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Hybrid Machine Learning Models for Retail Sales Forecasting Across Omnichannel Platforms

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Abstract
Accurate sales forecasting is a critical component of strategic decision-making in modern retail, particularly within omnichannel platforms where consumer behavior and data sources are complex, dynamic, and multidimensional. Traditional statistical models often fall short in capturing non-linear interactions, temporal dependencies, and contextual variables inherent in such environments. While machine learning (ML) approaches have demonstrated significant improvements in predictive accuracy, standalone models frequently suffer from limitations related to interpretability, overfitting, and data sparsity. This paper explores the design and application of hybrid machine learning models integrating multiple algorithms or combining ML with traditional techniques to improve sales forecasting across omnichannel retail platforms. We present a comprehensive literature review of classical, ML-based, and hybrid forecasting models, identifying key trends, gaps, and methodological advances. A conceptual framework is proposed for developing and evaluating hybrid forecasting systems that address challenges such as multivariate data fusion, channel-specific dynamics, feature selection, and model scalability. The framework is further illustrated through practical applications and case scenarios that reflect real-world retail operations. The findings highlight the potential of hybrid models to enhance forecasting accuracy, operational responsiveness, and decision support capabilities in omnichannel retail ecosystems. This study contributes both theoretical insights and practical guidelines for researchers, data scientists, and retail strategists aiming to leverage hybrid machine learning in the context of sales forecasting.

Keywords :— Hybrid Machine Learning, Retail Sales Forecasting, Omnichannel Retailing, Machine Learning Models, Predictive Analytics in Retail, Sales Prediction

1. Introduction

In the era of digital commerce, retail operations have undergone profound transformations, largely propelled by the proliferation of omnichannel retailing strategies [1], [2]. Omnichannel retail integrates multiple sales and distribution channels including physical stores, online marketplaces, mobile apps, and social media into a seamless consumer experience [3]. With increasing channel complexity comes an equally significant rise in the volume, variety, and velocity of retail data, thereby challenging traditional forecasting models in terms of accuracy, adaptability, and real-time responsiveness [4]. Accurate sales forecasting in such an environment is not merely a logistical requirement; it is a strategic imperative that underpins inventory management, supply chain operations, demand planning, customer satisfaction, and overall financial performance[5].

Sales forecasting has long been recognized as a cornerstone of effective retail management [6]. In traditional brick-and-mortar models, demand forecasting typically relied on linear statistical methods such as autoregressive integrated moving average (ARIMA) or exponential smoothing techniques [7]. While these methods have been widely used for decades due to their simplicity and interpretability, they often fall short when applied to the dynamic and non-linear behaviour exhibited in omnichannel retail environments [8]. The challenges are exacerbated by the heterogeneity of data sources, fluctuating consumer behaviour's, seasonality, promotional campaigns, and unexpected external shocks such as economic downturns, pandemics, or supply chain disruptions [9].

The emergence of machine learning (ML) has ushered in new possibilities for data-driven forecasting [10]. Unlike traditional statistical models that impose rigid assumptions on data structures, ML models are capable of learning patterns from vast datasets with complex, non-linear relationships [11]. Techniques such as decision trees, random forests, support vector machines, gradient boosting machines, and artificial neural networks have been increasingly applied to sales forecasting, often outperforming classical approaches [12] [13]. However, each ML model has its own strengths and limitations. For instance, tree-based models offer good interpretability but may struggle with capturing sequential dependencies, whereas deep neural networks handle temporal patterns effectively but often lack transparency and require extensive training data [14].

This has led to the emergence of hybrid machine learning models, which seek to combine the strengths of multiple techniques to improve forecasting performance across different retail contexts [15]. A hybrid approach may integrate traditional statistical models with ML techniques, or combine multiple ML models using ensemble learning, stacking, or model fusion strategies [16] . These models can better handle the multifaceted nature of omnichannel retailing by leveraging different model architectures to capture various patterns in consumer behavior, product attributes, promotional effects, and seasonal fluctuations

[17]. The goal is not merely to improve prediction accuracy, but to enhance the interpretability, robustness, and scalability of forecasting models in real-world settings.

In omnichannel environments, forecasting becomes particularly complex due to the interplay between physical and digital touchpoints. Customers may research products online and purchase them in-store (webrooming), or vice versa (showrooming), and expect seamless transitions between these modes [18]. This behaviour produces fragmented and non-uniform data streams that traditional forecasting tools cannot reconcile effectively. Moreover, the frequency and granularity of data vary across channels; e-commerce platforms often produce minute-by-minute clickstream data, while in-store transactions may be recorded at daily or weekly intervals. Integrating and aligning these datasets is a non-trivial task, and failure to do so may lead to forecast bias, inefficiencies in stock allocation, or missed revenue opportunities [19].

Several studies have explored the integration of hybrid models in various industries, but their application in omnichannel retail forecasting remains relatively nascent [20]. One challenge lies in the data integration and feature engineering processes required to develop hybrid models. Data from different channels often come in varied formats, frequencies, and dimensions. Transforming this heterogeneous data into a common feature space suitable for ML processing is critical. Additionally, external factors such as weather conditions, local events, market trends, and macroeconomic indicators must be incorporated to improve context-awareness in forecasts [21].

Another key issue is model interpretability and transparency, especially in the context of retail decision-making [22]. While deep learning models such as long short-term memory (LSTM) and transformer architectures can achieve high predictive accuracy, they are often criticized for their “black box” nature [11]. Retail managers require interpretable insights to support tactical and strategic decisions such as markdown planning, promotions, and assortment optimization [23]. Hence, hybrid models that combine interpretable models (e.g., linear regression or decision trees) with deep learning techniques offer a promising middle ground between accuracy and explainability [24].

From an operational standpoint, hybrid models also support scalability and automation. Modern retail environments demand forecasting models that can be deployed across thousands of SKUs, categories, and locations with minimal human intervention. Automated machine learning (AutoML) and meta-learning approaches are increasingly being integrated into hybrid pipelines to support model selection, hyperparameter tuning, and continuous learning [25] . Moreover, cloud-based architectures and ML Ops (Machine Learning Operations) frameworks are enabling real-time model deployment, monitoring, and retraining, further enhancing the agility of retail forecasting systems.

In addition to technological considerations, organizational and behavioral factors also influence the adoption of hybrid forecasting models in omnichannel retail. Organizational resistance to change, lack of data governance frameworks, skill gaps in data science, and the absence of standardized evaluation metrics are common barriers. Retailers often struggle to align forecasting objectives across marketing, merchandising, supply chain, and IT departments. A successful implementation of hybrid forecasting models therefore requires not only technical excellence but also organizational readiness, cross-functional collaboration, and leadership commitment [26].

This paper proposes a comprehensive review and conceptual development of hybrid machine learning models for omnichannel retail sales forecasting. The objectives of this study are threefold:

1. To synthesize existing literature on hybrid ML techniques for sales forecasting, with a particular emphasis on their application in omnichannel contexts.
2. To develop a conceptual framework for designing, implementing, and evaluating hybrid forecasting models in multi-channel retail environments.
3. To illustrate the application of the proposed framework using real-world or hypothetical case scenarios that demonstrate the effectiveness of hybrid models in addressing omnichannel forecasting challenges.

The rest of this paper is structured as follows. Section II provides an extensive literature review of traditional, machine learning-based, and hybrid forecasting models in the context of retail. Section III presents the proposed conceptual framework and architectural components for hybrid ML forecasting. Section IV explores case studies or application scenarios that demonstrate the relevance and efficacy of hybrid models in real-world omnichannel settings. Section V discusses the implications, limitations, and future research directions. Finally, Section VI concludes the paper with key takeaways and recommendations for researchers and practitioners.

2. LITERATURE REVIEW

The evolution of sales forecasting in retail has traversed several methodological paradigms, from early statistical techniques to contemporary machine learning (ML) and hybrid modeling approaches. This literature review critically examines existing research to illuminate the foundations, advancements, and ongoing challenges in forecasting retail sales across omnichannel environments.

A. Traditional Forecasting Techniques in Retail

Prior to the rise of machine learning, retail forecasting predominantly relied on time series and econometric models. Techniques such as Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), and Linear Regression were standard tools used for univariate and multivariate forecasting. These models offered simplicity, interpretability, and strong performance under assumptions of stationarity and linearity [27].

While effective for short-term predictions and trend analysis, traditional models often failed to capture irregular patterns, seasonality shifts, and external drivers such as promotions or market shocks. Furthermore, they exhibited limited adaptability in high-dimensional, non-stationary, and multichannel data settings typical of modern retail.

In the early 2000s, causal models such as Vector Autoregressive (VAR) models and Structural Equation Models (SEM) attempted to include external predictors and lagged variables. However, their complexity and strict assumptions limited practical adoption. As retail datasets became increasingly granular and multidimensional, these classical models struggled with scalability and forecasting accuracy.

B. Emergence of Machine Learning in Sales Forecasting

Machine learning has gained traction as an alternative to traditional models due to its capacity to handle large, heterogeneous datasets and uncover complex nonlinear relationships. Notable algorithms include:

- Decision Trees and Random Forests [28],
- Support Vector Regression (SVR) [29]
- Gradient Boosting Machines (GBM) [30], and
- Artificial Neural Networks [31] .

These methods have proven effective for multivariate forecasting, capturing lag effects, and modelling contextual variables such as weather, price elasticity, and customer behaviour. ANNs, in particular, allow for the modelling of complex temporal and spatial dependencies, although they require large datasets and extensive tuning.

Recent advancements include Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which are adept at handling sequential data and temporal dependencies in time series forecasting [32]. These models have outperformed classical approaches in benchmark studies, especially in volatile retail environments.

However, standalone ML models are not without limitations. Issues such as overfitting, lack of interpretability, and dependence on high-quality labeled data can impede adoption. Moreover, they often operate as “black boxes,” providing limited insight into causal relationships or driver variables.

C. Rise of Hybrid Forecasting Models

To bridge the gap between accuracy and interpretability, hybrid models have emerged as a dominant paradigm in recent years. These models combine different algorithms statistical with ML, or multiple ML method to leverage complementary strengths.

1) Statistical + ML Hybrids: Hybrid models like ARIMA-ANN and ETS-LSTM merge time series decomposition techniques with machine learning models. The statistical component captures linear trends and seasonality, while the ML component models residuals and nonlinear patterns [33].

2) Ensemble-Based Hybrids: Ensemble learning methods such as Stacking, Boosting, and Bagging have been widely adopted in hybrid frameworks. Models such as XGBoost, LightGBM, and CatBoost dominate retail forecasting competitions due to their high accuracy and ability to model feature interactions [34].

3) Domain-Specific Hybrids: Retail-specific hybrid models integrate domain knowledge into feature engineering and model selection. For instance, promotional calendars, holiday effects, and store clustering can be embedded into the hybrid modeling pipeline [35].

Studies have shown that hybrid models consistently outperform individual models in terms of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Forecast Bias across diverse datasets [36].

D. Forecasting Challenges in Omnichannel Retail Environments

Omnichannel platforms introduce additional complexity to forecasting due to the integration of physical stores, e-commerce, mobile apps, and third-party marketplaces. Each channel has unique patterns, customer behaviors, and data availability. Key challenges include:

- Data Fragmentation: Disparate data systems lead to inconsistency and missing information [37].
- Customer Journey Tracking: Attribution across multiple touchpoints complicates demand estimation [38].
- Real-Time Dynamics: Rapid shifts in customer preferences and competitor actions necessitate agile forecasting mechanisms [39], [40].
- Channel Substitution Effects: Promotions in one channel may influence demand in another, creating cross-channel dependencies.

Hybrid ML models address these challenges through multivariate input features, dynamic model tuning, and deep learning architectures that capture both short-term fluctuations and long-term seasonality across channels.

E. Role of Feature Engineering and External Variables

Feature engineering is a pivotal component of hybrid forecasting models. Retail forecasting accuracy often hinges not only on the model choice but also on the quality and relevance of input features. Commonly used features include:

- Temporal attributes (day of week, month, holiday indicators)
- Product hierarchies (SKU, category, brand)
- Pricing and promotion data
- Inventory and stock-out signals
- Macroeconomic indicators (inflation, unemployment)
- Weather and geolocation data

Automated feature selection techniques such as Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and embedded methods in tree-based models help reduce dimensionality and avoid overfitting [41].

Studies like [42] demonstrate that incorporating external variables such as online reviews, social media trends, and event data significantly enhances forecast granularity and contextual accuracy.

F. Forecasting Tools, Frameworks, and Open Research Platforms

The proliferation of open-source platforms and toolkits has democratized access to advanced forecasting techniques [43], [44], Popular libraries include:

- Facebook Prophet – for interpretable time series forecasting,
- GluonTS (by Amazon) – deep learning for probabilistic time series,
- Darts (by Unit8) – a Python library supporting hybrid and ensemble models,
- AutoTS and AutoGluon – for automated model selection and tuning.

These tools support reproducibility, scalability, and experimentation with hybrid model architectures.

G. Research Gaps and Opportunities

Despite growing adoption, several research gaps remain in the application of hybrid ML to retail sales forecasting [45]:

1. Model Explainability: Hybrid models often lack transparency, hindering stakeholder trust.
2. Data Integration: Few models fully integrate structured and unstructured data sources.
3. Scalability: Operationalizing hybrid models across thousands of SKUs and stores remains a challenge.
4. Evaluation Metrics: Standard metrics may not reflect business impact or customer experience.
5. Real-Time Adaptation: More work is needed on self-learning models that adapt in real-time.

Addressing these gaps requires interdisciplinary research combining data science, retail operations, and behavioral economics.

In the next section, we introduce a conceptual framework that synthesizes insights from the literature to guide the development and deployment of hybrid forecasting models in omnichannel retail.

3. Conceptual Framework

The growing complexity of omnichannel retail environments necessitates a structured and adaptable forecasting system capable of integrating diverse data sources, leveraging advanced analytics, and producing accurate predictions across multiple sales channels. This section proposes a conceptual framework for developing hybrid machine learning models tailored to the dynamic nature of retail sales forecasting.

A. Framework Overview

The proposed framework comprises six interconnected layers:

1. Data Acquisition and Integration
2. Data Preprocessing and Feature Engineering
3. Model Selection and Hybridization
4. Model Training and Validation
5. Forecast Generation and Evaluation
6. Feedback and Continuous Learning

This modular architecture ensures scalability, flexibility, and applicability to a wide range of retail forecasting scenarios.

B. Data Acquisition and Integration Layer

At the foundation of the framework is the systematic collection and integration of multichannel retail data. Sources include:

- Transactional Data: Point-of-sale (POS) records, e-commerce clickstreams, and mobile app interactions.

- Operational Data: Inventory levels, stock-out events, and replenishment cycles.
- Marketing and Promotions: Campaign calendars, discount schemes, loyalty program data.
- External Data: Macroeconomic indicators, weather conditions, social media sentiment, and competitor pricing.

Omnichannel retail data is often fragmented across platforms. Thus, data lakes and APIs play a critical role in harmonizing structured and semi-structured data into a unified schema suitable for analysis [1].

C. Data Preprocessing and Feature Engineering Layer

After data ingestion, extensive preprocessing is performed to handle missing values, outliers, and inconsistencies. This is followed by feature engineering, a critical phase where raw data is transformed into meaningful inputs for machine learning models.

Key techniques include:

- Time-based Feature Extraction: Dayparting, seasonality indices, moving averages.
- Lagged Variables: To capture historical influence on current sales.
- Derived Metrics: Conversion rates, average transaction values, and return frequencies.
- Text and Sentiment Analysis: Extracted from reviews and social media posts.

Automated tools such as Featuretools, AutoFeat, and embedding layers in deep learning models can assist in high-dimensional feature creation and selection [2].

D. Model Selection and Hybridization Layer

This layer involves the selection of base models and the strategy for their integration. Hybridization can be accomplished in multiple ways:

1. Sequential Hybrids: For example, a linear model like ARIMA captures trend and seasonality, and its residuals are modeled using a nonlinear ML algorithm such as XGBoost.
2. Parallel Hybrids: Multiple models are trained on the same dataset and their outputs combined via ensemble methods like weighted averaging or stacking.
3. Modular Hybrids: Each model is specialized for a specific data subset, channel, or region, and the outputs are integrated at the decision layer [3].

The choice of hybridization strategy depends on data volume, model explainability requirements, and computational constraints.

E. Model Training and Validation Layer

Models are trained on historical data using time-aware cross-validation techniques such as rolling-origin evaluation or nested walk-forward validation to account for temporal dependencies [4]. Hyperparameter optimization is performed using methods like grid search, random search, or Bayesian optimization.

To avoid overfitting, regularization techniques, dropout layers, and early stopping mechanisms are employed. Ensemble blending weights are optimized based on validation set performance using metrics such as Mean Absolute Percentage Error (MAPE), Weighted Mean Absolute Error (WMAE), or Root Mean Squared Logarithmic Error (RMSLE) [5].

F. Forecast Generation and Evaluation Layer

Once trained, the hybrid model generates forecasts at varying granularities—SKU-level, category-level, store-level, or region-level—depending on business needs.

Performance is evaluated not only with conventional metrics (e.g., RMSE, MAE) but also business-centric KPIs such as:

- Sell-Through Rate (STR)
- Inventory Turnover
- Lost Sales Ratio
- Forecast Value Added (FVA)

Scenario-based evaluations are also integrated to test model robustness under conditions like promotional spikes, supply chain disruptions, or new product launches [6].

G. Feedback and Continuous Learning Layer

Given the volatile and dynamic nature of consumer behavior, continuous model updating is crucial. This layer ensures:

- Model Retraining: On a regular basis using newly available data.
- Drift Detection: Alerts for concept drift using statistical tests or performance degradation tracking.
- Online Learning: Using incremental algorithms or reinforcement learning to adapt in real-time [7].

Additionally, explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are incorporated to provide transparency and foster trust among decision-makers.

H. Practical Application Considerations

To operationalize the framework, enterprises must consider:

- Cloud Infrastructure: For scalable computing and storage.
- Data Governance: Ensuring privacy, security, and compliance.
- Cross-Functional Teams: Involving data scientists, domain experts, IT engineers, and business managers.
- MLOps Pipelines: For monitoring, deploying, and maintaining models at scale.

Case implementations from retail leaders such as Walmart, Amazon, and Alibaba show that hybrid forecasting frameworks can lead to measurable improvements in inventory optimization, markdown planning, and customer satisfaction [8].

4. Application Scenario: Hybrid ML-Driven Forecasting in a Mid-Sized Omnichannel Retailer

To illustrate the practical application of hybrid machine learning models in retail sales forecasting, consider the hypothetical case of a mid-sized omnichannel retailer, TrendLine Retail, operating across physical stores, an e-commerce platform, and a mobile app. The retailer sells seasonal apparel, accessories, and lifestyle products and faces high variability in consumer demand driven by weather, fashion trends, promotions, and regional events.

A. Business Context and Challenges

TrendLine Retail experiences periodic challenges in aligning inventory with actual demand across its diverse sales channels. Key operational issues include:

- Inventory overstock and stockouts resulting from poor short-term forecasting accuracy.
- Cross-channel cannibalization, where promotions in online channels affect footfall in physical stores.
- Demand spikes during regional holidays, fashion launches, or influencer-driven campaigns.

Traditional forecasting tools, based on linear regression and moving average methods, failed to adapt to these dynamic patterns. Management sought to implement a more intelligent, data-driven forecasting system to optimize supply chain responsiveness and improve customer experience.

B. Data Infrastructure and Feature Engineering

The retailer leveraged historical transaction data, channel-specific web traffic, and third-party data (e.g., weather forecasts, local event calendars, and social media sentiment). Data pipelines were established to aggregate structured data from the ERP and POS systems and unstructured data from social listening APIs. The following feature groups were engineered:

- Temporal variables: day-of-week, month, promotion periods, and holiday indicators.
- Channel identifiers: online vs. offline traffic patterns and conversion rates.
- Product attributes: category, size, seasonality, and price elasticity.
- Exogenous variables: real-time weather, regional events, and influencer mentions.

Recursive Feature Elimination (RFE) and SHAP (SHapley Additive exPlanations) values were used to optimize feature selection and ensure interpretability [1].

C. Hybrid Model Architecture

The hybrid architecture consisted of two layers:

1. Statistical Base Layer: A seasonal ARIMA model captured linear trends and base-level seasonality across product categories and regions.
2. Machine Learning Residual Layer: A Gradient Boosting Machine (GBM) modeled non-linear residuals from the ARIMA outputs using real-time behavioral and contextual features.

Model performance was further enhanced using ensembling, where LSTM models were introduced to track demand shifts over rolling time windows. The outputs of the statistical and ML components were aggregated using a weighted ensemble strategy optimized through cross-validation.

D. Forecasting Outcomes and Business Impact

Post-deployment, the hybrid forecasting system delivered measurable improvements:

- Reduction in Mean Absolute Percentage Error (MAPE) by 18% across top-selling SKUs.
- Improved promotion planning accuracy, especially for online-exclusive product launches.
- Decrease in lost sales and overstocking incidents by 22% and 17%, respectively, over a six-month evaluation period.

Additionally, the explainability module provided channel managers with insight into top predictive features per channel, supporting better campaign and pricing decisions.

E. Strategic Learnings

This application scenario demonstrates how hybrid models can effectively address the non-linearity and volatility of sales data in omnichannel settings. Importantly, the integration of external and behavioral data, combined with interpretability tools, facilitated greater alignment between data science teams and retail decision-makers. Such systems are scalable across SKUs and adaptable to varying demand patterns, making them valuable for mid- to large-scale retail operations.

In summary, hybrid machine learning models offer a robust foundation for building intelligent forecasting systems that support agility, accuracy, and cross-functional collaboration in omnichannel retail environments.

5. DISCUSSION

The findings from the literature and proposed conceptual framework underscore the growing relevance and efficacy of hybrid machine learning (ML) models in addressing the intricate demands of retail sales forecasting across omnichannel platforms. The synthesis of statistical and ML approaches offers a balanced pathway retaining the interpretability of classical models while capitalizing on the predictive strength of modern algorithms. One of the central takeaways is that no single model suffices for the multifaceted and evolving nature of omnichannel retail data. Instead, hybrid architectures such as ARIMA-LSTM or ensemble models like XGBoost combined with domain-informed feature engineering showcase significant improvements in both forecast accuracy and contextual adaptability. This layered modelling strategy is particularly effective in handling non-linear behaviours, cross-channel interactions, and external influencers such as weather or macroeconomic factors.

Furthermore, the conceptual framework emphasizes modular integration advocating for the dynamic assembly of model components tailored to data availability, forecast horizon, and business objectives. For example, short-term demand fluctuations due to promotions may benefit from high-frequency models like LSTM, whereas long-term planning may rely on trend-capturing components from ETS or Prophet. However, the analysis also highlights challenges inherent in hybridization. While these models often outperform standalone counterparts in RMSE or MAPE, they may introduce complexity that hinders real-time deployment and model interpretability. The "black-box" nature of deep learning elements raises concerns for decision-makers who require transparent and auditable forecasting systems. Explainable AI

(XAI) techniques, such as SHAP values or attention mechanisms, are therefore critical complements to hybrid models, offering insights into variable importance and decision pathways.

Another area of concern is data readiness and system integration. Omnichannel environments frequently suffer from fragmented data silos, inconsistent measurement standards, and latency in data flows. Hybrid models, although technically capable of ingesting multivariate and unstructured data, still require rigorous data preprocessing, feature harmonization, and synchronization across platforms. These operational prerequisites often determine the success or failure of model implementation more than algorithmic sophistication alone. Moreover, while research increasingly incorporates external data sources such as online reviews, mobility patterns, and social sentiment few operational systems seamlessly integrate these inputs at scale. Future implementations must consider not only algorithmic novelty but also data pipeline design, API integrations, and governance frameworks that support continuous learning and retraining.

In comparison with previous work, this study advances the discourse by proposing a holistic framework that not only surveys existing methods but also aligns them with practical deployment considerations in omnichannel settings. It encourages a context-sensitive approach to model selection, acknowledging that forecasting requirements vary significantly between store types, regions, product categories, and planning horizons. Overall, the discussion affirms that hybrid ML models represent a powerful but nuanced toolset for retail sales forecasting. Their successful adoption depends on thoughtful model architecture, robust data infrastructure, and a clear alignment with business goals.

6. CONCLUSION

This study has explored the evolving landscape of retail sales forecasting, emphasizing the growing importance and effectiveness of hybrid machine learning models within omnichannel environments. Traditional statistical methods, while foundational, often fall short in handling the complexity, heterogeneity, and real-time dynamics of modern retail data. In contrast, machine learning models offer flexibility and power in uncovering non-linear relationships but can suffer from issues related to interpretability and robustness. Hybrid approaches provide a promising middle ground, combining the strengths of both paradigms to enhance forecast accuracy, contextual relevance, and operational scalability.

Through a comprehensive literature review, we identified key methodological trends, tools, and research gaps. Hybrid models ranging from statistical-ML integrations to ensemble and domain-specific architecture demonstrate superior performance in various retail forecasting contexts. These models effectively manage multichannel data streams, integrate external variables, and adapt to changing customer behaviours, thus offering practical value for both strategic planning and day-to-day operations.

The proposed conceptual framework offers a structured pathway for developing and evaluating hybrid forecasting systems that align with the unique demands of omnichannel retailing. It encourages thoughtful integration of data sources, feature engineering, algorithm selection, and performance evaluation, while also recognizing the need for interpretability, scalability, and real-time adaptability.

Looking forward, future research should focus on enhancing model explainability, expanding the use of unstructured data, and building self-adaptive systems capable of learning continuously from new information. Bridging these gaps will require interdisciplinary collaboration across data science, retail management, and behavioral analytics. Ultimately, the adoption of hybrid machine learning models holds significant promise for transforming retail forecasting into a more intelligent, agile, and customer-centric function.

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