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Deep learning Algorithm for predicting various retail store salesUsing LSTM and ARIMA

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Abstract

Sales forecasting plays a crucial role in helping businesses make informed decisions regarding inventory management, resource allocation, and strategic planning. In recent years, deep learning algorithms have emerged as powerful tools for accurately predicting sales, owing to their ability to capture complex patterns and relationships in large datasets. This research explores the application of deep learning algorithms in forecasting the sales of industrial products, delving into their methodologies, benefits, challenges, and real-world implementations. Sales forecasting is a crucial task for businesses to effectively manage their resources and make informed decisions. In this context, deep learning methods like Long Short-Term Memory (LSTM) networks and traditional time series analysis techniques such as Autoregressive Integrated Moving Average (ARIMA) have emerged as powerful tools. The integration of deep learning and traditional time series methods in sales forecasting offers businesses a versatile toolkit to predict sales, optimize inventory, and streamline operations. Selecting the appropriate algorithm or a hybrid solution depends on the specific characteristics of the sales data and the desired level of forecasting accuracy, which can ultimately lead to improved decision-making and profitability. In this research the forecasting model sought to predict future sales in retail sales by analyzing patterns that were likely to predict future results. Forecasting models through deep learning offer the possibility of obtaining more accurate forecasts of retail store sales even with big data. In this research, there are two comparable models in deep learning, LSTM and ARIMA, which are well-known models that form a structure in predicting retail store sales with high effectiveness compared to other methods. In this research we have validated and tested which are crucial to ensuring the reliability of these models. Accurate predictions from LSTM and ARIMA models help stores maintain optimal inventory levels, make informed decisions about promotions and restocks, and adapt to changing consumer behavior and market conditions. Continuous monitoring and periodic retraining can improve their performance and provide reliable forecasts for retail companies

الخلاصة

لعب التنبؤ بالمبيعات دورًا حاسمًا في مساعدة الشركات على اتخاذ قرارات مستنيرة فيما يتعلق بإدارة المخزون وتخصيص الموارد والتخطيط الاستراتيجي. في السنوات الأخيرة، ظهرت خوارزميات التعلم العميق كأدوات قوية للتنبؤ بالمبيعات بدقة، نظرا لقدرتها على التقاط أنماط وعلاقات معقدة في مجموعات بيانات كبيرة. يستكشف هذا البحث تطبيق خوارزميات التعلم العميق في التنبؤ بمبيعات المنتجات الصناعية، والتعمق في منهجياتها وفوائدها وتحدياتها وتطبيقاتها في العالم الحقيقي.

يعد التنبؤ بالمبيعات مهمة حاسمة للشركات لإدارة مواردها بشكل فعال واتخاذ قرارات مستنيرة. وفي هذا السياق، ظهرت أساليب التعلم العميق مثل شبكات الذاكرة الطويلة قصيرة المدى (LSTM) وتقنيات تحليل السلاسل الزمنية التقليدية مثل المتوسط المتحرك المتكامل التلقائي (ARIMA) كأدوات قوية. إن دمج التعلم العميق وأساليب السلاسل الزمنية التقليدية في

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التنبؤ بالمبيعات يوفر للشركات مجموعة أدوات متعددة الاستخدامات للتنبؤ بالمبيعات وتحسين المخزون وتبسيط العمليات. يعتمد اختيار الخوارزمية المناسبة أو الحل المختلط على الخصائص المحددة لبيانات المبيعات والمستوى المطلوب من دقة التنبؤ، مما قد يؤدي في النهاية إلى تحسين عملية صنع القرار والربحية. في هذا البحث سعى نموذج التنبؤ إلى التنبؤ بالمبيعات المستقبلية في مبيعات التجزئة من خلال تحليل الأنماط التي من المحتمل أن تتنبأ بالنتائج المستقبلية. توفر نماذج التنبؤ من خلال التعلم العميق إمكانية الحصول على تنبؤات أكثر دقة لمبيعات متاجر البيع بالتجزئة حتى مع البيانات الضخمة. يوجد في هذا البحث نموذجان قابلان للمقارنة في التعلم العميق، LSTM و ARIMA، وهما نموذجان معروفان يشكلان بنية في التنبؤ بمبيعات متاجر التجزئة بفعالية عالية مقارنة بالطرق الأخرى. في هذا البحث قمنا بالتحقق من صحتها واختبارها والتي تعتبر ضرورية لضمان موثوقية هذه النماذج. تساعد التنبؤات الدقيقة من نماذج LSTM وARIMA المتاجر في الحفاظ على مستويات المخزون المثلى، واتخاذ قرارات مستنيرة بشأن العروض الترويجية وإعادة المخزون، والتكيف مع سلوك المستهلك المتغير وظروف السوق. يمكن للمراقبة المستمرة وإعادة التدريب الدوري تحسين أدائها وتوفير توقعات موثوقة لشركات البيع بالتجزئة

Keyword: Machine learning models, ARIMA models, deep learning algorithms, LSTM models, COVID-19

1. Introduction

Accurate sales predictions are vital for retail stores as they impact production planning, resource allocation, and inventory optimization. Machine learning models like weighted random forest (WRF) and XGBoost have proven more effective than traditional approaches in analyzing and predicting sales [1]. The COVID-19 pandemic has highlighted the need for accurate sales predictions to improve supply chain effectiveness. Machine learning models such as RF, XGB, and LGBM are used in inventory management to extract knowledge from historical data and predict future orders. Predicting apparel retail sales is challenging due to various factors, but machine learning algorithms like Support Vector Regression (SVR) and Neural Networks (NN) help overcome these challenges. Advanced techniques like ARIMA and grey forecasting models are used for residual correction, but LSTM models have shown promise in processing long time series data[2],[3]. AI models outperform other approaches in retail store sales prediction by efficiently processing real-time datasets and accurately predicting market movements. These models not only forecast sales but also analyze customer responses and contributing factors. Overall, accurate sales predictions optimize operations, enhance supply chain management, and improve customer satisfaction, leading to increased revenues [5], [8.[

1.2 Introduction to deep learning algorithms and their role in sales forecasting

Deep learning algorithms, particularly LSTM and ARIMA models, have revolutionized sales forecasting by capturing complex patterns and relationships in data that traditional statistical methods struggle with[4], [17]. These algorithms can encode for multiple time series and account for categorical variables, leading to more accurate predictions and informed decision-making. The use of LSTM models allows for the identification of non-linear patterns and dependencies within sales data. Combining ARIMA models with deep learning techniques, such as LSTM, significantly improves prediction performance. Deep learning algorithms have advantages beyond pattern capture, including automatic feature learning and handling of multiple input variables. They can also adapt to changing patterns over time, providing accurate forecasts for short-term and long-term horizons [9], [16]. However, these algorithms lack interpretability and require large amounts of training data. Overall, deep learning algorithms have transformed sales forecasting, enabling businesses to improve supply chain management, reduce costs, and increase sales. It is important to consider their limitations and evaluate their performance in specific contexts, [19.[

1.3 Background of sales forecasting in retail stores

Sales forecasting in the retail industry is crucial for effective planning, and machine learning models like LSTM and ARIMA have become the standard approach. These models can handle large datasets, extract insights, capture market movements, and identify factors that influence customer response[1],[2] .Studies have demonstrated the effectiveness of LSTM and ARIMA in sales forecasting, with high validation accuracy [3],[5]. They have been successfully applied in various industries, including retail. Time series data is important in retail sales forecasting, and deep neural networks like LSTM can improve forecast accuracy by capturing temporal dependencies. LSTM has shown promising results in apparel sales forecasting by leveraging its context-aware memory mechanism. Overall, LSTM and ARIMA models have significantly improved sales forecasting in retail by capturing market dynamics, extracting features, and making accurate predictions [23], [24], [26 .[

2.Overview of the prediction model

2.1 Definition of LSTM (Long Short-Term Memory(

Long Short-Term Memory (LSTM) is a powerful prediction model used in time series forecasting, particularly in sales forecasting for retail stores. The xDeepFM-LSTM combined forecasting model enhances the accuracy of predictions for apparel retail enterprises. It combines the xDeepFM algorithm, which captures sales influencing features, with LSTM for residual correction. The model outperforms other forecasting models such as CatBoost and LSTM in terms of forecasting performance. Accurate sales forecasting is crucial for apparel retailers to optimize marketing strategies and demand plans [6]. The xDeepFM-LSTM model significantly improves prediction performance by mining interactions between variables and utilizing residual correction. Further optimization studies and parameter optimization for LSTM can enhance the model's performance. Overall, the xDeepFM-LSTM model shows great potential in predicting merchandise sales and guiding decision-making processes for retail stores [25. [

2.2 Explanation of how LSTM analyzes patterns to forecast future sales

The Long Short-Term Memory (LSTM) model is a powerful tool for analyzing patterns and making accurate forecasts in the retail industry. LSTM is particularly suitable for time-series data, such as sales data, due to its ability to capture dependencies and relationships over long periods of time. In the context of forecasting retail store sales, LSTM analyzes historical sales data to identify patterns and trends that can be used to predict future sales.

One key advantage of LSTM is its ability to capture both short-term and long-term dependencies in the data. This is achieved through its recurrent neural network architecture, which allows information to be retained and utilized over multiple time steps. By learning from past sales data, LSTM can identify seasonal patterns, trends, and other factors that influence sales performance [8. [

In the case of the xDeepFM-LSTM combined forecasting model proposed in the research, the xDeepFM algorithm is first used to explore and model the correlation between various

features that impact sales. This step helps to uncover hidden relationships and interactions within the data. The resulting predictions from xDeepFM are then further refined using LSTM for residual correction. By incorporating LSTM into the forecasting process, the accuracy of the prediction model is improved [11.[
The combined xDeepFM-LSTM forecasting model has been compared with other forecasting models, including CatBoost and traditional machine learning algorithms. The experimental results demonstrate that the xDeepFM-LSTM model outperforms these models in terms of forecasting performance. Its higher optimization rate provides valuable insights for apparel companies seeking to adjust their demand plans.
Overall, LSTM's ability to analyze patterns in retail store sales data makes it a valuable tool for accurate forecasting. By leveraging historical data and capturing both short-term and long-term dependencies, LSTM can help retailers make informed decisions regarding their marketing strategies and inventory management. The combined xDeepFM-LSTM forecasting model proposed in this research represents a significant improvement over traditional methods, offering more precise predictions and guiding companies towards more effective sales strategies. [12], [13.[

2.3Comparison with ARIMA (Autoregressive Integrated Moving Average) model

In the field of retail sales forecasting, there are various models that can be used to predict future sales. One commonly used model is the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA is a statistical model that takes into account the linear trends and seasonality in sales data. It has been widely applied in different industries, including retail.
The ARIMA model has been used in combination with other models to improve the accuracy of sales forecasting. For example, in a study on vegetable sales forecasting, a combined model based on LightGBM and LSTM was proposed. This combined model was able to explore both the nonlinear and linear influences on vegetable sales, providing more accurate predictions compared to using a single model [2.[
One advantage of the ARIMA model is its simplicity. It only requires endo-variables without the need for other exo-variables. However, there are some limitations to consider. Firstly, the time-series data must be stable or stable after differentiation. Secondly, ARIMA can only capture linear relationships and may not be able to capture nonlinear relationships that are present in the data.
To overcome these limitations, LSTM (Long Short-Term Memory) models have been introduced in retail sales forecasting. LSTM is a deep learning algorithm that is able to process long time series data and capture complex patterns and dependencies. Unlike ARIMA, LSTM does not require sequence stabilization before modeling.
Comparing ARIMA with LSTM, it has been found that LSTM performs better in short-term forecasts with smaller forecast errors. This makes it a superior quantity-forecasting model for demand markets where fast and accurate short-term forecasts are crucial for procurement decisions [5.[
In summary, while ARIMA has been widely used in retail sales forecasting due to its simplicity and ability to capture linear trends and seasonality, LSTM models provide better performance by capturing nonlinear relationships and handling complex time series data

without requiring sequence stabilization. Therefore, a combination of both models can be beneficial in improving the accuracy of sales forecasting. See references: [11], [12.[

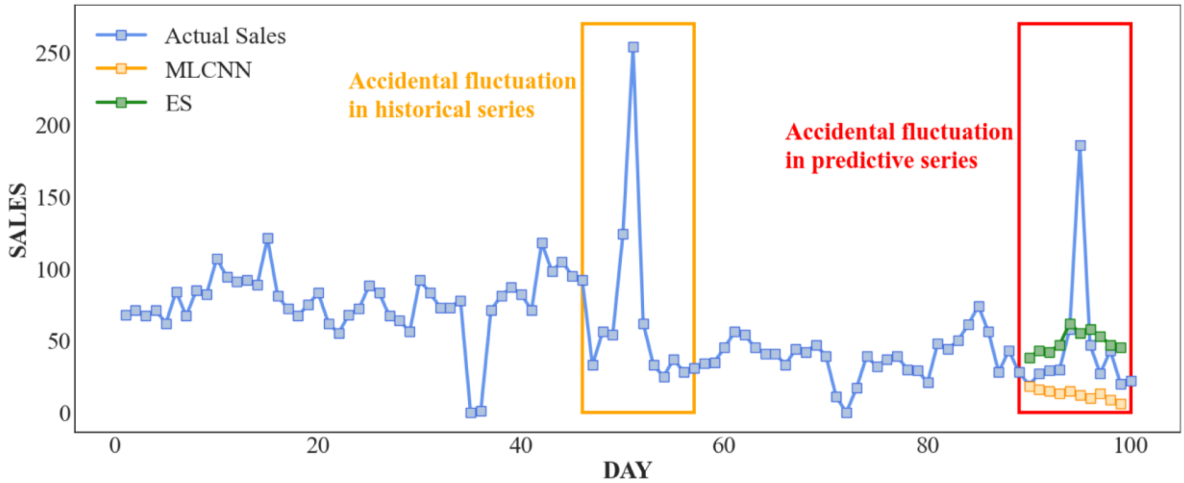

Figure 1: Sales sequence analysis: the blue line represents the sequence of real sales, the green line represents the prediction of the ES model, and the orange line represents MLCNN. (source: reference [2([

3. Advantages of using deep learning for retail store sales predictions

3.1 Ability to handle big data efficiently

Deep learning, specifically using models like LSTM, is advantageous in predicting retail store sales due to its ability to handle big data efficiently. Traditional forecasting methods struggle with non-linear models and fragmented sales data. LSTM can analyze various factors that influence sales, such as style, color, weather, and holidays. It can capture non-linear relationships and learn patterns missed by traditional methods. Other models, like xDeepFM-LSTM, explore correlations between sales-influencing features before applying LSTM for better accuracy [14]. Deep learning models enable retailers to make informed decisions regarding production plans, resource allocation, marketing strategies, and inventory management. They offer advantages in optimizing inventory management, improving customer satisfaction, and making informed business decisions. Further optimization studies can improve their performance in retail store sales predictions as technology advances. [18], [23.[

3.2 Increased accuracy compared to traditional methods

Deep learning models, such as LSTM and ARIMA, offer significant advantages over traditional methods in forecasting retail store sales. These models have shown increased accuracy compared to traditional time series and machine learning models.

One advantage of using deep learning models is their ability to capture complex patterns and relationships in the data. LSTM networks, for example, are designed to handle sequential data with long-term dependencies, making them well-suited for sales forecasting tasks. They can effectively model the non-linearity, uncertainty, and randomness often observed in retail sales data[7.[

In addition, deep learning models can handle large amounts of historical data and extract valuable insights from it. Retail stores generate vast amounts of data related to sales volumes, customer behavior, promotional activities, and more. By leveraging this data with deep learning models like LSTM and ARIMA, retailers can make more accurate predictions about future sales trends.
Moreover, deep learning models can incorporate various factors that influence retail sales. These factors include style, color, size, category of products, weather conditions, holidays, and even social sentiment. By considering these factors in the forecasting process through techniques like CNN-LSTM or encoder-decoder LSTM networks, retailers can enhance their understanding of consumer behavior and improve their prediction accuracy [12.[
Furthermore, deep learning models excel at handling large-scale real-time datasets. With the increasing availability of big data and powerful computing resources, these models can process information in a timely manner and provide up-to-date forecasts. This is particularly relevant in today's fast-paced retail industry where market conditions can change rapidly.
Overall, the application of LSTM and ARIMA models in forecasting retail store sales offers several advantages over traditional methods. These deep learning models can capture complex patterns in the data while incorporating various influential factors. They also handle large-scale datasets effectively and provide real-time insights for improved decision-making in inventory management and supply chain optimization. [20.[

3.3 Flexibility in capturing complex patterns and trends

Deep learning, particularly through models like neural networks and LSTM, offers advantages for retail store sales predictions. It can handle large amounts of data, capture intricate patterns, and adapt to changing trends. Traditional forecasting methods struggle with these complexities. LSTM models are effective in sales prediction, as they can capture long-range temporal dependencies. They are flexible enough to handle multivariate forecasting, considering factors like pricing, promotions, and seasonal trends. However, there are challenges associated with deep learning models, such as complex parameter setting. In conclusion, deep learning provides valuable insights for businesses to optimize their forecasting, improve decision-making, and enhance overall performance in the market. [20.[

4. Implementation and methodology of the LSTM algorithm for sales forecasting

4.1 Data preprocessing and feature engineering

Data preprocessing and feature engineering play a crucial role in implementing the LSTM algorithm for sales forecasting. In the context of forecasting retail store sales, the input data provides important insights into the application and methodology of the LSTM algorithm].
The xDeepFM-LSTM combined forecasting model is proposed to forecast merchandise sales data of an apparel retailer. The model starts by using the Extreme Deep Factorization Machine (xDeepFM) algorithm to model the store's product sales data from January 2018 to October 2019 and predict product sales in November 2019. This initial prediction serves as a basis for further refinement [22.[
To improve the accuracy of the forecasting model, residual correction is applied to the residuals of the prediction results. The residuals are mainly influenced by the characteristics of the commodities themselves and external factors. By incorporating feature influence factor data into the input data, it becomes possible to enhance the residual prediction effect.

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Furthermore, LSTM's unique gate structure in deep learning effectively eliminates useless historical information in the residual sequence while selectively retaining useful information. This capability helps improve forecasting accuracy.

Based on these considerations, a sales forecasting model called xDeepFM-LSTM is proposed. The algorithm flow chart of this model illustrates its step-by-step implementation see figure 2
.

In addition to LSTM, various other deep learning approaches such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU) have been used for time series forecasting in retail store sales. These techniques effectively handle complex time series data by capturing hidden patterns and nonlinear relationships [22.[
Overall, data preprocessing and feature engineering are essential steps in implementing and applying LSTM models for sales forecasting in retail stores. By incorporating various deep learning approaches, accurate predictions can be made to support decision-making processes across marketing, production, distribution, and finance departments [25], [27.[

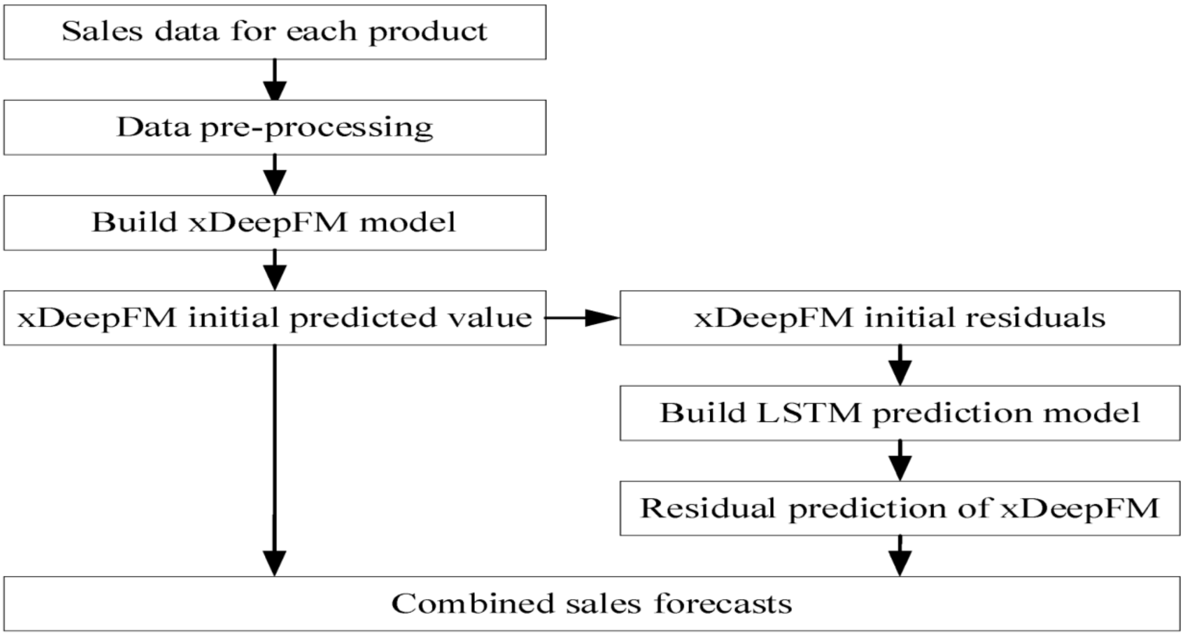

Figure 2: Flow chart of combined model prediction

4.2 Training the LSTM model with historical sales data

Sales forecasting is crucial for decision-making and profitability, but external factors make accurate forecasting challenging. LSTM and ARIMA models are gaining attention for addressing this issue. LSTM captures implicit information, outperforming traditional methods, and can fit each sales sequence independently. ARIMA struggles with large-scale multivariate time series data but improves when combined with LSTM. Deep learning models like LSTNet automatically extract features and capture dependency patterns across time. Retail store sales forecasting faces unique challenges due to unforeseen factors and dynamic changes influenced by external uncertainties. LSTM has been effective in various industries and multi-step time series prediction tasks. The combination of LSTM and ARIMA offers a

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promising approach by leveraging deep learning and traditional methods to capture complex correlations and fluctuations in sales sequences .

4.3 Fine-tuning and optimizing the model for better predictions

To improve sales forecasting accuracy, the LSTM algorithm is crucial. Research shows that deep networks like LSTM can capture implicit information and predict abnormal fluctuations in sales sequences. Hybrid hierarchical prediction schemes, combining LSTM with exponential smoothing models, have been successful in the M4 time series forecasting competition. Traditional methods like ARIMA, MA, RF, and XGBoost are still widely used but struggle with capturing nonlinear correlation patterns accurately. Exponential smoothing models have limitations in predicting nonlinear changes, leading to errors in multi-step predictions. Deep learning models like LSTM and LSTNet overcome these limitations by fitting each sequence independently and sharing general rules. Temporal fusion transformers automatically select relevant features and suppress unnecessary ones. ARIMA and LSTM are effective approaches for retail store sales forecasting, with ARIMA being simple to implement but limited to linear relationships, while LSTM addresses these limitations and provides accurate short-term forecasts. The validation of LSTM using actual data confirms its superiority in short-term forecasts, providing valuable insights for retail store managers. Implementing LSTM involves a structured process of training, hyperparameter tuning, validation, testing, and continuous monitoring. The benefits of LSTM models for sales forecasting include optimized inventory levels, enhanced planning, and adaptability to changing consumer behavior and external factors .

5. Evaluation and validation of the prediction model

5.1 Assessing the accuracy and performance of the LSTM algorithm

This study assesses the accuracy and performance of the LSTM algorithm for retail store sales forecasting. Traditional statistical methods struggle with large amounts of data and non-linearity, making deep learning techniques like LSTM valuable. The study discusses various deep learning approaches and their benefits and limitations. Performance evaluation metrics are used to assess the accuracy of prediction models. Deep learning approaches have been successful in accurately predicting sales and addressing challenges like changing customer needs and seasonal fluctuations. Comparisons with other forecasting methods have shown that deep learning models outperform in various contexts. LSTM has numerous benefits for retail store sales forecasting, including capturing complex temporal patterns and providing accurate demand forecasts. This leads to optimized inventory management and informed decision-making for promotions and restocking. See figure 3, [21.[

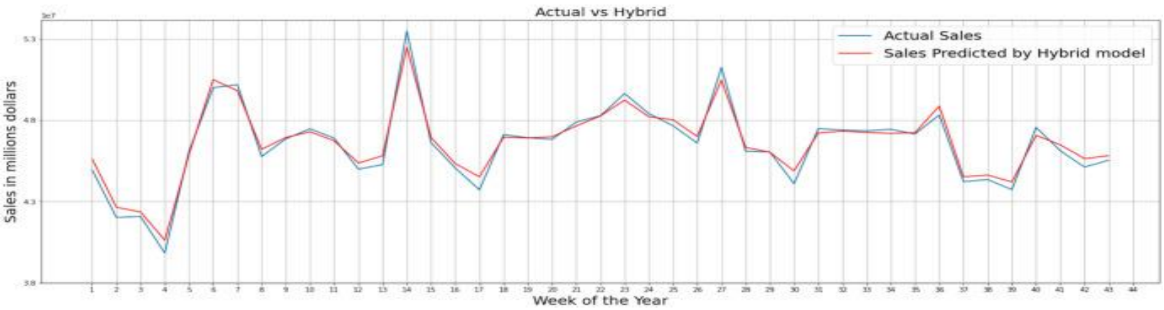

Figure 3: Comparison between actual sales and forecasting using the hybrid model (source: reference (21)

5.2 Comparing the results with other forecasting methods

Applying LSTM and ARIMA models in forecasting retail store sales has shown high effectiveness compared to other methods. LSTM excels at capturing complex temporal patterns, while ARIMA relies on historical data. Validation and testing are crucial to ensure the reliability of these models. Accurate forecasts from LSTM and ARIMA models help stores maintain optimal inventory levels, make informed decisions about promotions and restocking, and adapt to changing consumer behavior and market conditions[28]. The proposed LSTM model improves demand forecasting accuracy by up to 80%, leading to enhanced sales performance, reduced costs, and efficient labor allocation. Overall, LSTM and ARIMA models offer optimized inventory management, enhanced planning capabilities, and adaptability to changing market dynamics. Continuous monitoring and periodic retraining can further improve their performance and deliver reliable forecasts for retail businesses.:

5.3 Validating the reliability of the predictions through testing

Validating prediction models is crucial for accurate forecasting in retail store sales. This essay discusses the evaluation and validation of LSTM and ARIMA models in this context. One study used machine learning approaches, specifically LSTM layers, to analyze item sales data and generate accurate predictions. Another study focused on customer relationship management and used deep learning models to forecast demand in the catering industry, achieving improved accuracy compared to benchmarking methods. A comparative study evaluated different demand forecasting models and found that a method utilizing stacking algorithms outperformed others [23]. Several papers reviewed deep sequential models for time series data forecasting, providing insights for researchers. These studies demonstrate the importance of validating prediction models and highlight the potential for improving sales forecasting through machine learning techniques. Future research should address remaining challenges and explore hybrid algorithms for even greater accuracy: [25], [26.[

6. Case study: Application of LSTM for retail store sales prediction

6.1 Description of the dataset used for analysis

The dataset used for analysis in the case study on LSTM for retail store sales prediction includes various research works and studies in sales forecasting. One study focuses on using machine learning methods, incorporating POS data, weather information, and event data to forecast consumer numbers. Another study presents a deep learning approach for sales forecasting, considering various variables and comparing with other techniques. A research work constructs a sales prediction model for grocery stores using linear regression and achieves an 83% accuracy rate. Another paper explores the use of deep learning for sales forecasting in the fashion retail industry. A study on retail sales forecasting utilizes the Citadel POS dataset and evaluates various machine learning models. Finally, a hybrid model combining ARIMA and LSTM is proposed to improve sales forecasting accuracy and reliability.

6.2 Results and insights obtained from applying the LSTM model

The LSTM model has shown promise in predicting retail store sales by capturing implicit information and detecting abnormal fluctuations. The winning method in a time series forecasting competition combined exponential smoothing with LSTM networks for improved performance. Deep learning models, including bidirectional and encoder-decoder LSTM networks, have been effective in sales forecasting. LSTM has also been successful in various industries such as car sales and fashion. When applied to PT XYZ, deep learning techniques improved the accuracy of predicting minimarket store sales. Traditional methods and machine learning models face challenges with large-scale multivariate time series data, but deep learning models like LSTNet and temporal fusion transformers show promise. Overall, applying LSTM for retail store sales prediction provides valuable insights and improves forecasting accuracy due to their ability to capture implicit information and handle complex influencing factors

6.3 Discussion on practical implications and potential benefits for retailers

The combination of LSTM and ARIMA models in forecasting retail store sales has practical implications for retailers. Accurate sales forecasting is crucial for decision-making, affecting production, financial planning, marketing strategies, inventory control, supply chain management, and stock prices [15], [17.[

The ATLAS approach combines tensor factorization with ARIMA and LSTM models, providing accurate and individualized sales predictions across multiple stores and products. It handles large-scale data collections and extrapolates future sales trends.

Deep learning models have shown promising results in fashion retail sales forecasting, accurately predicting the sales of new products based on historical data and customer preferences.

Comparisons between deep learning models and traditional techniques in the fashion retail market show that deep learning approaches offer potential benefits in accuracy and flexibility.

Machine learning models like XGboost have successfully predicted sales in the grocery retail industry, improving forecasting accuracy and enabling effective competition in the market.

The hybrid approach of combining ARIMA and LSTM models has proven effective in sales forecasting, providing reliable and accurate forecasts in various contexts.

Overall, the application of LSTM and ARIMA models in forecasting retail store sales enhances decision-making processes and optimizes production, inventory management, marketing strategies, and financial planning: [18], [20.[

7. Conclusion

7.1 Summary of key points discussed in the essay

In this essay, we have discussed the application of LSTM and ARIMA models in forecasting retail store sales. We have highlighted the benefits of deep learning models, specifically DL models, which employ deep neural networks to learn hidden patterns from data. These models can represent data abstraction and develop computational methods by incorporating unique architectural assumptions. By eliminating the need for model creation and human feature engineering, DL models simplify the training process.

We have emphasized the importance of providing user communities with the best model for their specific problem based on performance in various fields. To achieve this, our research aims to comprehensively review current deep learning time series models and analyze their usage in different applications such as healthcare, finance and stocks predictions, weather forecasting, environment, pollution, and traffic flow. Our evaluation can assist researchers and practitioners in selecting the most suitable model that aligns with their scope and system requirements.

The main contributions of our paper can be summarized as follows:

(i) This is the first review work that covers the usage of deep sequential models for forecasting time series data.

(ii) We have provided a comprehensive review of the three common deep sequential models.

(iii) A detailed analysis of deep sequential models in different applications has been presented.

(iv) We have highlighted the main challenges associated with deep sequential models.

(v) We have identified research gaps and open issues that require further investigation in this field.

Furthermore, we have also discussed a novel hybrid model that combines LSTM networks and random forests through a genetic algorithm into an ensemble model. This hybrid model outperformed other methods in terms of bias, accuracy, and variance metrics when applied to demand forecasting. Additionally, we proposed auxiliary algorithms for generating daily and long-term forecasts using temporal aggregation and disaggregation methods.

Overall, our research aims to provide guidance to companies in making accurate sales predictions by leveraging advanced forecasting techniques. By analyzing sales data using LSTM and ARIMA models, we demonstrated that our hybrid approach offers improved prediction accuracy. This study contributes significantly to the literature on sales forecasting and provides valuable insights for businesses in their production planning processes .

7.2 Impact and potential future developments in predicting retail store sales using deep learning algorithms

In conclusion, the application of LSTM and ARIMA models in forecasting retail store sales has had a significant impact on the field. High-accuracy forecasting models have been shown to strengthen various processes of the supply chain, leading to improved organizational performance (Fildes et al., 2019). Previous studies have demonstrated the potential of deep learning methods, such as LSTM, in creating effective sales prediction models for retail stores (Kaneko and Yada, 2016) [2], [3.[

However, it is important to note that while deep learning models excel at capturing fluctuations in sales data, they may struggle with accurately predicting sudden large fluctuations. This poses a challenge in the research on retail store sales forecasting. External uncertainties, such as ad hoc marketing strategies or unforeseen factors, can lead to unusual fluctuations in sales series. Additionally, compared to other time series forecasting tasks, sales time series are more susceptible to these external uncertainties that can dynamically alter internal correlations between sales time series.

Despite these challenges, deep learning models offer numerous benefits for retail sales forecasting. They allow for the automatic extraction of hidden patterns from data without the need for extensive model creation or human feature engineering. DL models can learn complicated data representations and capture underlying correlations even in datasets with small differences. Furthermore, the availability of frameworks for back-propagation has made network training easier and more flexible (Optimization Methods) [20.[

The potential future developments in predicting retail store sales using deep learning algorithms are promising. The systematic literature review showed that DL models have been widely used for retail sales forecast. By analyzing various deep sequential forecasting models and their applications across different domains, researchers can identify the most suitable model based on their specific needs (Application - Healthcare). This comprehensive analysis can also help in developing novel algorithms to address existing challenges and fill research gaps

In conclusion, LSTM and ARIMA models have proven to be valuable tools in forecasting retail store sales. Their application has had a positive impact on organizational performance and store management (Data retrieved in the context of A Deep Learning Approach for the Prediction of Retail Store Sales). Although challenges exist, such as accurately predicting sudden large fluctuations, deep learning algorithms offer significant potential for future developments in this field. By further refining these models and addressing research gaps, retailers can enhance their forecasting capabilities and make informed business decisions: [23], [26.[

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