RESEARCH PAPER

Optimized Artificial Intelligence Framework for Retail Sales Prediction and Decision Support

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Abstract

The retail industry operates in a highly dynamic and competitive environment characterized by fluctuating consumer behavior, seasonal demand variations, and market uncertainties. Accurate sales forecasting is essential for effective inventory management, demand planning, pricing strategies, and overall business decision-making. However, traditional statistical forecasting techniques often fail to capture the complex nonlinear and temporal relationships present in large-scale retail datasets, resulting in limited predictive performance. To address these challenges, this study proposes an optimized Artificial Intelligence (AI)-based Decision Support System (DSS) for retail sales forecasting using hybrid machine learning techniques.

The proposed framework integrates multiple machine learning models to leverage their complementary strengths in capturing both linear and nonlinear patterns from historical sales data. Advanced optimization techniques are incorporated for hyperparameter tuning to enhance model accuracy, reduce overfitting, and improve computational efficiency. The system employs intelligent forecasting mechanisms capable of processing large volumes of retail data and generating accurate, scalable, and near real-time sales predictions. Furthermore, the integration of the forecasting framework within a decision support environment enables retailers to obtain actionable insights for inventory control, supply chain management, promotional planning, and resource allocation.

The proposed AI-based DSS aims to improve forecasting reliability, operational efficiency, and strategic decision-making in retail organizations. By combining hybrid machine learning models with optimization algorithms, the framework provides a robust and adaptive solution for modern retail sales forecasting, ultimately contributing to enhanced business performance, reduced operational costs, and improved customer satisfaction.

Keywords: Retail Sales Forecasting, Artificial Intelligence, Machine Learning, Hybrid Models, Decision Support System, Hyperparameter Optimization, Predictive Analytics, Retail Management

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1. Introduction

The retail sector faces significant challenges in accurately forecasting sales due to dynamic consumer behavior, seasonal variations, intense competition, and market uncertainties. Traditional statistical forecasting methods often struggle to capture the complex nonlinear and temporal patterns present in large-scale retail data. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of intelligent forecasting systems that can automatically identify hidden patterns and improve prediction accuracy. Hybrid machine learning models, which combine the strengths of multiple algorithms, have gained popularity for their enhanced robustness, generalization capability, and forecasting performance.

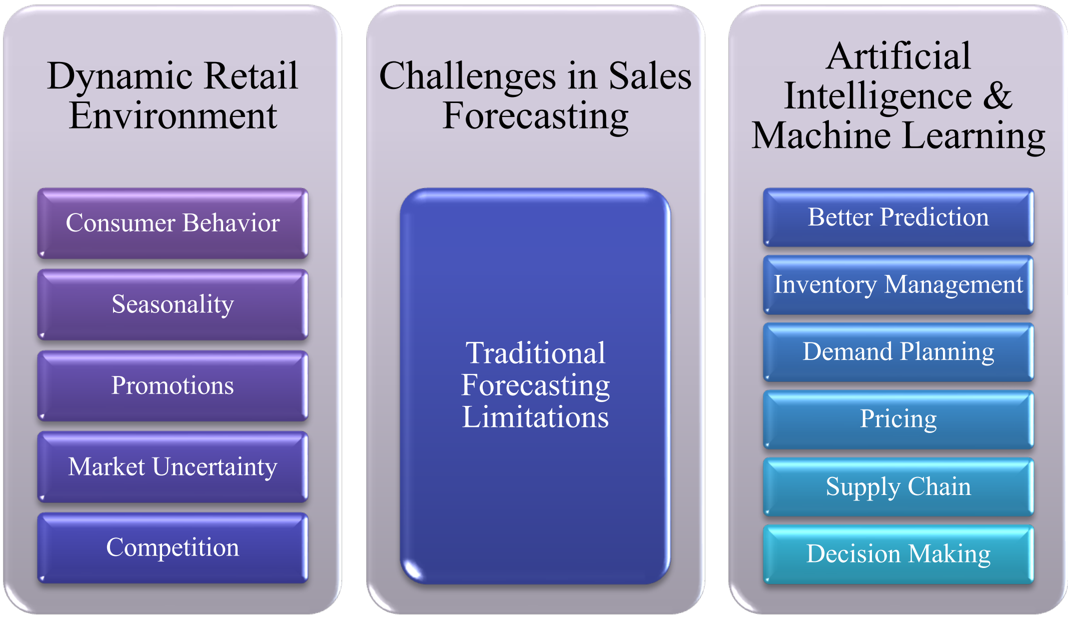

Figure 1. Retail Sales Forecasting: Challenges and Role of Artificial Intelligence

Additionally, hyperparameter optimization techniques such as Bayesian optimization, grid search, random search, and evolutionary algorithms further improve model effectiveness by identifying optimal parameter settings. Integrating these advanced forecasting models into Decision Support Systems (DSS) provides retailers with actionable insights for inventory management, demand planning, pricing, and supply chain optimization. Therefore, this study proposes an optimized AI-based DSS that utilizes hybrid machine learning techniques and optimization methods to deliver accurate, scalable, and near real-time retail sales forecasts, supporting effective business decision-making and operational efficiency.

1.1 Background of the Study

The retail industry has undergone significant transformation with the rapid growth of digital technologies, e-commerce platforms, and data-driven business practices. Modern retailers generate massive volumes of data from transactions, customer interactions, online purchases, inventory records, and market trends. This abundance of data presents valuable opportunities for extracting insights that can improve operational efficiency and business performance. Among various retail operations, sales forecasting is one of the most critical activities because it directly influences inventory management, demand planning, pricing strategies, workforce allocation, and supply chain optimization.

Accurate sales forecasting enables retailers to anticipate future demand, minimize stock shortages and overstock situations, reduce operational costs, and improve customer satisfaction. However, forecasting retail sales remains a challenging task due to the dynamic nature of consumer behavior, seasonal fluctuations, promotional campaigns, economic conditions, and competitive market environments. Traditional forecasting methods such as moving averages, exponential smoothing, and regression analysis often struggle to model complex nonlinear relationships and temporal dependencies inherent in retail datasets.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have provided new opportunities to enhance forecasting accuracy. ML algorithms can automatically learn patterns from large datasets and adapt to changing market conditions without relying heavily on predefined assumptions. Techniques such as Random Forest, Gradient Boosting, Support Vector Machines, Artificial Neural Networks, and Deep Learning models have demonstrated promising results in retail demand prediction. However, individual models may have limitations in capturing all aspects of retail sales behavior, leading researchers to explore hybrid machine learning approaches that combine multiple algorithms to exploit their complementary strengths.

Another important aspect of machine learning-based forecasting is hyperparameter optimization. The performance of predictive models depends significantly on the selection of appropriate parameters. Optimization techniques such as Grid Search, Random Search, Bayesian Optimization, and Evolutionary Algorithms have emerged as effective approaches for identifying optimal parameter configurations, thereby improving prediction accuracy and model robustness.

Furthermore, integrating intelligent forecasting models into Decision Support Systems (DSS) enhances their practical applicability in retail environments. A DSS provides managers with timely forecasts, analytical insights, and data-driven recommendations that support strategic and operational decisions. By leveraging AI-powered forecasting and optimization techniques, retailers can improve demand planning, inventory control, resource utilization, and overall business performance.

Therefore, there is a growing need to develop an optimized AI-based Decision Support System that combines hybrid machine learning models and advanced optimization techniques to provide accurate, scalable, and near real-time retail sales forecasting. Such a system can assist retailers in making informed decisions, improving competitiveness, and achieving sustainable growth in an increasingly complex and data-intensive marketplace.

1.2 Need of the Study

The retail industry operates in a highly dynamic environment characterized by rapidly changing customer preferences, seasonal demand fluctuations, promotional activities, and market uncertainties. Accurate sales forecasting has become essential for retailers to effectively manage inventory, optimize supply chains, reduce operational costs, and improve customer satisfaction. However, traditional forecasting techniques often fail to capture the complex nonlinear relationships and temporal dependencies present in modern retail datasets, resulting in inaccurate predictions and inefficient decision-making.

With the increasing availability of large-scale retail data, there is a growing need for intelligent forecasting systems capable of processing vast amounts of information and generating accurate predictions in real time. Machine Learning (ML) and Artificial Intelligence (AI) techniques have demonstrated significant potential in improving forecasting performance by automatically identifying hidden patterns and trends within data. Nevertheless, individual machine learning models may not adequately address all forecasting challenges due to variations in data characteristics and market conditions.

Hybrid machine learning approaches, which combine multiple algorithms, offer a promising solution by leveraging the strengths of different models to improve prediction accuracy and robustness. Additionally, the performance of these models depends heavily on optimal hyperparameter selection, creating a need for advanced optimization techniques. Therefore, there is a strong need to develop an optimized AI-based Decision Support System (DSS) that integrates hybrid machine learning models and optimization methods to provide accurate, scalable, and timely retail sales forecasts for effective business decision-making.

1.3 Significance of the Study

This study is significant because it addresses one of the most critical challenges in the retail sector: accurate sales forecasting. The proposed optimized AI-based Decision Support System contributes to both academic research and practical retail operations by combining hybrid machine learning techniques with advanced optimization strategies.

From a business perspective, the system enables retailers to make informed decisions regarding inventory management, demand planning, pricing policies, promotional campaigns, and supply chain operations. Improved forecasting accuracy can reduce inventory holding costs, minimize stockouts and overstock situations, enhance resource utilization, and increase customer satisfaction. The near real-time forecasting capability further supports proactive decision-making in rapidly changing market environments.

From a technological perspective, the study advances the application of artificial intelligence, machine learning, and hyperparameter optimization in retail analytics. The integration of multiple learning models enhances prediction reliability and model generalization, while optimization techniques improve computational efficiency and forecasting performance.

From an academic perspective, the research contributes to the growing body of knowledge on hybrid machine learning frameworks and AI-driven decision support systems. The proposed framework can serve as a foundation for future studies in retail analytics, predictive modeling, demand forecasting, and intelligent business systems. Ultimately, the study supports the development of data-driven retail strategies that improve competitiveness, profitability, and sustainable business growth.

2. Literature Review

Khade S. et al. (2026) propose a Causal-XAI framework for retail sales forecasting using Double Machine Learning (DML) and Causal Transformer models to improve prediction accuracy and interpretability. The study notes that traditional deep learning and ensemble models fail to distinguish causation from correlation and lack transparency. The proposed framework improves forecasting and provides actionable insights by identifying causal factors affecting sales, thereby supporting better decision making and return on investment. [1]

Munawar M. A. and Sudirman I. (2026) study LSTM-based models for hourly sales forecasting in SME food and beverage retail. The research compares LSTM with Naive Forecast and Moving Average models using point-of-sale data. Results show that LSTM achieves lower MAE and RMSE and effectively captures intra-day seasonal patterns. The study concludes that LSTM reduces losses due to overstocking and understocking, improving inventory management in retail environments. [2]

Devi D. G. et al. (2026) present a multi-granular machine learning approach for retail sales forecasting using exploratory data analysis and feature engineering. The study evaluates Linear Regression, Random Forest, and Gradient Boosting across daily, monthly, and quarterly datasets. Results show that selecting appropriate models for different time scales improves forecasting accuracy and supports better strategic decision-making in retail. [3]

Sangeetha S. et al. (2026) propose an adaptive and explainable Auto-ARIMA-based forecasting platform. The study highlights limitations of deep learning models in interpretability and computational cost. The proposed system integrates automated model selection, seasonal decomposition, and anomaly detection, achieving competitive accuracy with improved transparency and efficiency for retail decision support systems. [4]

Boyko N. and Salabay B. (2026) conduct a comparative study of classical and hybrid forecasting models using retail data. Models such as SES, Holt's, Holt-Winters, TheilWage, and SutteARIMA are analyzed. Results show that Holt-Winters and 8 SutteARIMA perform best by capturing trend and seasonality effectively, highlighting the importance of model selection and parameter optimization. [5]

Essien I. A. et al. (2025) compare hybrid AI models including XGBoost, LSTM, and Reinforcement Learning for real-time decision-making. The study shows that hybrid approaches improve adaptability and accuracy under dynamic conditions, with reinforcement learning aiding optimization and LSTM capturing temporal dependencies effectively. [6]

M. H. Zamil (2025) presents a systematic review of AI-based business analytics models for financial forecasting in SMEs. The study highlights the growing use of machine learning-based decision support systems, including regression models, neural networks, and ensemble methods. [7]

A. Zach (2025) focuses on retail supply chain forecasting and inventory optimization using hybrid machine learning models. The study shows that combining predictive analytics with inventory control improves demand forecasting and reduces stockouts, with hybrid models improving robustness under seasonal and uncertain demand. [8]

G. V. Radhakrishnan et al. (2025) propose an AI-based demand forecasting system for supply chain optimization. The results indicate improved responsiveness, reduced wastage, and better inventory planning, especially in large-scale industrial applications. [9]

S. Mansur et al. (2025) develop a hybrid neural network model for retail sales forecasting by incorporating external factors such as promotions, weather, and customer behavior. The study shows that hybrid models outperform standalone models by capturing nonlinear and contextual patterns, leading to more accurate forecasts. [10]

K. Srinivasan et al. (2024) propose an AI-based optimization model for e-commerce supply chains combining HMO, reinforcement learning, tabu search, and MDVRP. The approach improves demand forecasting, inventory management, and logistics efficiency, resulting in higher delivery performance and reduced operational costs. [11]

Suresh B. S. and Suresh M. (2024) present an AI-based retail sales management system using optimized metaheuristic algorithms. The study shows that evolutionary algorithms improve forecasting accuracy and recommendation quality, leading to better customer satisfaction and sales. [12]

H. Sharma et al. (2024) develop machine learning-based models for forecasting and inventory optimization. The study emphasizes integrating prediction with inventory control to improve cost efficiency and demand-supply balance, enhancing overall decision-making in supply chain management. [13]

E. M. Howard (2024) introduces AI-based demand sensing for improving forecast accuracy using real-time data and analytics. The study shows improved responsiveness to market changes and reduced forecasting errors, making it important for modern supply chains. [14]

Nkomo N. and Mupa M. N. (2024) analyze AI-driven predictive customer behavior analytics in e-commerce. The study shows that AI models outperform traditional methods by better identifying customer preferences and improving personalization and decision-making. [15]

M. Rahman et al. (2023) study automated hyperparameter optimization in deep learning. The work highlights methods such as Bayesian optimization and evolutionary algorithms, which improve model performance while reducing computational cost, thereby enhancing efficiency and accuracy in predictive systems. [16]

T. A. Rainy et al. (2023) review AI-enhanced decision support tools in information systems. The study discusses their applications in service-based enterprises, improving decision-making, operational efficiency, and business intelligence through AI integration. [17]

S. Suddala (2023) explores AI-based demand forecasting and inventory optimization in e-commerce fulfillment centers. The study shows that AI reduces inventory costs, improves order fulfillment, and enhances logistics efficiency. [18]

L. N. B. Long et al. (2023) propose a decision support system for inventory management under uncertainty. The model uses probabilistic analysis and machine learning to handle uncertainty, improving inventory control and reducing risk. [19]

H. Wagner and K. Becker (2022) design a cloud-based machine learning decision support system for business decision-making. The study highlights the scalability and flexibility of cloud AI systems for handling large datasets and complex analytics. [20]

M. Garouani et al. (2022) explore explainable AutoML in industrial data mining. The study emphasizes transparency, interpretability, and efficiency of AI models, which are important for industrial adoption and trust in AI systems. [21]

T. Vasugi (2022) proposes an AI-optimized multi-cloud resource management architecture for secure banking systems. The study highlights improved resource utilization, security, and scalability through AI-based optimization. [22]

A. Khan et al. (2022) examine AI-based demand response systems in smart grids. The study shows that AI improves energy consumption, grid stability, and real-time energy management. [23]

R. G. Goriparthi (2021) discusses AI and machine learning applications in supply chain logistics optimization. The study reports improvements in route optimization, demand forecasting, and operational efficiency. [24]

A. Göppert et al. (2021) propose artificial neural networks for predicting performance indicators in interconnected assembly systems. The study shows improved scheduling efficiency and production optimization using AI-based predictive models. [25]

Table 1: Comparison of Previous Studies on AI-Based Retail Sales Forecasting

S. No.	Author(s) & Year	Method / Model	Main Focus	Key Contribution / Findings	Identified Limitation / Gap
1	Khade et al. (2026)	Double Machine Learning (DML), Causal Transformer, XAI	Retail sales forecasting	Improves forecasting while identifying causal factors and enhancing interpretability	Causal-XAI integration requires further validation across diverse retail datasets
2	Munawar & Sudirman (2026)	LSTM	Hourly retail sales forecasting	LSTM outperforms Naive Forecast and Moving Average for intra-day forecasting	Focused mainly on hourly SME food and beverage retail data
3	Devi et al. (2026)	Linear Regression, Random Forest, Gradient Boosting	Multi-granular forecasting	Demonstrates that model selection according to daily, monthly, and quarterly time scales improves forecasting	Limited integration of multiple models into a unified optimized DSS
4	Sangeetha et al. (2026)	Auto-ARIMA, seasonal decomposition, anomaly detection	Explainable sales forecasting	Provides adaptive forecasting with improved transparency and computational efficiency	Classical forecasting may have limitations in highly nonlinear retail environments
5	Boyko & Salabay (2026)	SES, Holt's, Holt-Winters, SutteARIMA	Comparative forecasting	Holt-Winters and SutteARIMA effectively capture trend and seasonality	Does not provide a comprehensive hybrid AI-DSS framework
6	Essien et al. (2025)	XGBoost, LSTM, Reinforcement Learning	Real-time decision-making	Hybrid AI improves adaptability and forecasting under dynamic conditions	Further optimization and retail-specific validation are required
7	Zamil (2025)	ML, neural networks, ensemble models	AI business analytics	Reviews AI-based decision-support approaches for financial forecasting in SMEs	Broad financial focus rather than dedicated retail sales forecasting
8	Zach (2025)	Hybrid Machine Learning	Retail supply chain and inventory optimization	Combines forecasting and inventory control to reduce stockouts and improve robustness	Further development of real-time and adaptive forecasting is needed
9	Radhakrishnan et al. (2025)	AI-based forecasting	Supply-chain demand forecasting	Improves responsiveness, wastage reduction, and inventory planning	Focus primarily on supply-chain applications rather than integrated retail DSS
10	Mansur et al. (2025)	Hybrid Neural Networks	Retail sales forecasting	Incorporates promotions, weather, and customer behavior; hybrid models outperform standalone approaches	More advanced optimization and explainability mechanisms can be explored
11	Srinivasan et al. (2025)	HMO, MaxEnt-RL, Tabu Search, MDVRP	E-commerce supply-chain optimization	Improves demand forecasting, inventory management, and delivery efficiency	Complex framework; broader retail forecasting validation is required
12	Suresh & Suresh (2024)	Optimized Metaheuristic Algorithms	Retail sales management	Optimization improves forecasting and recommendation	Greater integration with real-time DSS and hybrid deep learning is

				performance	needed
13	Sharma et al. (2024)	Machine Learning Models	Forecasting and inventory optimization	Integrates demand prediction with inventory control for improved cost efficiency	Limited emphasis on advanced hybrid architectures
14	Howard (2024)	AI-based Demand Sensing	Supply-chain forecasting	Uses real-time data to improve responsiveness and reduce forecasting errors	Requires integration of broader retail variables and decision-support capabilities
15	Nkomo & Mupa (2024)	Traditional vs. AI-driven models	Predictive customer behavior	AI models improve customer preference identification and personalization	Customer behavior focus rather than complete sales forecasting framework
16	Rahman et al. (2023)	Bayesian Optimization, Evolutionary Algorithms	Hyperparameter optimization	Automated optimization improves deep-learning efficiency and predictive performance	Does not specifically address complete retail forecasting-DSS integration
17	Rainy et al. (2023)	AI-enhanced DSS	Decision support	Highlights AI integration for business intelligence and operational decision-making	General information-system focus; retail-specific implementation remains limited
18	Suddala (2023)	AI-based demand forecasting	E-commerce inventory optimization	AI reduces inventory costs and improves fulfillment and logistics	Limited exploration of hybrid models and advanced optimization
19	Long et al. (2023)	ML and probabilistic analysis	Inventory DSS under uncertainty	Improves inventory control and risk management under stochastic events	Primarily inventory-focused rather than comprehensive sales forecasting
20	Wagner & Becker (2022)	Cloud-based Machine Learning	Business DSS	Demonstrates scalability and flexibility of cloud-based AI decision support	Requires retail-specific forecasting and real-time implementation
21	Garouani et al. (2022)	Explainable AutoML	Industrial data mining	Improves transparency, interpretability, and efficiency of automated ML	Application is industrial rather than specifically retail forecasting
22	Vasugi (2022)	AI optimization, Multi-cloud architecture	Resource management	Improves resource utilization, security, and scalability	Banking/networking focus limits direct retail applicability
23	Khan et al. (2022)	Artificial Intelligence	Demand response and real-time management	Demonstrates AI potential for demand prediction and dynamic resource management	Smart-grid context; direct retail forecasting applicability is limited
24	Goriparthi (2021)	AI and Machine Learning	Supply-chain logistics	Improves route optimization, demand forecasting, and operational efficiency	Limited emphasis on hybrid forecasting and retail DSS
25	Göppert et al. (2021)	Artificial Neural Networks	Predictive performance and scheduling	ANN-based prediction improves scheduling and production optimization	Manufacturing focus; retail sales forecasting remains unexplored

From the above literature, it is observed that significant research has been conducted in retail sales forecasting using machine learning, hybrid models, and decision support systems. However, most studies focus on individual models and lack effective integration of hybrid approaches with systematic hyperparameter optimization. Limited work has also been done on combining forecasting models with decision support systems for practical retail use. Therefore, there is a need to develop an optimized hybrid AI-based decision support system that improves forecasting accuracy, robustness, and real-world applicability.

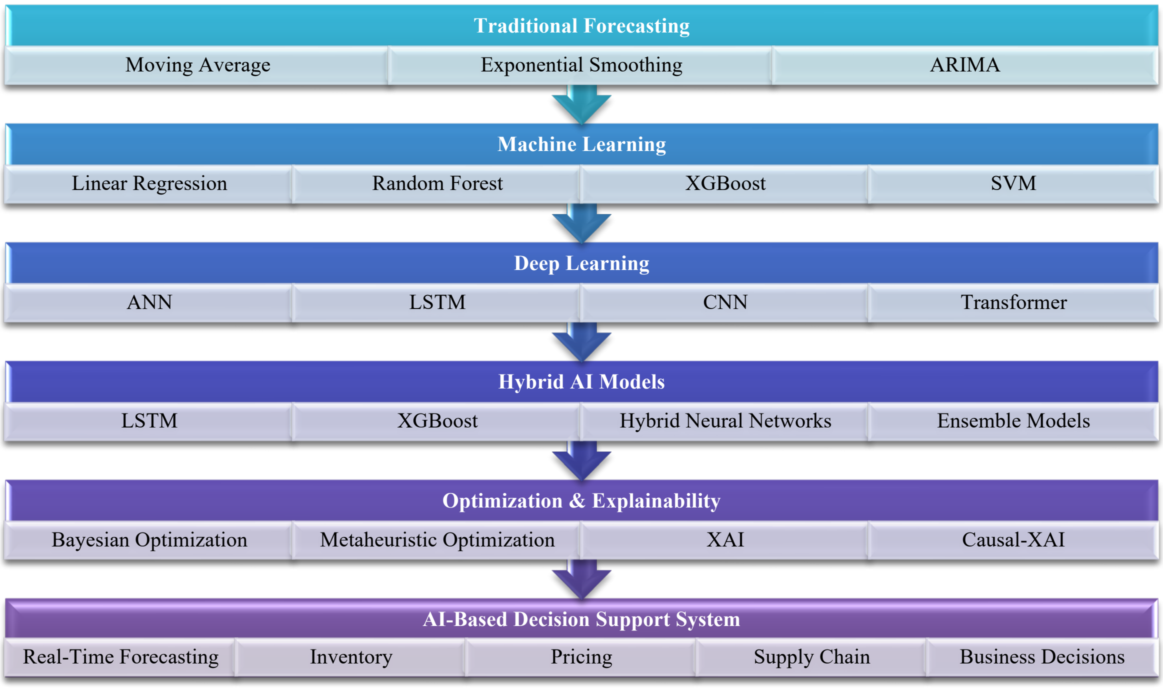

Figure 2. Technology and Model Evolution in AI-Based Retail Sales Forecasting

2.1 Literature Synthesis

All the reviewed literature showed that there is a clear shift towards Artificial Intelligence (AI), Machine Learning (ML), deep learning, hybrid models and intelligent Decision Support Systems (DSS) in the field of retail sales forecasting. The traditional methods like ARIMA, Exponential Smoothing and Holt-Winters are capable of detecting trend and seasonal components, but are not suitable for addressing complex nonlinear relationships and shifting consumer behavior [4,5]. Random Forest, Gradient Boosting, XGBoost, ANN and LSTM are examples of models that have proven better at learning complex sales patterns and temporal relationships, such as machine learning and deep learning models [2,3,6]. In addition to this, hybrid models use complementary algorithms and external parameters like promotions, weather and customer behavior to boost forecasting accuracy [8,10].
Additionally, it is important to optimize the hyperparameters of the model to enhance its performance and efficiency, which can be done through various techniques such as Bayesian optimization, evolutionary optimization, and metaheuristic optimization as highlighted in the literature [12,16]. Moreover, the use of AI forecasting is growing in combination with inventory management, supply-chain optimization, and DSS [9,11,18,19]. In summary, research so far has shown considerable advancement, but it is still scattered and fragmented according to the models used for forecasting, optimization methods, explainability, and decision support application. This underscores the need to have an integrated hybrid AI framework that integrates the optimized forecasting models with a smart DSS in order to empower retailers with accurate, robust and actionable decisions.

3. Research Gap

A comprehensive review of recent studies reveals that substantial progress has been made in retail sales forecasting through the application of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Decision Support Systems (DSS). Various approaches, including LSTM, Random Forest, Gradient Boosting, Reinforcement Learning, AutoML, Explainable AI (XAI), and hybrid forecasting models, have demonstrated improved prediction accuracy and operational efficiency. Moreover, several studies have explored inventory optimization, demand forecasting, supply chain management, and customer behavior analytics using AI-driven techniques.

Despite these advancements, several research gaps remain:

1. Limited Integration of Hybrid Models: Most existing studies focus on standalone forecasting models such as LSTM, XGBoost, Random Forest, or ARIMA. Although hybrid models have shown promising results, there is limited research on developing optimized hybrid frameworks that effectively combine multiple machine learning and deep learning algorithms to capture both linear and nonlinear sales patterns.
2. Insufficient Hyperparameter Optimization: The performance of forecasting models is highly dependent on parameter selection. Many studies employ default settings or basic tuning approaches, resulting in suboptimal performance. Comprehensive integration of advanced optimization techniques such as Bayesian

Optimization, Evolutionary Algorithms, and Metaheuristic Optimization within retail forecasting frameworks remains underexplored.

3. Lack of Unified Decision Support Systems: Existing research primarily emphasizes forecasting accuracy without integrating prediction models into a comprehensive Decision Support System. Retail managers require actionable insights for inventory planning, pricing, procurement, and supply chain management; however, few studies provide an end-to-end DSS framework that supports practical decision-making.
4. Limited Real-Time Forecasting Capability: Many forecasting models are developed and evaluated using static datasets and offline environments. There is a lack of scalable AI-based systems capable of generating near real-time forecasts and adapting dynamically to changing market conditions and customer behavior.
5. Inadequate Consideration of Multi-Dimensional Retail Factors: Several forecasting approaches rely mainly on historical sales data while neglecting external influencing factors such as promotions, seasonal events, economic conditions, customer preferences, and market trends. Integrating these heterogeneous factors remains a significant challenge.
6. Trade-off Between Accuracy and Interpretability: Advanced deep learning models often provide high prediction accuracy but suffer from poor interpretability. Conversely, interpretable models may compromise forecasting performance. Research is needed to develop frameworks that achieve both high accuracy and explainability for improved managerial trust and adoption.
7. Limited Focus on Scalable and Generalizable Frameworks: Many proposed models are dataset-specific and may not generalize well across different retail domains, product categories, or geographical regions. There is a need for robust and scalable forecasting systems that can perform effectively in diverse retail environments.

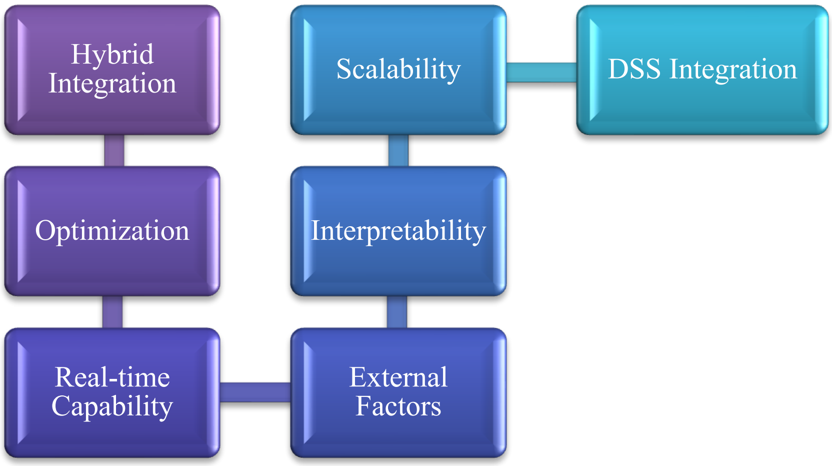

Figure 3: Research Gap

4. Problem Statement

Although machine learning techniques are widely adopted in retail sales forecasting, several limitations continue to affect their overall effectiveness and practical applicability. One of the primary challenges is the inherent volatility and seasonality present in retail data, which often results in unstable and less reliable predictions. In addition, standalone machine learning models are generally limited in their ability to capture complex nonlinear relationships and rapidly changing patterns within retail environments. Another significant issue is poor model generalization, where models trained on specific datasets tend to perform inconsistently when applied to different retail contexts or unseen data distributions. Furthermore, the absence of systematic and automated hyperparameter optimization often leads to suboptimal model configurations, thereby reducing both predictive accuracy and computational efficiency. In addition, the integration of forecasting models into decision-making frameworks remains limited, particularly in terms of supporting structured and practical decision support in real-world retail operations. These limitations collectively restrict the effectiveness of existing approaches in addressing dynamic retail forecasting requirements. To overcome these challenges, this research proposes a hybrid and optimized AI-based Decision Support System aimed at improving forecasting accuracy, robustness, adaptability, and overall decision-making efficiency in retail environments.

5. Future Scope

The proposed AI-based Decision Support System (DSS) for retail sales forecasting offers significant opportunities for future enhancement and expansion. One important direction is the integration of real-time data streams from Point-of-Sale (POS) systems, Internet of Things (IoT) devices, RFID sensors, and online retail platforms. Such integration would enable continuous forecasting and dynamic decision-making, allowing retailers to respond immediately to changing customer demands and market conditions.

Future research can explore advanced deep learning architectures such as Transformers, Temporal Fusion Transformers (TFT), Attention Mechanisms, Graph Neural Networks (GNNs), and Large Language Models (LLMs) to further improve forecasting accuracy and capture complex temporal dependencies. These models can better handle long-term trends, seasonal variations, and multivariate relationships in retail datasets.

Another promising area is the incorporation of Explainable Artificial Intelligence (XAI) techniques to improve model transparency and interpretability. Explainable forecasting systems can help retail managers understand the key factors influencing predictions, thereby increasing trust, accountability, and adoption of AI-driven decision-making tools.

The forecasting framework can also be enhanced by incorporating external data sources such as weather conditions, social media sentiment, economic indicators, public holidays, promotional campaigns, competitor pricing, and market trends. The integration of these heterogeneous data sources can provide a more comprehensive understanding of demand patterns and improve prediction reliability.

Cloud-based deployment and edge computing technologies can be utilized to improve system scalability, accessibility, and computational efficiency. A cloud-enabled DSS would support large-scale retail operations across multiple stores and geographical regions while enabling real-time analytics and centralized decision-making.

Furthermore, reinforcement learning and adaptive optimization techniques can be integrated to create self-learning forecasting systems that continuously update their models based on new data and feedback. Such intelligent systems can automatically optimize inventory levels, pricing strategies, replenishment schedules, and promotional activities in response to evolving market dynamics.

Future studies may also investigate personalized forecasting models for different product categories, customer segments, and regional markets. Multi-objective optimization techniques can be incorporated to simultaneously optimize forecasting accuracy, inventory costs, customer satisfaction, and supply chain performance.

Overall, the integration of advanced AI technologies, real-time analytics, explainability, cloud computing, and adaptive learning mechanisms can transform the proposed framework into a highly intelligent, scalable, and autonomous retail decision support system capable of supporting next-generation retail operations and strategic business planning.

6. Conclusion

The retail industry faces increasing challenges in accurately forecasting sales due to dynamic customer behavior, seasonal fluctuations, market uncertainties, and growing competition. Traditional forecasting methods often struggle to capture the complex relationships present in large-scale retail data, creating the need for more intelligent and adaptive forecasting solutions. Advances in Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated significant potential for improving forecasting accuracy and supporting data-driven decision-making in retail environments.

This study highlights the importance of developing an optimized AI-based Decision Support System (DSS) that integrates hybrid machine learning techniques and advanced optimization methods for retail sales forecasting. The literature review reveals that while numerous forecasting models have been proposed, limitations remain in terms of model integration, hyperparameter optimization, scalability, interpretability, and practical decision support capabilities. Addressing these limitations requires a comprehensive framework capable of leveraging the strengths of multiple forecasting approaches while providing actionable business insights.

The proposed framework aims to combine hybrid machine learning models with optimization techniques to improve prediction accuracy, robustness, and computational efficiency. By integrating forecasting outcomes into a decision support environment, the system can assist retailers in inventory management, demand planning, pricing strategies, resource allocation, and supply chain optimization. Such a data-driven approach can reduce operational costs, minimize stockouts and overstock situations, and enhance customer satisfaction.

Overall, the development of an optimized hybrid AI-based DSS represents a promising solution for modern retail forecasting challenges. The proposed system has the potential to improve business intelligence, support strategic decision-making, and enhance organizational competitiveness in a rapidly evolving retail landscape. Furthermore, future integration of real-time analytics, explainable AI, cloud computing, and adaptive learning techniques can further strengthen the effectiveness and applicability of intelligent retail forecasting systems.

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