A Real-Time Prediction System for Restaurant Orders Using Time Series and Behavioural Analytics: A Conceptual Framework

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Abstract

Effective demand forecasting is critical for optimizing operational efficiency within the food-service industry, which is characterized by inherently volatile consumer preferences and dynamic market conditions. This work addresses the shortcomings of conventional forecasting methodologies that frequently neglect the integration of real-time behavioural analytics, thereby leading to inadequate inventory management and diminished customer satisfaction. The principal aim of this study is to propose a framework for innovative real-time prediction system that synthesizes advanced time series analysis with behavioural insights garnered from customer interactions. By employing methodologies such as Seasonal AutoRegressive Integrated Moving Average (SARIMA) alongside machine learning algorithms, This work seeks to propose a method to improve demand forecasting accuracy. The proposed framework seeks to amalgamate historical order data with behavioural analytics, providing restaurant operators with a comprehensive understanding of consumer demand patterns. This study contributes to the field by introducing a novel approach that not only enhances forecasting precision but also promotes improved resource allocation and service delivery within the restaurant sector. This research aims to provide actionable insights to inform strategic decision-making, benefiting operators and consumers.

Keywords

Real-time prediction, Time series analysis, Behavioural analytics, Machine learning, Demand Forecasting, Deep Learning

1. Introduction

Catering within the food-service industry is currently facing a pressing need for accurate demand forecasting. With consumer preferences changing rapidly and market conditions often unpredictable, maximising operational efficiency while maintaining customer satisfaction is a significant challenge. This work directly addresses the shortcomings of traditional forecasting methodologies, which struggle to integrate real-time consumer insights and behavioural trends, leading to inefficiencies and potential revenue losses.

This study addresses inadequate predictive demand forecasting systems within the restaurant sector, which often need to pay more attention to the dynamic interplay between historical order data and real-time behavioural analytics. The primary objective is to develop a real-time prediction system that combines advanced time series (TS) analysis with behavioural analytics derived from customer interactions and preferences. Unlike existing systems that primarily rely on historical data, the novelty of the proposed system lies in its ability to incorporate real-time behavioural insights, thereby enhancing forecasting accuracy and responsiveness. The system is unique in its comprehensive approach, augments

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traditional forecasting models and incorporates behavioural data, providing a holistic view of consumer demand. The proposed approach is intended to lead to optimized resource allocation and improved service delivery in the food-service industry [1]. The proposed framework focuses on developing a real-time order prediction model that combines traditional time series methods, such as Autoregressive Integrated Moving Average (ARIMA) and SARIMA, with Long Short-Term Memory (LSTM) networks to handle linear and nonlinear patterns in historical order data. Additionally, incorporating behavioural analytics introduces a new dimension by capturing real-time customer preferences and decision-making patterns, offering a more dynamic and responsive approach to demand forecasting. By integrating these elements, the proposed system addresses key limitations in current models. It provides actionable insights, leading to improved inventory management, targeted marketing, and overall operational efficiency within the food-service industry.

2. Literature Review

2.1. Advancements in Time Series Analysis for Demand Forecasting Across Industries

The application of TS analysis and artificial intelligence in demand forecasting has gained significant interest across the healthcare [2], energy, automotive, and food industries, highlighting its contribution in improving predictive accuracy and boosting operational efficiency. Wang [3] investigates TS forecasting within the automotive industry, highlighting the integration of K-means clustering with ARIMA and SARIMA models. This combination enhances forecast precision and emphasizes the importance of selecting appropriate TS methodologies that align with the unique characteristics of automotive demand patterns. However, while the study yields promising results, it raises critical inquiries regarding the model's adaptability to other industries that may exhibit differing demand dynamics. Matsumoto et al. [4] applies TS analysis to forecast remanufacturing needs in the automotive parts sector. The work demonstrates TS models capacity to effectively predict demand even in contexts where complete historical sales data is inaccessible. Nonetheless, the reliance on historical data may pose limitations, potentially overlooking emerging market trends and shifts in consumer behaviour that are crucial for accurate forecasting.

In the food service industry, Mihirsen et al. [5] explore the application of machine learning (ML) systems for forecasting dish sales, emphasizing the role of TS analysis in addressing food waste issues. Their research suggests that time series-based forecasting models can significantly optimize inventory management and reduce waste. However, the practical implementation of ML in forecasting hinges on the quality of historical data and the ability to integrate these systems within existing operational frameworks, thereby highlighting the inherent challenges of applying advanced TS methods in real-world scenarios. Mohammed et al. [6] illustrate the potential of employing various TS models for forecasting clinical laboratory test volumes. While the work showcases the benefits of integrating statistical techniques in healthcare demand forecasting, it necessitates a comprehensive critique of the model's applicability across diverse healthcare settings, which can vary due to data availability and operational constraints.

The exploration of TS methodologies extends to the broader food sector, as evidenced by Suhardi et al. [7], who examine demand forecasting for roasted coffee production. The approach underscores the necessity of employing TS techniques that can adapt to shifting consumer preferences and market trends. However, the study could benefit from a more profound analysis of how macroeconomic factors and competitive dynamics influence demand, indicating the need for a more comprehensive model. Concurrently, Kumar et al. [8] applies seasonal ARIMA and exponential smoothing techniques for electricity demand forecasting, illustrating the effectiveness of seasonal adjustments in enhancing prediction accuracy while raising questions regarding the robustness of these models in the face of unpredictable external factors such as regulatory changes and technological advancements in energy production. Similarly, Panda and Mohanty [9] advocate for integrating regression models with TS analysis to improve forecasting precision in the food supply chain. Although their findings provide valuable insights into enhancing forecasting methodologies, the implications of such integrations warrant further exploration to understand their impact on real-time decision-making processes. Collectively, these works attest the capacity of sophisticated TS techniques to address the unique challenges faced in their respective industries. To conclude, the proposed approach recommends a hybrid model that combines traditional time series algorithms with LSTM networks to enhance the accuracy of order pattern forecasting in restaurant settings.

2.2. Behavioural Analysis in Demand Forecasting

Demand forecasting has increasingly integrated behavioural analysis to enhance predictive accuracy and adapt to dynamic consumer preferences. Traditional forecasting models, such as ARIMA and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), have established a baseline understanding of TS data; however, the associated limitations in capturing nonlinear relationships and external factors warrant the adoption of more sophisticated methodologies [10, 11]. Incorporating ML techniques, particularly hybrid models like Complete Ensemble Empirical Mode Decomposition with Sample Entropy Support Vector Regression (COEMD-S-SVR), demonstrates significant advancements in demand forecasting. These models leverage big data and behavioural insights, improving forecasting accuracy by incorporating real-time inputs from social media interactions and online search patterns [12]. However, the practical implementation of these advanced techniques has its challenges. Managing large volumes of unstructured data, such as social media posts and online search patterns, can be complex and time-consuming, complicating the modelling process and hindering effective analysis [13].

Furthermore, ML models such as LSTM networks and ensemble methods have emerged as beneficial tools for integrating consumer behaviour into forecasting models. LSTMs are particularly adept at capturing long-term dependencies in TS data, enhancing the predictive power of models when combined with behavioural signals [14]. Ensemble methods, such as random forests, improve reliability by aggregating predictions from diverse data sources, thereby mitigating risks of overfitting and enhancing model performance for short- and long-term forecasts [15]. However, the growing complexity of these models raises concerns about transparency and interpretability, which are vital for gaining stakeholder trust, and understanding it, in forecasting outcomes. As decision-makers increasingly rely on these predictive models, transparency plays a key role in furthering this research.

In addition to behavioural signals, economic and social variables significantly impact demand forecasting, particularly in volatile sectors such as tourism [16, 17]. The flexibility of statistics models such as the Grey Model (GM) allows for incorporating external economic variables into time series forecasting, improving adaptability to changes in consumer behaviour under uncertain market conditions. Specifically, GM(1,1), a first-order model that predicts a single variable, is mostly used because it requires limited data while effectively capturing trends [17]. While hybrid models that blend traditional and ML approaches have shown promise in enhancing forecasting accuracy, achieving a balance between model complexity and interpretability is an important consideration for practical applications. Future research should refine these methodologies to capture a broader spectrum of consumer behaviours and external influences, thus addressing the challenges of increasingly dynamic market conditions. In summary, integrating behavioural analysis into demand forecasting is a promising pathway towards more accurate and adaptable predictive models.

Despite advancements in TS analysis and behavioural analytics, a significant gap exists in integrating real-time data streams for effective demand forecasting. Current models often need a comprehensive framework that combines these methodologies, particularly in fast-paced environments such as the food-service industry. Addressing this deficiency is crucial for developing a real-time integrated system leveraging TS and behavioural analytics.

3. Proposed Methodology

The proposed architecture for integrating behavioural data with TS analysis to enhance predictive modelling capabilities systematically is depicted in Figure 1. The proposed methodology is explained in the following stages:

Stage 1: Once the data is collected, it undergoes TS data preprocessing, cleaning and preparing for analysis to address any inconsistencies or missing values. The workflow progresses to TS modeling and analysis, where statistical models, followed by TS model evaluation, ensuring the selection of only the most accurate models for further analysis. In parallel, consumer data is gathered on user interactions and behaviours through Behavioural Data Collection, which is subsequently preprocessed to ensure it is structured and ready for analysis.

Stage 2: Following the initial model evaluations, Feature engineering for behavioural data is applied to derive new features that encapsulate significant behavioural patterns. The Integration of Behavioural Data with TS merges the processed datasets, resulting in a comprehensive dataset for modelling. Then this dataset undergoes Model Testing and validation to ensure its robustness and accuracy.

Stage 3: Thereafter, models are ready to be evaluated in a real-world context during the final model deployment phase. Real-Time data API acquisition facilitates continuous updates and monitoring of the model's performance. This workflow-based approach ensures a thorough integration of behavioural and TS data, ultimately leading to meaningful analytical outcomes and actionable insights in real-time contexts.

3.1. Historical, Behavioural and Real-time Data

Required data must be collected, including historical sales information, order patterns, and inventory levels. This data will provide insights into customer demand fluctuations over time. Additionally, contextual information must be gathered such as events, holidays, and weather data, which can significantly impact ordering behaviour. Obtaining behavioural data from online ordering platforms is essential for analysing customer behaviour. This data captures critical metrics that provide valuable insights into consumer preferences and purchasing patterns. Table 1 presents a comprehensive overview of these key metrics and their descriptions.

Table1: Key Behavioral Data Metrics Captured from Online Ordering Platforms and Their Descriptions

Data Type	Description
Order Hesitation Data	Measures the time users take to decide on an order and the frequency of changes before finalizing it—for example, tracking delays between item selection and checkout.
Session Time	This record shows the total duration of a user's session on the platform, including time spent on product pages, offers, and checkout.
Web Page Visits	Counts the number of visits to individual menu items or sections, helping identify popular and less-visited areas on the platform
Click Data	Tracks the frequency and location of clicks throughout the ordering process, such as clicks on promotions, product details, or the "Add to Cart" button
Scroll Depth	Measures user engagement by recording how far down a webpage users scroll, indicating interest in specific sections, such as item descriptions or reviews

Abandonment Rates	Tracks the percentage of users who leave their carts without completing the purchase, providing insights into potential barriers in the checkout process
Engagement Metrics	Evaluates user interactions with promotional content, such as banner ads or special deals, by tracking click-through rates and time spent viewing
Search Behaviour	Captures keywords used in search queries, the number of results viewed, and the corresponding click-through rates, identifying patterns in product discovery
User Interaction Data	This Record shows actions such as adding items to the cart, modifying selections, navigating between pages, offering insights into user preferences
Time of Day Analysis	Identifies peak activity periods by analyzing user behaviour based on the time of day, such as lunch or dinner hours for restaurant orders
Demographic Data	Groups users based on characteristics like age, gender, and location, providing valuable insights for targeted marketing strategies
Transactional Data	This section details completed orders, including order frequency, values, and items purchased, offering insights into customer loyalty and spending patterns

There are several open-source datasets that can be used as a sample to test the proposed research. The most useful dataset that researchers found was on the Kaggle website, titled Restaurant Order Details [18]. This dataset has 500 records for restaurant orders with some customers' demographic information on a day. However, the limitation of the dataset is that it only records the total number of items the customer placed, not the details of the menu item they ordered.

After finding an online ordering platform, the system will leverage APIs and web scraping techniques to continuously monitor and collect relevant behavioural data. This dual approach enables a comprehensive understanding of customer engagement and preferences alongside the temporal dynamics of restaurant orders. This ensures a robust dataset that supports effective predictive modelling.

Combining SARIMA and LSTM models offers a robust approach to TS forecasting, particularly suitable for restaurant order data that often exhibit seasonal patterns and complex nonlinear relationships. SARIMA effectively captures linear trends and seasonality through its parameters, represented as SARIMA$(p, q, d)(P, Q, D)$s, where p is the number of autoregressive terms, q is the differencing order, q is the number of lagged forecast errors, and the seasonal components are similarly defined. The SARIMA model can be expressed as follows:

$$\varphi(B^s)(1 - B^d)(1 - B^D B^s)Y_t = \theta(B)\varepsilon_t$$

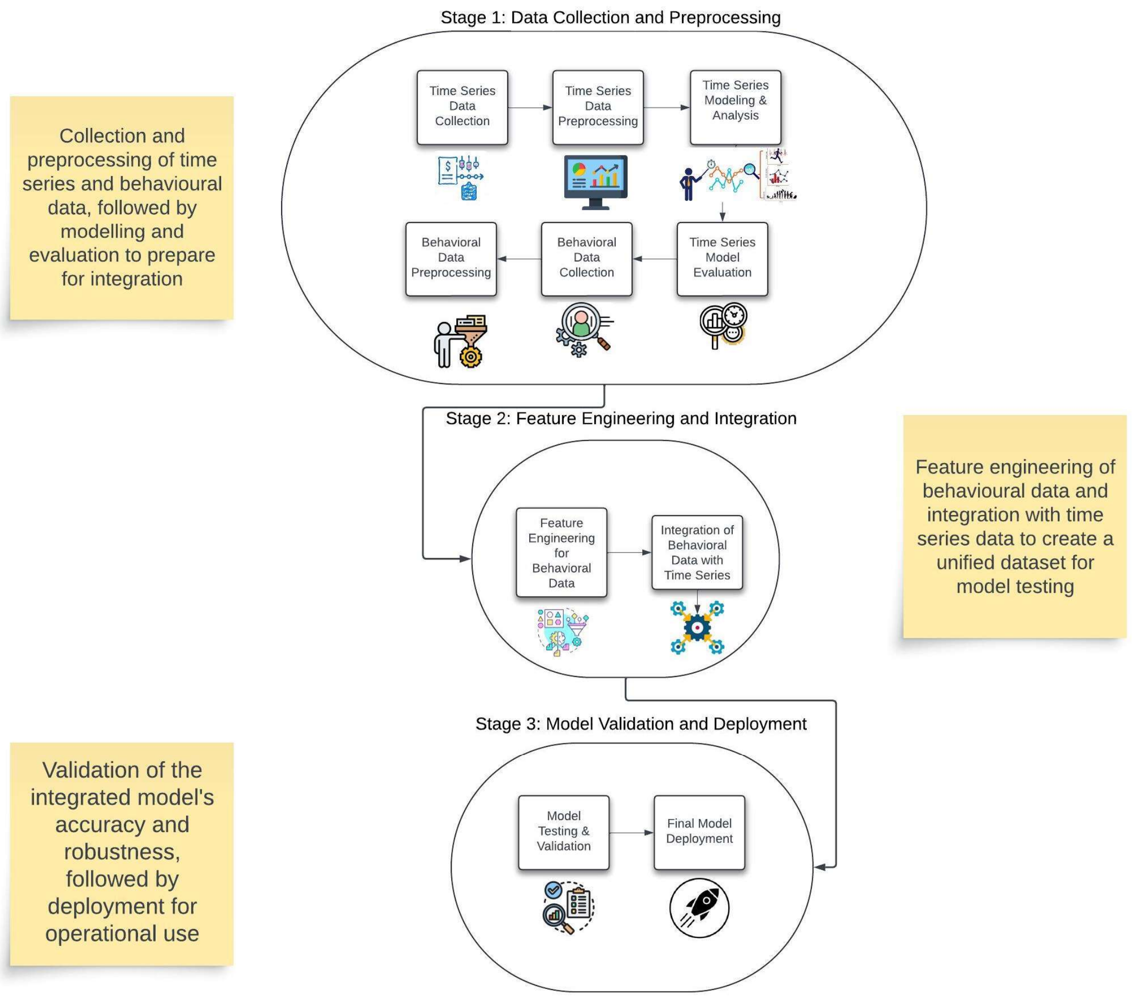

Figure1: Stages of the Proposed Framework for a Hybrid Order Prediction System

Y_t represents the TS value at time t $\varphi(B^s)$ and $\theta(B)$ are the seasonal autoregressive and moving average parts, respectively, and ε is the white noise error term. After fitting the SARIMA model to the historical data, the residuals are analysed— the differences between observed values and SARIMA forecasts— to detect any remaining patterns or autocorrelations that the linear model might have overlooked.

Once the SARIMA model is established its residuals are used as input for the LSTM model. LSTMs excel at capturing long-term dependencies and nonlinear relationships in sequential data. The architecture of the LSTM model typically includes input layers, one or more LSTM layers, and output layers. The residuals, alongside additional features such as promotional events or weather conditions, are fed into the LSTM model for training. The LSTM can learn to predict these residuals, enabling it to capture complex behaviours in customer ordering patterns. The final forecasting output is obtained by summing the SARIMA forecast with the LSTM predictions:

$$\text{Final Forecast} = \text{SARIMA Forecast} + \text{LSTM Prediction}$$

This hybrid approach enhances forecasting accuracy by combining the strengths of both models, addressing the limitations inherent in using each model independently. By effectively modelling linear trends and complex interactions, the combined SARIMA-LSTM framework can provide more reliable forecasts, leading to improved decision-making for restaurant operations.

The impact of behavioural analytics on order prediction is profound, as it facilitates a nuanced understanding of customer interactions and preferences, enhancing forecasting accuracy. Utilizing the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, the proposed approach will address the collection, preprocessing, and analysis of various behavioural data types, including order hesitation data, session duration, clickstream data, abandonment rates, and demographic information. These metrics elucidate how customers engage with the online ordering system, highlighting influential factors in their purchasing decisions. Preprocessing behavioural data is critical to ensuring its quality and relevance for subsequent analysis. This stage encompasses data cleaning to rectify inconsistencies, managing missing values, and normalizing features to a standard scale. For instance, the time to finalize an order may vary considerably across users; thus, normalizing this feature enhances accurate comparisons across different user sessions. Furthermore, categorical variables, such as user demographics, will be transformed into numerical formats via one-hot encoding, rendering them suitable for integration into ML models.

Following preprocessing, feature engineering will concentrate on identifying and constructing features that exert the most significant influence on the predictive model. This may involve deriving metrics such as the average order hesitation time over specified intervals, total session duration per customer, or the frequency of visits to particular menu items. The synthesis of these behavioural features with TS data enables the modelling of relationships between historical ordering behaviours and future demand patterns. Researchers can execute this integration using advanced algorithms such as LSTM networks, which excel in identifying complex patterns within sequential data. By incorporating behavioural and TS features into the LSTM model, the study aims to capture the interactions between these domains, thus enhancing the model's capacity to learn from past behaviours and produce accurate future order predictions. Consequently, this comprehensive approach seeks to improve the precision of order predictions and aspires to yield valuable insights into customer preferences and behavioural trends. This empowerment will enable restaurant management to make informed decisions regarding inventory management, staffing, and targeted marketing strategies, ultimately contributing to developing robust order prediction systems within the restaurant industry.

In addition to historical and behavioural data, contextual factors such as events, holidays, and weather conditions must be incorporated into the framework to capture their significant impact on customer ordering behaviour. For instance, public holidays or major local events often lead to sudden demand for specific menu items or services. At the same time, adverse weather conditions can shift customer preferences from dining to delivery options. These fluctuations are critical for businesses to anticipate, as they directly influence inventory management, staffing, and service efficiency. Integrating these contextual variables into the predictive model requires advanced preprocessing techniques to align temporal and spatial data with historical trends and behavioural metrics. This approach involves handling challenges such as incomplete data, mismatched timeframes, or varying levels of granularity across datasets.

Additionally, the influence of these factors can vary significantly based on geographical location and customer demographics. For example, the demand impact of a rainy day may differ in regions accustomed to frequent rain compared to those where such weather is uncommon. As such, the model must account for localized and demographic-specific nuances to enhance its adaptability and predictive power. By effectively incorporating and analyzing these external variables alongside historical and behavioural data, the framework can better capture dynamic market conditions, thereby improving the accuracy and relevance of its predictions. This capability is essential for enabling food service businesses to make informed decisions in real-time, optimizing operations and improving customer satisfaction.

3.2. Limitations of the Proposed Approach

The proposed framework for real-time order prediction in the food service industry presents an innovative approach by integrating time series analysis with behavioural analytics. However, several limitations may impact its practical applicability and effectiveness. A key challenge lies in the availability and quality of data. The framework relies heavily on historical order data and behavioural metrics, but many food service businesses may need more comprehensive data collection systems, resulting in incomplete or inconsistent datasets. For example, specific behavioural metrics, such as order hesitation time or scroll depth, may not be uniformly available across all users or sessions, potentially affecting the model's reliability.

Integrating behavioural and time series data also presents technical complexities, particularly in ensuring temporal alignment and consistency between datasets. Discrepancies in timestamps, differences in data granularity, and the need for extensive preprocessing increase the computational effort required. Furthermore, the hybrid approach, which combines statistical models like SARIMA with deep learning models such as LSTMs, demands substantial computational resources. Training and testing these models on large-scale datasets can be resource-intensive, which may pose a barrier for small or resource-constrained businesses.

Another limitation arises from the dynamic nature of external factors. While the framework incorporates behavioural data, it does not explicitly account for variables such as sudden market changes, promotional events, or macroeconomic trends that could significantly impact predictions. This issue could result in reduced accuracy in highly volatile scenarios. The framework's scalability and generalization also pose challenges, as it is specifically designed for the food service industry. Expanding its application to larger enterprises or other sectors with unique behavioural patterns may require significant customization and retraining.

Finally, the model's interpretability is a critical consideration. Advanced machine learning techniques and intense learning models like LSTMs often function as "black-box" systems, making it difficult for stakeholders to understand the rationale behind predictions. Improving model interpretability will be essential for building trust and facilitating adoption among decision-makers. Addressing these limitations through future research will enhance the framework's practicality, scalability, and effectiveness in real-world applications.

4. Results and Discussion

Integrating behavioural analytics with TS modelling presents a transformative approach to demand forecasting that offers considerable advantages over traditional systems relying exclusively on TS data. Established models such as SARIMA and LSTM excel at capturing historical trends, seasonal variations, and external factors like holidays and weather conditions. However, these models often need to be revised in their adaptability to abrupt shifts in consumer behaviour. For instance, during peak dining seasons or local events, customer preferences can shift rapidly, resulting in demand spikes or drops requiring adequate historical data reflection. Consequently, traditional TS models may produce inaccurate predictions, resulting in inefficient resource allocation, staffing issues, and potential loss of customer satisfaction due to longer wait times or out-of-stock items.

In contrast, the proposed hybrid model enhances demand forecasting by incorporating behavioural data, enabling a more dynamic and responsive forecasting mechanism. The proposed model captures real-time insights into customer interactions and preferences by utilizing behavioural data such as order hesitation data, session duration, clickstream analysis, and engagement metrics. This additional layer of information allows for improved predictions of demand fluctuations, as it considers historical sales data and immediate factors influencing consumer decision-making. The proposed model enables restaurants to forecast demand, allowing them to place orders for ingredients or prepare dishes based on predicted customer behaviour before receiving actual orders. For example, the proposed model can identify patterns in user engagement that precede increases in orders, such as a rise in menu item views or heightened interaction with promotional offers.

The distinctive nature of the proposed approach lies in its combination of behavioural analytics with TS forecasting, which sets it apart from existing methodologies that primarily focus on historical sales data alone. While many traditional models rely solely on past performance metrics, this study emphasizes the importance of real-time behavioural indicators in enhancing demand predictions. By incorporating these elements, the proposed model offers insights into the immediate drivers of consumer behaviour, allowing for proactive adjustments in restaurant operations. Moreover, these improvements are aligned with the European Union's sustainability goals, particularly to reduce food waste and end hunger by 2030. The proposed framework will offer a significant advancement in demand forecasting, providing restaurants with the tools to optimize resource allocation, order preemptively based on predicted demand, and improve customers' overall dining experience - thereby contributing to operational efficiencies and broader sustainability goals.

5. Conclusion and Future Work

This proposed framework introduces an innovative approach to real-time order prediction in the food service industry by integrating time series analysis with behavioural analytics. The model addresses significant gaps in current predictive models by combining dynamic time series forecasting with customer behavioural insights. Through this hybrid approach, the model aims to enhance the accuracy and adaptability of demand forecasting, offering real-time solutions to operational challenges such as inventory management and order fulfilment.

Despite advancements in predictive modelling across various sectors, including retail, healthcare, and energy, hybrid models are still limited in their application to real-time order prediction in the food service industry. The full potential of behavioural and historical order data in improving forecasting accuracy has yet to be fully realized. This work seeks to bridge this gap by integrating behavioural and historical order data to improve prediction precision.

Future work will focus on validating the proposed model in real-world food service settings. This approach includes collecting and integrating real-time behavioural data, followed by pilot studies to assess the model's effectiveness in predicting order volumes. To enhance the robustness of the model, further exploration of advanced machine learning techniques and the inclusion of additional external factors, such as market trends and competitor analysis, will be pursued. The framework's scalability across different food service environments will also be evaluated to refine the model for broader industry applications and further operational optimization.

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