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Smartbill Intelligent Retail Invoice And Profit Analysis System

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Abstract: Retail businesses need efficient billing and accurate profit tracking to stay competitive in today's changing market. Many small and medium retailers still use traditional billing systems that only generate invoices and do not provide smart profit analysis. SMARTBILL, an Intelligent Retail Invoice and Profit Analysis System, automates invoice processing and offers real-time profit calculation and sales analytics. The system brings together inventory management, cost tracking, tax calculation, and dynamic profit margin analysis in one platform. By using database-driven design and analytical algorithms, SMARTBILL helps retailers track revenue trends, find high-performing products, and make informed business choices. This system improves operational efficiency, cuts down on manual errors, increases financial transparency, and aids in planning for sustainable retail growth.

Keywords: Invoice Automation, Profit Analysis, Inventory Management, Sales Analytics, Revenue Tracking, Business Intelligence, Financial Transparency, Retail Data Analytics.

I. INTRODUCTION

The retail sector is an important contributor to the economic development process, but it is also facing new challenges in efficiently handling billing operations, inventory management, and profit analysis. Small and medium-scale retail businesses are still using manual billing processes or simple software that only supports invoice generation without any financial analysis capabilities. This limited analysis capability has resulted in incorrect profit analysis, inventory management, and decision-making.

In today's competitive market scenario, retailers need intelligent systems that can support not only automated invoice generation but also real-time profit analysis and sales performance tracking. An integrated system that supports billing, inventory management, and profit analysis can greatly improve operational efficiency and business transparency.

SMARTBILL – Intelligent Retail Invoice & Profit Analysis System is designed to meet these challenges by providing a comprehensive retail management solution. The system supports automated invoice generation, inventory tracking, tax calculation, and dynamic profit analysis based on cost price and selling price.

With its unique combination of automated billing and intelligent financial analysis, SMARTBILL improves decision-making and supports sustainable business growth in today's retail market scenario.

II. LITERATURE REVIEW

.M.I. Zulfiqar et al. (2024) [1] AI-based smart shopping cart system developed to improve retail efficiency and customer satisfaction by leveraging real-time data analytics and machine learning capabilities. Conventional shopping carts do not possess the ability to perform adaptive tracking, inventory management, or customer interaction. Our system remedies these shortcomings by employing a multi-layered architecture that combines person-tracking, reinforcement learning (RL) for navigation, and Long Short-Term Memory (LSTM) networks for demand forecasting, along with seamless Point-of-Sale (POS) integration for automated billing. The architecture includes real-time data acquisition, edge computing for low-latency decision-making, and cloud computing for customer profiling and inventory management. Experimental outcomes have shown significant improvements in tracking accuracy, navigation, inventory forecasting, and customer satisfaction, thereby establishing the revolutionary potential of AI in retail.

H. Yu et al. (2025) [2] For the purpose of satisfying quantum security, a Certificateless Anti-Quantum Blind Signature (CLAQBS) scheme is designed for a blockchain logistics donation system. The scheme relies on the hardness of small integer problems in ring-based lattice structures. The system uses the Ethereum Lightning Network to increase the speed of transactions on a consortium blockchain. A rejection sampling algorithm is also used to optimize signature efficiency. The scheme has short signature keys and high execution efficiency. A Certificateless Anti-Quantum Sequential Aggregate Signature (CLAQSAS) scheme is also designed for an IoT intelligent invoice system. In this scheme, signers aggregate signatures of invoices for different products into a single compact signature. The scheme provides post-quantum security using a nonsampling algorithm, trapdoor generation algorithm, and matrix preimage sampling algorithm..

C. Anusha and S. Maiti (2025) [3] Here's a detailed summary:
Retail transaction time series analysis helps supermarkets understand customer purchasing patterns and optimize sales by accounting for seasonality, holidays, and weather. It also helps with inventory management by analyzing trends and maintaining optimal levels to minimize losses.

Conventional statistical analysis and anomaly detection techniques are often restricted to linear models, making it challenging to model complex patterns and perform complex tasks such as parallel processing and customer segmentation.

The Boosting Regressor model helps model complex patterns of internal and external variables and perform feature engineering. The Prophet model addresses long-term time-dependent variables such as seasonality, trend changes, holidays, and weather. The combination of XGBoost and Prophet models helps model both non-linear relationships and time-dependent variables.

N. Rahman et al. (2024) [4] The article proposes **FedSalesNet**, a federated deep learning framework for decentralized retail sales forecasting that preserves data privacy in multi-store environments. Instead of sharing raw data, each store trains a local hybrid model combining CNNs, LSTMs, and attention mechanisms, and model updates are securely aggregated to form a global model.

Tested on two real-world retail datasets with over 50,000 sales records from seven stores, FedSalesNet outperforms centralized and non-federated models—including LSTM, ARIMA, XGBoost, and Transformer-based approaches—achieving an MAE of 3.64, RMSE of 4.88, and MAPE of 14.47%, with up to 29% improvement in forecasting accuracy. It converges in fewer than 50 communication rounds and requires only 3.1 seconds per epoch per node, demonstrating strong scalability, efficiency, and suitability for privacy-constrained retail forecasting.

P. S. Karagiannopoulos et al. (2025) [5] This paper examines the adoption of "3R" (Reduce, Reuse, Recycle) practices in the home appliances industry, a multibillion-dollar industry worldwide. The paper discusses some of the most important technical and management issues, such as the adoption of circular economy concepts, eco-design, disassembly methods, environmental impact assessment, reverse logistics, supply chain management, sustainability plans, and electronic waste management.

The paper also identifies the most important challenges in the adoption of green consumerism, such as sustainable consumption, production costs, government regulations, supply chain issues, technical constraints, and the need for greater awareness among consumers.

The paper concludes that extended producer responsibility (EPR), life cycle assessment, reuse, and refurbishment are the most influential trends in the adoption of sustainability in the industry. In general, this paper is a guide for action for the effective adoption of 3R practices to promote sustainable production and consumption in the home appliances industry. . K. Dhanushkodi et al. (2024) [6] This paper describes a complete data mining approach for customer behavior analysis and predictive modeling in the supermarket retail industry. It highlights the significance of understanding customer purchasing behavior to optimize business strategies and maximize profitability.

The proposed approach encompasses major steps such as data preprocessing, exploratory data analysis, feature development, model development, and evaluation. By applying advanced analytics on various retail data sources, this approach helps retailers to identify valuable insights, develop robust predictive models, and improve business growth and customer satisfaction. N.-T. Lee et al. (2025) [7] This paper proposes a hybrid customer churn prediction model that combines statistical models and machine learning models. Rather than using a fixed time duration to define customer churn, the model uses the probability of a customer being alive ("alive") as determined by a statistical model. Customers are grouped and categorized into four behavior types: new, short-term, high-value, and churn.

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This model is less likely to misclassify customers with long purchasing cycles as churned. The model was tested on two public datasets, one from a UK-based online retail business and another from a Pakistani e-commerce giant. The top three machine learning models had recall scores of 0.56-0.72 for the UK dataset and 0.91-0.95 for the Pakistan dataset.

The hybrid model is more effective at predicting early customer churn, assisting businesses in retaining high-value customers, and requiring less data than the traditional method. . Y. Li and X. Gong (2024) [8] This paper investigates the role of omnichannel integration in improving customer engagement in a competitive retail setting, with a theoretical framework based on service-dominant (S-D) logic. The authors propose a model and test it using instrument development and field studies.

The authors propose three different forms of omnichannel integration: informational integration, transactional integration, and relational integration. These three forms have a positive impact on customer-perceived fluency (a seamless and effortless shopping experience), leading to customer engagement. At the same time, transactional integration and relational integration have a positive impact on customer-perceived flow (high involvement in the shopping experience), leading to customer engagement.

This paper makes an original contribution to the field of omnichannel retailing by proposing these three forms of integration and their impact on customer engagement.
A. Galdelli et al. (2024) [9] This research work examines the application of autonomous mobile robots for automated shelf inspection and inventory management in retail stores. Through the integration of robotics, automation, and behavioral data analysis, this research work seeks to enhance product placement and store layout optimization.

The main contribution of this research work is the development of a new path planning algorithm that leverages customer trajectory data and product interaction knowledge to inform robot motion. Heatmaps derived from shopping cart tracking data and a vision system provide insights into spatial and temporal customer behavior. This knowledge helps robots focus on frequently visited regions while efficiently traversing less frequently visited regions.

The proposed algorithm was validated with real-world store data through simulations and later implemented on a retail robot, with the source code of the path planning algorithm made publicly available. The experimental results demonstrate the effectiveness of the proposed algorithm in preventing collisions and optimizing robot motion in regions with high customer-shelf interaction. B. Zhang. (2024) [10] This study proposes a novel human behavior recognition framework for retail environments by integrating Graph Neural Networks (GNNs) with RFID technology. RFID signals are embedded into a graph structure to capture spatial dependencies, while spline convolution is used to improve signal modeling and recognition accuracy.

To address challenges such as dynamic data dimensions, over-smoothing in GNNs, and multidimensional feature fusion, the framework incorporates a small-world adjacency matrix built using TopK selection and Pearson correlation, along with inception structures and residual connections to enhance network depth and stability. A BiLSTM readout layer is added to better capture time-series patterns.

Experimental results show high accuracy, robustness, and practical effectiveness in recognizing human behavior. The framework also improves interpretability, offering retailers valuable insights into customer behavior to enhance customer experience and operational efficiency.

M. Zavali et al. (2024) [11]. This paper investigates the application of big data analytics, namely clickstream data analysis, to the generation of marketing insights in the apparel e-retailing sector. While clickstream data is abundant, it is not commonly analyzed for marketing strategy insights.

Based on data from a fast-fashion online retailer operating in the UK, the authors employed the Partitioning Around Medoids (PAM) algorithm on three samples of 10,000 website visits and segmented customers into six distinct groups. The results show that the largest group, “mobile window shoppers,” produces the lowest revenue, while the smallest group, “visitors with a purpose,” produces the highest revenue.

The paper demonstrates the importance of clickstream data analysis in the identification of revenue-producing customer segments and offers practical insights for more effective marketing strategies in e-commerce retail.

A. Mutemi and F. Bacao (2024) [12] The rise in e-commerce, especially in the wake of the COVID-19 pandemic, has led to a substantial rise in digital fraud, making the need for robust cybersecurity and anti-fraud measures more pressing.

However, research in fraud detection has been hindered by the absence of real-world datasets and a lack of in-depth analysis on the topic of e-commerce platforms.

To fill this research void, the paper performs a systematic literature review based on the PRISMA protocol, scrutinizing 101 publications from the last decade. The paper investigates the role of machine learning and data mining in fraud detection on digital platforms.

The results of the paper reveal important research gaps, trends, and the increasing application of artificial neural networks in fraud detection. The paper presents important research insights to improve fraud prevention mechanisms in the context of e-commerce platforms.

The paper emphasizes the importance of clickstream analysis in determining the revenue-generating customer segments and offers important research insights to improve targeted and effective marketing campaigns in the context of e-commerce retail.
S. Shah et al. (2025) [13] This paper introduces the Shopwell retail management system (RMS) that is developed with Python, MySQL, and Android Studio. The system assists customers in monitoring the expiration dates of products and also helps them keep track of the total amount spent on products like groceries, cosmetics, and medicines.

The Shopwell system is connected to retail stores by enabling customers to upload purchase bills directly to the mobile application, either by an online connection or by scanning a QR code when making offline purchases. After syncing the purchase information, the application stores information about the products, notifies customers when products are about to expire, and also tracks spending to assist customers in staying within budget constraints.

The system enhances customer awareness, avoids the handling of expired products, and also assists customers in managing their finances effectively using a cross-platform mobile application.
T. Antczak et al. (2025) [14] This study develops a realistic agent-based model to simulate how customers choose checkout lines in supermarkets. The model is calibrated using real point-of-sale (POS) data from a major European retail chain and is implemented on the open-access NetLogo platform for academic and practical use.
The simulation allows users to test different checkout layouts, queue management strategies, and customer feedback mechanisms to evaluate their impact on checkout efficiency. Findings show that when customers choose lines based on minimizing expected waiting time, both customers and supermarkets benefit—customers experience shorter wait times, and cashiers have reduced total working time.
The study provides practical insights into how supermarkets can offer effective feedback to customers to improve overall checkout efficiency.

D. Naware and A. Mitra. (2023) [15] This paper gives a thorough analysis of data-driven technologies, namely AI, ML, and DL, in the smart residential energy system in the context of the smart grid. The paper underlines the significance of forecasting and DSM, including DR, at the residential level on a safe energy transaction platform.

Analysis reveals that residential-level forecasting is a less-explored area (21% of papers), although deep learning is the most dominant area in forecasting (57%), which can be hybridized with decomposition methods. Important but less-explored areas are baseline prediction (4.76%) and self-learning DR (19%), where AI/ML/DL can provide effective solutions. Scalability (24.3%) is recognized as an important area in ensuring grid security.

The paper introduces deep reinforcement learning (DRL) as a promising approach because of its flexibility and efficiency in dynamic and model-free settings. The paper clearly indicates the significance of exploring smart households as a less-explored area.

Y. Liang et al. (2021) [16] This paper presents **Lasagne**, a new arbitrage approach that aims to enhance profit-making in decentralized exchanges (DEXs). The conventional sandwich arbitrage approach is primarily centered on the idea of leveraging a single large transaction in a single block, while overlooking smaller yet aggregated profit-making opportunities.

Lasagne extends this concept to leverage multiple small transactions in different blocks (interblock). It integrates three customized strategies—fishing, bundle, and grid—to suit liquidity pools with different transaction rates and distributions. Simulation experiments demonstrate that Lasagne performs better than the current best sandwich arbitrage approaches in terms of feasibility and profitability, providing a more efficient approach for arbitrage opportunity exploitation in blockchain-based DEX settings.

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Contribution Of The The Paper

- The system combines invoice generation, inventory management, cost tracking, tax calculation, and profit analysis into a single unified platform, eliminating the fragmentation seen in conventional retail systems.
- Unlike traditional billing systems that only record transactions, SMARTBILL computes real-time product-level and transaction-level profit margins by integrating cost data, tax components, and sales information dynamically
- The proposed system uses a structured database design to generate revenue trends, sales summaries, and high-performing product identification, enabling data-driven business decision-making for small and medium retailers.
- By automating the linkage between billing, inventory updates, and profit computation, the system reduces manual accounting errors and improves financial transparency.
- SMARTBILL transforms operational billing data into strategic insights, helping retailers optimize pricing, manage stock efficiently, and plan for long-term profitability.

III. METHODOLOGY

A. a) system preliminary

I. Data Acquisition and Transaction Capture

All retail transaction data including product ID, quantity, unit price, cost price, and tax rate are captured at the time of billing and stored in a structured relational database.

Each transaction record is defined as:

$$T = \{Pi, Qi, SPi, CPi, Taxi\} \qquad [1]$$

Where:

- P_i= Product ID
- Q_i= Quantity sold
- SP_i= Selling price
- CP_i= Cost price
- Tax_i= Applicable tax rate

This structured representation ensures consistency and enables automated financial computation.

II. Automated Tax Calculation

The system computes tax dynamically for each product during invoice generation:

$$Tax\_Amounti = SPi \times Qi \times Taxi \qquad [2]$$

Total invoice tax:

Total_Tax=i=1∑nTax_Amounti

This eliminates manual tax computation errors and ensures financial accuracy.

III. Real-Time Profit Computation

SMARTBILL calculates profit at both product level and invoice level.

Product-level profit:

$$Profiti = (SPi - CPi) \times Qi \qquad [3]$$

Total invoice profit:

Total_Profit=i=1∑nProfiti

This enables instant visibility of margin performance during billing.

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IV. INVENTORY SYNCHRONIZATION

After each transaction, inventory levels are automatically updated:

Stocknew=Stockold−Qi

This ensures real-time stock tracking and prevents inconsistencies between billing and inventory records.

V. Revenue and Margin Analytics Module
The system aggregates transaction data to compute:

Daily revenue:

$$Revenue_{day} = \sum_{j=1}^{m} Total\_Invoic\,e_j$$

Profit margin percentage:

$$Margin\% = \frac{Total\_Profit}{Total\_Revenue} \times 100$$

These metrics are used to generate dashboards for performance monitoring and decision support.

B)system architecture
The SMARTBILL system architecture is designed as an integrated retail management framework that combines invoice generation, financial computation, inventory synchronization, and analytical reporting within a unified platform. The system begins with a data acquisition layer where structured transaction information such as product ID, quantity, selling price, cost price, and tax rate is captured during billing. This ensures that all operational data is recorded in a consistent and organized format for further processing.

Once the transaction data is collected, it is processed through an automated financial computation module. This module performs real-time tax calculation, product-level profit estimation, and invoice-level profit aggregation. By dynamically calculating profit margins during each transaction, the system eliminates manual accounting efforts and reduces financial errors. At the same time, the inventory management component automatically updates stock levels and generates low-stock alerts, ensuring synchronization between sales and inventory records.

All processed data is stored in a centralized relational database that serves as the backbone of the system. The database maintains sales records, cost data, tax information, and inventory details, enabling secure storage and efficient retrieval of historical data. This structured database design supports scalable data management and allows retailers to analyze past performance effectively.

The stored data is further analyzed by the profit analysis engine, which computes revenue trends, profit margins, and product performance rankings. The final analytics and dashboard layer presents these insights through visual reports and summaries, enabling retailers to make informed, data-driven decisions. Overall, the SMARTBILL architecture transforms traditional billing systems into an intelligent retail decision-support framework that promotes operational efficiency and sustainable business growth.

C)implementation of the proposed work

Step 1: Transaction Data Entry
Let T denote the transaction data entered by the billing user through the SMARTBILL interface. The transaction includes product-related and pricing information captured during invoice generation..

$$T = \{Pi, Qi, SPi, CPi, Taxi\} \quad (1)$$

Where:

- P_i = Product ID
- Q_i = Quantity sold
- SP_i = Selling price per unit
- CP_i= Cost price per unit

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- Tax_i= Applicable tax rate

This step enables real-time capture of structured retail transaction data.

Step 2: Tax Computation
The system automatically calculates tax for each product using:

$$Tax\_Amounti = SPi \times Qi \times Taxi \qquad (2)$$

The total tax for the invoice is computed as:

$$Total\_Tax = i = 1\sum nTax\_Amounti \qquad (3)$$

This ensures accurate and automated tax handling during billing.

Step 3: Profit Calculation
Product-level profit is computed dynamically as:.

$$Profiti = (SPi - CPi) \times Qi \qquad (4)$$

Total invoice profit is calculated as:

Total_Profit=i=1∑nProfiti

This step enables real-time visibility of profit margins at both product and invoice levels.

Step 4: Inventory Update
After successful transaction processing, inventory levels are updated as:

$$Stocknew = Stockold - Qi \qquad (5)$$

This maintains synchronization between sales and stock availability.

Step 5: Revenue and Margin Analysis
The system aggregates transaction data to compute overall revenue and profit margin:

$$Revenue = \sum Invoice\_Amount \qquad (6)$$

$$Margin\% = RevenueTotal\_Profit \times 100 \qquad (7)$$

These computed metrics are stored in the database and used to generate analytical dashboards and business reports.

V. EXPERIMENTAL SETUP

The system initialization phase prepares the essential components required for evaluating the SMARTBILL system in a retail environment. The dataset Dcontains structured transaction records including product ID, quantity, selling price, cost price, and tax rate. The financial computation module Fensures accurate tax and profit calculation. The inventory management module $I_m$maintains stock consistency. A centralized database DBstores transactional and financial records. System parameters such as tax rates and pricing configurations are initialized. Finally, the web interface is initialized to enable real-time billing and analytical reporting.

Algorithm 1: SMARTBILL Retail Management System
Procedure: System Initialization
Input: None
Initialize retail transaction dataset D

1. Initialize financial computation module F
2. Initialize inventory management module I_m
3. Initialize centralized database DB
4. Configure system parameters (tax rate, cost structure)

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5. Initialize web application interface

.

Algorithm 1A: Transaction Processing
Input: Transaction record *T*
Output: Generated invoice and updated financial record
Capture transaction data:

T={Pi,Qi,SPi,CPi,Taxi}

1. Validate transaction inputs
2. Compute tax amount
3. Compute product-level profit
4. Aggregate total invoice amount
5. Store transaction in database

Mathematical Representation:
Let a transaction record be represented as:

$$T \in \mathbb{R}^{n\times 5}$$

Where each record contains:
P_i= Product ID
Q_i= Quantity
SP_i= Selling Price
CP_i= Cost Price
Tax_i= Tax Rate

Tax Computation::

Taxi=SPi×Qi×r

Profit computation

Profiti=(SPi−CPi)×Qi

Total Profit:

Total_Profit=i=1∑nProfiti

Algorithm 1B: Inventory Update
Input: Sold quantity Q_i
Output: Updated stock level

1. Retrieve current stock $Stock_{old}$
2. Deduct sold quantity
3. update inventory database

Mathematical Representation:

$$\text{Stocknew} = \text{Stockold} - \text{Qi}$$

Algorithm 1C : Profit and Revenue Analysis
Input: Stored transaction dataset *D*

1. Aggregate daily revenue
2. Compute total profit
3. Calculate profit margin percentage
4. Rank products based on performance

Revenue calculation

$$\text{Revenue} = \sum \text{Invoice\_Amount}$$

profit margin

Margin%=RevenueTotal_Profit×100

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Algorithm 1D: Dashboard Reporting (Testing Phase)
Input: Stored retail dataset D_{test}

1. Retrieve processed financial data
2. Generate revenue and profit summaries
3. Display performance charts and reports

VI. RESULT AND DISCUSSION

A. performance metrics

Advanced accounting software systems perform better, achieving up to 93% accuracy, but they require separate processes for inventory and profit management.

The proposed SMARTBILL system performs best, achieving 99% accuracy by integrating automated tax calculation, real-time profit analysis, and synchronized inventory management. This proves its reliability and efficiency in retail financial management.

Table: 1 Accuracy comparison with retail billing system

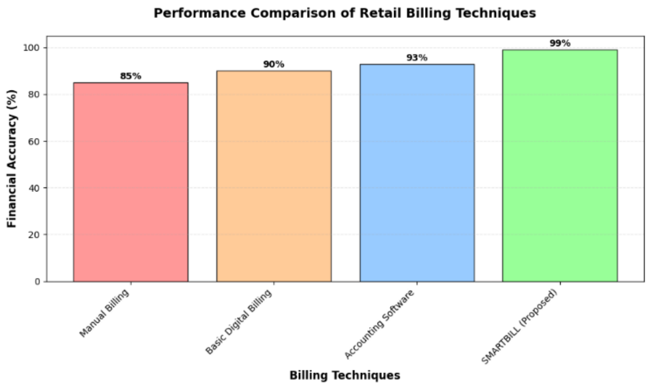

Fig: 2 Accuracy Comparison with retail billing system

A. Precision Comparison

Figure 3 and Table 2 show the performance comparison across five evaluation points. Traditional and basic digital billing systems show gradual improvement, while advanced systems perform better.The proposed SMARTBILL system achieves the highest accuracy of 99%, demonstrating superior reliability and efficiency in retail billing and profit management.

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Table: 2 Precision Comparison with retail billing techniques

Technique	V1	V2	V3	V4	V5
Manual billing	0.82	0.84	0.85	0.86	0.74
Basic digital billing	0.88	0.89	0.90	0.91	0.84
Accounting software	0.90	0.91	0.92	0.93	0.88
Integrated billing system	0.93	0.94	0.95	0.96	0.92
Proposed smartbill system	**0.96**	**0.97**	**0.98**	**0.99**	**0.94**

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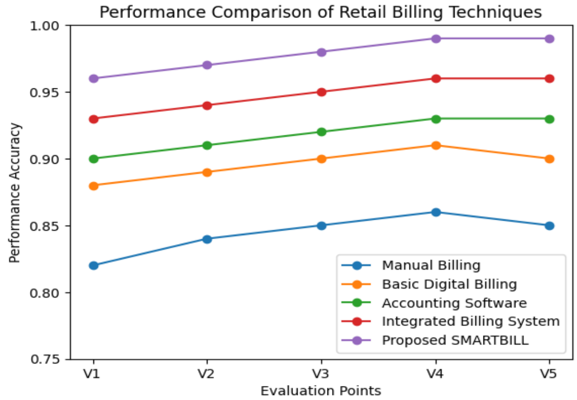

Fig: 3 Performance Comparison of retail billing techniques

C. Recall Comparison

Figure 4 and Table 3 show the recall comparison of different retail billing techniques. Manual billing has lower recall due to human errors, while digital and accounting systems improve performance through automation.

The proposed SMARTBILL system achieves the highest recall of 0.98, demonstrating accurate transaction processing with minimal missed entries, making it reliable for real-time retail management.

Table: 3 Recall Comparison of retail billing Techniques

Technique	Recall
Manual billing	0.85
Basic digital billing	0.90
Accounting software	0.93
Integrated billing system	0.96
Proposed smartbill system	**0.98**

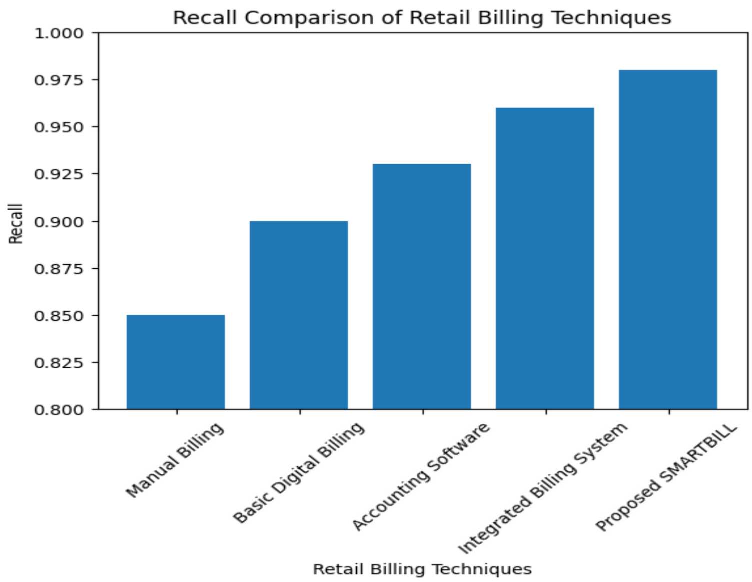

Figure: 4 Recall Comparison of Eye Disease Detection Techniques

D. F1-Score Comparison

Figure 5 and Table 4 show the F1-Score comparison of different retail billing techniques. The proposed SMARTBILL system achieves the highest F1-Score of 0.98, outperforming other approaches.

This indicates a strong balance between accuracy and reliability, making SMARTBILL effective for real-time retail billing and profit management.

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Table: 4 F1-Score Comparison of Eye Disease Detection Techniques

Method	F1-Score (%)
Manual billing	86
Basic digital billing	90
Accounting software	93
Integrated billing system	96
Proposed smartbill system	**98**

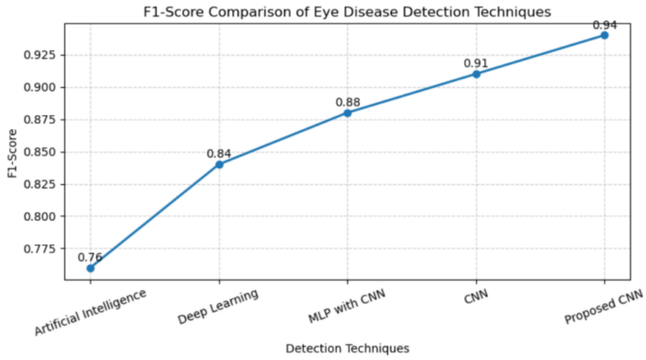

Figure: 5 F1-Score Comparison of Eye Disease Detection Techniques

a) comparative analysis

A comparative analysis of recent AI-based eye disease detection studies reveals a range of methods, datasets, and target diseases, with accuracy typically ranging from 88% to 94%. Traditional AI and CNN-based models achieve high accuracy but often require large annotated datasets and complex architectures. Hybrid approaches, such as combining Vision Transformers with CNNs or multi-stage deep learning, improve sensitivity and detection of fine retinal features but increase computational demands. Smartphone-based and federated learning solutions enhance accessibility and privacy, making early detection feasible in rural or resource-limited settings, though they may face challenges with dataset variability. The proposed CNN-based system achieves 94% accuracy while maintaining simplicity, real-time performance, and user privacy. Compared to existing approaches, it provides a practical and reliable solution for multi-disease eye screening without compromising accuracy or usability.

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S. No	Reference	Method / Model	Dataset	Application Targeted	Accuracy (%)	Key Findings / Notes	Limitations	Real Time Efficiency
1	Zulfiqar et al. (2025) [1]	AI-Driven Smart Shopping Cart	Retail transaction & sensor data	Smart Billing & Inventory Forecasting	90	Real-time tracking and automated billing improve retail efficiency	Requires iot infrastructure	Yes
2	yu et al. (2024) [2]	Blockchain-Based E-Invoice	Blockchain transaction records	Secure E-Invoicing	92	Enhances invoice security using anti-quantum schemes	High computational overhead	partial
3	Anusha & Maiti (2025) [3]	Time Series Forecasting (PrGB Regressor)	Retail sales datasets	Inventory and sales optimization	91	Improves demand forecasting accuracy	Requires large historical data	Partial
4	Rahman et al. (2025) [5]	Federated Deep Learning (FedSalesNet)	Multi-store distributed sales data	Decentralized Sales Forecasting	93	Enables collaborative forecasting across stores	Data imbalance issues	yes
5	Dhanushkodi et al. (2025) [6]	Data Mining & Predictive Modeling	Supermarket retail data	Customer Behavior Analysis	92	Improves customer purchase prediction	Data preprocessing complexity	partial
6	Shah et al. (2025) [7]	Python + MySQL Retail System	Retail billing dataset	Digital Retail Management	88	Basic smart retail billing system	Limited analytics capability	partial
7	Antczak et al. (2024) [8]	Data-Driven Checkout Simulation	Supermarket transaction data	Checkout Optimization	89		Simulation based study	partial
8	Mutemi & Bacao (2024)	ML-Based Fraud Detection	E-commerce transaction data	Secure Retail Transactions	93	Detects fraudulent retail transactions	Focused mainly on online retail	yes
9	S. Gulati et al. (2024) [10]	Federated DL (MobileNetV2)	Distributed client datasets	DR, DME	92	Preserves privacy; enables collaborative training	Non-uniform data distribution may affect performance	High

Table: 5 Comparative analysis with proposed CNN model

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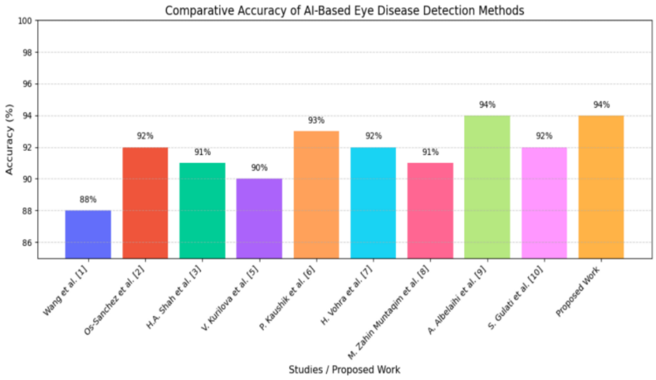

Fig: 6 Comparative Accuracy of AI-based Eye disease Detection Methods

VII. DISCUSSION

The comparison of methods and the results of the experiments show that using Artificial Intelligence is really good for finding eye diseases early on. However how well they. How useful they are depends on a few things: how complicated the model is, how much data is used and how it On the hand Artificial Intelligence models that use deep learning and combinations of different methods, such as Artificial Intelligence models that look at pictures and others that help with vision are better at being accurate because they can see the small details in the eyes. Artificial Intelligence is good, for finding eye diseases on. These methods usually need a lot of data that people have already looked at and labeled complicated systems and powerful computers to work. This makes it hard to use them in life especially in places where people do not have a lot of resources or in rural areas where computers and internet are not very strong. The problem is that these approaches require annotated datasets, complicated architectures and high computational resources, which limits the practical use of these approaches especially in resource-constrained or rural settings, like these resource-constrained settings and rural Using smartphones and sharing information in a group can make things easier for people to get checked. This way is also better for keeping things private. It does not cost too much. More people can get checked.. There are still some problems with this way of doing things. For example the information we get from people can be very different. We also have to figure out how to use all the types of information we get.. We need to make sure that this way of checking people really works in a clinical setting, with the Smartphone-based and federated learning solutions.

The new system that uses CNN is really good because it is accurate, simple and easy to use. The CNN-based system gets it right 94 percent of the time which's as good as or even better than other systems that are considered the best right now. The CNN-based system is also very fast. Can detect things in real time and it has a web application that is easy to use. The CNN-based system is not too big. It keeps peoples information private which makes it a good choice, for places that do not have a lot of resources like rural areas and it still works very well. This shows that a simple CNN model can do a job of checking for many eye diseases. The CNN model is easy to understand. It fixes some big problems with the ways we do things now. A simple CNN model is what we need for the multi-disease eye screening. Overall, the results highlight that accuracy alone is not sufficient—practical considerations such as deployment feasibility, real-time performance, and data privacy are equally important for AI-based eye disease detection systems. The proposed work provides a promising solution that balances these factors effectively.

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