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| RESEARCH ARTICLE

Enhancing Retail Checkout Efficiency Through a Hybrid YOLOv8-Based Grocery Detection and Billing System

Safaina Khan Oishi[1], Md. Minhazul Islam[1]✉, Shakhar Das Rony[1], Rabbi Sadnan Khan[1], Md. Moshiur Rahman[2], Mustak Ahmmed[3]

[1]*Student, Department of Computer Science and Engineering, University of Liberal Arts Bangladesh, Dhaka, Bangladesh*
[2]*Lecturer, Department of Software Engineering, Bangabandhu Sheikh Mujibur Rahman Digital University, Bangladesh*
[3]*Student, Software Engineering, Institute of Information Technology, University of Dhaka, Bangladesh*
Corresponding Author: Md. Minhazul Islam, E-mail: minhazul.islam3874@gmail.com

| ABSTRACT
Traditional retail checkout systems that rely on barcodes are limited at handling the non barcoded shopping items like fresh produce. To tackle this problem, this paper will introduce a deep learning approach to grocery item detection and automated billing system through computer vision. A local dataset comprising 1,109 images in 27 grocery classes was gathered and labelled and augmented with Roboflow to enhance stability. Several object detection models based on the YOLO algorithm such as, YOLOv5s, YOLOv8n, YOLOv8s, YOLOv11n and YOLOv12n were trained and tested in unvaried conditions. Experimental outcomes demonstrate that more recent architectures are far superior in detecting, with YOLOv12n having the best localization accuracy on the test set (mAP@0.5:0.95 of 0.847), and the YOLOv8s giving good tradeoffs between accuracy and efficiency to be used in the real world. The chosen model (YOLOv8s) was incorporated into a web-based image-based billing system, which confirmed the possibility of a scalable and inexpensive AI-based checkout system. The suggested framework provides a platform upon which future research can proceed to enhance the real-time performance and dataset generalization.

| KEYWORDS
Automated billing system, grocery item detection, object detection, YOLO, computer vision, deep learning, retail automation

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1. Introduction
The rapid growth of the retail industry is creating demand for faster and more accurate checkout systems. Traditional barcode-based checkouts have difficulty with non-barcode items, such as fruits, vegetables, bakery products, and loose items, which translates into longer processing times, human errors, and dissatisfaction among customers. Deloitte estimates that poor checkout efficiency and pricing errors globally cause retailers to lose more than $100 billion every year [4]. Recently, with developments in the fields of artificial intelligence and computer vision, especially deep-learning models like YOLO, automated identification of items can be realized, offering contactless checkout in real time. In this context, the proposed work introduces a hybrid grocery item detection and automatic billing system using YOLOv8 [6] to overcome bar-code limitations. With AI-powered retail solutions expected to grow by 21% between 2024 and 2030 [7], such hybrid, multi-domain intelligent systems hold significant global potential.

1.1 Background and Motivation
Effective billing system implementation has always remained a challenge in the international retail industry, mainly in the supermarket environment. The existing barcode scanning system for billing contains various inaccuracies and inefficiencies that generate substantial losses of funds. In the United States alone, inaccuracies in pricing and inventory management result in a loss

of around \$61.7 billion to retailers every year [8]. Accuracy remains particularly important for items that remain unbarcoded, like fruits and veggies, which account for almost 30% of total goods in supermarkets. The process of unbarcoded items involves manual scanning and increases the processing time by 20-30 seconds [9]. In developing nations such as Bangladesh, where agriculture contributes around 13% of the country's overall GDP value, it may often prove difficult for small retailers to afford automatic solutions. High-tech solutions like Amazon Go remain unaffordable for almost 70% of the total number of stores [10]. The global crisis surrounding the COVID-19 pandemic has led to an increased requirement for contactless and efficient billing solutions.

1.2 Problem Statement and Research Gap

Despite the growing adoption of artificial intelligence and computer vision in retail automation solutions, existing solutions tend to work ineffectively in real-life scenarios. Several researches prove promising efficacy within controlled setups but tend to be less robust within practical settings. Xia et al. [11] proposed an intelligent self-service vending system that has 93.73% accuracy. Similarly, Tan et al. [12] proposed an enhanced retail checkout system based on the YOLOv10 algorithm that has 89% mAP. However, Jain et al. [13] noted that these models may suffer a 30% decrease in performance due to varied lighting conditions, cluttered scenes, and occlusion. This further hampers the implementation of these models into supermarket settings. Furthermore, Kim et al. [14] presented an IoT-based payment system that needs constant internet connectivity. Hence, it may not be ideal for rural settings that have limited internet connectivity. The system proposed by Zhong [10] uses Jetson Nano and targets the inventory management system alone. Dataset limitations also remain a challenge. Pham et al. [15] reported that their DeepACOv2 model achieved an F1-score of 0.9792 using synthetic data but showed a 23.2% drop in mAP@0.5 when tested on cluttered real-world scenes [12]. Additionally, as observed by Wolniak et al. [9], very few solutions have been proposed that incorporate input modes, dynamic pricing mechanisms, and offline functionality within a single billing system. At least from the perspective of the problem at hand, there appears to be a quotient within reach.

1.3 Objectives and Contribution

The work proposes a hybrid grocery billing system using the YOLOv8 architecture for addressing key checkout challenges. The YOLOv8s model was trained with 1,109 annotated images over 27 classes and obtained an mAP@0.5 of 95.2%, outperforming YOLOv5-based work proposed by Jain et al. [13] and the AlexNet model proposed by Ghanti [8]. The detector is integrated into a PHP/MySQL web interface that currently supports image-upload detection and dynamic billing; further updates will allow offline use for low-connectivity regions. It correctly identifies grocery items from uploaded images and includes the development of a real-time webcam module. In addition, improvement plans include enabling a manual quantity adjustment for bulk items, addressing limitations identified by Xia et al. This reduces hardware costs by more than 60% compared to existing RFID-based systems [10]. Progressive training between 20–50 epochs yielded a 50.2% improvement over the baseline mAP. This platform is fully open source to enable further research and local deployment. Overall, the system moves closer to a practical, scalable, and accessible retail automation solution.

2. Literature Review

In recent years, AI-driven retail technologies have advanced automatic checkout systems significantly. Xia et al. [11] proposed a single-camera vending system for identifying and weighing multiple non-barcode items in real time. With similar inspiration, Kim et al. [14] developed a contactless payment system where object detection recognizes food items. Selfcheckout and mobile shopping using AI were among other important enabling innovations reviewed by Wolniak et al. [9] in digital grocery transformation. Several works focus on improving object detection models for retail. Pham et al. [15] improved the recognition of products and trays using YOLOv8 and data augmentation. Tan et al. [12] developed a YOLOv10-based system that is more suitable for complex retail environments. Jain et al. [13] did not require any barcode dependence for quicker transactions using YOLOv5. According to Zhong [10], deep learning–powered checkout systems reduce reliance on cashiers, minimize human errors, and hence enhance store efficiency. Ghanti [8] recorded training accuracy of more than 98% and billing accuracy of 99.94% on a conveyor-based grocery setup using deep learning**.**Technically, Viswanathan [16] showed that Fast R-CNN gives product recognition accurately and efficiently, hence minimizes computational cost. Guimaraes et al. [17] gave a ˜ general review on the systems of grocery label detection, indicating their worth for visually impaired users but stated that some challenges still remain such as packing variations, light conditions, and processing speed. A comparative summary of existing grocery detection and billing systems, including the proposed model, is presented in Table 1.

3. Methodology

In this work, we propose a hybrid grocery item detection and billing system using deep learning and computer vision techniques. Our approach utilizes the YOLOv8 object detection model trained on a custom dataset comprising 1,109 annotated images across

28 grocery product classes. The dataset was collected and manually annotated using Roboflow to ensure appropriate labeling for real-world grocery environments. Workflow of our proposed hybrid grocery item detection and automated billing system is shown in Fig. 1. The methodology of the system is divided into three main stages:

- Data Collection and Model training
- Web application integration
- Workflow of the Whole Process

3.1 Data Collection and Model training

The dataset for this study was collected through manual photography of 27 packaged grocery products under various lighting conditions and angles to simulate real-world retail environments. This diversity was crucial for ensuring the robustness of the model in real-world settings. The dataset initially included 28 product categories but was later refined to 27 after data cleaning. A total of 1,109 images were annotated using Roboflow, a platform that supports the YOLO annotation format. Each item in the images was labeled with bounding boxes and associated class labels. Data augmentation techniques, including random rotation, flipping, and brightness variation, were applied to further enhance the dataset and improve model generalization. The dataset was automatically split into training (80%), validation (10%), and testing (10%) sets by Roboflow, and exported in the YOLO format. The model training was performed on Google Colab using a Tesla T4 GPU, which provided sufficient computational power for deep learning tasks. Five lightweight and state-of-the-art YOLO variants were evaluated namely, YOLOv5s, YOLOv8n, YOLOv8s, YOLOv11n and YOLOv12n, from which YOLOV8s was chosen for deployment. The models were all trained to 50 epochs with pretrained weights and an input size of 640×640. The training, validation, and test sets were evaluated individually with the help of the standard object detection rates, such as precision, recall, mean Average Precision at IoU 0.5 (mAP@0.5), and mean Average Precision at IoU 0.5:0.95 (mAP). Challenges encountered during data collection included lighting variations and class imbalance, which were mitigated through data augmentation and careful sampling of training images. The model's strong performance validates the feasibility of using deep learning for efficient and accurate grocery item detection. These results are crucial for the development of automated billing systems that can be deployed in small and medium-sized retail environments.

3.2 Web application integration

The web-based billing system was developed using PHP for backend processing, with HTML, CSS, and JavaScript comprising the frontend interface.

Table 1. Comparative analysis of existing grocery detection and billing systems

Reference	YOLO Used Image Augmentation	YOLO Used Image Augmentation	Dataset Type	Image Upload	Real-time Detection	Accuracy Reported	Database Integration	Billing Automation	Website Integration	Barcode Free
Xia et al. [11]	✓	✓	Custom	×	✓	✓	✓	✓	×	✓
Kim et al. [14]	×	×	Custom	×	✓	×	✓	✓	×	✓
Wolnaik et al. [9]	✓	✓	Real-world	×	✓	✓	✓	✓	×	✓
Pham et al. [15	✓	✓	Synthetic + Custom	×	✓	✓	✓	×	×	✓
Tan et al. [12]	✓	✓	Real-world	×	✓	✓	×	✓	×	✓
Jain et al. [13]	✓	✓	Custom	✓	×	×	×	✓	×	✓
Zhong et al. [10]	×	✓	Custom	×	✓	✓	✓	✓	✓	✓
Ghanti [8]	×	✓	Real-world	×	✓	✓	✓	✓	×	✓
Viswanathan [16]	×	×	N/A	✓	×	✓	✓	×	✓	×
Guimaraes et al. [17]	×	✓	Real-world	×	✓	✓	✓	✓	×	✓
Proposed System	YOLOv8s	✓	Custom	✓	×	✓	✓	✓	✓	✓

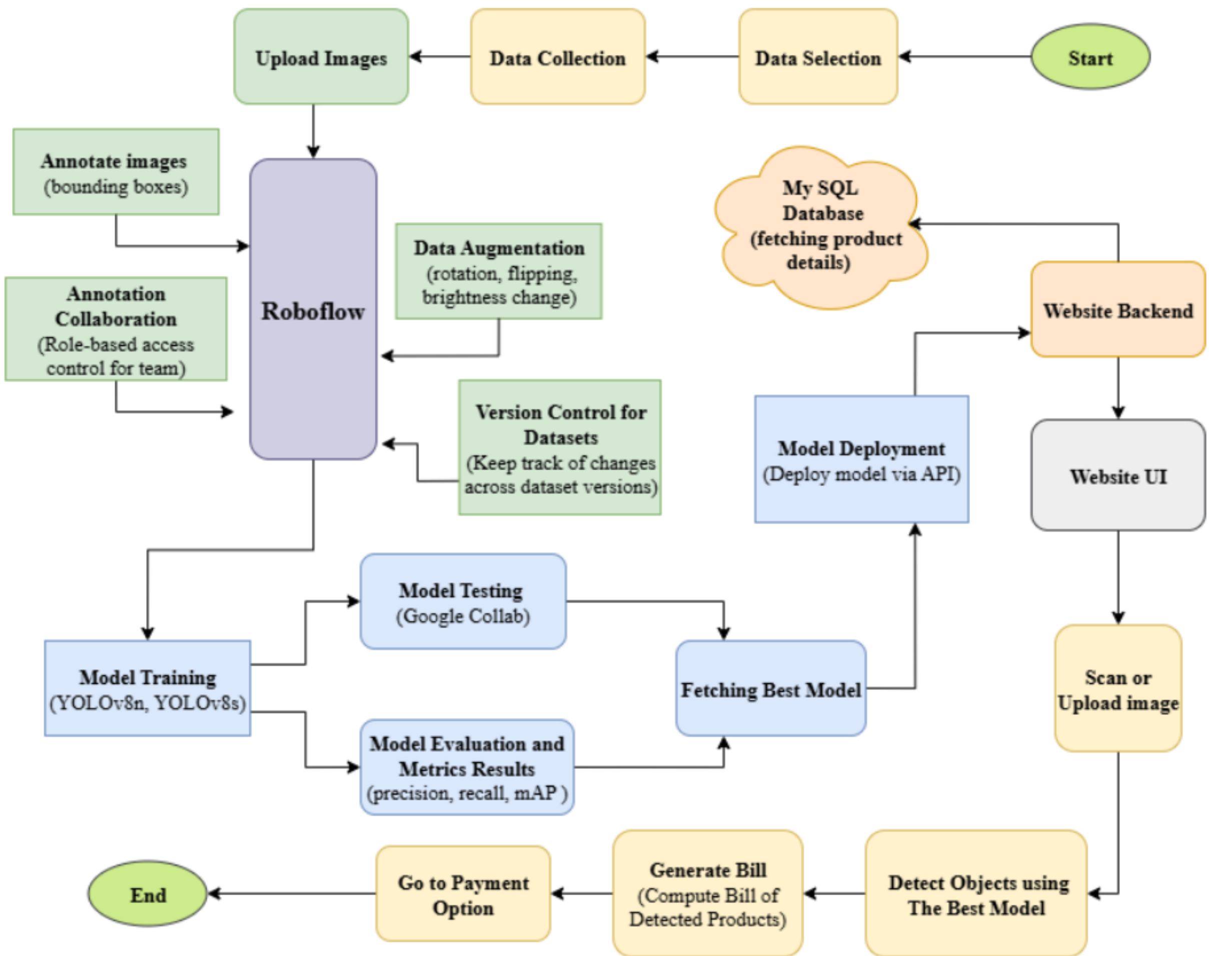


Fig. 1. Workflow of the proposed hybrid grocery item detection and automated billing system

The application is hosted locally via an XAMPP server, which enables seamless communication between the PHP backend, the Python-based object detection module, and the MySQL database. The database stores product information, including item names, categories, and prices which allows for dynamic retrieval and updates throughout the billing workflow. The list of APIs along with their usage can be seen in Table 2. The trained YOLOv8s model, saved in PyTorch format (.pt), is integrated using Python and OpenCV. When a user uploads an image through the web interface, the PHP backend issues a system call that triggers a Python script to load the trained model and perform object detection. The detected items and their confidence scores are returned to the PHP layer and displayed on the billing interface. The system then seamlessly queries the MySQL database for the respective product prices, calculates the total bill, and presents the complete invoice to the user, ensuring an automated and user-friendly process.

Table 2. List of APIs and their usage in our proposed system

API Name Purpose	API Name Purpose
Add Banner	Uploads and manages promotional banners in the system.
Product Upload	Adds new products into the system’s catalog (admin function).
Register	Handles new user registration by storing user data in the database.
Login	Authenticates users by checking credentials and starting a session.
Logout	Ends the user session and logs them out of the system
Upload Image	Handles image uploads.
Image Result	Processes and returns results of uploaded images.
Insert Product	Inserts new product information into the database.

Payment Process	Handles order payments (checkout process, transaction logic).

Currently, the system supports image upload–based detection for static images, while a real-time webcam module is under development to enable live item recognition. Although the system requires an internet connection for certain dependencies, future iterations are intended to support full offline functionality, thereby enhancing accessibility in low connectivity environments.

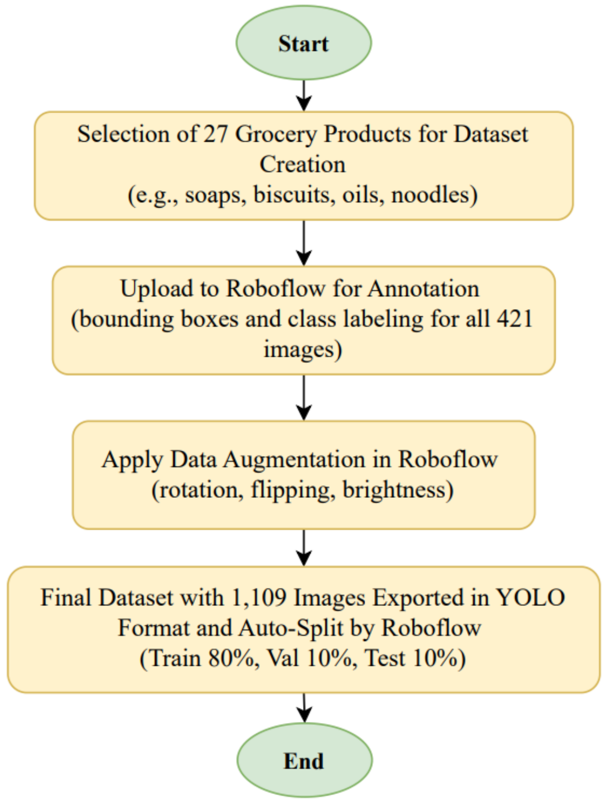


Fig. 2. Phase I- Creating Custom Dataset

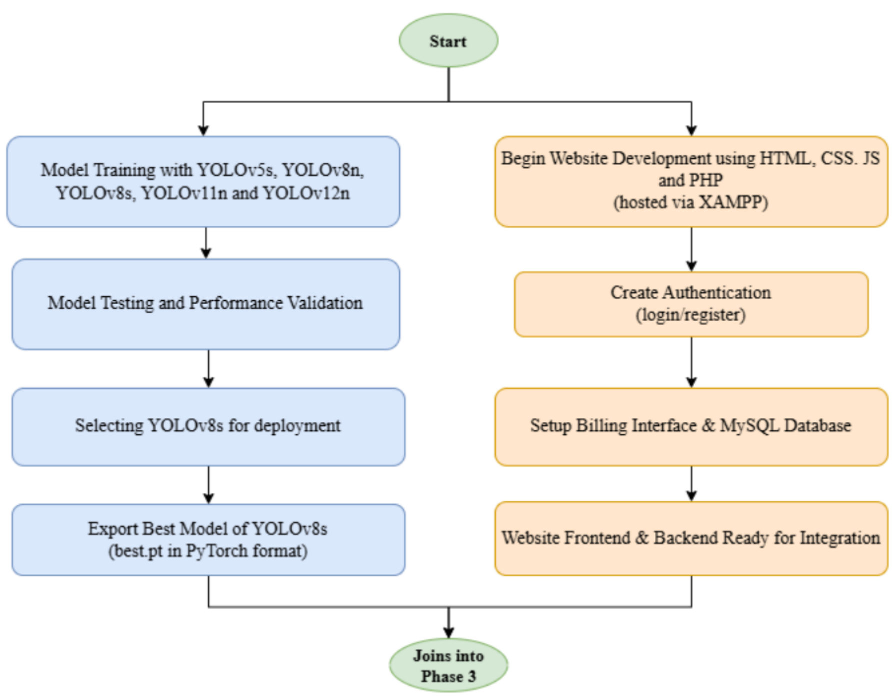


Fig. 3. Phase II- Model Training and Website Building

3.3 Workflow

The complete development process of the grocery billing system is illustrated in a series of workflow diagrams. Fig. 2 presents Phase I, which includes the selection of 27 grocery products, image acquisition under varied lighting conditions, and annotation of 1,109 images using Roboflow. Augmentation techniques were applied, and the annotated dataset was exported in YOLO format and divided into training, validation, and testing sets. Phase II, shown in Fig. 3, outlines the parallel development of the object detection model and the web application. Various YOLO models were trained. Simultaneously, the web interface was developed using PHP, HTML, CSS, and JavaScript, with a MySQL database managing product information and user authentication modules. Fig. 4 details Phase III, which connects the trained model to the website backend. The best.pt model of YOLOv8s was deployed using Python and OpenCV, integrated with the PHP interface through system calls. Backend scripts enable the detection results to interact with the MySQL database to retrieve item prices and generate a complete bill. Testing confirmed accurate item recognition through image uploads. Finally, Fig. 1 presents the complete end-to-end workflow of the system. In addition to image upload functionality, a real-time detection extension using a webcam and OpenCV was experimentally implemented.

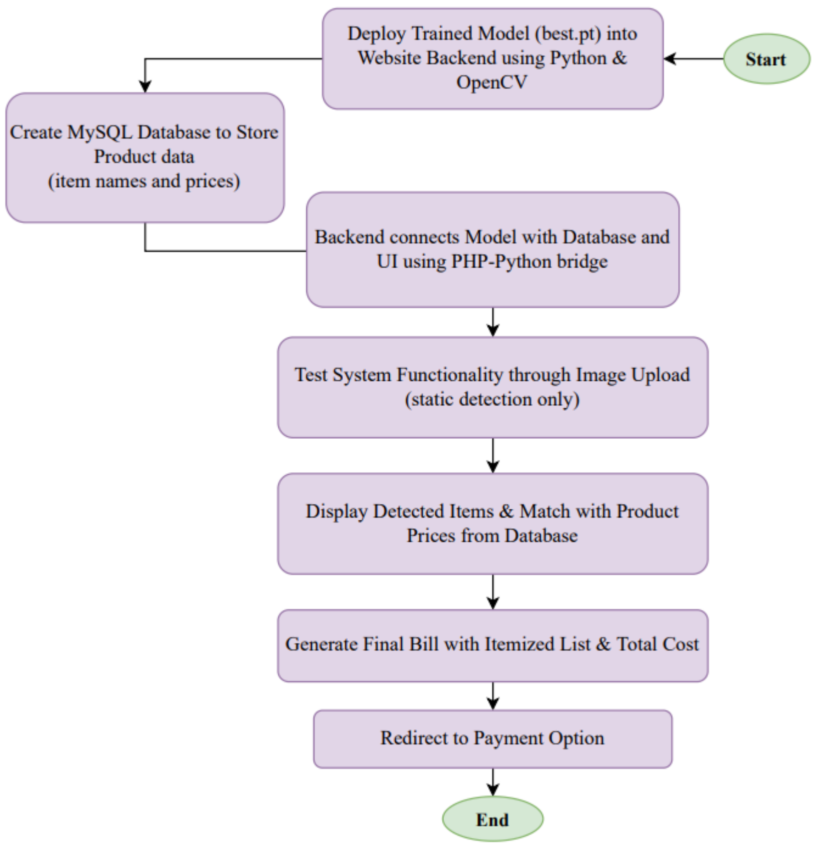


Fig. 4. Phase III- Connecting the model into website backend and final testing

4. RESULT AND PERFORMANCE ANALYSIS

In this section, a detailed review of the suggested grocery item detection system is made based on comparative experiments with various YOLO-based object detection models. The collected and annotated dataset, along with the web interface and all relevant source code, is publicly available at https://github.com/safaina-khan/ Smart-Grocery-Detection-and-Billing-System. Table 3 summarizes training performance across models. YOLOv12n achieved the highest mAP@0.5:0.95 (0.933), while YOLOv8s delivered competitive performance with consistently high precision and recall. YOLOv5s showed high recall but weaker mAP@0.5:0.95, and YOLOv11n remained stable without outperforming newer models.

Table 3. Train metrics result comparison

Models	Precision	Recall	mAP@0.5	mAP@0.5-0.95
YOLOV5s	0.951	0.988	0.988	0.757
YOLOv8n	0.989	0.992	0.992	0.876
YOLOv8s	0.995	0.992	0.994	0.915

YOLOv11n	0.936	0.960	0.974	0.845
YOLOv12n	0.988	0.991	0.993	0.933

Table 4. Validation Metrics Result Comparison

Models	Precision	Recall	mAP@0.5	mAP@0.5-0.95
YOLOv5s	0.843	0.884	0.941	0.759
YOLOv8n	0.915	0.842	0.952	0.833
YOLOv8s	0.870	0.957	0.952	0.859
YOLOv11n	0.877	0.871	0.942	0.854
YOLOv12n	0.958	0.951	0.952	0.853

Table 4 shows that YOLOv8s achieved the highest validation mAP@0.5:0.95 (0.859), while YOLOv12n closely followed with the highest precision (0.958). In contrast, YOLOv5s exhibited lower validation performance, highlighting the limitations of earlier YOLO variants on visually similar grocery datasets.

Table 5. Test metrics result comparison

Models	Precision	Recall	mAP@0.5	mAP@0.5-0.95
YOLOv5s	0.660	0.979	0.938	0.725
YOLOv8n	0.873	0.891	0.965	0.829
YOLOv8s	0.876	0.922	0.973	0.844
YOLOv11n	0.809	0.887	0.930	0.832
YOLOv12n	0.954	0.962	0.962	0.847

Table 5 presents test set performance, where YOLOv12n achieved the best overall results (precision 0.954, recall 0.962, mAP@0.5:0.95 0.847). YOLOv8s showed similar object detection accuracy with slightly lower precision, indicating that newer YOLO variants are well suited for automated grocery billing applications.

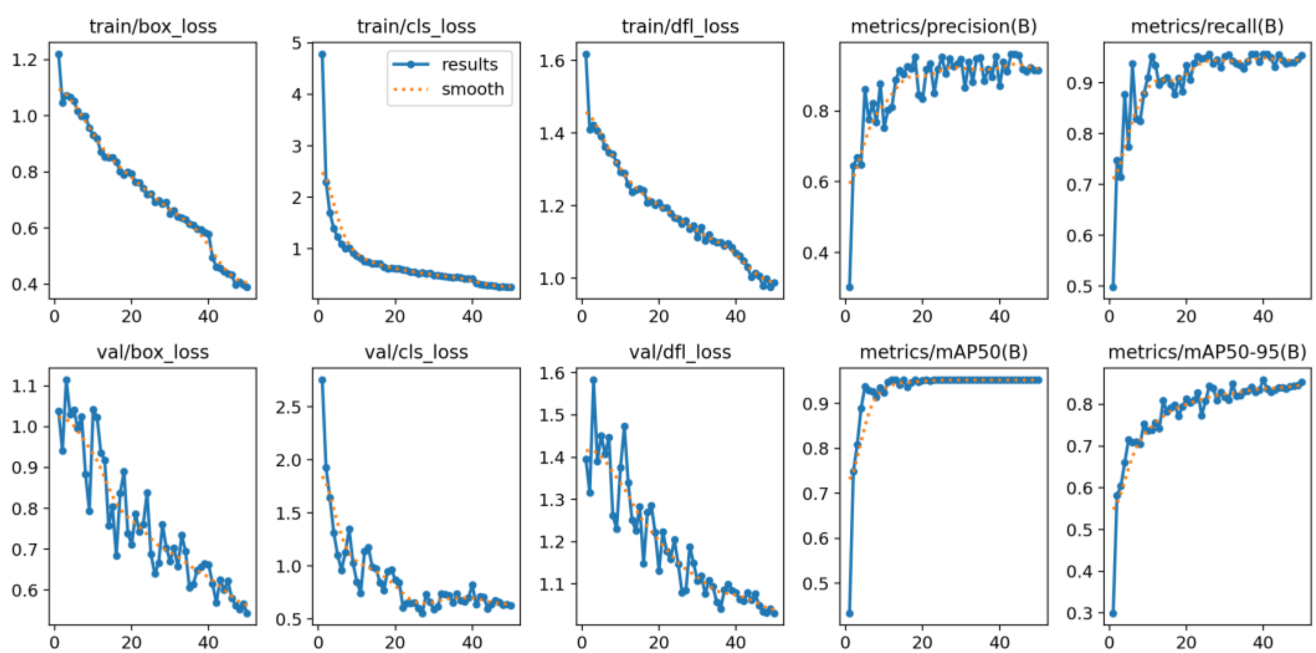


Fig. 5. Training and validation performance curves of the YOLOv8s model on the grocery item detection dataset

Overall, newer YOLO architectures show clear improvements in detection accuracy and robustness. While YOLOv12n achieves the highest performance across all splits, YOLOv8s provides the best balance between accuracy and computational efficiency and was therefore selected for web-deployment. Figures 5 and 6 illustrate the training and validation performance curves for YOLOv8s and YOLOv12n, respectively, further confirming stable convergence behavior and effective learning across epochs.

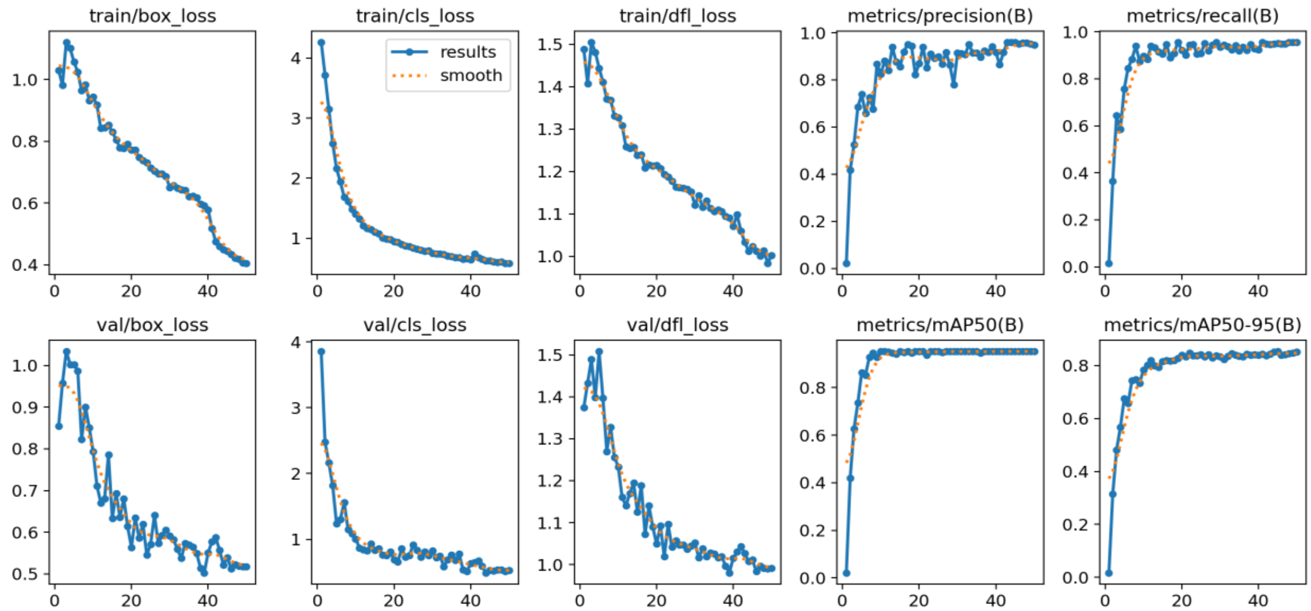


Fig. 6. Training and validation performance curves of the YOLOv12n model on the grocery item detection dataset

5. SYSTEM INTERFACE OVERVIEW

The designed web-based billing system for groceries helps users have a smooth experience from login to automatic billing and finally to the completion of payments. The system's design helps users easily navigate from uploading the images to the successful completion of payments. The following figures show the overall workflow of the designed system.

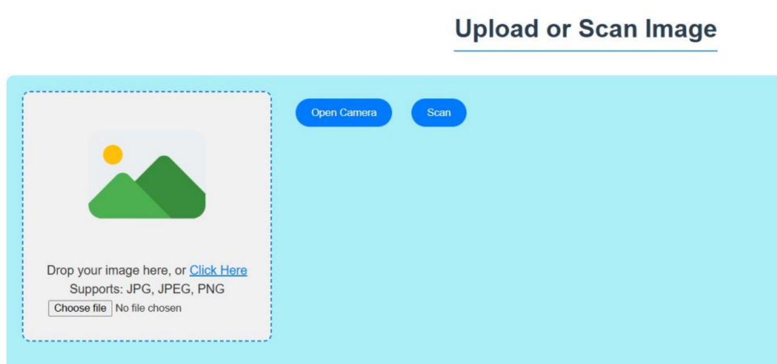


Fig. 7. Image Uploading Page

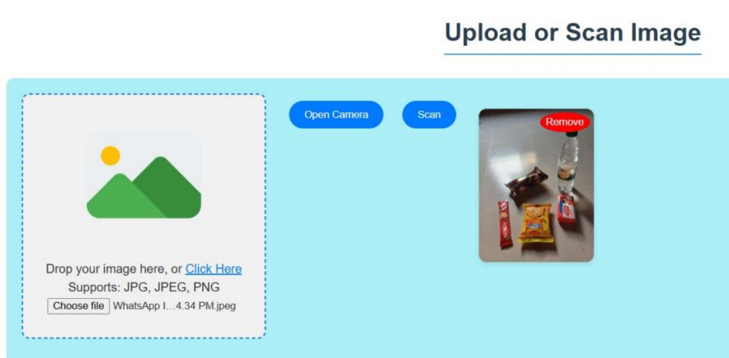
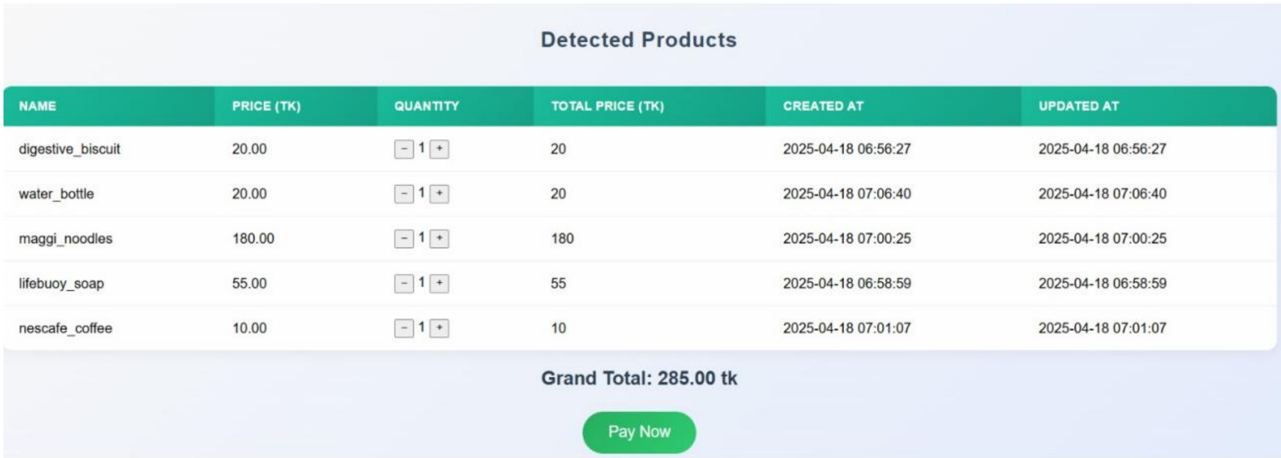


Fig. 8. Web Page after Uploading an Image

Automatic image-based billing system allows users to log in, create an account, and remain as a guest. The upload page, as illustrated in Figure 7, gives a user the opportunity to upload images of their groceries by drag and drop or by choosing the images. Once uploaded, Figure 8 shows the page on which the uploaded image is displayed, and this can be modified or removed prior to scanning.



NAME	PRICE (TK)	QUANTITY	TOTAL PRICE (TK)	CREATED AT	UPDATED AT
digestive_biscuit	20.00	- 1 +	20	2025-04-18 06:56:27	2025-04-18 06:56:27
water_bottle	20.00	- 1 +	20	2025-04-18 07:06:40	2025-04-18 07:06:40
maggi_noodles	180.00	- 1 +	180	2025-04-18 07:00:25	2025-04-18 07:00:25
lifebuoy_soap	55.00	- 1 +	55	2025-04-18 06:58:59	2025-04-18 06:58:59
nescafe_coffee	10.00	- 1 +	10	2025-04-18 07:01:07	2025-04-18 07:01:07

Fig. 9. Page showing the Detected Products with their Prices

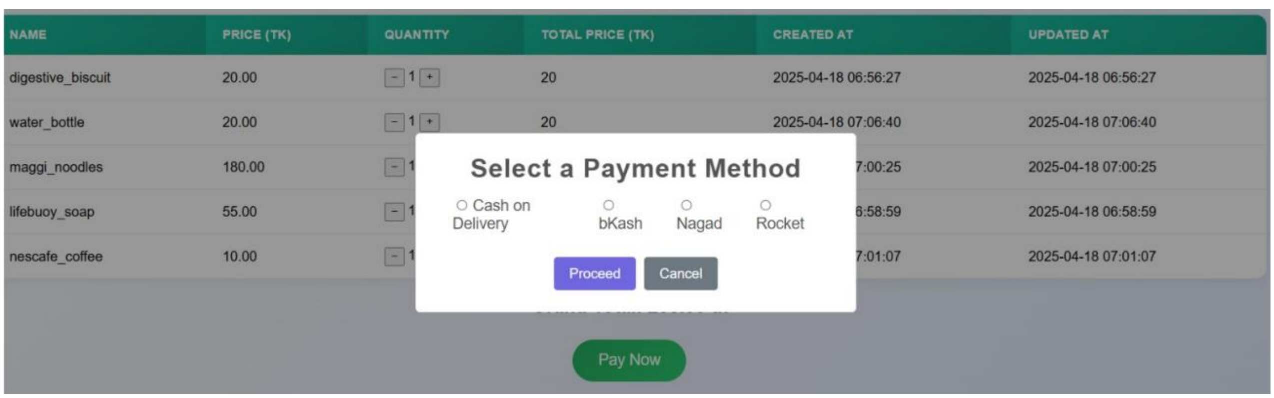


Fig. 10. Selecting any Payment Method

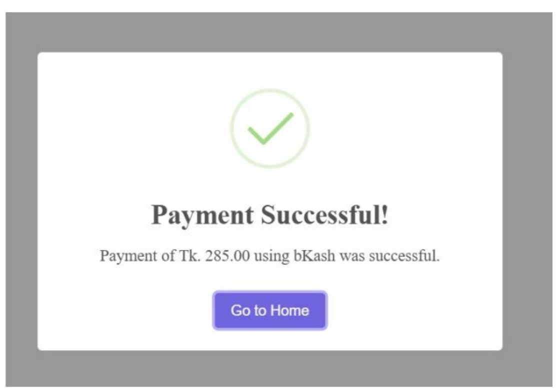


Fig. 11. Page showing Successful Payment

When the "Scan" button is pressed, item recognition and automatic bill printing is activated as demonstrated in Figure 9 Customers can set the quantity of several items of the same type. The check-out (Fig. 10) will enable users to choose the mode of payment they want and a successful sale is confirmed in Figure 11. In summary, the above series of web interfaces illustrates an end-to-end checkout system powered by artificial intelligence that uses both image-detection capabilities and automated billing.

6. CONCLUSION AND FUTURE WORK

This paper has introduced image-based grocery detection and automated billing system as an alternative to the old system of checkouts that relied on barcodes. The proposed framework can be used to detect the grocery items in an image effectively in accordance with deep learning and develops billing information with a high degree of reliability. Experimental analyses of arious YOLO systems show that recent systems perform well in detection accuracy, which confirms the practicability of vision-based retail billing systems in small to medium-sized retail settings. Although the detection pipeline relying on images has a consistent performance, real-time deployment is still restricted due to the size of the dataset and other environmental conditions like lighting and perspectives changes. Such limitations point to the necessity of the further enlargement of the datasets and enhanced resiliency in live inference scenarios. Additional work will be done to improve real-time performance by diversifying the dataset, using techniques to optimize models like pruning and quantization, and lightweight architectures usable to deploy models to the edge. Other additions will encompass price tags can be recognized with optical character and closer connection with inventory systems to enhance commercial applicability. On the whole, the proposed framework offers a scaled base of intelligent automation of the retail business and gives clear guidelines on further studies and implementation.

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ORCID iD:

Mustak Ahmmed, https://orcid.org/0009-0008-6365-6767

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