generalizing well to unseen data.

- val/clsloss: Similar to the training classification loss, this is for the validation dataset. It should ideally decrease and plateau as the model learns and then converges.

- val/dflloss: This represents the validation loss for the same component as the training differential loss graph. The decrease in loss suggests the model's predictive performance is improving on the validation data.

- metrics/mAP@50(B): This is the mean Average Precision at an Intersection over Union (IoU) threshold of 50 percent for class "B". It combines precision and recall into a single metric, showing YOLO's overall object detection performance on the validation dataset. Improvement over epochs is visible.

- metrics/mAP@50-95(B): This metric is the mean Average Precision calculated over multiple IoU thresholds from 50 percent to 95 percent (in increments of 5 percent) for class "B". It's a more stringent metric since it considers a range of IoU levels, and an upward trend shows the model performs well across these different thresholds.

In summary, the graphs indicate that our YOLO v8 is learning as expected: losses are decreasing, and performance metrics (precision, recall, and mAP) are increasing. This would typically suggest a successful training phase, provided that the model is not overfitting, which would require additional checks not visible in these graphs.

4.2 Robotic Sysetm

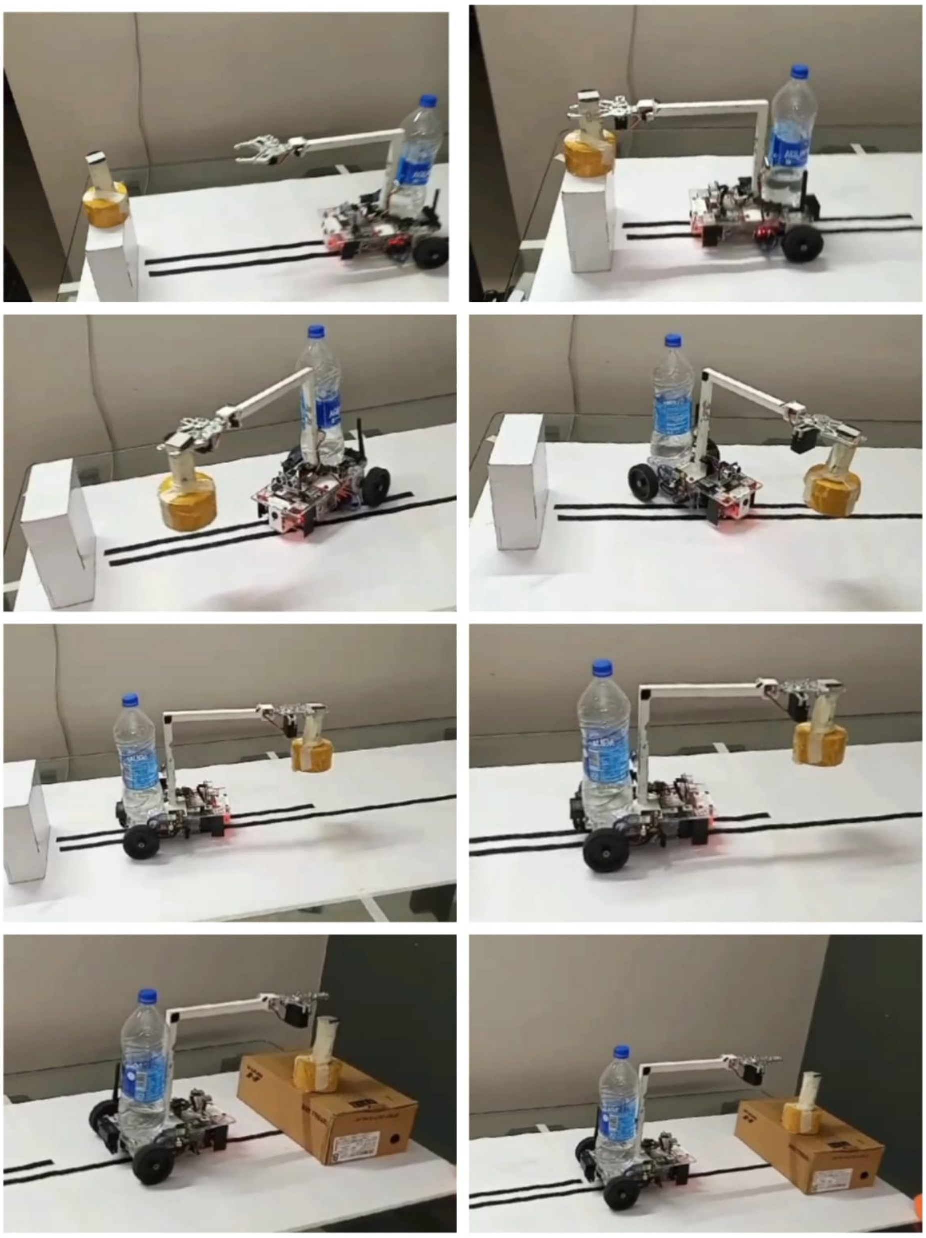

Figure 4.5: Pick and Place

In this futuristic setting, advanced algorithms like YOLOv8 (You Only Look Once version 8) are deployed to monitor product shelves in real-time. These algorithms constantly scan the shelves, accurately counting and identifying products.But it doesn't stop there. The system is designed to maintain a predefined stock level for each product. If the real-time count falls below this predetermined threshold, a seamless communication mechanism is triggered. A wireless transmitter swiftly relays a message to the robotic system, setting off a chain of automated actions.

The robotic system, equipped with sophisticated sensors and actuators, promptly springs into action. Guided by an infrared (IR) sensor, the robot navigates through the store, seamlessly following the black line pathways laid out on the floor. These pathways serve as a guiding beacon, leading the robot directly to the designated aisle.Upon reaching the targeted shelf, the robot deftly picks up the required product, ensuring minimal disruption to the shopping environment. With precision and efficiency, it retrieves the item and embarks on its journey back to the aisle.But the robot's mission doesn't end there. It meticulously follows a predefined coordinate path, carefully avoiding obstacles and other shoppers. As it approaches the designated position within the aisle, the robot seamlessly transitions into its delivery phase.

With a gentle maneuver, the robot deposits the product at the specified location, aligning it perfectly with the surrounding merchandise. This seamless integration ensures that the replenishment process is both efficient and inconspicuous, enhancing the overall shopping experience for customers.Once the task is complete, the robot seamlessly retraces its steps, navigating back to its starting position. With another successful mission accomplished, it stands ready to tackle the next challenge, ensuring that the shelves remain stocked and customers leave satisfied.In this cutting-edge retail ecosystem, the fusion of artificial intelligence, robotics, and automation revolutionizes inventory management, setting new standards for efficiency, accuracy, and customer service.

Conclusion

In conclusion, the Autonomous Wheeled Robot for Intelligent Supermarket Restocking represents a pioneering leap forward in the realm of retail automation, harnessing cutting-edge technology to revolutionize the restocking process. Through the seamless integration of advanced sensors, computer vision, and autonomous navigation capabilities, this innovative system offers a transformative solution to the challenges faced by traditional supermarket restocking methods.The robot's ability to autonomously navigate the store environment, identify low-stock products using YOLO-based product detection algorithms, and precisely restock shelves sets it apart from conventional restocking systems. The incorporation of real-time data processing ensures that the robot can respond promptly to dynamic inventory changes, optimizing restocking operations and enhancing overall efficiency.The connectivity of the system to a centralized server enables remote monitoring and control, allowing retailers to manage restocking operations efficiently through a user-friendly interface. This not only enhances the adaptability of the system but also facilitates a more streamlined and responsive approach to inventory management.Beyond technological innovation, the Autonomous Wheeled Robot for Intelligent Supermarket Restocking holds the promise of significant labor and resource savings, translating into cost-efficiency for retailers. By empowering supermarkets to achieve precise restocking with minimal manual intervention, the system contributes to increased operational efficiency and customer satisfaction.In essence, this project serves as a beacon for the future of supermarket restocking, setting new standards for precision, efficiency, and productivity in the retail sector. The potential impact extends beyond operational enhancements, positioning the system as a key player in advancing the broader goals of automation, sustainability, and improved customer experiences in modern retail environments.

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