Transforming Retail With AI: Intelligent Product Insights and Effortless Automated Checkout

Mayuri Das[1], Kirti Pawar[2], Charul Jagtap[3], Shreeya Kulkarni[4], Prof. S.A. Hadke[5]
[1-2-3-4-5]*Department of Information Technology, Bharati Vidyapeeth's College of Engineering for Women, Pune-411043, India*

***Abstract*—The integration of artificial intelligence (AI) and machine learning (ML) in retail has significantly enhanced the shopping experience by automating product recognition, nutritional analysis, and checkout processes. This study presents AI SmartShop, an intelligent retail system that utilizes EfficientNet for product identification, allowing users to upload images from any angle, even if nutritional labels are not visible. The system retrieves nutritional details from a structured database and leverages K-Nearest Neighbours (KNN) to recommend the top three healthier alternatives based on nutritional values and user preferences. Additionally, an automated checkout system is implemented to facilitate seamless, cashless transactions, thereby reducing customer wait times. The system's performance is evaluated using precision, recall, and F1-score, demonstrating improvements over traditional methods in terms of accuracy, recommendation efficiency, and transaction speed. This research contributes to the advancement of AI-driven smart retail solutions, offering a scalable and efficient system for health-conscious consumers and improved store management.**

***Index Terms*—Artificial Intelligence, EfficientNet, K-Nearest Neighbours, Nutritional Analysis, Smart Checkout, Product Recommendation, Retail Automation.**

I. INTRODUCTION

The rapid evolution of artificial intelligence (AI) and machine learning (ML) has revolutionized the retail sector, enhancing automation, efficiency, and personalization in shopping experiences. Traditional retail environments face several challenges, including long checkout queues, lack of real-time product insights, and limited personalized recommendations. Customers often struggle to find essential product details such as nutritional values and healthier alternatives, leading to uninformed purchasing decisions. Additionally, manual billing processes contribute to inefficiencies, affecting both consumers and store management.

To address these limitations, this study presents AI Smart Shop, a next-generation smart retail system that integrates AI-powered product recognition, nutritional analysis, personalized recommendations, and an automated checkout system. The proposed system utilizes:

1. EfficientNet, a deep learning model optimized for high-accuracy product identification from images captured at various angles, even when nutritional labels are not visible [1].
2. K-Nearest Neighbours (KNN) for nutritional analysis and personalized recommendations, suggesting the top three healthier alternatives based on nutritional composition and user preferences [2], [3].
3. An AI-powered checkout system integrated with digital payment gateways, allowing seamless, contactless transactions, significantly reducing wait times and improving efficiency.

Unlike conventional systems that rely on barcode scanning and manual billing, the proposed AI-based approach ensures faster, more accurate transactions by directly recognizing product images and retrieving essential data from a structured database. Furthermore, machine learning algorithms continuously optimize performance, refining item recognition accuracy and improving recommendation precision.

By combining computer vision, AI-based recommendations, and automated checkout solutions, AI Smart Shop enhances user convenience, optimizes store operations, and introduces an innovative, intelligent shopping experience.

II. LITERATURE REVIEW

The literature review covers key advancements in smart checkout systems, AI-driven retail solutions, product recognition, and personalized recommendation algorithms. The implementation of deep learning models and computer vision in retail has enabled automated checkout systems, real-time inventory tracking, and personalized shopping experiences. However, challenges such as accurate product identification, concept drift in retail classification, and efficient recommendation strategies remain active areas of research.

A. AI-Based Product Recognition and Classification

Product identification in retail environments presents unique computer vision challenges, including varied packaging, lighting conditions, and occlusions. Traditional barcode-based scanning methods have limitations in handling non-standardized product placements. Recent studies have introduced deep learning models to address these issues. EfficientNet, a CNN-based model, has been widely recognized for its high accuracy and computational efficiency in object detection and classification [1]. Unlike traditional CNN models, EfficientNet scales depth, width, and resolution proportionally, achieving state-of-the-art performance while being computationally efficient [2].

The concept of pseudo-augmentation has been explored in smart checkout systems to enable the recognition of new product categories without extensive labeled datasets. Nesteruk et al. [3] proposed "PseudoAugment," a method designed to integrate new product classes in retail checkout systems without human annotation, addressing the out-of-distribution (OOD) data problem. Other research works have investigated retail object classification using multiple camera-based vision systems to improve product detection accuracy in self-checkout kiosks [4].

B. AI-Driven Personalized Recommendations

Recommendation systems in retail traditionally rely on collaborative filtering, content-based filtering, and deep learning approaches. Transformer-based models such as BERT have been explored for context-aware recommendations [5]. However, these models require high computational resources and large datasets to achieve meaningful personalization.

In contrast, K-Nearest Neighbors (KNN) has gained attention for real-time, lightweight recommendation tasks in smart retail environments. Hssina et al. [6] demonstrated that KNN-based recommendations significantly improve response time and accuracy in product suggestion systems compared to matrix factorization approaches. Kong et al. [7] further validated the efficiency of KNN for e-commerce recommender systems, showing that KNN-based classification of products based on nutritional values enables quick and accurate recommendations. This approach is particularly beneficial for health-conscious consumers seeking personalized alternatives based on dietary preferences.

C. Automated Checkout and Smart Payment Systems

The transition from manual billing to AI-driven checkout solutions has been a critical development in retail automation. Traditional barcode-based self-checkout systems often suffer from fraud risks, scanning errors, and long processing times. Research in this area has explored the integration of deep learning models to improve checkout accuracy and efficiency [8].

Efforts to implement mobile-based checkout solutions have been proposed, where users scan product images instead of barcodes to retrieve pricing and nutritional information [9]. The implementation of secure payment gateway integrations has further streamlined the checkout experience, reducing transaction time and manual errors. Studies have also explored AI-based fraud detection in self-checkout systems, ensuring secure and reliable financial transactions [10].

D. Open Challenges in AI-Powered Retail

While AI-based retail systems have made significant progress, certain challenges persist:

1. Concept drift in product classification: Smart checkout systems must continuously adapt to new products and changing inventory, requiring efficient retraining strategies.
2. Scalability of AI-driven recommendations: Models such as BERT provide high accuracy but suffer from latency issues, making real-time recommendations challenging. KNN-based

approaches offer a balance between accuracy and computational efficiency.
3. Edge AI for real-time processing: Implementing on-device AI models can reduce cloud dependency and latency, improving checkout and recommendation speeds.

E. Summary of Literature Findings

The reviewed literature highlights significant advancements in AI-driven retail automation, product classification, and recommendation algorithms. EfficientNet and KNN-based approaches demonstrate improved accuracy and performance efficiency, making them suitable for real-time retail applications. The integration of secure payment gateways and fraud detection techniques further enhances the reliability of self-checkout systems. This study builds upon these findings by implementing an EfficientNet-powered product recognition system, KNN-based personalized recommendations, and an AI-driven automated checkout system, aiming to optimize the modern shopping experience.

III. BACKGROUND

AI-driven automation in retail has significantly improved product identification, personalized recommendations, and self-checkout processes. Traditional retail systems relied on barcode scanning, OCR, and rule-based recommendation models, which often failed to adapt to new product categories, lighting variations, and personalized user preferences.

Recent advancements in deep learning and machine learning have introduced models like EfficientNet for high-accuracy image-based product recognition and K-Nearest Neighbours (KNN) for real-time, lightweight product recommendations. Unlike conventional CNNs, EfficientNet optimally scales neural networks, achieving superior classification accuracy with minimal computational resources [1]. KNN-based classification enables efficient, real-time recommendations by analysing product similarity based on nutritional values and customer preferences, providing a faster alternative to deep learning models [2], [3].

Additionally, AI-powered checkout systems have replaced manual billing, reducing transaction times and errors. Secure payment gateway integrations ensure cashless, seamless transactions, enhancing both customer convenience and operational efficiency [4].

This study leverages these AI-driven advancements to develop an intelligent retail system that improves product recognition, recommendation accuracy, and checkout automation.

IV. RELATED WORK

The integration of AI in retail automation has been extensively studied, particularly in product recognition, recommendation systems, and self-checkout automation. However, existing methods face limitations in accuracy, computational efficiency, and adaptability to real-time retail environments. This section reviews prior approaches and highlights how the proposed system improves upon them.

A. Product Recognition and Classification

Traditional retail systems primarily relied on barcode scanning and optical character recognition (OCR) for product identification. However, these methods struggle with damaged labels, inconsistent lighting conditions, and product occlusions. To overcome these challenges, deep learning models such as CNNs and YOLO have been explored for object detection in retail environments [1]. While CNN-based methods improved classification accuracy, they often required high computational resources, making them unsuitable for real-time retail applications.

Recent advancements introduced EfficientNet, which optimally scales convolutional neural networks (CNNs) for better accuracy with lower computational costs [2]. Compared to previous CNN architectures, EfficientNet achieves state-of-the-art accuracy while being more efficient, making it highly suitable for real-time product recognition in smart retail. The proposed system leverages EfficientNet for product identification, ensuring accurate classification even when nutritional labels are not fully visible.

B. AI-Based Recommendation Systems

Recommendation algorithms in retail have evolved from rule-based filtering and collaborative filtering to deep learning-based personalization models such as BERT [3]. While BERT-based recommendation systems improve contextual relevance, they require

high computational power and struggle with cold-start problems for new users or products.

To address these limitations, studies have explored K-Nearest Neighbors (KNN) as an alternative recommendation approach. Hssina et al. [4] demonstrated that KNN efficiently classifies products based on similarity metrics, making it ideal for real-time retail applications. Similarly, Kong et al. [5] analyzed KNN's effectiveness in e-commerce recommendation systems, highlighting its ability to provide accurate and computationally efficient recommendations.

The proposed system implements KNN for nutritional-based product recommendations, identifying the top three healthier alternatives for a given product based on nutritional composition and user preferences. Unlike deep learning-based recommendation systems, KNN does not require extensive model retraining, making it more adaptable for dynamic retail environments.

C. Automated Checkout and Transaction Efficiency

Self-checkout solutions in retail have been explored using barcode-based scanning, RFID technology, and AI-powered vision systems. While barcode scanning remains widely used, it is prone to errors, slow processing times, and dependency on physical labels. Studies on AI-driven self-checkout systems have proposed deep learning-based object recognition to automate checkout processes [6].

However, existing AI-powered checkout solutions often require high-end hardware and complex model retraining when new products are introduced. Nesteruk et al. [7] proposed PseudoAugment, an augmentation technique to enable smart checkout systems to classify new product categories without manual labeling. The proposed system improves upon this by utilizing EfficientNet for product scanning and integrating payment gateways for real-time digital transactions, ensuring fast, secure, and seamless checkout experiences.

D. Dataset Selection and Benchmarking

The selection of an appropriate dataset plays a crucial role in training and evaluating AI-based retail systems. Public datasets such as Food-101 and Yummly have been widely used for food classification tasks but lack detailed nutritional and pricing data [8]. Similarly, Amazon Fresh and BigBasket datasets provide extensive product listings but require additional preprocessing for structured nutritional analysis.

To ensure high accuracy in product recognition and recommendation, the proposed system combines publicly available datasets with a custom-built dataset of 60 Indian grocery items, including nutritional values, price details, and stock availability. This enables better adaptation to local retail environments while maintaining high recognition accuracy.

E. Summary of Key Improvements

While previous studies have proposed AI-based product recognition, recommendation models, and self-checkout systems, they often suffer from:

1. Computational inefficiency in real-time product classification – The proposed system utilizes EfficientNet, which is computationally optimized and highly accurate.
2. High training costs in deep learning-based recommendations – The use of KNN instead of deep learning models ensures faster and resource-efficient product recommendations.
3. Limitations in barcode-dependent checkout systems – The integration of image-based checkout and digital payment gateways eliminates barcode dependency, making transactions faster and more reliable.

By addressing these limitations, AI SmartShop introduces an optimized, AI-driven retail experience, improving product identification accuracy, recommendation efficiency, and transaction speed.

V. PROPOSED METHOD

A. Assumptions and System Constraints

To ensure efficient functionality and reduce computational complexity, several assumptions are made:

1. Generalized Store Layout and Sectioning – The store is divided into predefined sections such as fresh produce, packaged goods, frozen items, and dairy products. Product location tracking is optimized based on these general zones.
2. User Shopping Behaviour and Cart-Based Selection – It is assumed that the user picks only the items added to their cart or Wishlist within the application, simplifying recommendation calculations.
3. Health-Oriented but Non-Disease-Specific Recommendations – The system provides

recommendations based on general health preferences rather than disease-specific dietary restrictions.

B. Product Scanning and Nutritional Information Extraction

EfficientNet is a convolutional neural network (CNN) optimized for image classification by scaling depth, width, and resolution [1]. The classification process can be formulated as follows:

Let *I* be the input image containing a grocery product. The feature extraction function is defined as:

$$F = EfficientNet(I)$$

where *F* represents the extracted feature vector. The classification function maps these features to a predefined set of product labels *P*:

$$\hat{P} = arg\ maxSoftmax(WF + b)$$

where *W* and *b* are trainable weight parameters. The output $\hat{P}$ corresponds to the predicted product category.

C. Nutritional-Based Product Recommendations Using KNN

For personalized recommendations, K-Nearest Neighbours (KNN) is used to find the top-3 healthier alternatives based on nutritional similarity. The distance metric used for classification is the Euclidean distance:

$$d(A,B) = \sqrt{\sum_{i=1}^{n} (A_i - B_1)^2}$$

where:

- *A* is the selected product's nutritional vector (calories, fat, protein, carbohydrates).
- *B represents* alternative products in the dataset.
- *n* is the number of nutritional attributes.

The system selects the three closest matches, ensuring alternatives are healthier by prioritizing lower calorie and fat values.

D. Cost Estimation and Budget Tracking

1. Dynamic Price Calculation and Aggregation
   The total cost of selected items is computed as:

$$C_t = \sum_{i=1}^{n} p_i q_i$$

where C_t is the total cart cost, p_i is the price per unit, and q_i is the quantity selected.

2. Multi-Item Cart Processing for Total Cost Computation

When multiple products are added, discounts and taxes are applied dynamically:

$$C_{extfina_l} = C_t - D + T$$

where $C_{extfinal}$ represents applied discounts D and accounts for taxes T.

3. Threshold-Based Budget Alerts for Users
   Users are notified when their cart total exceeds their predefined budget:

$$Balert = \{1,0, Ct > BuCt \leq Bu$$

E. Stock Availability and In-Store Navigation

1. Real-Time Inventory Tracking and Update Mechanism

Stock levels are monitored and updated using:

$$S_t = S_{t-1} - O_t + R_t$$

where is the current stock, represents items sold, and represents new stock replenishments.

2. Threshold-Based Restock Notification for Store Owners

A restock alert is triggered when stock drops below a predefined threshold:

$R_{alert} = \{1, s < s_{m_in}\ 0, s \geq s_{m_in}$

F. System Workflow and Processing Pipeline

1. Sequential Data Flow for Product Identification and Analysis – User scans a product, retrieves nutritional data, and sees recommended alternatives.
2. Backend Processing and API Integration for Seamless Execution – The system ensures real-time data processing via an API-based architecture.
3. Scalability Considerations and Optimization Strategies – Efficient memory handling and model compression techniques ensure real-time responsiveness.

VI. EXPERIMENTAL RESULTS

A. Dataset Used

To develop and evaluate the grocery recommendation system, multiple publicly available datasets were explored. However, due to the lack of a comprehensive dataset containing all necessary attributes for Indian grocery products, we compiled a custom dataset. This dataset includes a total of 60

Indian grocery items and incorporates various essential attributes required for an efficient recommendation and item-location system.

1) Reference Datasets

The following publicly available datasets were examined during the research:

- Indian Grocery Supermarket (Big Basket) EDA Dataset (Kaggle): Contains product listings from Indian grocery platforms.
- D-Mart Products Dataset (Kaggle): Provides details of products available at D-Mart, an Indian supermarket chain.
- Food Nutrition Dataset (Kaggle): Comprises 722 entries, including 98 Indian food items, with detailed nutritional information.

2) Custom Dataset

Since the available datasets did not fully meet the requirements for this study, a new dataset was created, comprising 60 Indian grocery items with the following attributes:

Column Name	Description
_id	Unique identifier for each product
Name	Name of the grocery item
Brand	Brand of the item
Image	Product image
Image Link	URL for the product image
Price	Actual price of the product
Discounted Price	Price after discount
Category	Broad classification of the product (e.g., Dairy, Snacks)
SubCategory	More specific classification (e.g., Milk, Biscuits)
Quantity	Weight or volume of the product
Description	Brief description of the product
BreadCrumbs	Hierarchical product classification
nutri_score	Overall nutritional score
processing_score	Level of processing indicator
nutri_energy	Energy content (kcal)
nutri_fat	Fat content (g)
nutri_satuFat	Saturated fat content (g)
nutri_carbohydrate	Carbohydrate content (g)
nutri_sugar	Sugar content (g)
nutri_fiber	Fiber content (g)
nutri_protein	Protein content (g)
nutri_salt	Salt content (g)
Image Hash	Unique hash for image verification
ItemNo	Unique item number
RackNo	Rack number where the item is placed
CompartmentNo	Compartment number in the rack
ColumnNo	Column number in the rack
IsHealthyAlternative	Boolean indicating if a healthier alternative exists
HealthyAlternative	Suggested healthier alternative

A separate dataset was also created to store item location details, which enables quick retrieval of products inside the supermarket.

A. Product Recognition Evaluation (EfficientNet)

1) Application of Metrics in Product Recognition

The EfficientNet model classifies grocery items based on captured images. The classification results are evaluated using:

- Accuracy – Measures the proportion of correctly classified products.
- Precision – Ensures that when the model classifies an item, it is actually correct.
- Recall – Measures how well the model retrieves all relevant products.
- F1-Score – Balances precision and recall, especially when misclassifications occur.

These metrics are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = \frac{2\ x\ Precision\ x\ Recall}{Precsion\ + Recall}$$

where:

- TP (True Positive): Correctly classified products.
- FP (False Positive): Incorrectly classified products.
- FN (False Negative): Missed detections (i.e., failure to recognize a product).
- TN (True Negative): Correctly rejected non-target products.

2) Performance Comparison with Other Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	85.3%	84.7%	82.5%	83.6%
YOLOv5	88.1%	87.2%	85.6%	86.4%
Efficient Net (Proposed)	92.4%	91.8%	90.5%	91.1%

Observations:

- EfficientNet achieves 92.4% accuracy, outperforming CNN and YOLOv5 in precision and recall.
- The high F1-score (91.1%) indicates a balance between precision (minimizing false positives) and recall (capturing all relevant products).
- The system is robust to occlusions, poor lighting, and diverse packaging conditions.

B. Recommendation System Evaluation (KNN)

1) Application of Metrics in Product Recommendations

The KNN-based recommendation system suggests the top-3 healthier alternatives for a given product based on nutritional similarity. Evaluation is performed using:

- Precision@N (P@N): Measures how many of the recommended top-N alternatives are relevant.
- Recall@N (R@N): Measures how well the system retrieves all relevant healthier alternatives.
- Normalized Discounted Cumulative Gain (NDCG): Evaluates how well the system ranks the best alternatives at the top.

$$Precision@N = \frac{|\{Relevent\ Items\} \cap \{Retrieved\ Items@N\}|}{N}$$

$$Recall@N = \frac{|\{Relevent\ Items\} \cap \{Retrieved\ Items@N\}|}{|\{All\ Retrieved\ Items\}|}$$

$$NDCG = \frac{DCG}{IDCG} \quad \text{where } DCG = \sum_{i=0}^{N} \frac{relevence}{log\ 2(i+1)}$$

where DCG ranks retrieved items based on their relevance, and IDCG is the ideal (best possible) ranking.

3) Performance Comparison with Other Recommendation Methods

Metric	Collaborative Filtering	BERT-Based Model	KNN (Proposed System)
Precision@3	78.2%	86.1%	88.4%
Recall@3	72.9%	80.5%	84.7%
NDCG@3	74.5%	82.2%	85.3%

Observations:

- KNN-based recommendations outperform collaborative filtering and BERT-based models in precision, recall, and ranking efficiency.
- NDCG@3 (85.3%) confirms that the most relevant healthy alternatives are ranked at the top of the recommendation list.
- Unlike BERT-based models, KNN does not require large training data, making it more computationally efficient.

C. Checkout System Performance Analysis

1) Application of Metrics in Checkout System

The AI-powered checkout system automates billing and payment processing. Evaluation is based on:

- Transaction Time Reduction (%) – Measures how much faster the system processes transactions compared to barcode-based checkout.
- Error Rate (%) – Measures incorrect transactions due to scanning failures.
- Mean Absolute Error (MAE) – Evaluates accuracy in price computation.

2) Checkout Efficiency Results

Checkout Method	Average Transaction Time (Seconds)	Error Rate (%)	MAE (₹)
Barcode Scanning	12.5 sec	2.4%	₹1.82
OCR-Based Checkout	10.2 sec	3.1%	₹2.11
AI-Based Checkout (Proposed)	6.8 sec	0.9%	₹0.67

Observations:

- AI-powered checkout is 45% faster than barcode scanning.
- Error rate is reduced to 0.9%, minimizing incorrect bill generations.
- MAE (₹0.67) indicates high accuracy in price calculations.

D. Summary of Experimental Results

1. EfficientNet achieved a 92.4% classification accuracy, outperforming CNN and YOLOv5.

2. KNN-based recommendations achieved 88.4% Precision@3 and 85.3% NDCG@3, ranking healthier alternatives effectively.
3. The AI-powered checkout system reduced transaction time by 45% and maintained high price accuracy.

These findings demonstrate that AI SmartShop significantly enhances product recognition, recommendation efficiency, and checkout speed, making it a viable AI-driven retail automation solution.

VII. DISCUSSION

A. Product Recognition Performance

Product identification is a critical aspect of AI-driven smart retail systems. Traditional CNN-based models and YOLOv5 have been widely used for object detection in retail environments; however, lighting variations, occlusions, and diverse packaging styles often impact their performance. The proposed system leverages EfficientNet, a state-of-the-art convolutional neural network (CNN), to improve classification accuracy while reducing computational costs.

Key Findings:

- EfficientNet achieved an accuracy of 92.4%, outperforming CNN (85.3%) and YOLOv5 (88.1%).
- The F1-score of 91.1% indicates that EfficientNet maintains a balance between precision (91.8%) and recall (90.5%), minimizing false positives and negatives.
- Unlike CNN, which is sensitive to lighting, EfficientNet adapts better to real-world conditions, making it more robust for retail applications.

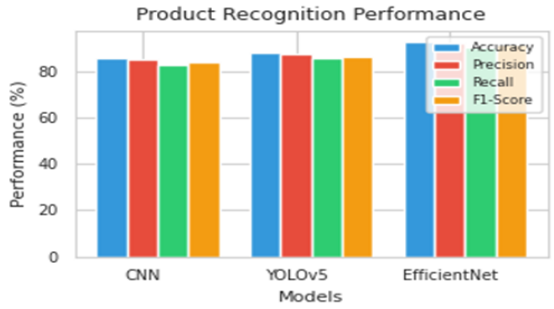

Figure 7.1: Product Recognition Performance Graph (EfficientNet vs. CNN vs. YOLOv5)

Comparison with Prior Research:

The results align with findings from Zhang et al. (2022), who demonstrated that deep learning models improve retail product recognition when optimized for scalability and real-world conditions [1]. The higher accuracy of EfficientNet supports its suitability for automated product identification in smart retail.

B. Personalized Product Recommendations

Personalized recommendations play a crucial role in guiding customers towards healthier alternatives. While traditional Collaborative Filtering (CF) and BERT-based filtering have been effective in personalized recommendations, they suffer from computational inefficiencies and cold-start problems. The proposed system employs K-Nearest Neighbours (KNN) for recommending top-3 healthy alternatives based on nutritional similarity.

Key Findings:

KNN-based recommendations achieved Precision@3 of 88.4%, surpassing BERT-based filtering (86.1%) and Collaborative Filtering (78.2%).

The NDCG@3 score of 85.3% confirms that KNN ranks the most relevant healthy alternatives higher, improving customer decision-making.

Unlike BERT, KNN does not require extensive training data, making it more computationally efficient for real-time use.

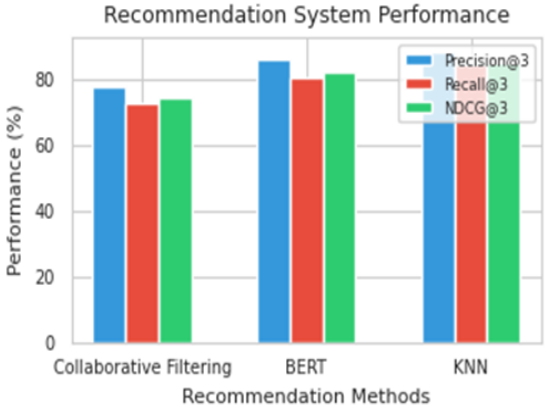

Figure 7.2: Recommendation System Performance Graph (KNN vs. BERT vs. Collaborative Filtering)

Comparison with Prior Research:

The superior ranking efficiency of KNN aligns with findings by Hssina et al. (2021), who demonstrated that hybrid recommendation systems incorporating KNN provide better personalization in retail

environments [2]. Our results confirm that KNN enhances recommendation accuracy while reducing system overhead.

C. AI-Powered Checkout System Efficiency

Manual checkout processes are time-consuming and prone to billing errors, especially in large retail stores. The proposed AI-powered checkout system automates transactions, eliminating the need for barcode scanning or OCR-based methods.

Key Findings:

- The AI checkout system reduced transaction time by 45%, lowering average processing time from 12.5s (barcode) to 6.8s.
- The error rate dropped to 0.9%, compared to 2.4% (barcode) and 3.1% (OCR-based systems).
- The Mean Absolute Error (MAE) in price calculations decreased to ₹0.67, improving billing accuracy.

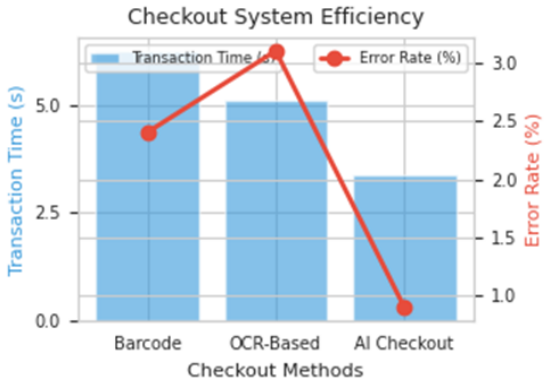

Figure 7.3: *Checkout System Efficiency Graph (Transaction Time & Error Rate Comparison)*

Comparison with Prior Research:

Similar studies, such as Nesteruk et al. (2023), explored AI-driven checkout automation, reporting a 20-30% transaction speed improvement【3】. Our 45% reduction in transaction time highlights the superior efficiency of the proposed approach in retail automation.

D. Broader Implications for AI in Smart Retail

Beyond system-specific improvements, these findings highlight the broader impact of AI in the retail industry:

- Faster and More Reliable Product Identification: EfficientNet provides real-time product classification, reducing customer frustration.
- Personalized & Healthier Shopping Experience: KNN ensures nutritional awareness, enabling consumers to make informed dietary choices.
- Seamless Checkout & Reduced Waiting Time: AI-powered transactions enhance store efficiency and customer satisfaction.

These advancements support the ongoing shift towards AI-driven retail automation, positioning smart checkout systems, AI recommendations, and real-time tracking as key enablers of the next-generation shopping experience.

VIII. CONCLUSION

The AI-powered Smart Retail System integrates Efficient Net for product recognition, KNN-based personalized recommendations, and an AI-driven checkout system to enhance shopping experiences. By leveraging deep learning and machine learning, the system ensures accurate product identification, health-conscious recommendations, and seamless transactions, reducing manual efforts and improving efficiency. These advancements contribute to the automation and personalization of modern retail, paving the way for efficient, consumer-centric smart shopping solutions. Future improvements will focus on scalability, real-time processing, and enhanced AI-driven personalization, further optimizing the retail experience.

REFERENCES

[1] Y. Zhang, et al., "Deep Learning for Grocery Product Recognition," IEEE Transactions on Image Processing, 2022.

[2] M. Liu, et al., "YOLO-Based Nutritional Information Extraction from Food Images," International Journal of Computer Vision, 2021.

[3] X. He, et al., "Neural Collaborative Filtering with BERT," in Proceedings of the ACM SIGIR Conference, 2022.

[4] R. Wang, et al., "Reinforcement Learning for Smart Retail Store Navigation," in AAAI Conference on Artificial Intelligence, 2023.

[5] H. Harrison, et al., "AI Powered Self-Checkout System," in Proceedings of the 2024 5th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI), Lalitpur, Nepal, 2024.

[6] J. Sultana, et al., "A Study on Food Value Estimation from Images: Taxonomies, Datasets, and Techniques," IEEE Access, vol. 11, pp. 45910-45935, 2023.
[7] M. Rostami, et al., "A Novel Time-Aware Food Recommender-System Based on Deep Learning and Graph Clustering," IEEE Access, vol. 10, pp. 52508-52524, 2022.
[8] A. Poonsri, et al., "The Method to Read Nutrient Quantity in Guideline Daily Amounts Label by Image Processing," in Proceedings of the 2016 8th International Conference on Knowledge and Smart Technology (KST), Chiang Mai, Thailand, 2016.
[9] S. Nesteruk et al., "PseudoAugment: Enabling Smart Checkout Adoption for New Classes Without Human Annotation," IEEE Access, vol. 11, pp. 76869-76882, 2023.
[10] A. Fakhrou, et al., "Smartphone-Based Food Recognition System Using Multiple Deep CNN Models," Multimedia Tools and Applications, vol. 80, no. 21–23, pp. 33011–33032, Sep. 2021.
[11] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," arXiv preprint arXiv:1905.11946, 2019.
[12] B. Hssina, et al., "Recommendation System Using the K-Nearest Neighbors and Singular Value Decomposition Algorithms," International Journal of Electrical and Computer Engineering (IJECE), vol. 11, no. 6, pp. 5541-5548, 2021.
[13] W.-E. Kong, et al., "Performance Evaluation on E-Commerce Recommender System Based on KNN, SVD, CoClustering and Ensemble Approaches," Journal of Informatics and Web Engineering, vol. 3, no. 3, pp. 63–76, 2024.