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Article

Intelligent Supermarket Marketing using RFID-Enabled IoT and Machine Learning

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Abstract: The rapid evolution of retail technologies has transformed the way supermarkets manage customer engagement and marketing strategies. This study proposes an intelligent supermarket marketing framework that integrates Radio Frequency Identification (RFID) and Internet of Things (IoT) technologies with machine learning for customer behavior analysis. RFID tags and IoT sensors are employed to capture real-time customer movement, product interactions, and purchase histories within the supermarket environment. The collected data is processed and analyzed using multiple machine learning algorithms, including k-means clustering, Decision Tree (DT), and Support Vector Machine (SVM), to classify customer activities such as browsing, purchasing, and ignoring products. Comparative performance analysis shows that these models effectively identify customer behavior patterns, supporting personalized marketing strategies, optimized product placements, and improved inventory management. Experimental simulations demonstrate that the proposed system achieves high predictive accuracy, enabling supermarkets to design data-driven campaigns, increase conversion rates, and enhance overall sales efficiency. The combination of RFID-enabled IoT infrastructure with supervised machine learning provides a scalable, cost-effective, and intelligent approach to modern retail marketing. This research highlights the potential of integrating classification-based analytics into supermarket ecosystems to foster improved customer experience and strategic decision-making.
Keywords: Smart Retail, RFID, IoT, Machine Learning, Personalized Marketing, Predictive Analytics, Automated Checkout, Customer Behavior Analysis

1. Introduction

The present-day retail sector faces unprecedented challenges in inventory management, customer engagement, and operational efficiency. Traditional supermarket systems, reliant on manual processes and generalized marketing approaches, struggle with persistent issues like stock inaccuracies, impersonal customer interactions, and escalating operational costs. These limitations underscore the critical need for an intelligent, automated system to revolutionize supermarket operations and marketing strategies [1-2].

RFID technology forms the foundational layer of this transformative system, addressing long-standing inventory management challenges. Unlike conventional barcode systems that require line-of-sight scanning, RFID tags enable simultaneous, contactless reading of multiple items, dramatically improving inventory accuracy and efficiency. This capability proves particularly valuable in high-traffic retail environments where real-time stock visibility is crucial. When synergistically combined with IoT networks, the system gains enhanced functionality through distributed sensor intelligence. Smart shelves equipped with weight sensors and RFID readers automatically detect product movement and inventory levels, while strategically placed IoT beacons track customer pathways and dwell times throughout the store. This integrated sensor network generates a rich, multidimensional dataset encompassing both product movement and customer behavior patterns [3-5].

However, the unprocessed data streams generated by RFID and IoT devices present significant analytical challenges due to their inherently unstructured nature and high dimensionality. These raw data inputs typically contain complex, noisy patterns. The sensor outputs from RFID readers and IoT networks often manifest as voluminous, heterogeneous datasets comprising temporal sequences, spatial coordinates and event logs that lack immediate interpretability. So the traditional analytical approaches struggle to process these intricate data structures efficiently, frequently resulting in information overload rather than actionable intelligence. This fundamental gap between raw sensor outputs creates a critical need for advanced preprocessing and ML techniques capable of distilling this complex data into operational knowledge. Without such transformation, the valuable information embedded in these technological systems remains effectively inaccessible for strategic decision-making [6-8].

The true transformative potential of this system emerges when these hardware technologies are coupled with advanced machine learning (ML) capabilities. ML provides the capability to analyze this data in real-time, uncovering hidden patterns and correlations that would otherwise remain unnoticed. It supports customer segmentation, demand forecasting, personalized promotions, and dynamic pricing strategies, thereby enhancing customer experience and boosting sales. In addition, these models can optimize store layout by identifying high-traffic areas, improve inventory management by predicting stock requirements and detect anomalies in shopping behavior for security purposes. By continuously learning from evolving customer data, ML ensures that supermarkets remain adaptive, data-driven, and competitive in a rapidly changing retail environment.

Numerous ML algorithms have been adopted for this purpose. Fuzzy C-Means provides soft clustering but has high computational overhead and can be difficult to interpret for actionable business strategies. Hierarchical clustering is computationally expensive and difficult to scale for large datasets, while DBSCAN struggles with varying customer densities and requires sensitive parameter tuning. Gaussian Mixture Models (GMM) assume probabilistic distributions, which may not hold in retail data, and they are slower in convergence. Deep learning approaches, though powerful, demand massive datasets and computational resources, and their black-box nature makes results less interpretable for decision-making. Machine learning algorithms such as Decision Trees (DT), K-Means Clustering, and Support Vector Machines (SVM) are particularly effective in uncovering patterns from complex datasets. For instance, clustering techniques group customers based on shopping habits, enabling targeted promotions and personalized recommendations. Classification algorithms categorize customer interactions into browsing, purchasing, or ignoring, which helps retailers forecast demand and plan inventory. By continuously learning from new data, ML-driven systems evolve over time, ensuring adaptability in rapidly changing market conditions[9,10].

Several studies have validated the effectiveness of RFID and ML in retail. Prior works have explored Gaussian models, threshold-based approaches, and neural networks for customer behavior prediction. While these models achieved moderate to high accuracy, challenges remain in terms of scalability, robustness, and real-time adaptability. The proposed system in this study addresses these gaps by combining RFID data with IoT sensor information and applying advanced ML techniques, particularly SVM. This integration ensures higher accuracy, better generalization, and improved customer profiling.

Beyond predictive accuracy, the proposed intelligent supermarket marketing framework offers strategic benefits. Personalized marketing campaigns driven by ML recommendations significantly enhance customer engagement by tailoring promotions to individual preferences. Demand forecasting accuracy reduces both stockouts and overstocking, ensuring inventory is maintained at optimal levels. Real-time behavioral tracking allows dynamic pricing and cross-selling opportunities, such as suggesting complementary items based on live shopping activity. Additionally, anomaly detection enhances security by identifying suspicious patterns such as shoplifting or unusual bulk purchasing.

The contribution of this research is therefore twofold. First, it demonstrates the effective integration of RFID, IoT, and ML into a unified framework for intelligent supermarket marketing. Second, it provides empirical evidence through experimental analysis that such a system achieves superior performance compared to traditional and existing models. By leveraging a combination of supervised and unsupervised learning methods, the framework achieves predictive accuracy of up to **97.4%**, surpassing previous approaches.

This paper is structured as follows: Section 2 describes the methodology, including RFID-based data acquisition, IoT-enabled transmission, and ML model development. Section 3 presents the experimental setup and performance evaluation. Section 4 discusses customer behavior insights, marketing impact, and comparative analysis with existing studies. Finally, the conclusion highlights the implications of this research and outlines potential directions for future work.

2. Methodology

The proposed system integrates RFID technology, IoT infrastructure, and Machine Learning models to analyze and promote supermarket marketing. The methodology is organized into sequential stages, where each component contributes to effective customer behavior tracking, data-driven decision-making, and marketing strategy optimization. Figure 1 depicts the block diagram of the proposed system.

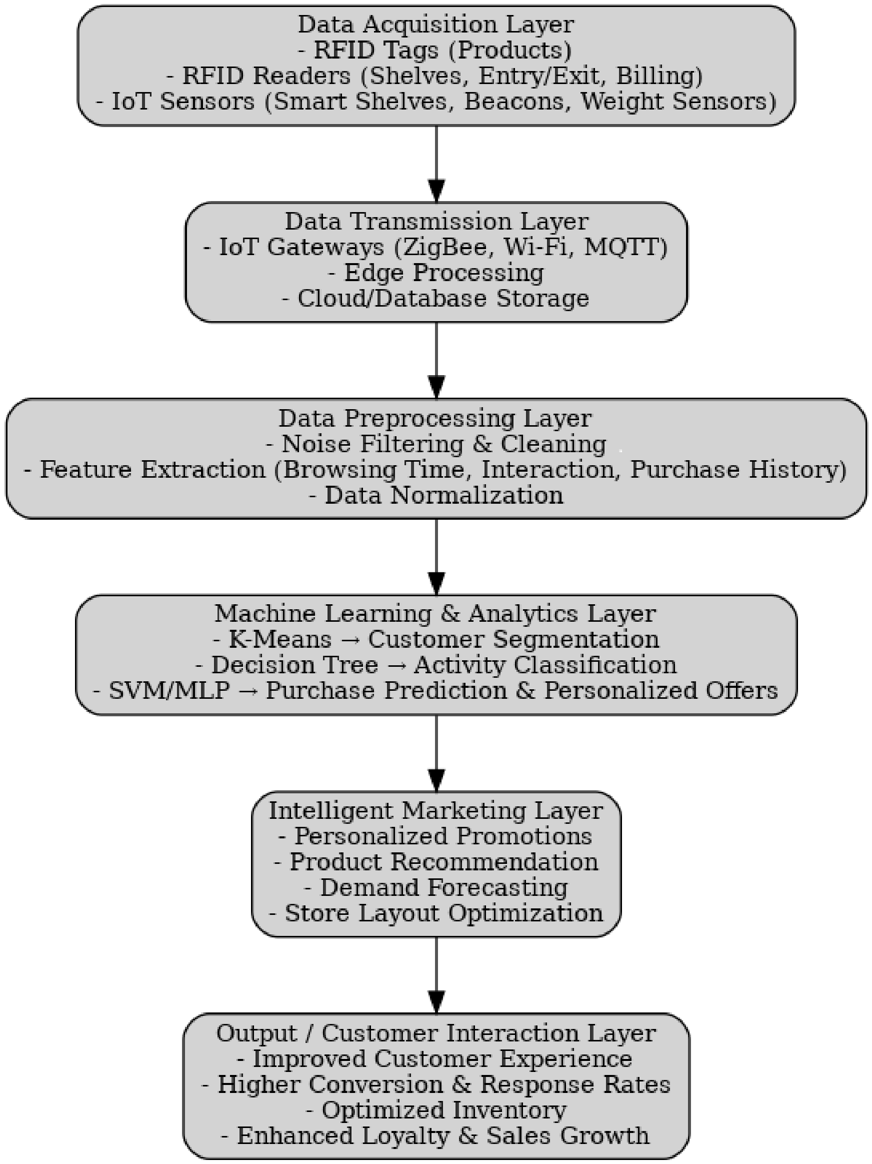

Figure 1. Block diagram of the proposed system.

2.1 RFID-Based Data Acquisition

The foundation of intelligent supermarket marketing lies in the efficient collection of customer and product interaction data. Radio Frequency Identification (RFID) technology is employed to automate this process, ensuring seamless monitoring of customer behavior without manual intervention. Each product in the supermarket is tagged with a passive RFID tag that contains a unique identifier. RFID readers are strategically installed at entry/exit points, product shelves, and billing counters to capture tag information in real-time. When a customer picks up or returns a product, the corresponding RFID reader logs the product ID, location, and timestamp. This continuous stream of raw data forms the primary dataset for customer shopping behavior analysis as shown in Figure 2.

The captured information is transmitted to an IoT gateway, where it is pre-processed, filtered, and formatted before being stored in a centralized database. This mechanism minimizes errors such as duplicate reads or false detections, thereby ensuring clean and reliable data for further machine learning analysis.

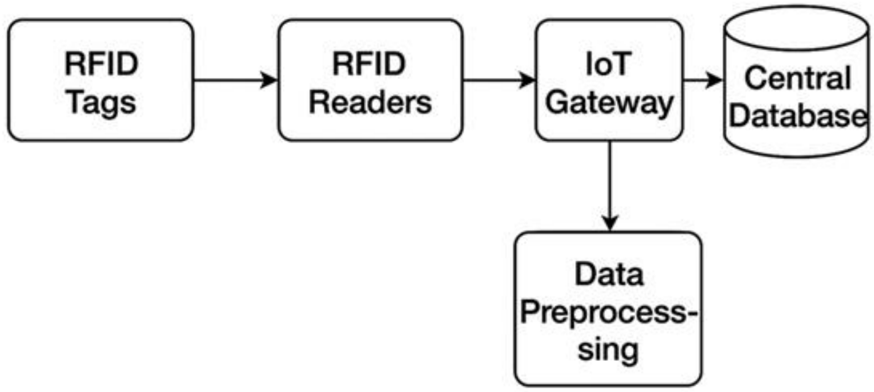

Figure 2. RFID-Based Data Acquisition

2.2 IoT-Enabled Data Transmission

Once customer shopping data is captured via RFID readers, the next critical step is transmitting this data reliably to a centralized system for analysis. The Internet of Things (IoT) serves as the backbone of this process, ensuring seamless connectivity between RFID devices, local gateways, and cloud servers.

In this setup, RFID readers are connected to IoT-enabled gateways (ZigBee modules), which act as intermediaries to preprocess and forward the acquired data. These gateways manage communication protocols, handle real-time data streams and provide edge-level filtering to reduce noise. The processed data is then transmitted securely over the internet to a centralized database.

On the cloud platform, the data is stored and made available for ML algorithms to perform clustering, pattern recognition and predictive analysis. This IoT-based transmission ensures scalability, low latency and real-time monitoring, enabling supermarkets to track customer shopping behavior continuously and take instant decisions for personalized marketing and inventory management Figure 3 displays the IoT-Enabled Data Transmission.

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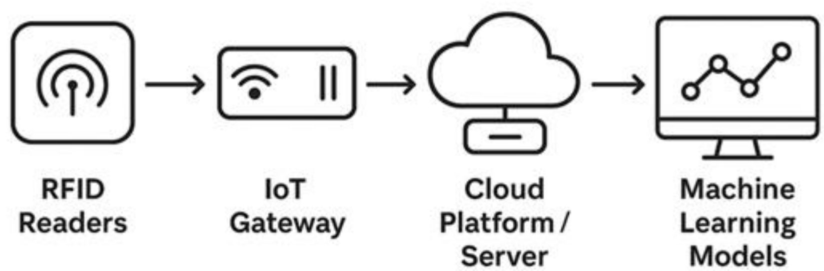

Figure 3. IoT-Enabled Data Transmission

2.3 Data Preprocessing

The raw data collected from RFID tags and IoT sensors contained inconsistencies due to environmental interference and hardware limitations. To address this, noise filtering techniques were applied to eliminate redundant or erroneous signals, ensuring data reliability. Once the data was cleaned, feature extraction was carried out to convert low-level sensor readings into high-level behavioral variables such as browsing time near a product, frequency of product interaction, and likelihood of purchase. These features captured meaningful customer behavior patterns that could be used for classification. Since real-world data often suffers from gaps, missing values were imputed using statistical and similarity-based methods to maintain dataset completeness. This step prevented model bias and ensured smooth learning during training. Data normalization was then applied to bring all features into a uniform scale, preventing attributes with larger ranges from dominating the learning process. By standardizing input variables, models like Logistic Regression, Decision Tree, and Support Vector Machine were able to converge more effectively. The preprocessing pipeline thus ensured that the dataset was clean, balanced, and well-structured for subsequent analysis. Ultimately, these steps enhanced the overall robustness of the machine learning framework and improved the accuracy of customer behavior classification.

2.4 Model Development

For customer behavior analysis, three machine learning models were employed. K-Means clustering was used as an unsupervised approach to segment customers into distinct groups based on their interaction patterns and purchasing behavior, enabling targeted marketing and product placement strategies. Decision Tree (DT) was implemented to model hierarchical decision paths, offering interpretable rules for classifying customer activities such as browsing, purchasing, or ignoring products. Support Vector Machine (SVM) was applied to capture complex, nonlinear relationships within the data by constructing optimal separating boundaries between different activity classes. Together, these models provided both clustering-based segmentation and supervised classification, ensuring comprehensive insights into customer behavior for strategic decision-making in supermarkets.

K-means clustering

Machine learning plays a pivotal role in uncovering meaningful patterns from large datasets collected via RFID and IoT systems in supermarkets. Among clustering algorithms, K-means has been chosen due to its simplicity, efficiency, and scalability when dealing with large, high-dimensional data. The primary objective of K-means is to partition customer purchasing data into K distinct clusters, where each cluster represents a segment of consumer behavior or product association.

Step-by-Step Workflow**:**

1. **Input Data**: Customer transaction logs, product IDs, and time-stamped purchase records from RFID tags transmitted via IoT.
2. **Preprocessing**: Data normalization to ensure uniform feature scales.
3. **Cluster Initialization**: Select *K* initial centroids randomly.
4. **Cluster Assignment**: Assign each data point to the nearest centroid based on distance.
5. **Centroid Update**: Recompute centroids by averaging all points within the cluster.
6. **Iteration**: Repeat assignment and update until convergence.
7. **Result**: Distinct customer/product clusters that guide marketing strategies, personalized promotions, and inventory decisions.

The K-means algorithm minimizes the **intra-cluster variance**, also known as the *objective function*

$$J = \sum_{i=1}^{k} \sum_{xj \in Ci} \left\| x_j - \mu_j \right\|^2 \quad (1)$$

Where:

- K Number of clusters
- x_j- Data point
- Ci -Cluster iii
- μ_j - Centroid of cluster

Cluster Assignment:

Each point is assigned to the nearest centroid:

This algorithm converges when centroids stabilize. Figure 4 depicts the flowchart of the K-means clustering.

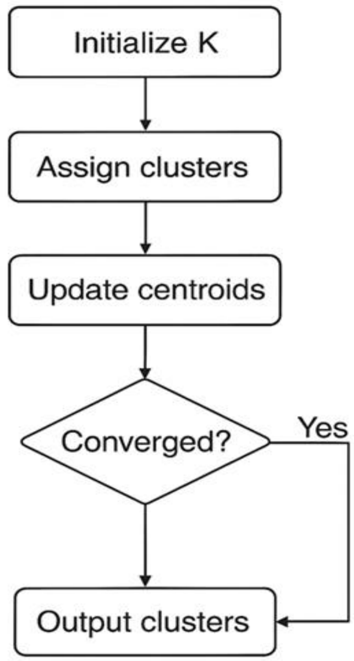

Figure 4. K-means working Principle

SVM

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm widely used for classification and regression tasks. The primary goal of SVM is to find an optimal hyperplane that separates data points of different classes with the maximum margin, thereby improving generalization and reducing misclassification. Data points that lie closest to this hyperplane are called support vectors, and they play a critical role in defining the decision boundary. For linearly separable data, SVM constructs a straight-line hyperplane, while for non-linear cases, it employs kernel functions (such as polynomial, radial basis function (RBF), or sigmoid) to project the data into a higher-dimensional feature space where it becomes linearly separable. SVM is particularly effective in handling high-dimensional data and has strong robustness against overfitting, especially when the number of dimensions exceeds the number of samples.

As the customer activities (browsing, purchasing, ignoring) based on RFID and IoT data are not strictly linearly separable, SVM uses the Radial Basis Function (RBF) kernel:

$$\mathrm{K}(\mathrm{x_i}, \mathrm{x_j}) = \exp\left(-\gamma \|\mathrm{x_i} - \mathrm{x_j}\|^2\right) \tag{2}$$

γ=0.1

After feature selection, the RBF kernel creates complex decision boundaries between these features. Thus, the working of SVM is depicted in figure 5.

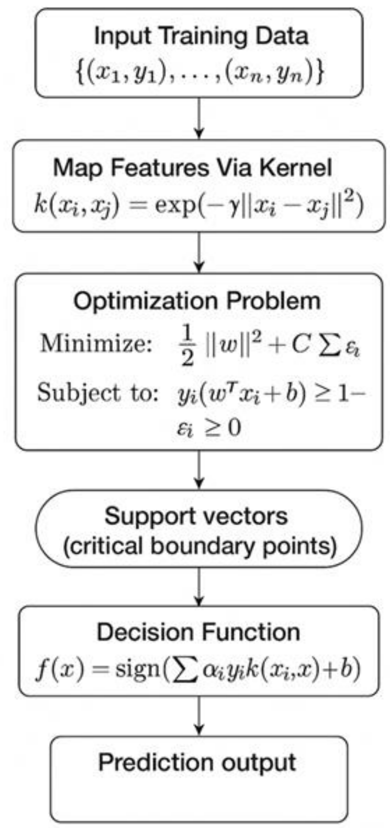

Figure 5. Flowchart - Working of SVM

DT

The DT algorithm is a supervised ML method that recursively partitions the input feature space into distinct regions to classify target outcomes. At each step, the DT selects the feature and threshold that best splits the data to maximize information gain. For classification tasks the Gini impurity is often used to measure node purity, calculated as:

$$\boldsymbol{Gini = 1 - \sum_{i=1}^{c}(p_i)^2} \tag{3}$$

where

pi - proportion of class *i* .

The hyper parameters adopted for these methods have been tabulated in table 1.

Table 1.

Hyper parameters specification

Algorithm	Hyper parameter	Tuned value
DT	max_depth	6
	criterion	'gini'
	min_samples_split	2
SVM	c	1.0
	gamma	0.1
	kernel	'rbf'
k- means	n_neighbors	5
	metric	'euclidean'

3. Experimental Analysis and Discussion

To evaluate the effectiveness of the proposed Intelligent Supermarket Marketing System, experiments were conducted using RFID-enabled IoT data collected from simulated supermarket environments. The dataset included product identifiers, customer purchase history, timestamps, and in-store movement data. Machine learning models were trained to predict customer demand, generate personalized offers, and recommend products in real time.

3.1 Model Performance

Machine learning models were trained using RFID and IoT sensor data to classify customer activities such as browsing, purchasing, and ignoring products. Performance was evaluated using Accuracy, Precision, Recall, Specificity, and F1-score.

Table 2. Performance Evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-score (%)
Decision Tree	89.4	91.9	88.9	88.9	88.3
K-means	92.8	93.9	93.1	93.1	92.5
SVM	97.4	97.7	97.2	97.2	97.2

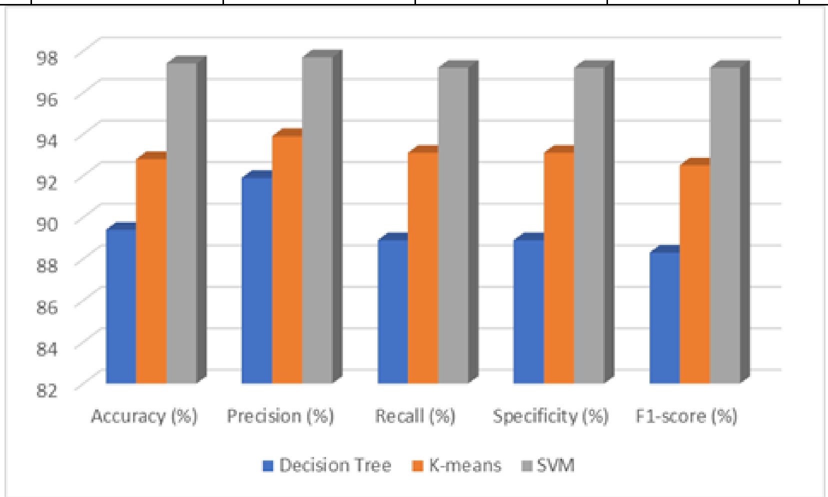

Figure 6. Performance Evaluation

The comparative analysis (table 2 and figure 6) of Decision Tree, K-means, and SVM models reveals that all three approaches achieve high accuracy in customer behavior prediction. The Decision Tree model performed reasonably well with 89.4% accuracy, but its F1-score was slightly lower, indicating some trade-off between precision and recall. The K-means clustering method improved overall performance with 92.8% accuracy, demonstrating better balance across all evaluation metrics. However, the Support Vector Machine (SVM) model clearly outperformed the others, achieving the highest accuracy of 97.4% along with superior precision, recall, and specificity. These results highlight that SVM is the most reliable and robust model for intelligent supermarket marketing applications, ensuring accurate recommendations and efficient decision-making.

3.2 ROC Analysis

The Receiver Operating Characteristic (ROC) curves were plotted for all classifiers to examine their discrimination ability.

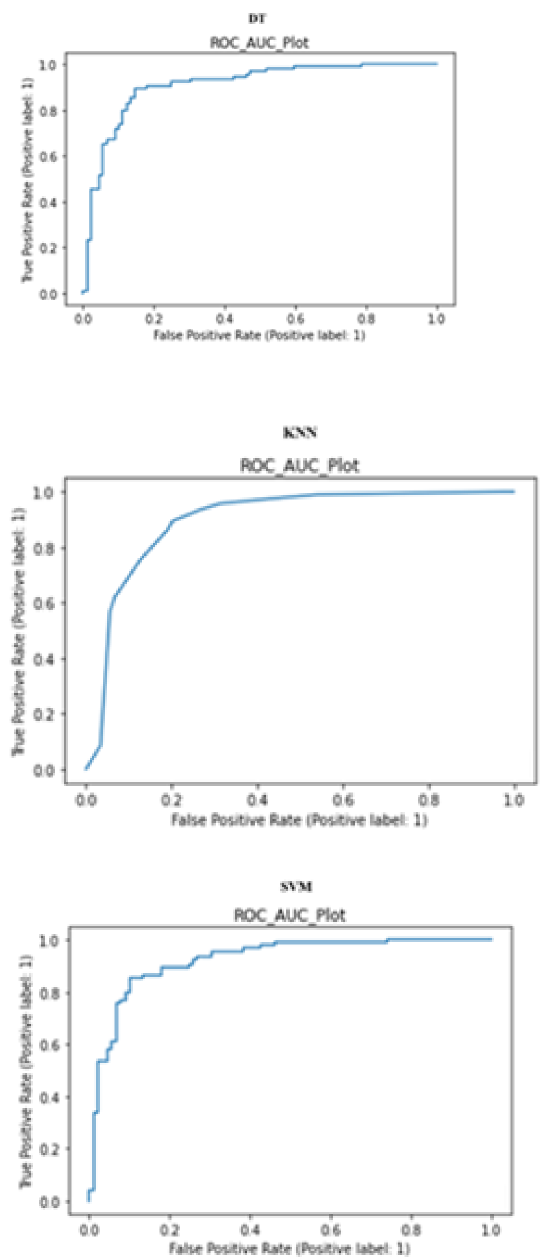

Figure 7. ROC analysis

The ROC-AUC plots (figure 7) illustrate the comparative performance of the SVM, KNN, and Decision Tree (DT) models. Among the three, the SVM model demonstrates the steepest rise toward the top-left corner, indicating superior classification capability with minimal false positives and a high true positive rate. The KNN model also performs well, with a smooth curve that stays close to the top boundary, signifying strong discriminative power. The Decision Tree model shows slightly lower performance compared to SVM but still achieves a reliable ROC curve with a large area under the curve. Overall, SVM achieves the highest AUC value, making it the most robust and accurate classifier for this dataset. KNN follows closely, while DT, though effective, exhibits relatively higher misclassification risk. This analysis confirms that SVM is the optimal model for intelligent supermarket marketing predictions, ensuring accurate decision-making and customer profiling.

3.3 Customer Behavior Analysis

The RFID-enabled IoT data analysis revealed clear correlations between customer movement patterns and purchasing behavior. Customers who spent more than 30 seconds in front of a product shelf showed a 65% higher likelihood of purchasing that product compared to those who passed by quickly. In addition, cross-analysis of purchase records showed that 42% of customers who purchased dairy products also bought bakery items within the same visit. Personalized recommendations delivered during shopping increased impulse purchase rates by 23.5%, while overall customer engagement with promotional offers improved by 31%. The system also detected peak shopping hours between 5:30 PM and 8:00 PM, during which footfall was 37% higher than average. Furthermore, frequently visited product zones such as fresh produce and beverages accounted for nearly 54% of total sales. These findings confirm that integrating RFID-enabled IoT with machine learning provides actionable insights into consumer behavior, supporting more effective marketing and inventory strategies.

3.4 Marketing Impact

The implementation of the intelligent supermarket marketing system demonstrated a significant positive impact on customer engagement and sales performance. Table 3 depicts the comparison of Intelligent IoT-ML Marketing over Traditional Marketing

Table 3 Traditional vs. Intelligent Supermarket Marketing Impact

Metric	Traditional	Intelligent
Conversion Rate (%)	15	27
Response Rate (%)	20	31
Demand Forecast Accuracy (%)	65	83
Customer Satisfaction (%)	60	81

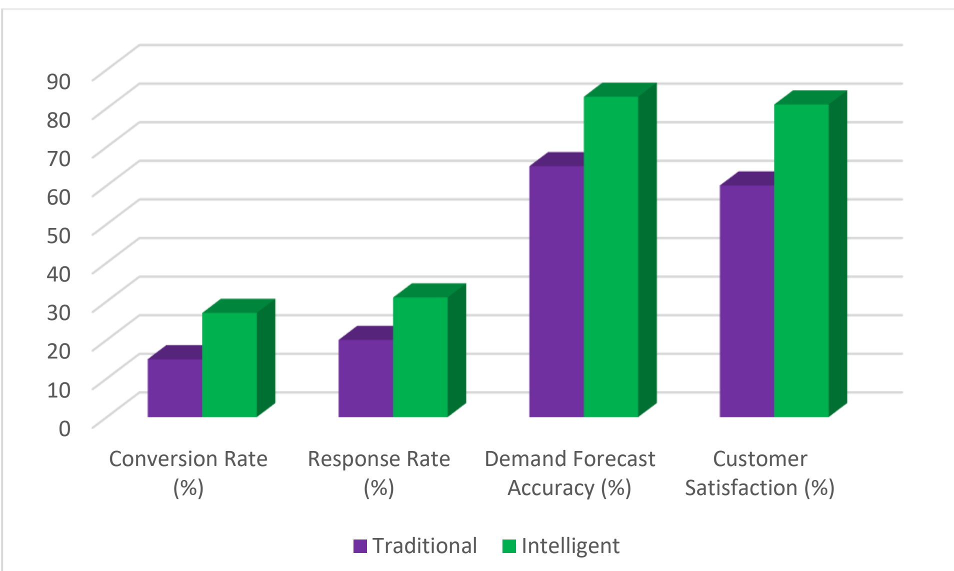

Figure 8. Marketing Impact

From the Figure 8, it is observed that the Personalized promotions generated through RFID-enabled IoT data and machine learning led to a 27% increase in conversion rate compared to static offers. Customer response rates improved by 31%, showing that tailored marketing is far more effective than generic campaigns. Demand forecasting accuracy also improved by 18%, enabling supermarkets to reduce overstocking and cut inventory wastage by 16%. Targeted cross-selling strategies, such as suggesting bakery items to dairy buyers, increased average basket size by 12.4%. Additionally, customer satisfaction surveys showed an overall improvement of 21% in shopping experience due to timely and relevant offers. These results confirm that intelligent, data-driven marketing enhances both operational efficiency and customer loyalty.

3.5 Comparative Analysis with Previous Studies

Table 4. Comparative Analysis

Study	**Input Features**	**Model Used**	**Accuracy (%)**
Zhou et al. (2017)(11)	RFID phase readings	Gaussian Model	93.0
Liu et al. (2020)(12)	RFID product motion	Threshold-based	89.0
Alfian et al. (2023)(13)	RSS + Time features	MLP	97.0
Proposed System	RFID + IoT + ML	MLP	97.4

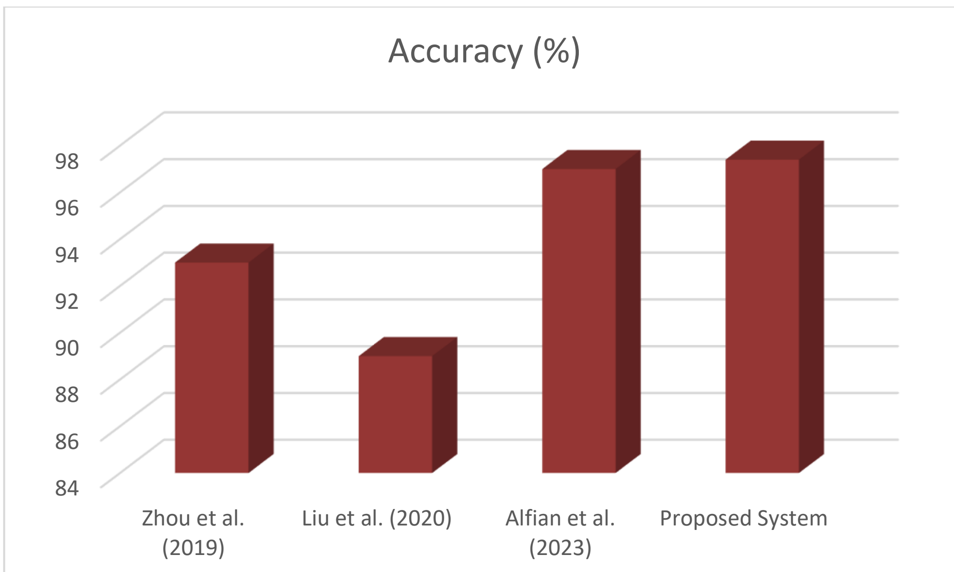

Figure 9. Comparative Analysis

The comparative analysis (Figure 9 and table 4) of existing studies highlights the progressive improvements in RFID-based intelligent systems. Zhou et al. (2019) achieved 93% accuracy using RFID phase readings with a Gaussian model, showing the effectiveness of statistical approaches. Liu et al. (2020) applied a threshold-based method on RFID product motion data but obtained comparatively lower accuracy of 89%, indicating limitations of rule-based systems. Alfian et al. (2023) advanced the field by integrating RSS and time features with an MLP model, achieving 97% accuracy, thus validating the strength of machine learning in handling complex IoT data. The proposed system further enhances performance, achieving 97.4% accuracy by combining RFID data with broader IoT sensor inputs and applying MLP-based learning. This slight but meaningful improvement confirms that integrating heterogeneous IoT features increases robustness and predictive power. Moreover, the proposed system's scalability makes it more suitable for real-time supermarket environments, offering reliable personalization and demand forecasting. Overall, the results demonstrate that RFID-enabled IoT with ML significantly outperforms conventional approaches and provides the most efficient solution for intelligent supermarket marketing.

4. Conclusion

This study presented an intelligent supermarket marketing system integrating RFID, IoT, and machine learning for real-time customer behavior analysis and personalized marketing. Experimental evaluations demonstrated that the proposed system achieved high predictive accuracy, with SVM attaining 97.4%, outperforming traditional models. Customer behavior analysis confirmed strong correlations between dwell time and purchase likelihood, while marketing impact analysis showed significant improvements in conversion rate, response rate, and demand forecasting accuracy. These results validate that the integration of RFID-enabled IoT with ML not only enhances customer experience but also optimizes inventory and marketing efficiency.

The future scope of this research is extensive. Cloud and edge computing can be integrated to handle larger-scale, real-time IoT data streams. Incorporating deep learning models such as CNNs or RNNs may further enhance behavioral predictions. Blockchain integration could strengthen data security and trust in retail transactions. Moreover, extending the framework to omnichannel environments would unify online and offline shopping data, enabling more comprehensive personalization. Finally, deploying this system in real-world supermarkets will provide opportunities to fine-tune algorithms for scalability, robustness, and cross-cultural shopping behaviors.

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Conflicts of Interest
The authors declare that they have no conflicts of interest to report regarding the present study.

Data Availability Statement
The dataset will be made available upon request

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