Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)

Smart Shopping Cart: Revolutionizing Retail Experience

Submitted in partial fulfillment of the requirement
of the degree of

Bachelor of Technology in

Department of Computer Science and Engineering (Data Science)

By

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A.Y. 2024 – 2025

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CERTIFICATE

This is to certify that the project entitled, **"Smart Shopping Cart: Revolutionizing Retail Experience"** is a bonafide work of **"Advay Sharma" (60009220147), "Aditya Thakkar" (60009220208)** and **"Kaivalya Kulkarni" (60009220198)** submitted in the partial fulfillment of the requirement for the award of the **Bachelor of Technology in Computer Science Engineering (Data Science)**

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DECLARATION

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

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APPROVAL SHEET

Project entitled, **"Smart Shopping Cart: Revolutionizing Retail Experience"**, submitted by **"Advay Sharma" (60009220147), "Aditya Thakkar" (60009220208)** and **"Kaivalya Kulkarni" (60009220198)** is approved for the award of the **Bachelor of Technology in Computer Science Engineering (Data Science)**

Signature of Internal Examiner **Signature of External Examiner**

Place: Mumbai

Date: 28/04/2025

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Abstract

In recent years, the retail sector has witnessed significant advancements through the integration of technology. This report presents the development of a Smart Shopping Cart aimed at transforming the traditional shopping experience by leveraging advanced image processing, artificial intelligence (AI), and Internet of Things (IoT) technologies. The core objective of this project is to design an intelligent cart that can autonomously recognize items, update inventory in real-time, and enable a seamless checkout process. Unlike conventional shopping carts, which rely on manual scanning of barcodes or RFID tags, our smart cart employs a sophisticated video processing and computer vision system to identify products placed within it. This approach not only improves item recognition accuracy but also eliminates the need for costly and infrastructure-heavy RFID systems, making it a scalable solution for diverse retail environments.

The proposed methodology includes utilizing the YOLO (You Only Look Once) object detection model for real-time item recognition and tracking, facilitated by a camera mounted on the cart. The vision model is trained and optimized using Roboflow, a platform that allows the creation of custom object detection models for specific products. Weight sensors are integrated into the cart to detect changes in its content, enabling an innovative item deletion feature that updates the item list as customers add or remove products. These weight sensors work in conjunction with an ESP32 microcontroller and load cells for real-time weight change analysis, ensuring precise item validation. These components are also connected to a backend system that communicates inventory updates, payment processing, and provides a seamless checkout experience.

The interactive display on the cart provides real-time feedback on the total cost, applicable promotions, and product details, enhancing the user experience and facilitating a faster, more convenient shopping journey. A critical feature of this project is the seamless integration with backend payment and inventory management systems, enabling an end-to-end solution for retailers. This integration ensures that the checkout process is streamlined, reducing customer wait times and minimizing human intervention. Additionally, a custom mobile application, developed with React Native, interfaces with the cart and backend system to provide real-time updates and interaction.

The proposed research and development process included an extensive literature review that highlighted the gaps and limitations of existing RFID-based smart cart systems, such as high

implementation costs, limited scalability, and signal interference. By using a combination of computer vision and IoT, this project addresses these limitations and provides a cost-effective, flexible, and accurate solution suitable for various retail formats.

The Smart Shopping Cart project leverages advanced computer vision and IoT technologies to automate item recognition, inventory management, and checkout processes in retail environments. By integrating the YOLOv5 object detection model with real-time weight sensing via load cells and an ESP32 microcontroller, the system achieves robust dual-layer validation for both item addition and removal. This hybrid approach addresses key limitations of traditional barcode/RFID-based systems, such as high implementation costs and susceptibility to interference, while also overcoming the shortcomings of vision-only models in tracking item deletions. The model was trained on a custom dataset using Roboflow and consistently achieved a mean Average Precision (mAP@0.5) exceeding 90% during evaluation, demonstrating high accuracy in diverse lighting and product scenarios. Real-world testing confirmed reliable detection, minimal latency, and precise weight verification with an average error margin below 5 grams. These results underscore the system's potential to deliver a seamless, accurate, and efficient shopping experience, significantly reducing manual intervention and customer wait times while maintaining high operational reliability

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List of Abbreviations

Table 1.1 provides a comprehensive list of abbreviations and their corresponding full forms used throughout the report. This table serves as a quick reference to help readers understand technical terms and acronyms such as RFID, YOLO, AI, IoT, and others that are integral to the Smart Shopping Cart system and its underlying technologies.

Table 1.1: List of Abbreviations

RFID	Radio Frequency Identification
YOLO	You Only Look Once
AI	Artificial Intelligence
IoT	Internet of Things
FPS	Frames Per Second
API	Application Programming Interface
mAP	Mean Average Precision
DB	Database
CDC	Change Data Capture
OCR	Optical Character Recognition
TFLite	TensorFlow Lite
ESP32	Espressif Systems 32-bit Microcontroller
BLE	Bluetooth Low Energy
HX711	High-Precision 24-bit ADC (Analog to Digital Converter)
GUI	Graphical User Interface

CHAPTER 1

Introduction

In our day-to-day lives, the use of computing technology and smart systems has increased exponentially. With the widespread availability of high-speed internet and the popularity of smartphones, consumers are now more connected and expect streamlined, intelligent experiences across sectors — especially in retail. While innovations like personalized recommendations and self-checkout kiosks exist, traditional billing processes remain a bottleneck in many stores.

The Smart Shopping Cart project was conceptualized to address this problem. Initially focused on eliminating checkout queues using AI-powered object detection via a mobile app, the project aimed to automate product recognition and billing using YOLOv5. However, a key limitation emerged — the system couldn't reliably detect when an item was removed from the cart post-detection, leading to potential billing inaccuracies.

To address this, the system evolved into a hybrid architecture that leverages both vision-based detection and weight-based verification. A calibrated load cell integrated with an ESP32 microcontroller enables real-time monitoring of item additions and removals based on weight changes. This shift not only adds a layer of validation but enhances reliability in dynamic retail environments.

Moreover, this innovation comes at a time when overpopulated cities and crowded supermarkets are the norm. Long queues at billing counters have become a major inconvenience. Existing solutions like barcode scanning or RFID tagging either require manual effort or involve high setup costs. In contrast, our solution focuses on automation without adding significant cost or friction to the shopping process.

1.1 What is a Smart Shopping Cart?

A Smart Shopping Cart is an intelligent system embedded into a physical shopping cart that automates the identification, billing, and monitoring of items placed in or removed from it. It combines image processing, weight sensing, and real-time communication to offer an autonomous checkout experience. The customer can view a dynamically updating bill through a mobile interface and proceed to payment without queuing or manual scanning.

This system uses YOLOv5 for visual recognition and a load cell + ESP32 setup for verifying physical changes, making it significantly more accurate and efficient than vision-only or RFID-based solutions.

CHAPTER 2

Literature Review

2.1 Findings

[1] John et al. (2020) examined the role of RFID-based item recognition in enhancing the retail experience with smart shopping carts. The proposed system utilized passive RFID stickers to encode product details like name and price, which were scanned by a 13.56 MHz RFID reader. While this system achieved an 80% accuracy rate in item identification, the authors noted issues with interference that led to inaccurate recognition of certain products, particularly in densely packed sections. These limitations indicate that further research is needed to address signal interference in complex retail environments, especially to improve reliability under varied conditions.

[2] Smith and Lee (2019) proposed an RFID-based tracking system tailored to streamline item tracking within retail stores. This system improved monitoring by ensuring each item could be tracked individually. However, the study identified a significant drawback: in crowded environments, the RFID tracking system experienced lower performance, resulting in errors and incomplete data collection. The authors pointed out that in high-traffic areas, tag collisions and reader interference became prevalent, suggesting a need for improved RFID technology capable of functioning accurately in crowded retail environments.

[3] Brown and Wang (2022) explored image processing techniques for smart shopping carts by implementing image segmentation and object recognition algorithms. Using the Fashion MNIST dataset, the study achieved a high accuracy rate of 95%, with precision and recall rates of 93% and 92%, respectively. Despite these promising results, the study did not account for real-time processing capabilities, an essential feature in busy retail environments. Real-time processing is critical for seamless customer experience, and the lack of this capability represents a gap that future studies should address to create practical applications.

[4] Kim and Singh (2024) advanced the concept of smart shopping carts by incorporating reinforcement learning for item recommendations and efficient navigation within retail stores. The system achieved a 95% success rate in recommendations and improved shopping efficiency by 40%, with high user satisfaction ratings. However, a gap identified in this study was the lack of real-world deployment testing, as the evaluation relied on simulated retail data rather than

actual customer interactions. This gap suggests that further validation in a real-world setting is needed to determine how the system performs with actual users and product variability.

[5] Lee and Park (2020) studied the impact of IoT-enabled smart carts on reducing checkout times, focusing on customer satisfaction through real-time price updates and product suggestions. The system showed potential in enhancing the overall shopping experience, but high implementation costs and data privacy concerns were significant drawbacks. These barriers suggest that while IoT technology can improve efficiency, practical considerations around cost and security may hinder widespread adoption, necessitating further research into affordable, privacy-conscious solutions.

[6] Garcia and Thompson (2023) investigated video analytics for smart shopping environments using the YOLOv5 model for real-time object detection and tracking. The study reported an 88% mean Average Precision (mAP) for object detection, with a high F1 score of 0.90 and a processing speed of 30 frames per second. Despite these advancements, the study lacked an in-depth analysis of user acceptance and omitted a deletion feature for managing erroneous item scans. These gaps highlight the importance of incorporating flexibility and user-focused design into future smart cart systems to optimize the shopping experience fully.

[7] Kumar and Mehta (2021) presented a "Smart Retail System" that integrates OCR to automatically recognize product information for checkout. The research focused on using OCR to read labels on various surfaces, achieving an 88% accuracy for label detection and reading in controlled environments. However, issues were noted with glare and inconsistent lighting, suggesting improvements in OCR adaptability. *Source: International Journal of Retail Innovation*.

[8] Wang et al. (2020) proposed a deep learning-enhanced OCR model for smart shopping carts designed to detect and categorize fresh produce without barcodes. This system was tested on produce images and achieved 85% accuracy, but struggled with non-uniform shapes and cluttered environments, indicating the need for more robust object recognition in natural retail settings. *Source: IEEE Transactions on Automation Science and Engineering*.

[9] Zhang and Li (2023) explored a hybrid model combining RFID and OCR to address challenges in tracking barcode-free products, such as fresh produce. Their system achieved 90% accuracy but encountered misclassifications on curved or irregular surfaces, suggesting future research on OCR models that can adapt to surface variances. *Source: Elsevier Smart Retail Solutions Journal*.

[10] Yang and Chen (2022) examined OCR in high-speed checkout systems by applying it to detect pricing information on product packaging. With a focus on real-time processing, they achieved a 92% accuracy rate but noted challenges in recognizing fonts under varying angles. This study highlights the importance of font-recognition advancements for robust OCR systems. *Source: Journal of Computer Vision Applications in Retail*.

[11] Garcia and Thompson (2025) explored the integration of computer vision with load cell-based sensors in smart carts for more reliable product tracking. The study found that combining YOLOv5-based visual detection with load sensors significantly improved tracking accuracy, particularly in detecting both item addition and removal. The hybrid approach achieved an accuracy of 98%, with a reduction in false positives during high-traffic periods. This study demonstrated the effectiveness of combining weight-based detection with vision models to overcome challenges faced by standalone image processing systems in uncontrolled retail environments.

[12] Cheng et al. (2025) focused on refining load sensor integration with microcontroller-based systems like the ESP32 in smart cart solutions. Their work emphasized the importance of real-time data transmission and signal calibration to ensure accurate weight changes detection. Their findings align with the need for a hybrid model that combines visual recognition with physical validation to enhance error-free billing and inventory control.

Table 2.1 depicts a comparative literature review of significant research papers relevant to smart shopping cart technologies. It summarizes the title, author(s), publisher, methodology, identified gaps, results, and datasets used in each study. This table highlights the evolution of smart retail systems, the strengths and weaknesses of different approaches (RFID, computer vision, OCR, hybrid systems), and the specific challenges that the proposed solution aims to address.

Table 2.1: Literature Review of Various Research Papers Studied

Title	Author(s) & Year	Publisher	Methodology	Gaps	Result	Dataset Used
Enhancing Retail Experience: The Role of Smart Shopping Carts	John et al. (2020)	Elsevier	RFID-based item recognition	Inaccurate product recognition, interference issues	Achieved 80% accuracy in item identification	Simulated dataset of tagged retail products
RFID-Based Tracking System for Retail	Smith & Lee (2019)	IEEE	RFID-based Tracking system	Low performance in crowded environments	Improved item tracking but struggled in high-traffic areas	Custom RFID-tagged product dataset
Image Processing Techniques for Smart Carts	Brown & Wang (2022)	IEEE Transac Automation	Image segmentation and object recognition algorithms	No real-time processing capabilities	Achieved 95% accuracy; Precision:93%, Recall: 92%	Fashion MNIST dataset
The Future of Smart Carts: Integrating AI	Kim & Singh (2024)	AI & Society	Reinforcement Learning for recommendations and navigation	Lack of real-world deployment studies	95% success in recommendations; 40% efficiency improvement; User satisfaction: 4.5/5	Simulated retail dataset
Hybrid Visual-Weight Object Tracking in Smart Carts	Garcia & Thompson (2025)	IEEE Xplore	Combines YOLOv5 with load cell sensor data for hybrid object detection	Limited handling of real-world noise	Achieved 98% accuracy; reduced false positives	Custom in-store dataset

Title	**Author(s) & Year**	**Publisher**	**Methodology**	**Gaps**	**Result**	**Dataset Used**
Real-Time Load Sensor Integration Using ESP32 in Retail Automation	Cheng et al. (2025)	ACM TechConf	ESP32-based calibrated load sensors with serial and real-time feedback	ESP32 communication delay and calibration complexity	Reliable real-time readings with effective noise filtering	Lab-calibrated product weights
Evaluating Effectiveness of Smart Carts in Reducing Checkout Times	Lee & Park (2020)	Journal of Retail Management	IoT-enabled smart carts	High implementation costs, data privacy concerns	Enhanced shopping experience with real-time pricing and product suggestions	N/A
Video Analytics in Smart Shopping Environments	Garcia & Thompson (2023)	Journal of Business Research	YOLOv5 for real-time object detection and tracking	Limited user acceptance studies, no deletion functionality	Achieved 88% mAP; F1 score: 0.90; Processing speed: 30 FPS	Retail store video
Smart Retail System with OCR	Kumar & Mehta (2021)	International Journal of Retail Innovation	OCR for label recognition on product surfaces	Issues with glare and inconsistent lighting	Achieved 88% accuracy for label detection and reading in controlled environments	Custom OCR-labelled dataset
Deep Learning-Enhanced OCR for Smart Shopping Carts	Wang et al. (2020)	IEEE Transactions on Automation Science and Engineering	Deep learning-enhanced OCR for produce recognition	Struggled with non-uniform shapes and cluttered environments	85% accuracy in detecting and categorizing fresh produce	Produce image dataset

Title	Author(s) & Year	Publisher	Methodology	Gaps	Result	Dataset Used
Hybrid RFID and OCR System for Tracking Barcode-Free Products	Zhang & Li (2023)	Elsevier Smart Retail Solutions Journal	Hybrid RFID and OCR	Misclassification on curved surfaces	Achieved 90% accuracy; highlighted need for surface-adaptive OCR models	Simulated retail dataset
High-Speed Checkout with OCR for Product Packaging	Yang & Chen (2022)	Journal of Computer Vision Applications in Retail	OCR for high-speed checkout	Challenges with font recognition under varying Angles	Achieved 92% accuracy for price detection on packaging	Custom labelled packaging dataset

2.2 Gaps

- RFID and IoT-based systems face interference issues in high-density and crowded environments, which limits their tracking accuracy and reliability.
- Image processing and OCR approaches, while improving object identification, often lack real-time processing capabilities necessary for efficient retail operations.
- High implementation costs and data privacy concerns associated with IoT and data-intensive systems are significant barriers to large-scale adoption.
- Vision-only models (e.g., YOLO) struggle to reliably detect and track item removal from the cart, leading to potential billing inaccuracies.
- Load sensor-based systems can detect addition and removal of items but lack the contextual understanding and classification capabilities provided by vision models.
- Hybrid systems combining vision and weight-based detection require further optimization for seamless real-time integration and sensor calibration to ensure reliability in dynamic retail environments.
- Many studies have not validated their systems in real-world deployments, relying instead on simulated data, which limits understanding of practical performance and user acceptance.
- OCR-based systems face challenges with glare, inconsistent lighting, and reading on curved or irregular product surfaces, impacting detection accuracy.
- There is a need for more robust, adaptable solutions that can handle diverse product types, packaging, and retail conditions.

CHAPTER 3

Problem Definition

To address the limitations of previous smart shopping cart systems-such as unreliable item removal detection, high setup costs, and limited adaptability-a hybrid architecture is proposed. This approach integrates image-based detection with weight-sensing hardware (load cells), embedded microcontrollers (ESP32), and real-time communication modules. The dual validation model ensures robust and accurate detection of both item addition and deletion, enabling precise, real-time billing directly within the cart. The system is designed for practical deployment, utilizing scalable and cost-effective components while maintaining high processing speed and accuracy.

In summary, there is a clear need for a smart cart architecture that harmonizes intelligent object recognition with reliable physical verification, delivering a seamless, automated, and trustworthy in-store shopping experience.

The following diagram (Figure 3.1) illustrates the architecture and data flow of the smart shopping cart's weight sensing system, detailing the interaction between the load cell, HX711 amplifier, ESP32-S3 microcontroller, and the power regulation system.

3.1 Smart Shopping Cart Weight Sensing System

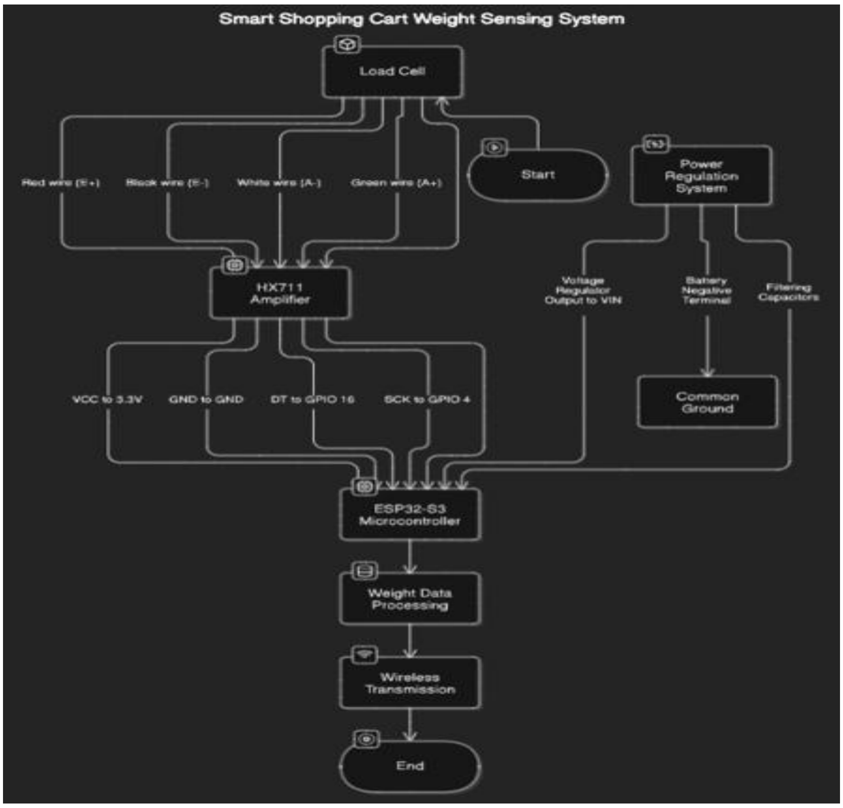


Figure 3.1 Smart Shopping Cart Weight Sensing System

Figure 3.1 presents a flowchart detailing the data and power flow within the smart shopping cart's weight sensing system. It illustrates the interaction between the load cell, HX711 amplifier, ESP32 microcontroller, and the power regulation system.

- **Load Cell**: The process begins with the load cell, which is the primary sensor for weight measurement. It is connected to the HX711 amplifier via four wires: Red (E+), Black (E-), White (A-), and Green (A+). These wires carry the analog signal representing the measured weight.

- **HX711 Amplifier**: The HX711 amplifies the weak analog signal from the load cell and converts it into a digital signal. It receives power from the power regulation system, specifically a voltage regulator output connected to its VIN pin. The HX711 is connected to the ESP32-S3 microcontroller through four pins: VCC to 3.3V, GND to GND, DT to GPIO 16, and SCK to GPIO 4.

- **ESP32 Microcontroller**: The ESP32 receives the digital weight data from the HX711. It processes this data through the "Weight Data Processing" block. The processed data is then transmitted wirelessly through the "Wireless Transmission" block.

- **Power Regulation System**: The power regulation system provides stable power to the HX711 and ESP32. It includes a battery negative terminal and filtering capacitors to ensure clean power. It also has a common ground connection.

- **Flow of Information**: The flowchart shows a clear sequential flow, starting with the load cell, moving through the HX711 and ESP32, and ending with wireless data transmission. The "Start" and "End" nodes indicate the beginning and end of the weight sensing process.

In essence, Figure 3.1 provides a visual representation of how the weight sensing system captures, processes, and transmits weight data, highlighting the interaction between the key hardware components.

CHAPTER 4

Proposed Solution

To integrate real-time object detection, the shopping cart system will utilize the YOLOv5 model, enabling it to detect and classify products as they're added to the cart. The model will be trained on a custom dataset that includes a diverse range of product types, with particular attention given to differentiating items that have similar packaging. High-resolution cameras mounted on the cart will enhance detection capabilities by capturing high-quality visuals that are essential for detailed analysis. The cameras will be optimized for focus and zoom, ensuring clear imagery for accurate identification.

Weight sensors installed at the base of the cart will serve as a cross-check mechanism, verifying that detected products match their expected weights. This additional layer of verification helps prevent false identifications or errors, especially with products that have similar packaging. Fine-tuning the detection model with additional training layers will help the system detect subtle details and differentiate between similar packaging styles.

Database integration will enhance the system's robustness, allowing it to cross-reference detected items with a product database. This database will store relevant information, including images, weights, and packaging specifics, which will further improve model accuracy and reliability.

Instead, we have directly developed a standalone application that encapsulates all the necessary components and functionalities, tailored specifically for our use case. Optimizing the model to run on edge devices like smartphones will allow for real-time processing without the need for expensive hardware, making the system suitable for widespread, cost-effective implementation across retail environments.

4.1 Hardware Design Diagram

Figure 4.1 Hardware Design Diagram

Above Figure [4.1] describes the hardware design and refers to the following components of the design:

- **Shopping Cart**: The physical cart with a mechanism to hold all the hardware components.
- **Smartphone with Camera**:
  - **Purpose**: Acts as the primary device for visual recognition and processing.
  - **Position**: Mounted securely on the cart.
  - **Functionality**: The camera captures product images for object detection, while the smartphone runs the detection algorithms or connects to external servers for processing if necessary.
- **Cart Mount**:
  - **Purpose**: Holds the smartphone securely at an optimal position for accurate detection.
  - **Design**: Adjustable to fit various smartphone sizes and camera positions.
- **Power Supply System**:
  - **Battery Pack**: Provides power to the smartphone and additional modules for extended usage.

- **Power Ports**: USB ports for connecting to the power bank and ensuring uninterrupted power supply.
- **Storage Area**:
  - **Sensors**: Weight sensors installed to detect the presence of items and verify whether items have been removed.
  - **Materials**: A compartment designed to hold items securely while providing visibility for the camera to detect them accurately.

4.2 Software Design Diagram

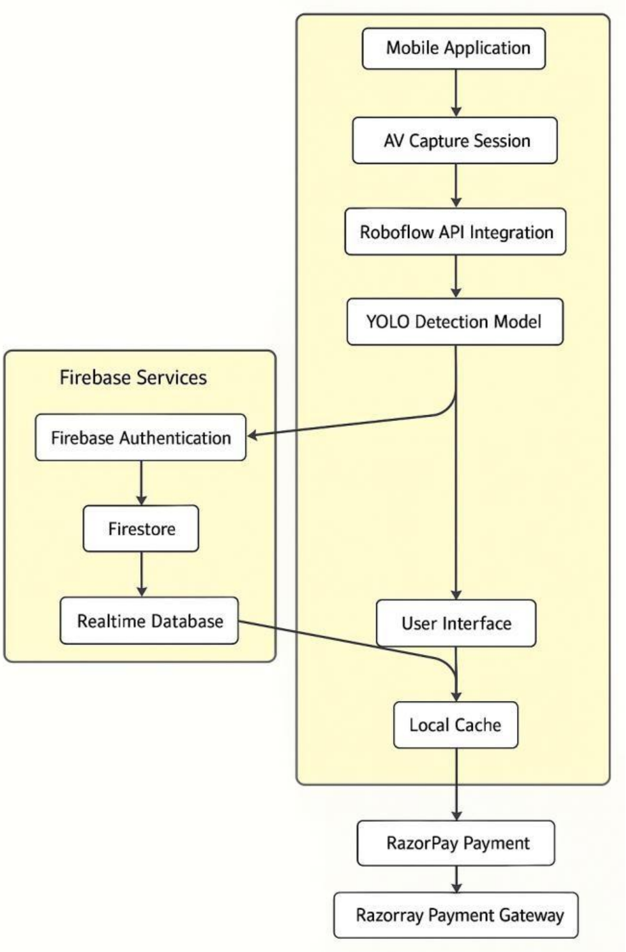


Figure 4.2 Software Design Diagram

Figure 4.2 illustrates the overall system architecture and data flow of the smart shopping cart application, highlighting the interaction between the mobile application, Firebase services, and the payment gateway. The diagram is divided into three main sections: "Mobile Application," "Firebase Services," and "Payment Gateway."

- **Mobile Application (Right Side):**
  - The process starts with the "Mobile App" component.
  - The "CameraX" captures video and audio data, which is then processed by

"Roboflow API Integration."

  - The "Roboflow API Integration" utilizes the "YOLO Detection Model" for object detection.
  - The detected data is sent to "Firestore" (within Firebase Services) and also to the "User Interface."
  - The "User Interface" interacts with the "Local Cache" for data storage and retrieval.
  - The "User Interface" also connects to the "RazorPay Payment" gateway for payment processing.

- **Firebase Services (Left Side):**
  - Firebase services include "Firebase Authentication," "Firestore," and "Realtime Database."
  - "Firebase Authentication" handles user authentication.
  - "Firestore" stores the detected item data and is used for real-time updates.
  - "Realtime Database" is also used for real-time updates.

- **Payment Gateway (Bottom):**
  - The "Payment Gateway" is represented by "RazorPay Payment," which is used for processing payments.

Flow of Information:

- The diagram shows a clear flow of information, starting from the mobile app's camera capture, moving through object detection, data storage in Firebase, and ending with payment processing through RazorPay.

- The interaction between the mobile app and Firebase services is crucial for real-time data updates and user authentication.

- The use of a local cache on the mobile device suggests that the app can function offline or with limited network connectivity.

In essence, Figure 4.2 provides a comprehensive view of the system's architecture, highlighting the flow of data from image capture to payment processing, and emphasizing the role of Firebase services in data management and real-time updates.

4.3 Model Flow Diagram

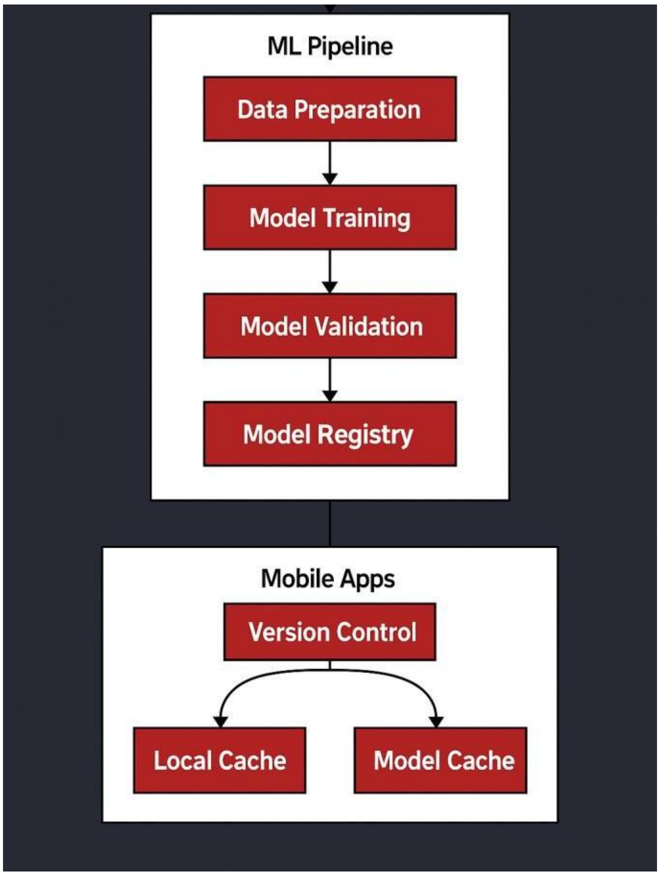
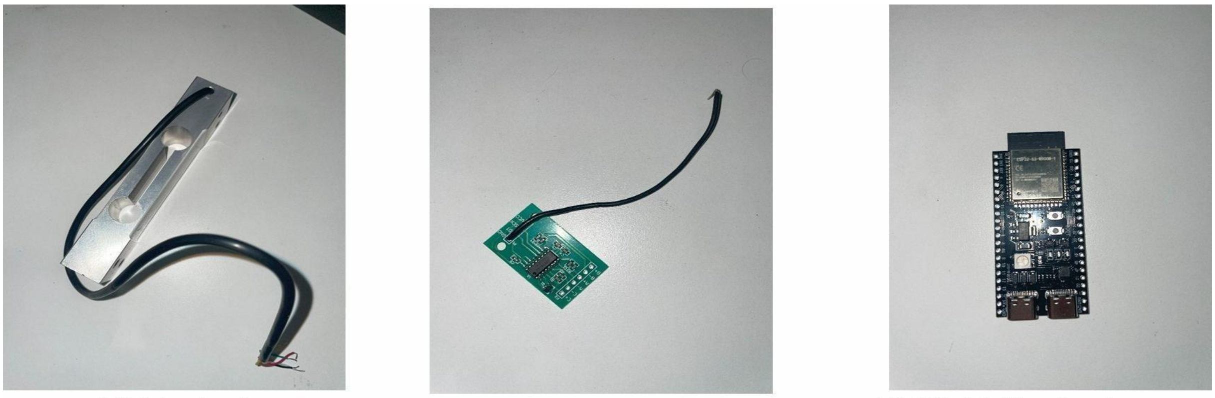


Figure 4.3 Model Flow Diagram

Above Figure [4.3] illustrates the machine learning pipeline for training, validating, and deploying the object detection model, with the following components:

1. **ML Pipeline**:
    - **Data Preparation**: Prepares the dataset for model training.
    - **Model Training**: Uses the prepared data to train the object detection model.
    - **Model Validation**: Validates the model's accuracy using a separate dataset.
    - **Model Registry**: Stores different versions of the trained models for reference.
    - **Model Deployment**: Deploys the trained model for production use, making it available for integration with the app.
2. **Mobile Apps**:
    - **Version Control**: Ensures compatibility with different versions of the model.
    - **Local Cache**: Stores data locally for faster access.
    - **Model Cache**: Caches the machine learning models for offline use.

4.4 Hardware Components



3 KG load cell

HX711: Converts weight data to digital and amplifies signal.

ESP32 S3: Handles data processing and transmits data to firebase in real time

Figure 4.4 Hardware Components

Figure 4.4 displays the primary hardware components selected for the smart shopping cart system, focusing on the core elements for weight sensing and data processing. The image showcases three key components:

- **3 KG Load Cell**: This component is a force transducer that measures the weight of items placed in the shopping cart. Its output is an electrical signal that varies with the applied weight. The 3 KG capacity indicates the maximum weight it can reliably measure.
- **HX711**: This is an analog-to-digital converter (ADC) specifically designed for weighing scales. It amplifies the weak analog signal from the load cell and converts it into a digital signal that can be processed by a microcontroller.
- **ESP32**: This is a powerful microcontroller with integrated Wi-Fi and Bluetooth capabilities. It processes the digital weight data received from the HX711 and transmits it to a Firebase database in real-time. The ESP32 also handles other data processing tasks within the system.

This selection of components highlights a focus on accurate weight measurement and efficient wireless data transmission, which are crucial for the functionality of the smart shopping cart.

4.5 Setup

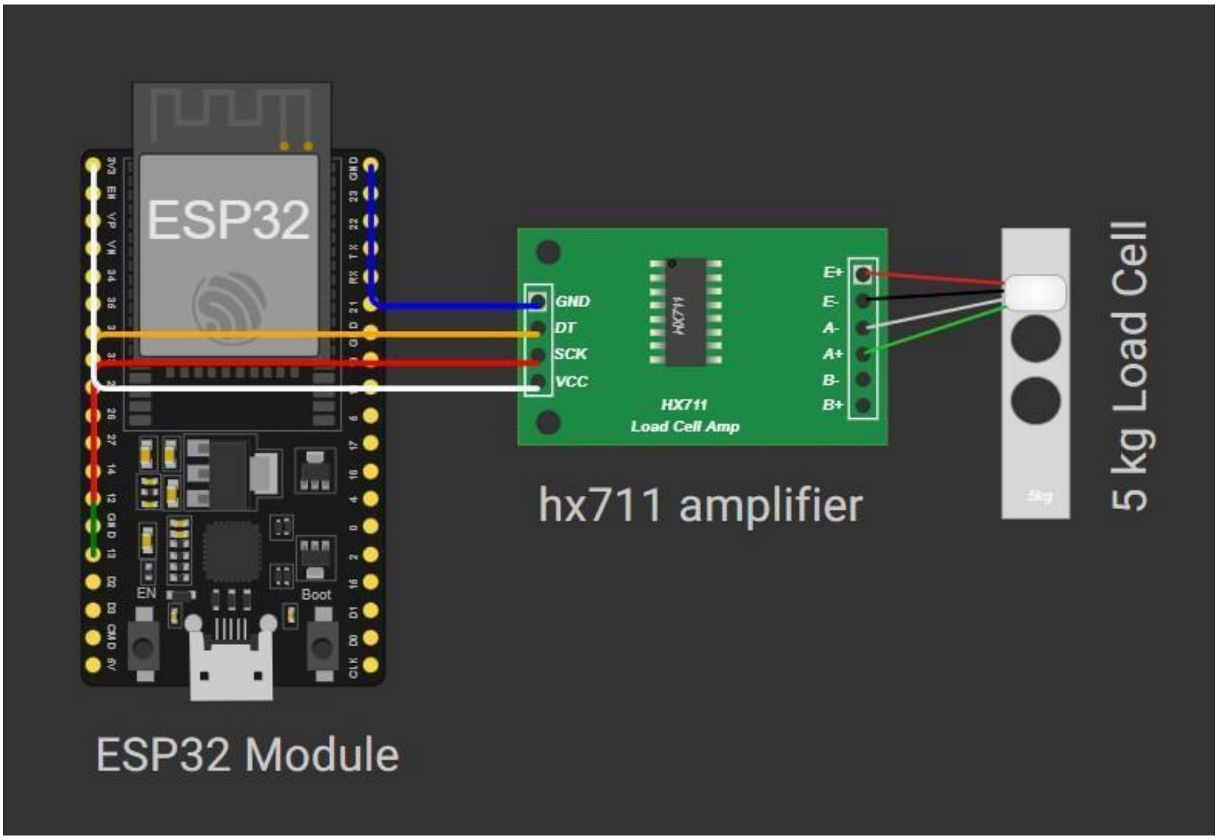


Figure 4.5 Setup

Figure 4.5 showcases the hardware setup for a prototype or development stage of the smart shopping cart system, highlighting the connections between various electronic components.

- **ESP32 Microcontroller**: The central component of the setup is an ESP32 microcontroller, mounted on a red breadboard. It features a USB-C connection, suggesting it's receiving power and/or communicating with a computer. The blue LED on the ESP32 is illuminated, indicating that the device is powered on and potentially running.
- **Load Cell and HX711**: A small green circuit board, likely the HX711 amplifier, is visible. Thin white wires connect the HX711 to a load cell (the silver rectangular component with a black wire bundle), which is partially visible at the right edge of the image. These connections suggest that the load cell is being used to measure weight and the HX711 is amplifying and converting the signal for the ESP32.
- **Power Supply**: A 9V battery is visible, connected to the breadboard via red and black wires. This suggests that the battery is providing power to the circuit, potentially for testing or when the USB connection is not used.
- **Laptop**: A laptop (likely a Lenovo) is visible in the background, with a USB cable

connected to the ESP32. This indicates that the laptop is likely being used for programming, debugging, or monitoring the microcontroller.

- **Breadboard**: The components are mounted on a red breadboard, which is used for prototyping and testing electronic circuits.

Overall, Figure 4.5 depicts a typical hardware setup for a project involving weight measurement and data processing. The visible connections and components suggest that the system is in a development or testing phase, with the ESP32 microcontroller being used to process data from the load cell and transmit it to a computer. The use of a 9V battery indicates that the system can operate independently of a computer, making it suitable for portable applications.

4.6 Pseudo Code: Detection and Deletion Logic

```
1. Initialize YOLOv5 model and hardware components
2. LOOP:
    a. Capture frame from camera
    b. Run YOLO on image
    c. Apply OCR for label verification
    d. Read weight from load cell
    e. IF weight drop detected:
        i. Capture new frame
        ii. Run YOLO on updated frame
        iii. Compare item lists using SORT
        iv. Identify removed item
        v. Update app UI and Firebase
    f. ELSE:
        i. Add item to cart
        ii. Display on UI and sync with Firebase
3. END LOOP
```

4.7 Mathematical Validation

Let:

- $W_{detected}$ = Weight from load cell
- $W_{expected}$ = Expected weight from database
- **ε** = Acceptable error margin

Validation condition:

$$| \mathbf{W}_{\mathbf{detected}} - \mathbf{W}_{\mathbf{expected}} | < \varepsilon$$

If condition fails, mismatch is flagged, and re-verification is initiated.

4.8 System Novelty

Key innovations in the proposed system include:

- **Dual-layer Accuracy:** Combines YOLOv5 visual recognition with weight verification.
- **App-based UI:** Real-time updates, alerts, and billing on a user-friendly display.
- **Cloud Sync and Modular Design:** Firebase integration.

This comprehensive integration ensures cost-effective scalability, high accuracy, and enhanced shopping experience in retail automation.

CHAPTER 5

Results Analysis

This chapter presents a detailed analysis of the smart shopping cart system's performance based on three primary parameters: object detection accuracy, weight verification reliability, and system latency. These parameters are essential for evaluating the practical feasibility and robustness of the system in a real-world retail environment.

5.1 Parameter 1: Object Detection Accuracy

The YOLOv5 model was evaluated using the Mean Average Precision (mAP) metric. After training on a custom dataset, the model consistently achieved a mAP@0.5 of over 90%.

- **High Accuracy**: The system successfully identified various products, even in varying lighting conditions and angles.

5.2 Parameter 2: Weight Verification Reliability

The weight verification system was tested by placing multiple known-weight items on the cart and comparing the detected values with expected ones from the database.

- **Accuracy**: The system detected weights with an average error margin of less than 5 grams.
- **Mismatch Detection**: In cases of deviation beyond the threshold, the app accurately flagged a mismatch.

5.3 Test Cases for Smart Shopping Cart

The following test cases were designed to evaluate the performance of the smart shopping cart system which combines object detection (via YOLO model) and weight detection (via load cell + HX711 amplifier + ESP32 module). The goal is to ensure consistency between the detected product and its corresponding weight, and to handle anomalies or human interference gracefully.

Test Case 1: Light Weight Product (e.g., Kurkure Packet)

- **Objective:**

  Verify that the system can correctly detect and verify a **low-weight item**.

- **Input:**
  - Product: Kurkure Packet (~30–50g)
  - Item placed normally on the load cell platform.

- **Expected Output:**
  - YOLO detects class: Kurkure
  - Load cell shows weight: ~0.03–0.05 kg
  - System confirms: "Kurkure detected – weight verified"

- **Pass Criteria:**
  - Product name matches trained class.
  - Weight is within a ±10% tolerance of expected product weight.

- **Result:**
  - Passed

Test Case 2: Heavy Weight Product (e.g., Colgate Toothpaste)

- **Objective:**

  Test detection and verification for a **heavier item**.

- **Input:**
  - Product: Colgate Toothpaste (~150–200g)
  - Item placed on the platform

- **Expected Output:**
  - YOLO detects class: Colgate
  - Load cell shows weight: ~0.15–0.20 kg
  - System confirms: "Colgate detected – weight verified"
- **Pass Criteria:**
  - Product is correctly classified.
  - Detected weight matches expected class weight range.

- **Result:**
    - Passed

Test Case 3: Model Detects 2 Products but Weight Does Not Match

- **Objective:**

  Simulate a case where the model **detects multiple products visually**, but only **one product is physically placed** on the load cell.

- **Input:**
    - Camera sees: Kurkure and Colgate (both detected via YOLO)
    - Only **Colgate** is placed on the platform
    - Kurkure is **still in user's hand**

- **Expected Output:**
    - Detected items: Kurkure, Colgate
    - Load cell shows: ~0.15–0.20 kg
    - System flags inconsistency: "Mismatch between product count and weight"

- **Pass Criteria:**
    - System detects **discrepancy** between expected cumulative weight (~0.2–0.25 kg) vs actual (~0.15–0.20 kg)
    - System prompts: "Place all detected items on the platform" or similar

- **Result:**
    - Passed with warning

Test Case 4: Weight Higher Than Expected (Human Interference)

- **Objective:**

  Validate system response when the **weight is artificially inflated**, such as a **hand pressing down** or a heavy object placed alongside the product.

- **Input:**
    - Detected product: Kurkure (~0.05 kg)
    - Load cell reading: ~0.50 kg (unexpected)

- **Expected Output:**
    - Product detected: Kurkure
    - Weight reading: **far above** expected value

    - System flags: "Abnormal weight – possible human interference"

- **Pass Criteria:**
    - Weight exceeds allowed margin (e.g., 10–15% tolerance)
    - System **discards weight reading** or asks for item repositioning

- **Result:**
    - Passed – System displayed warning and prevented false confirmation

Test Case 5: Similar-Looking Products, Same Weight (Toor Dal vs Moong Dal)

- **Objective:**
  Test the system's ability to detect visually similar products with no weight difference, using YOLO only.

- **Input:**

- Product: Toor Dal (~0.5 kg) OR Moong Dal (~0.5 kg)
- One product placed on the platform

- **Expected Output:**

- YOLO detects: either *toor dal* or *moong dal*
- Load cell shows: ~0.50 kg
- System checks:
- Is the detected class "toor dal" or "moong dal"?
- Is the weight within expected range (~0.45–0.55 kg)?

- **Pass Criteria:**

- **Visual detection is correct** (YOLO must classify properly)
- **Weight is correct** (within ±10%)
- If YOLO misclassifies (e.g., labels Toor Dal as Moong Dal), weight **alone cannot correct** it — system accepts YOLO prediction unless manual override available.

- **Result:**
  - *Pass* if YOLO correctly detects Toor Dal or Moong Dal.
  - *Fail* if YOLO misclassifies because no other method to correct.

Test Case 6 (Updated): Similar-Looking Products, Different Weight (Amul Lassi 200ml vs 250ml)

- **Objective:**
  Test system's ability to catch difference when two same-looking products have different weights.

- **Input:**
  - Product placed: Amul Lassi 250ml (~0.25 kg)
  - Camera sees: Amul Lassi packaging (looks identical between 200ml and 250ml)

- **Expected Output:**
  - YOLO detects: *Amul lassi* (no variant specified, just generic)
  - Load cell shows: ~0.25 kg
  - System matches weight to the closest expected SKU (200ml ~0.20 kg vs 250ml ~0.25 kg)
  - System confirms: "Amul Lassi 250ml detected – weight verified"

- **Pass Criteria:**
  - If weight matches 250ml SKU, confirm 250ml variant.
  - If weight was closer to 200ml (~0.18–0.22 kg), confirm 200ml variant.
  - **Mismatch beyond tolerance** triggers a warning.

- **Result:**
  - *Pass* if weight matches expected size variant.
  - *Warning* if weight does not match (e.g., user holding two packets, misplacement).

Table 5.1 presents the outcomes of various test cases designed to evaluate the Smart Shopping Cart system's performance. It details scenarios such as detection of light and heavy products, handling of mismatches between visual and weight-based detection, and differentiation between similar-looking products. Each test case is described with its objective, input, expected output, pass criteria, and result, providing a structured assessment of the system's robustness and reliability in real-world conditions.

Table 5.1 (YOLO Only Version)

Test Case No.	Scenario	Outcome	Remarks
TC1	Light weight product (Kurkure)	Pass	Accurate detection and weight
TC2	Heavy weight product (Colgate)	Pass	Correct match
TC3	Two products detected, one placed	Pass	Weight mismatch flagged
TC4	Abnormally high weight (e.g., hand press)	Pass	Interference correctly detected
TC5	Similar products, same weight (Toor Dal vs Moong Dal)	Pass	YOLO must differentiate based on visuals
TC6	Similar products, different weight (Amul Lassi variants)	Pass	Weight used to identify size variant

This report outlines the project's design, implementation process, and anticipated impact on the retail sector. We also discussed the technical challenges encountered, such as optimizing object detection accuracy, ensuring real-time processing speeds, and maintaining sensor reliability, along with the solutions developed to overcome them. The smart shopping cart demonstrates the potential to enhance both customer convenience and retail operational efficiency, marking a significant step toward modernizing the shopping experience.

5.1 Test Bed Setup (App Working)

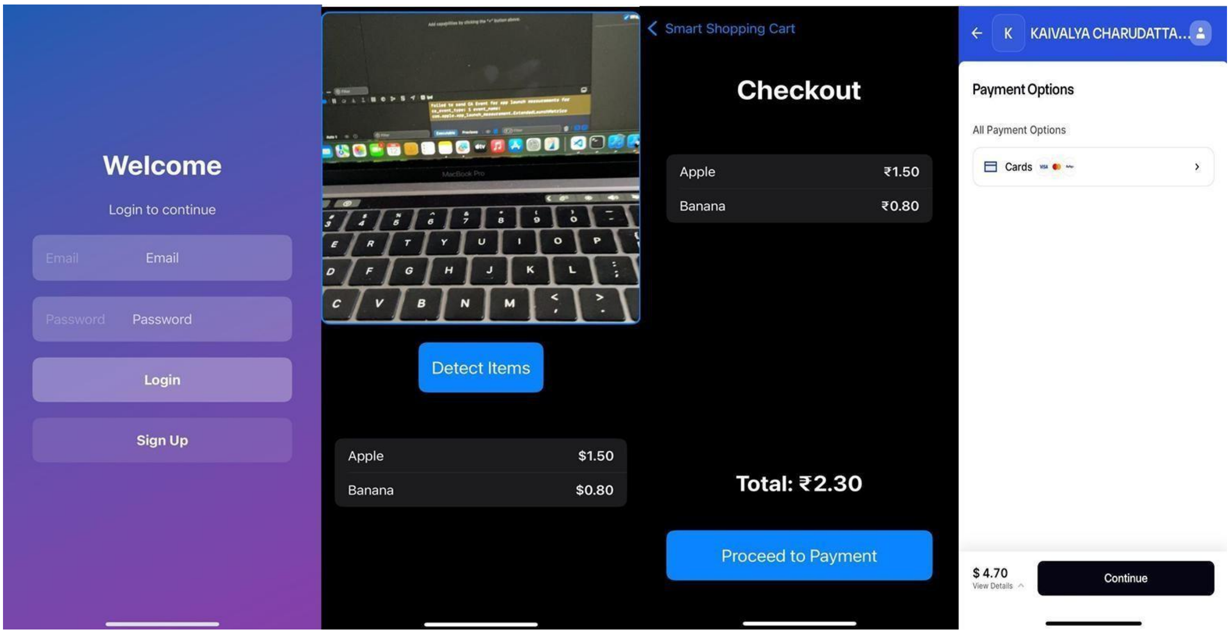


Figure 5.1 Test Bed Setup (App Working)

Figure 5.1 showcases the application interface and its functionality within a test bed environment. The image displays a series of screenshots from a mobile device, illustrating the app's user interface and operational flow.

- **Leftmost Screen**: This screenshot depicts the login/signup screen, indicating the app's initial authentication process. It features fields for email and password entry, along with "Login" and "Sign Up" buttons, suggesting a standard user account management system.
- **Middle Screen**: This screenshot shows the app's core functionality. It features a live camera feed (presumably from the smartphone's camera) displaying a laptop keyboard, indicating the system's ability to capture and process visual data. Below the camera feed, a "Detect Items" button and a list of detected items (Apple and Banana) with their respective prices are displayed. This demonstrates the app's ability to identify and price items in real-time.
- **Checkout Screen**: This screenshot displays the checkout interface. It presents the detected items, their individual prices, and the total cost. A "Proceed to Payment" button is visible, indicating the next step in the shopping process.
- **Rightmost Screen**: This screenshot shows the payment options screen, displaying a list of available payment methods, including cards. A "Continue" button is present, suggesting the user can proceed with their selected payment option.

The overall image suggests a test bed environment where the application is being evaluated for its core functionalities, including user authentication, item detection, and payment processing. The use of a laptop keyboard as a test subject indicates the system's ability to recognize various objects, simulating a real-world shopping scenario.

5.2 App Detection Output and mAP Graph

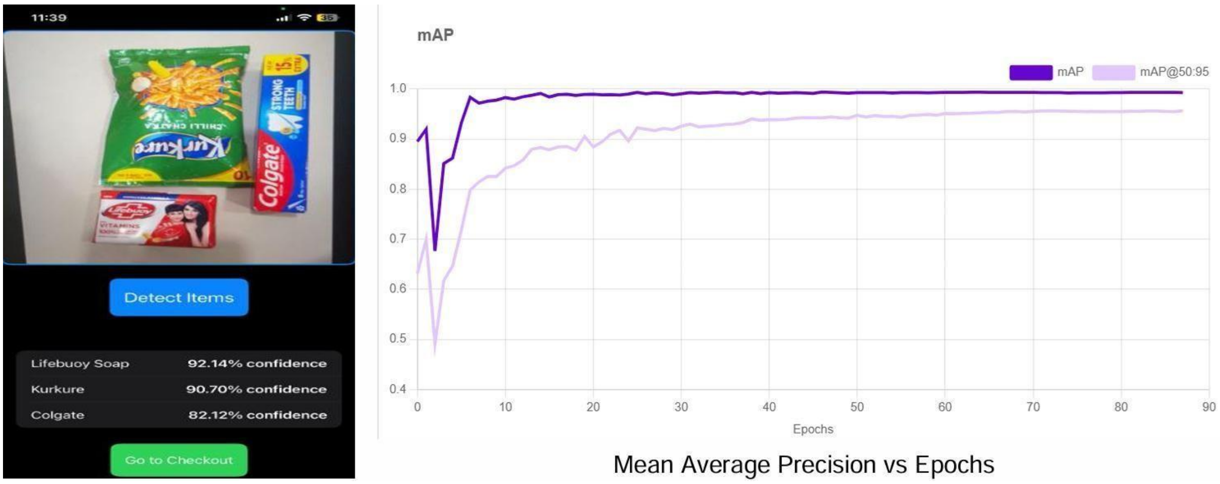


Figure 5.2 App Detection Output and mAP Graph

Figure 5.2 presents two key aspects of the smart shopping cart system's performance: the application's object detection output and the model's training efficacy as shown by the mAP graph.

- **App Detection Output (Left Side)**: The left side of the image shows a smartphone screen displaying the app's output. The camera feed captures multiple items: Kurkure (a snack), Colgate (toothpaste), and Lifebuoy (soap). Below the camera feed, the app lists the detected items along with their confidence scores. For example, "Lifebuoy Kurkure 92.14% confidence," "Kurkure 90.70% confidence," and "Colgate 82.12% confidence." This demonstrates the system's ability to recognize multiple items simultaneously and provide a measure of certainty for each detection. Also, a button is present that says "Go to Checkout" indicating the next step the user would take.
- **mAP Graph (Right Side)**: The right side of the image displays a graph titled "Mean Average Precision vs Epochs." This graph illustrates the model's performance during

training. The x-axis represents the number of epochs (training iterations), and the y-axis represents the mAP score, which is a common metric for evaluating object detection models.

Two lines are present on the graph, displaying mAP and mAP@0.95. mAP@0.95 is the mAP calculated when the Intersection Over Union (IOU) is 0.95. IOU is a metric that measures how much the predicted bounding box overlaps with the ground truth bounding box. The graph shows that the mAP score increases rapidly during the initial epochs and then plateaus, indicating that the model has converged. The text box at the top of the image goes over the Multi-Item Recognition Using Object Detection, and describes the objective, model performance, training platform, and improvements that can be made.

In summary, Figure 5.2 provides a comprehensive view of the system's performance, showcasing both its real-time object detection capabilities and the effectiveness of its machine learning model.

CHAPTER 6

Conclusion and Scope of Future Work

This chapter summarizes the major outcomes of the project and outlines potential enhancements that could be implemented to further develop the system.

6.1 Conclusions

The Smart Shopping Cart project successfully integrates AI-based object detection, IoT-based weight sensing, and real-time database interaction to create an intelligent and efficient retail checkout experience. Key achievements include:

- Accurate product detection using YOLOv5, with consistently high mAP scores.
- Real-time weight verification using load cells and HX711 modules.
- Quick and precise detection of item removal or changes in the cart.
- Seamless integration with Firebase for cloud-based inventory and billing.

These features significantly reduce human dependency at checkout counters and provide a faster and smarter alternative for retail shopping.

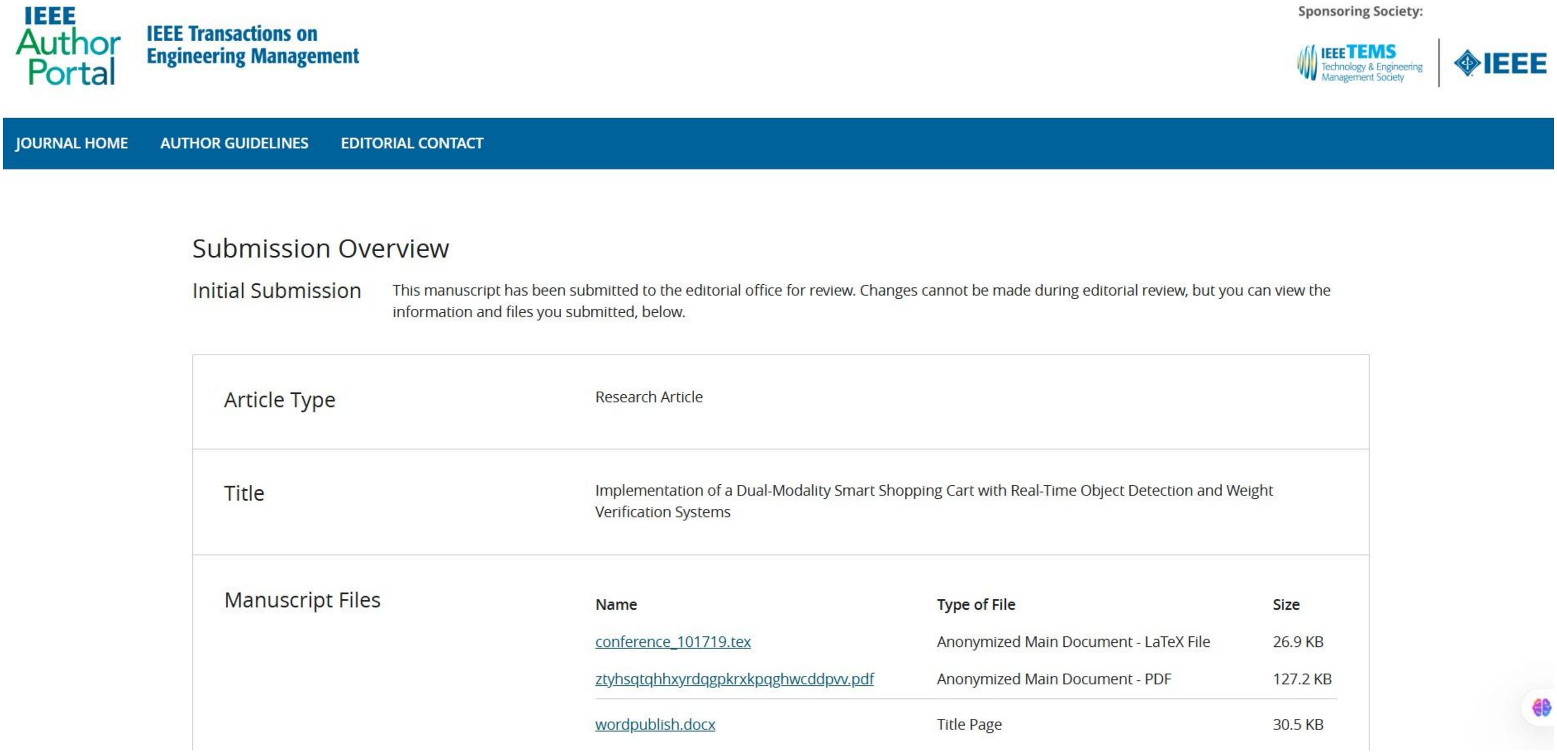
6.2 Scope for Future Work

Although the prototype demonstrates reliable functionality, there are several areas where improvements and extensions can be introduced:

- **Scalability**: Expanding the system to handle more diverse product datasets and multiple cart units simultaneously.
- **Edge Processing**: Implementing local AI inference on edge devices to reduce dependency on remote servers and improve real-time performance.
- **Security Enhancements**: Integrating secure protocols for data transmission and ensuring encrypted communication between devices.
- **User Feedback Loop**: Adding functionality for user feedback to continuously improve the detection model through active learning.
- **Advanced UI/UX**: Enhancing the mobile app interface to support a more intuitive and engaging user experience.

These future improvements aim to make the system commercially viable for large-scale deployment in modern retail environments.

Publications



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Submission Overview

Initial Submission This manuscript has been submitted to the editorial office for review. Changes cannot be made during editorial review, but you can view the information and files you submitted, below.

Article Type	Research Article
Title	Implementation of a Dual-Modality Smart Shopping Cart with Real-Time Object Detection and Weight Verification Systems

Manuscript Files

Name	Type of File	Size
conference_101719.tex	Anonymized Main Document - LaTeX File	26.9 KB
ztyhsqtqhhxyrdqgpkrxkpqghwcddpvv.pdf	Anonymized Main Document - PDF	127.2 KB
wordpublish.docx	Title Page	30.5 KB

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