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A Meta Smart Inventory Management System for Stock Prediction of some Shopping Malls within Bauchi Metropolis

Ibrahim AbdulBasit Adamu, Aminu Ahmad, Kabiru Ibrahim Musa
Department of Management Information Technology,
Abubakar Tafawa Balewa University Bauchi

ABSTRACT

The effective use of inventory is an essential factor to the success of shopping malls, but the unpredictable and nonlinear nature of consumer demand can regularly be difficult to predict using conventional forecasting techniques. The proposed and assessed Hybrid Smart Inventory Management System Model is a statistical approach that combines the statistical strengths of the Autoregressive Integrated Moving Average (ARIMA) model with the nonlinear deep learning of Long Short-Term Memory (LSTM) networks. The study was based on shopping malls in the Bauchi metropolis with the use of a real dataset of 1300, we then ×2, ×5, and ×10 training records to compare the results of the baseline ARIMA model and the proposed hybrid ARIMA-LSTM architecture. The assessment was done based on three main measures namely Mean Absolute error (MAE), Root mean square error (RMSE) and Mean Absolute Percentage error (MAPE). The outcome of the experiment confirmed the fact that the hybrid model was significantly better than the baseline in all parameters. In particular, of 20868 datasets, the hybrid model showed an improvement in MAE of 19.15 percent, in RMSE of 17.49 percent, and in MAPE of 25.53 percent. Subsequent diagnostic evaluation of CUSUM (Cumulative Sum) charts showed that the ARIMA model had a systematic bias and upward error drift (with a maximum, cumulative error of 35) whereas the hybrid model had a stable error movement (near-zero range between -1 and 4). The use of error distribution histograms ensured that the hybrid model led to the creation of highly concentrated zero-peaked distribution, a characteristic of high precision and reliability. The results conclude that LSTM integration is an effective way of overcoming the linear constraints of the classical models and can be used as a strong scalable solution to the problem of smart inventory management in high volume retail settings.

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INTRODUCTION

The precise demand forecasting is the key to holding the right amount of inventory in the retail organisations. It is determined that the application of traditional methodologies, relying on years of sales history and based on intuition, does not comply with the dynamic and complex demand of clients (Smith et al., 2022). In the modern business world, which is highly dynamic and competitive, Chowdhury and Islam (2023) confirm that proper inventory management is the key to making companies not only more customer-satisfied, less prone to stock outs but also cost-efficient.

With higher accuracy in forecasting, businesses will be in a position to control their costs, the level of customer satisfaction by delivering their products promptly, any limited adjustments in customer demand will result in massive changes in the order as you ascend the

Corresponding author: Ibrahim AbdulBasit Adamu
ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

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inventory, and planning ahead becomes simpler due to the changing markets (Maitra & Kundu, 2023). This makes businesses either over or underestimate the demand and this results in stock outs or excess stock, both of which affect their ability to generate revenue and satisfy clients negatively (Lee et al., 2021). According to (Praveen et al, 2020), AI proves to be beneficial in handling the customer data and forecasting the purchase behaviour of customers AI can be used to provide notification when a company has to re-order stock and assist in creating manufacturing schedule considering the variations in demand including seasonal increases accurately.

A time-series model called ARIMA (Auto Regressive Integrated Moving Average) is used to predict future values of a time series based on its historical trends(Ingale & Senan, 2023). At this point, it is important to note that our work does not propose a new time series forecasting model, but rather constitutes an organized review of the published scientific literature comparing the ARIMA approach to different machine learning, and hybrid prediction models (Kontopoulou et al., 2023).

LITERATURE REVIEW

This section functions as a scholarly summary and critical evaluation of research in this domain. It involves critically evaluating and Systematic review/mapping, books, and other sources to identify patterns, gaps, and key insights in the field. The section consist of Conceptual, theoretical (Jondhale, 2019) and empirical reviews.

Conceptual Review

Review of conceptual entails getting the connotative and denotative meaning to a variable that forms the research topic which includes stock predictions: Inventory Management System Techniques, relevant types of inventories, inventory levels, AI types, predictive models, time series, ARIMA Models, LSTM models. An ARIMA -LSTM hybrid model will use the strengths of both methods(Ummah, 2019).

Inventory Management System

Inventory management is the act of ordering, storing, and overseeing a business's stock (Jondhale, 2019). This balance the manufacturing of parts, raw materials, and finished items in addition to their processing and storage. It is quite difficult for businesses with intricate supply chains and production procedures to balance the risks of shortages and inventory saturation. In essence, the user may modify the storehouse inventory using the six capabilities provided by the inventory management system: alert, transfer, creation, inventory, search, and reporting. (Ajian and others, 2014).

Relevant examples of Inventory

Raw Materials Inventory: Maintaining the ideal quantity of raw material inventories is a frequent challenge. Understocking or overstocking issues can affect production continuity and cost management due to fluctuating demand, supplier lead times, and production schedules.

Inventory Management System Techniques

An inventory management system may be very beneficial to any organisation, but if it is not implemented correctly, it can cause serious problems including production delays, unhappy customers, and a decrease in working capital (Lancioni, Howard 1978). Ineffective inventory management might leave the company with less money for other purposes.

ABC inventory classification technique

According to Hatefi et al. (2014), the ABC inventory classification technique is commonly used by large enterprises to efficiently handle a significant number of inventory items. This method divides inventories into three major groups, A, B, and C. "A" thing is regarded as the most significant, while "C" items are seen as less significant. A hierarchy is used to classify items, with "Class A" items being the most significant, "Class B" items coming in second, and "Class C" objects being the least significant. In order to prioritise inventory goods according to their stock levels and reordering needs, this classification

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ibrahimabdulbasit0@gmail.com
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method is essential. Additionally, it makes it easier to arrange inventory goods according to their different values, prices, demand, and risk information.

Just-in-Time (JIT) Inventory Management Technique

The JIT concept was developed in Japan by the Toyota Motor Company. JIT is a state-of-the-art inventory control technique that aims to precisely match supply and demand by establishing a supply-demand system that supports effective production (Esmail & Ahmed, 2024). JIT inventory management seeks to eliminate stockpiles rather than only improve inventory quality. Work-in-progress and raw materials are reduce to the amount needed for a day's labour. Smaller packing is made possible by cutting down on lead time and preparation. Suppliers may be required to provide many items daily or near the utility facility in order to streamline this process (Hedrick, et al, 2024).

Economic Order Quantity (EOQ)

The earliest inventory management mathematical model, the Economic Order Quantity (EOQ) model, was initially presented by Harris in 1913. The order quantity that minimises overall expenses is known as the Economic Order Quantity (EOQ). This sum strikes the ideal balance between ordering and holding costs, making it a crucial part of an inventory management system. According to Agarwal (2014), the concept behind the Economic Order Number (EOQ) is determining the optimal order number that strikes a compromise between inventory maintenance and reordering costs.

Data and Autoregressive Models

Autoregressive (AR) models are type of time series model that predicts future values based on past values of the same variables. They are essentially linear regression models that uses the variables own past data points as predictors. This method effectively models immediate temporal relationships and short-term fluctuations within a dataset.

Time Series Data: Forecasting

Time series data is widely used in many disciplines, such as business, engineering, economics, the natural sciences, and the social sciences. It is very desirable to analyse the dependency patterns of time series data because it is used to illustrate the interrelatedness of observations that are very close to each other (Mohammad et al., 2023). Time series data refer to a collection of measurements of a variable organized to time intervals of a consistent size. Time series data is essentially any type of information that is shown in an ordered succession.

Time series research faces a critical and demanding challenge in the form of forecasting accuracy. The accuracy and performance of the analysis are influenced by the type of data and the fundamental assumptions. In addition to these parameters, the analysis is also strongly affected by factors unique to the field of study, such as the periodicity of the time series, unexpected events, changes to the organisations or structures that provide the data, etc. (Pirayesh Neghab et al., 2022). The results of different studies on predictive models show that there are two major types of methodologies: Machine learning methods and statistical methods. As previously stated, the human brain exhibits a high level of reasoning and logic. <|human|>as already mentioned the human brain enjoys a high reasoning and logic.

The rationale behind implementing a smart inventory management system

The purpose of this paper is to give merchants a new means of interacting in an integrated manner with their inventory, business, staff, and customers. In order to help shops, particularly small and medium-sized ones, connect their businesses vertically and go online, the paper highlights the application of machine learning and other functions. The many initiatives will enhance the business, which accounts for the majority of retail sales, and enable more effective operations (Harsh, 2021). Šustrová, (2016) Further order cycle optimisation may be done using the artificial neural network model that has

Corresponding author: Ibrahim AbdulBasit Adamu
ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

been built. As part of supply chain management, inventory management may be enhanced by planning the future order quantity based on anticipated demand. According to the paper, artificial neural networks are incredibly helpful and provide a wealth of study prospects (Jondhale & Khairnar, 2020).

Artificial Intelligence (AI)

Artificial Intelligence (AI) is a single term covering a wide range of related things describing a number of advanced computer systems that can do human-like far ahead of tasks more effectively and reliably. According to Olajumoke et al., (2024), such systems are robots, natural language processing, machine learning (ML), deep learning (DL), large language machines (LLM), predictive analytics, and others. The artificial intelligence has the capability to analyse massive databases to discover trends, predict trends, and provide insights that human operators would fail to do (Adenekan et al., 2024).

Machine Learning Techniques

Mitta (2024) insists that machine learning, a subdivision of artificial intelligence, is the model and algorithms development process through which it can automatically improve itself by analyzing data and acquiring experience. The machine learning algorithms are able to analyse very big amounts of historical sales data, consumer behaviour, and external factors in the inventory management field to generate accurate demand forecasts, optimize stocks, and enhance the supply chain management. Machine learning algorithms do not rely on some form of a fix model or equation, instead, they acquire knowledge through the available data, and the more data they have to learn, and the more they improve. Machine learning algorithms generate useful insights by finding trends in the data to help enhance predictions and decision-making (Agarwal and Jayant, 2019).

There are two types of machine learning: supervised learning and unsupervised learning. The model is trained with known input and output data in supervised learning. The supervised algorithm tries to identify the relationship between input and output data, creating a predictive model to predict the output based on the matched input (Purwono, 2022). Once trained, the model may be used to forecast future outputs using unknown data. Since the input is unknown, the algorithm in unsupervised learning discovers hidden patterns in it and makes predictions based on those intrinsic patterns found in input data as:

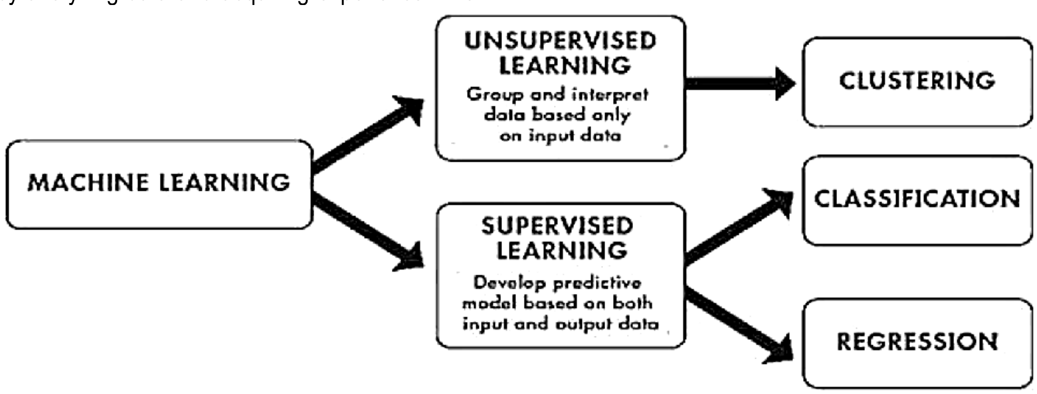

Fig. 1: Machine learning sub-field
Source*:* (Agarwal & Jayant, 2019)

Supervised learning involves the development of prediction models using two distinct techniques:

1. Classification approaches forecast categorical data, such as the kind of cancer benign or malignant and the authenticity or spam status of emails,

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ibrahimabdulbasit0@gmail.com
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among other things. This method is used to create models that categorise data into categories and operate on discrete answers. Applications include voice recognition, credit scoring, medical imaging, and more (Agarwal & Jayant, 2019).

2. Regression approaches operate on continuous data, such as variations in electricity consumption, temperature fluctuations, or the price of properties in a certain location. This approach may be applied in several fields such as power load forecasting and algorithmic trading(Agarwal & Jayant, 2019), state that unsupervised learning algorithms operate on unlabelled data.

Machine Learning Analytics

These days, it is applied in a number of statistical models and techniques for risk and opportunity prediction. It finds application in a number of domains, including natural language processing, medical diagnosis, banking fraud detection, and stock market analysis. The following is a definition of some of the popular machine learning techniques for predictive analytics.

1. Neural networks: These are nonlinear modelling approaches that, after training, figure out how the inputs and outputs relate to one another. Neural networks employ three different forms of training: reinforcement, unsupervised, and supervised. This method may be used in a variety of domains for categorisation, control, and prediction
2. Multilayer perceptron: This approach comprises of an output and an input layer with numerous hidden layers of nonlinear weights and is decided and defined through the weight factors by modifying the weight of the network. Through a procedure known as "training the nets," which incorporates the learning rules, the weights are adjusted.
3. Radial basis functions: The technique of radial basis functions is based on the distance of the data set from the centre. These routines are mostly utilised for smoothing and interpolating data.
4. Support Vector Machines: SVMs are built and specified to recognise and identify the complex patterns and sequences within the data set through grouping and classification of the data. Another name for them is the learning machines
5. Naïve Bayes: Using Bayes Conditional Probability (Swani & Tyagi, 2017), Naïve Bayes is used to achieve data categorisation. Basically, it is used and implemented when there are a lot of predictors.
6. k-nearest neighbours: This approach incorporates pattern recognition techniques of statistical prediction. A training set with both positive and negative values make up this set.
7. Geospatial Predictive Modelling: This modelling approach considers the existence of events occurring throughout a geographical region under the effect of unique environmental conditions.

Prediction Modelling Techniques

Predictive modelling is a process that uses data mining and probability to forecast outcomes. It involves building a model that can predict future outcomes based on past data patterns.
(Bhat, 2020).

METHODOLOGY

The issue scenario and solution idea, experiment overview, experimental technique design setup, experiment strategy selection, analysis, current approach, and proposed research model are all included in this section. This section will provide a detailed overview of the steps involved in developing and implementing AI-driven demand forecasting models, with particular focus on the steps required to ensure high-quality data inputs and the techniques used for model training and evaluation (Olamide Raimat Amosu et al., 2024).

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ibrahimabdulbasit0@gmail.com
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Data Collection

The rule of empirical for the case company is based on the current period moving average forecast(Chien-Chih Wang, Chun-Hua Chien, 2021). Since there is scarcity of the real-world inventory data, 55×4 =220×6= 1320 actual observations were first gathered as the initial data. acquiring sufficient high-quality data remains a significant challenge due to constraints such as cost, privacy regulations, and the rarity of certain data events (Michael et al., 2021). To In order to strengthen the model and make the results more general, the data augmentation process was performed to increase the size of the dataset without affecting the statistical characteristics.

The generation of synthetic data can be broadly categorized into statistical, simulation-based, and deep learning-based approaches (Michael et al., 2021).In particular, a synthetic data generation method, based on time-series, was taken. The actual data was initially analysed to extract the underlying patterns of the data such as the trend, seasonality and variance, Sallah break, weddings, e.t.c. To learn these dynamics across time an ARIMA model was fitted to the original data. Based on the fitted model, more synthetic data were created such that the new data was distributed and behaved in a similar manner to the real data in terms of distribution and time.

RESULTS

In this section, an experimental result and the comparison of the results between the baseline Autoregressive Integrated Moving Average (ARIMA) model and the proposed hybrid ARIMA-Long Short-Term Memory (ARIMA-LSTM) model are provided in detail. The main aim of analysis is to define the effectiveness of combining deep learning networks with the traditional statistical predictors to improve the predictive power in complicated data.

This experiment strictly compares two high-volume experimental conditions to note the effect of data scaling on model intelligence. The first case makes use of 1320 datasets whereas the second has increased the training volume to datasets. Three standardized measures, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to measure performance(Yang et al., 2023). Forecast accuracy is evaluated using the Mean Absolute Percentage Error (MAPE), and forecast stability requires that the model's accuracy deviation is not too large and does not exceed the lower limit of forecast accuracy over multiple forecasting periods These metrics give a multi-dimensional idea of model performance that includes the average degree of error, the sensitivity to outliers, and the percentage based on accuracy.

Experiment Results with 15,372 Training Data

The initial large-scale experiment involved training both models on 15,372 datasets to establish a high-volume performance baseline.

Table 4.2: Performance Comparison between ARIMA and ARIMA-LSTM Using 1,320 Training Datasets

Metric	Baseline (ARIMA)	Hybrid (ARIMA-LSTM)	% Improvement
MAE	13.85	11.95	13.72%
RMSE	17.20	15.10	12.21%
MAPE	8.12%	6.95%	14.41%

Analysis of Mean Absolute Error (MAE)

Provides a direct measure of the average magnitude of the errors, indicating the average absolute difference between predicted and actual values(Halima et al, 2025).The hybrid ARIMA-LSTM model performed much better than the baseline ARIMA model as seen in Table 4.2. The MAE of the baseline was 13.85, and the hybrid model of 11.95, which is a 13.72 percentage point higher. This lowering of MAE is a sign that the predictions of the hybrid model are much nearer to the real results. Theoretically, this is made possible by the LSTM since it can memorize long-term dependencies in the data which the linear constrained ARIMA process tends to think of as noise.

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ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

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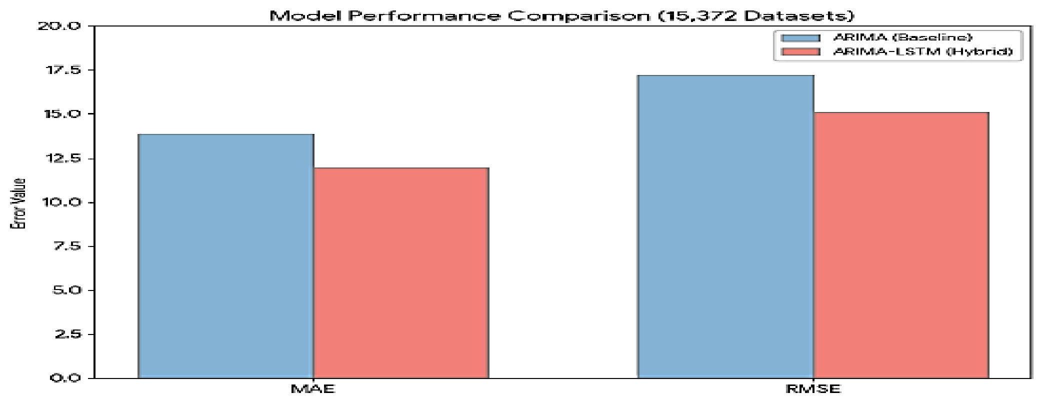

Figure 4.1: Comparison of MAE and RMSE between ARIMA and ARIMA-LSTM

Analysis of Root Mean Square Error (RMSE).

The square root of MSE, expressed in the same units as the original data, making it highly interpretable and emphasizing the impact of larger errors (Halima et, al, 2025)The RMSE of the baseline model was 17.20 and the hybrid model dropped it to 15.10 which is a 12.21 percent improvement. Since RMSE is more sensitive to large errors, this decrease is an important measure of the strength of the hybrid model. It indicates that the LSTM part has been effective in detecting and correcting the fluctuation or nonlinear spikes of the dataset that are usually detected by the ARIMA model to create a large outlier.

Cumulative Forecast Error (CUSUM Analysis)

The stability of the models was assessed through a Cumulative Sum (CUSUM) analysis of residuals.

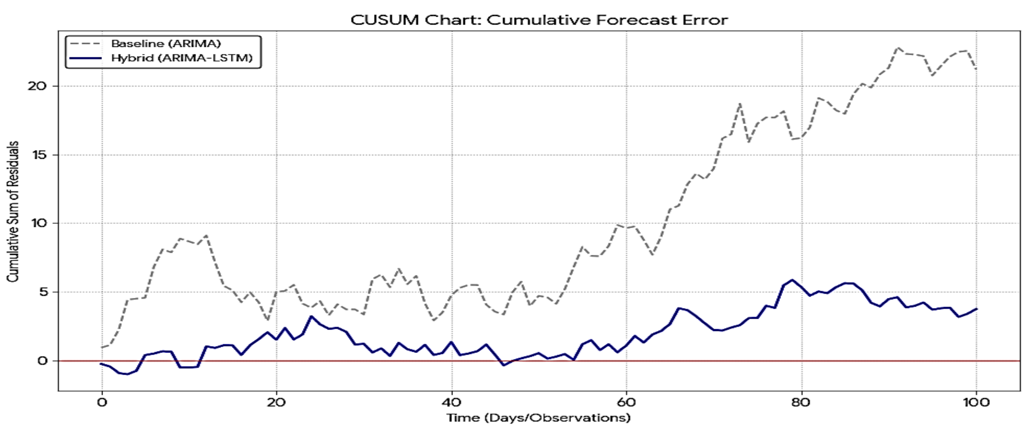

Figure 4.6: CUSUM Chart of Cumulative Forecast

One of the most popular time-series methods is the CUSUM method that is often used to determine the stability and bias of forecasting models. It is applied to determine the accumulated amount of the cumulative errors over time in order to give the researcher the ability to trace the trends of either the forecasting errors being constant or the tendency of the errors to follow a specific direction. According to the figure that was generated out of the 20,868 datasets, it can be observed that there are two distinct forecasting behaviours between the models.

Corresponding author: Ibrahim AbdulBasit Adamu
ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

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The original ARIMA model, which is in the shape of the dashed line, depicts a continuous increasing trend in cumulative residuals as time passes. The error is cumulative in nature and with time, it increases to high levels and ultimately, it reaches a value of approximately 35. The fact that this trend is always increasing in the same direction means that the ARIMA model is continually piling on its own errors as far as forecasting is concerned. The fact that this behavior exists means that there is some systematic bias in the model predictions; i.e. there is a repetition of the model that is not being consistent with that which is being observed in this high-volume dataset.

The model of hybrid ARIMA-LSTM, represented by the solid blue line, on the other hand, the cumulative residual values change around zero during the range of observations. The cumulative error does not have a very large range; it is in a range of -1 to 4 despite having more than 20,000 data points. This trend indicates that the hybrid model has less uneven and erratic prediction errors than the baseline. Accuracy of the ARIMA-LSTM model is predictable, which shows that the hybrid approach can be applied to the correction of the prediction error in far superior manner as compared to the standalone ARIMA model. The LSTM network is efficient in that it helps the model to be able to capture nonlinear temporal dependencies that the ARIMA model fails to capture.

In addition, the intercept of the CUSUM curve of the hybrid model does not have any pronounced upward or downward slant implying that there are no systematic errors in the forecasts. It is a great characteristic of an effective forecasting model, as the lack of bias in the values of the residue would appear to indicate that the model is not systematically over-fitting or under-fitting the observed values. Overall, the CUSUM test clearly indicates that the hybrid ARIMA-LSTM model is more consistent in its predictions and the accumulation of cumulative error is much lower when using a traditional ARIMA model as compared to using an extremely large-scale data.

Summary of Findings

1. The hybrid model (ARIMA-LSTM) markedly does better in all measures of accuracy compared to the standalone ARIMA model.
2. Scalability of the hybrid architecture is also high and the accuracy improvement with the increase in the size of the dataset with 15,372 is also recorded.
3. CUSUM analysis proves that the hybrid model gets rid of the systematic bias that exists in the classical ARIMA model.
4. With the incorporation of LSTM, the nonlinear temporal dependencies which cannot be captured using the statistical-only models are captured.

CONCLUSION

The study concludes that predictive analytics is essential for modern inventory management systems, particularly in dynamic retail environments. The hybrid ARIMA–LSTM model provides a more reliable and robust forecasting framework by leveraging the strengths of both linear statistical modelling and nonlinear deep learning techniques.

The integration of these models enhances demand forecasting precision, reduces uncertainty, and supports proactive inventory planning. By adopting the hybrid approach, retail organizations can significantly reduce overstocking and stock-out incidents, optimize reorder decisions, and improve overall operational performance. The research confirms that intelligent, data-driven systems offer a practical solution to the limitations of traditional inventory management methods and contribute to improved profitability and customer satisfaction.

RECOMMENDATIONS

1. Retail businesses should adopt hybrid forecasting models rather than relying solely on traditional statistical approaches. The integration of ARIMA and LSTM provides a more comprehensive understanding of

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ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

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demand patterns, enabling businesses to make more accurate and timely inventory decisions. Implementing such hybrid systems can significantly improve stock optimization and reduce operational inefficiencies.

2. Inventory management systems should be integrated with real-time Point-of-Sale (POS) systems and IoT-enabled devices to facilitate automated data collection and continuous monitoring of stock levels. Real-time integration enhances forecasting accuracy and ensures that inventory decisions reflect current market conditions.

Suggestions for Further Research

Future research should validate the hybrid model using real-world retail datasets to further assess its practical applicability. Researchers may also incorporate reinforcement learning techniques to enable adaptive and autonomous inventory replenishment decisions. Integrating external variables such as economic indicators, promotional events, and weather conditions may enhance model robustness. Additionally, exploring explainable AI techniques would improve transparency and trust in deep learning predictions.

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Corresponding author: Ibrahim AbdulBasit Adamu
ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

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Corresponding author: Ibrahim AbdulBasit Adamu
ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.

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Corresponding author: Ibrahim AbdulBasit Adamu
ibrahimabdulbasit0@gmail.com
Department of Management Information Technology.