ISNN:2181-1296

SHAROF RASHIDOV NOMIDAGI
SAMARQAND DAVLAT UNIVERSITETI

САМАРКАНДСКИЙ ГОСУДАРСТВЕННЫЙ
УНИВЕРСИТЕТ ИМЕНИ ШАРОФА РАШИДОВА

SAMARKAND STATE UNIVERSITY NAMED
AFTER SHAROF RASHIDOV

ILMIY AXBOROTNOMA

НАУЧНЫЙ ВЕСТНИК
SCIENTIFIC JOURNAL

ANIQ VA TABIIY FANLAR SERIYASI

Matematika, Mexanika, Informatika
Fizika, Kimyo, Biologiya, Geografiya

№ 3/2 (151)
2025

ISSN 2181-1296

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Samarqand viloyat matbuot boshqarmasida ro‘yxatdan o‘tish tartibi 09-25.
Jurnal 1999-yildan chop qilina boshlagan va OAK ro‘yxatiga kiritilgan.

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Obuna indeksi – yakka tartibdagi obunachilar uchun **- 5583,**
tashkilot, korxonalar uchun **- 5584**

M U N D A R I J A
C O N T E N T S

№	Maqola nomi	Article title	Bet/ page
1	Kasr psevdoparabolik tenglama uchun Samarskiy-Ionkin ikki nuqtali chegaraviy shartlar **Sagdullaeva M.U., Xasanov G.A., Yuldashev T.K.**	Samarskii-Ionkin two-point boundary conditions for a fractional pseudoparabolic equation **Sagdullaeva M.U., Khasanov G.A., Yuldashev T.K.**	**5-14**
2	Gerasimov-Kaputo turidagi kasr tartibli nochiziqli differensial tenglamalar **Shukurova M.D., Xasanov G.A., Yuldashev T.K.**	Nonlinear differential equation with Gerasimov-Caputo type fractional operator and degenerator **Shukurova M.D., Khasanov G.A., Yuldashev T.K.**	**15-22**
3	NaH da lazer ta'sirida dissotsiatsiya dinamikasi **Umarov O., Jumabaev A.**	Laser-induced dissociation dynamics in NaH **Umarov O., Jumabaev A.**	**23-30**
4	Radon transformasidan foydalanish, tasvirni tanishda aylana sfera proyeksiyasini yaratish **Khatamov O., Mamanova B.**	Using the radon transform to create a projection of a circular sphere in image recognition **Khatamov O., Mamanova B.**	**31-38**
5	Flavonoid komplekslarining metal ionlari bilan sintezi, spektroskopik tadqiqotlar va supramolekulyar tizimlar **Ergashova Sh., Muxamadiyev N.**	Synthesis of flavonoid complexes with metal ions, spectroscopic studies and supramolecular systems **Ergashova Sh., Mukhamadiev N.**	**39-45**
6	2-benzil-6,7-dimetoksi-1,2,3,4-tetragidroizoxinolin hosilalari sintez reaksiyalarini o'rganish **Suyunova S.N., Quljonov J.X., Xudoyberdiyeva A.A., Urunbayeva Z.E. Z.E., Saidov A.Sh., Vinogradova V.I.**	Study of the reactions of synthesis of 2-benzyl-6,7-dimethoxy-1,2,3,4-tetrahydroisochinoline derivatives **Suyunova S.N., Kuljonov J.X., Khudoyberdieva A.A., Urunbaeva Z.E. Z.E., Saidov A.Sh., Vinogradova V.I.**	**46-50**
7	Keyingi qo'shni tugunlargacha o'zaro ta'sirlanuvchi ikki bozonli panjara gamiltoniani **Axmadova M., Axmatova Sh.**	A two-boson lattice hamiltonian with interactions up to next-neighboring sites **Akhmadova M., Akhmatova Sh.**	**51-58**
8	Sekin aylanishli magnitlangan neytron yulduzlarning plazma magnitosferasi o'zgartirilgan gravitatsiyada **Sayfiyev Sh.**	Plasma magnetosphere of slowly rotating magnetized neutron stars in modified gravity **Sayfiev Sh.**	**59-65**
9	Vaqtli qatorlar va mashinaviy o'qitish asosida sotuvdagi kechikishlarni aniqlash usullari **Nazarov F., Sayidqulov A.**	Methods for detecting delays in sales based on time series and machine learning **Nazarov F., Sayidkulov A.**	**66-71**
10	Integrallashgan matematik modellar va ularning qo'llanilishi **Safarov R., Xudoyberdiyev S.I.**	Integrated mathematical models and their applications **Safarov R., Khudoyberdiyev S.I.**	**72-77**
11	Chekli zichlikka va qator ko'rinishdagi moslangan manbaga ega Hirota tenglamasi uchun boshlang'ich qiymat masalasi **Eshbekov R.**	The initial value problem for the Hirota equation with finite density and self-consistent series source **Eshbekov R.**	**78-84**
12	L-sistein bilan modifikatsiyalangan mezog'ovak silikagel yordamida og'ir metall kationlarini ajratish **Ulugboyeva G.O., Kuliboyeva N.Sh., Uzokov J.R., Fazliyeva N.T., Muxamadiev N.Q.**	Removal of heavy metal cations using mesoporous silicagel modified with L-cysteine **Ulugboeva G.O., Kuliboeva N.Sh., Uzokov J.R., Fazlieva N.T., Mukhamadiev N.Q.**	**85-90**
13	Titan nano oksidi sintezi va uning fotokatalitik xossalarini zarracha o'lchamiga bog'liqligi **Mamaziyeva S., Avazova N., Tashmatova R., Muxamadiev N., Muxamadiev A., Uzokov J.**	Synthesis of nano titanium oxide and dependence of its photocatalytic properties on particle size **Mamazieva S., Avazova N., Tashmatova R., Mukhamadiev N., Mukhamadiev A., Uzokov J.**	**91-96**
14	$SrTiO_3$ nanozarrachalarini sintez qilish va ularning o'lcham-fotokatalitik xossalari **Hayitova M., Baxranova M.A., Muxamadiyev N.Q.**	Synthesis of $SrTiO_3$ and its size-dependent photocatalytic properties **Hayitova M., Bakhranova M.A., Mukhamadiyev N.Q.**	**97-102**

№	Maqola nomi	Article title	Bet/ page
15	Rekreatsiya maqsadlarida tabiatdan foydalanishni boshqarish **Rafikova N.**	Management of nature utilization for recreational purposes **Rafikova N.**	**103-110**
16	Modifikatsiyalangan faollashgan ko‘mir yordamida eritma tarkibidagi organik bo‘yoqlarni ajratish **Ergasheva D., Muxamadiyev A., Muxamadiyev N., Uzokov J.**	Separation of organic dyes from solutions using modified activated carbon **Ergasheva D., Mukhamadiyev A., Mukhamadiyev N., Uzokov J.**	**111-116**
17	Neyron tarmoqli modellar asosida qandli diabetni tashxislashning intellektual algoritmlari **Sariyev Sh.N.**	Intelligent algorithms for diagnosing diabetes mellitus based on neural network models **Sariev Sh.N.**	**117-123**
18	Mahalliy kaolindan seolitlar sintez va fizik-kimyoviy tahlili **Magdiev Sh., Majidova F., Nasimov A., Tashpulatov X., Toshpulatov D., Mirzayev Sh., Norboev K., Normuradov O.**	Synthesis and physicochemical analysis of zeolite from local kaolin **Magdiev Sh., Majidova F., Nasimov A., Tashpulatov Kh., Toshpulatov D., Mirzaev Sh., Norboev K., Normuradov O.**	**124-129**
19	Densenet modelini transfer o‘qitish asosida masofadan zondlash sahnalarini tasniflash aniqligini oshirish maqolaning o‘zbek tilidagi nomi **Yusupov O.R., Eshonqulov E.Sh.**	Enhancing the accuracy of remote sensing scene classification using transfer learning with densenet **Yusupov O.R., Eshonkulov E.Sh.**	**130-144**
20	Neft va gaz quduqlari minerallashgan qatlam suvlarining kimyoviy tarkibi va fizik-kimyoviy xususiyatlarini o‘rganish **Kenjaev N.A., Igamkulova N.A.**	Chemical composition and physico-chemical properties of mineralized formation waters from oil and gas wells **Kenjaev N.A., Igamkulova N.A.**	**145-148**

UDC: 004 (004.8) **DOI: https://doi.org/10.59251/2181-3973.2025.v1.138.1.3556**

METHODS FOR DETECTING DELAYS IN SALES BASED ON TIME SERIES AND MACHINE LEARNING

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Received: 16.06.2025
Revised: 30.06.2025
Accepted: 14.07.2025
Published: 31.07.2025

Publisher: Samarkand State University named after Sharof Rashidov.

Abstract. Delays in product delivery or failure to promptly meet demand during the sales process negatively impact economic efficiency. This article explores the use of time series analysis and machine learning algorithms to detect delays in sales. Based on data analysis, the study identifies patterns, temporal dependencies, and other influencing factors of such delays. ARIMA, SARIMA, and LSTM models are utilized and their performance metrics are compared. The research results provide opportunities to forecast potential delays and minimize their impact on business processes.

Keywords: time series, machine learning, sales delay, ARIMA, SARIMA, LSTM, forecasting, sales analysis, intelligent analytics.

Vaqtli qatorlar va mashinaviy o‘qitish asosida sotuvdagi kechikishlarni aniqlash usullari

Annotatsiya. Sotuv jarayonida mahsulotlarning kechikib yetkazilishi yoki talabga javoban o‘z vaqtida ta'minlanmasligi iqtisodiy samaradorlikka salbiy ta'sir ko‘rsatadi. Ushbu maqolada sotuvdagi kechikish holatlarini aniqlashda vaqtli qatorlar tahlili va mashinaviy o‘qitish algoritmlarining imkoniyatlari o‘rganiladi. Ma'lumotlar tahliliga asoslangan holda kechikishlarning takroriyligi, vaqtga bog‘liqligi va boshqa omillar aniqlanadi. Model sifatida ARIMA, SARIMA, LSTM kabi usullar qo‘llanib, ularning samaradorlik ko‘rsatkichlari solishtiriladi. Tadqiqot natijalari, biznes jarayonlarida kechikishni oldindan bashorat qilish va uni minimallashtirish imkonini beradi..

Kalit so‘zlar: vaqt qatorlari, mashinaviy o‘qitish, sotuvdagi kechikish, ARIMA, SARIMA, LSTM bashoratlash, savdo tahlili, intellektual tahlil.

Алгоритмы выявления задержек в продажах на основе временных рядов и методов машинного обучения

Аннотация. Задержка в доставке товаров или невозможность оперативного удовлетворения спроса в процессе продаж негативно влияет на экономическую эффективность. В данной статье рассматриваются возможности анализа временных рядов и алгоритмов машинного обучения для выявления случаев задержек в продажах. На основе анализа данных определяются повторяемость задержек, их временная зависимость и другие факторы. В качестве моделей применяются методы ARIMA, SARIMA и LSTM, а также проводится сравнительный анализ их эффективности. Результаты исследования позволяют прогнозировать возможные задержки и минимизировать их влияние на бизнес-процессы.

Ключевые слова: временные ряды, машинное обучение, задержки в продажах, ARIMA, SARIMA, LSTM,

прогнозирование, анализ продаж, интеллектуальный анализ.

Introduction. In today's fast-paced and competitive economic environment, timely delivery of products and prompt fulfillment of customer demands is one of the key strategic factors for any company. Delays that occur, especially in the field of sales—meaning that products are not delivered promptly in response to demand or that stock levels are insufficient—negatively impact customer satisfaction and the company's reputation. Such delays can result in lost sales, decreased customer flow, and increased operational costs.

To effectively address this issue, modern analytical approaches, particularly time series analysis and machine learning algorithms, are becoming increasingly relevant. These approaches allow for the forecasting of delays in the sales process, identifying their recurring characteristics, and analyzing time-dependent patterns.

This article analyzes algorithmic approaches to identifying and predicting delays in sales using time series models such as ARIMA, SARIMA, and LSTM, as well as machine learning methods like Random Forest, based on historical sales data. Based on the research findings, useful recommendations are developed for companies regarding inventory management, logistics planning, and improving service levels.

Related Literature. The task of detecting and forecasting delay situations in sales systems has become one of the most pressing issues today. Addressing this problem requires the use of models and algorithms that capture temporal variability. From this perspective, time series models such as ARIMA and its advanced form SARIMA, as well as deep learning models like LSTM (Long Short-Term Memory), are considered highly relevant methods.

The ARIMA (AutoRegressive Integrated Moving Average) model, first introduced by Box and Jenkins in the 1970s, is designed to work with time-dependent and non-stationary data. This model captures the internal structure of time series data using autoregressive (AR), differencing (I), and moving average (MA) components. Numerous studies have demonstrated the high forecasting accuracy of ARIMA, particularly in applications related to sales volume and price dynamics.

SARIMA (Seasonal ARIMA) is an extension of the ARIMA model that accounts for seasonal patterns in time series data. It enables modeling of recurring cycles such as yearly, monthly, or weekly trends, making it especially useful in sales processes where seasonality plays a significant role. The SARIMA model effectively captures variations in purchasing volume that occur due to external factors.

In addition, LSTM (Long Short-Term Memory), a deep learning model based on recurrent neural networks (RNN), was proposed by Hochreiter and Schmidhuber in 1997. LSTM has the capability to retain long-term dependencies, making it particularly useful for forecasting based on time series data. By leveraging input, output, and forget gates, the LSTM model can learn complex patterns in sequential data. In recent years, LSTM has seen increasing use in the analysis of sales data and the identification of delay patterns.

Each of these three models—ARIMA, SARIMA, and LSTM—has its own strengths and limitations, and their performance varies depending on the characteristics of the data. Therefore, applying them to real-world sales data allows for comparative analysis and evaluation of their effectiveness.

Research Methodology. In this study, real sales data from a poultry product distribution company operating in Samarkand city was analyzed. The primary objective of the research is to identify and forecast sales delay events that occur over time by utilizing time series and machine learning models.

The first and most crucial step involved the collection of the dataset. The data consisted of daily sales transactions recorded by the company between the years 2023 and 2025. Each entry represents detailed information about an individual product sale (Table 1). The dataset includes the following columns:

- *day* – the specific day on which the sale occurred;
- *month* – the month of the sale;
- *year* – the year of the sale;
- *product_id* – the identifier of the product;
- *agent_id* – indicates the region or agent responsible for the sale;
- *quantity_sold* – the number of units sold in a single transaction;

— *unit_price* – the price per unit of the product sold;
— *category* – the category to which the product belongs;
— *week_name* – the day of the week on which the sale occurred;
— *holiday* – holiday indicator (1 for a holiday, 0 for a regular day).

Table 1. Product Sales Data.

day	month	year	product_id	agent_id	quantity_sold	unit_price	category	week_name	holiday
31	10	2023	3	43	1	41000	0	1	0
1	11	2023	3	38	30	1260000	0	2	0
1	11	2023	7	38	5	160000	0	2	0
1	11	2023	11	38	5	170000	0	2	0
1	11	2023	3	38	10	420000	0	2	0
1	11	2023	11	38	20	680000	0	2	0
1	11	2023	3	38	30	1290000	0	2	0

Data Preparation. Initially, the data was converted into datetime format and structured as a time series. Subsequently, the following cleaning and preprocessing steps were applied:

— Duplicate and incorrect entries were removed;
— A unified time series was constructed based on daily sales volume (quantity × unit price);
— Missing days were filled with zero values to ensure continuity;
— Statistical analysis was performed to decompose the series into seasonality, trend, and noise components;
— Normalization using MinMaxScaler was applied for LSTM modeling.

Since sales delays are time-dependent phenomena, approaches based on time series models were selected. These models are effective in capturing seasonality and long-term dependencies in sequential data. The ARIMA model consists of three components:

— AR (p): Autoregressive part;
— I (d): Differencing to achieve stationarity;
— MA (q): Moving average component.

The mathematical formulation is provided in Equation (1):

$$\phi(B)(1-B)^d y_t = \theta(B)\epsilon_t \quad (1)$$

Here:

y_t– time series value at time *t*, B– backshift operator, $\phi(B)$– autoregressive operator of order *p* (AR component),$\theta(B)$– moving average operator of order *q* (MA component) (q) operatori,ϵ_t– white noise term.

The SARIMA (Seasonal ARIMA) model is an extension of the ARIMA model that incorporates seasonal repetitions. It is expressed as follows (Equation 2):

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^C)^D y_t = \Theta(B^s)\theta(B)\epsilon_t \quad (2)$$

Here:

s– seasonal period, Φ, Θ– seasonal autoregressive operator.

The SARIMA model improves forecasting accuracy when weekly or monthly recurring patterns are present in sales data. In retail, sales often vary depending on the day of the week—making SARIMA particularly suitable for such cases.

LSTM (Long Short-Term Memory) is a deep learning model based on recurrent neural networks (RNN) that is specifically designed for time series data. It is capable of retaining long-term dependencies, making it highly effective in capturing complex temporal patterns.

$$f(t) = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3)$$

The LSTM model is capable of learning complex patterns in time series data and is particularly effective in capturing nonlinear dynamics, such as delay phenomena.

Analysis and Results. In this study, the dataset was split into 80% for training and 20% for testing across all models. For the ARIMA and SARIMA models, the parameters *(p, d, q)* and the seasonal components were selected based on the Akaike Information Criterion (AIC) to ensure optimal model fit.

For the LSTM model, the following hyperparameters were used: *Epochs: 100, Batch size: 32, Sequence length: 7 (to capture weekly patterns), Optimizer: Adam, Loss function: MSE (Mean Squared Error).*

Evaluation Metrics and Performance Analysis:

— **MSE (Mean Squared Error)** – the average of the squared differences between predicted and actual values;

— **MAE (Mean Absolute Error)** – the average of the absolute differences between predictions and actual observations;

— **R² (Determination Coefficient)** – the proportion of variance in the dependent variable explained by the model.

The performance of the models was compared and evaluated based on the aforementioned metrics. For each model, the differences between the predicted values and the actual values in the test set were thoroughly analyzed.

During the study, the effectiveness of the ARIMA, SARIMA, and LSTM models was evaluated using real-world sales data. The performance of each model was analyzed based on the evaluation metrics described above.

The **ARIMA model** showed slightly better results compared to the SARIMA model, particularly in terms of MAE, indicating that it performed more consistently in short-term forecasting. However, it was outperformed by the LSTM model in learning deeper temporal patterns and capturing delay phenomena.

odel	est MSE	est MAE	est R²
RIMA	.38	.69	0.3745

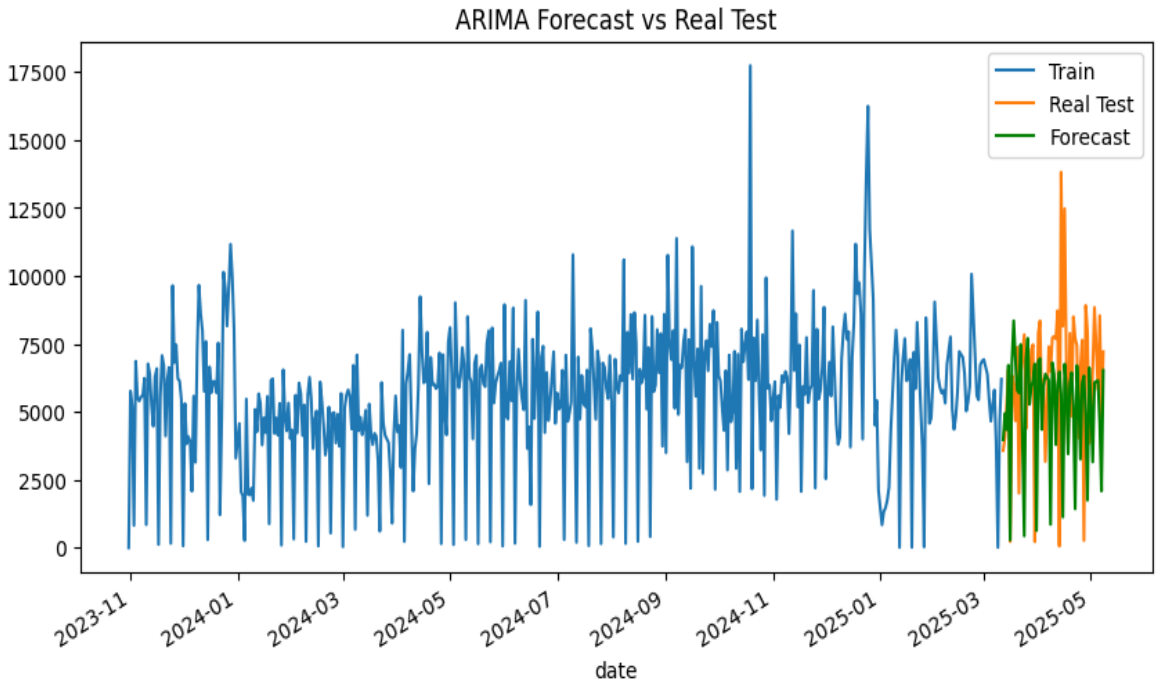

Figure 1. Results of the ARIMA Model

The **SARIMA model** attempted to learn the time series by accounting for seasonality. However, higher prediction errors were observed in the test set, which may indicate either weak seasonal patterns in the data or the relative simplicity of SARIMA compared to the more complex LSTM model.

odel	est MSE	est MAE	est R²
ARIMA	.91	.97	0.9066

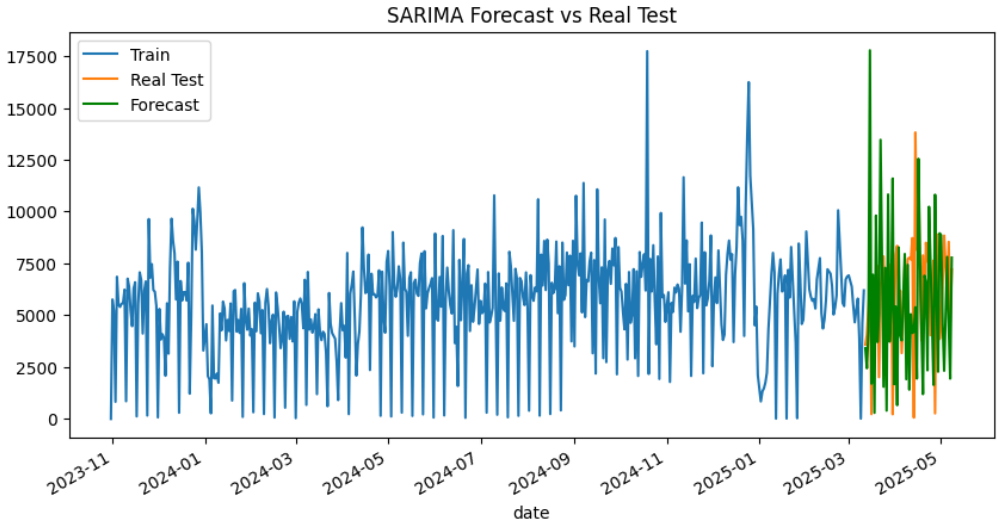

Figure 2. Results Obtained Using the SARIMA Model

The **LSTM model** demonstrated high forecasting accuracy, as evidenced by its low MSE and MAE values. Despite the negative R^2 score, LSTM recorded the smallest prediction errors compared to the other models. This highlights the model's capability to effectively learn nonlinear patterns in time series data.

odel	est MSE	est MAE	est R²
STM	.02	.06	0.0853

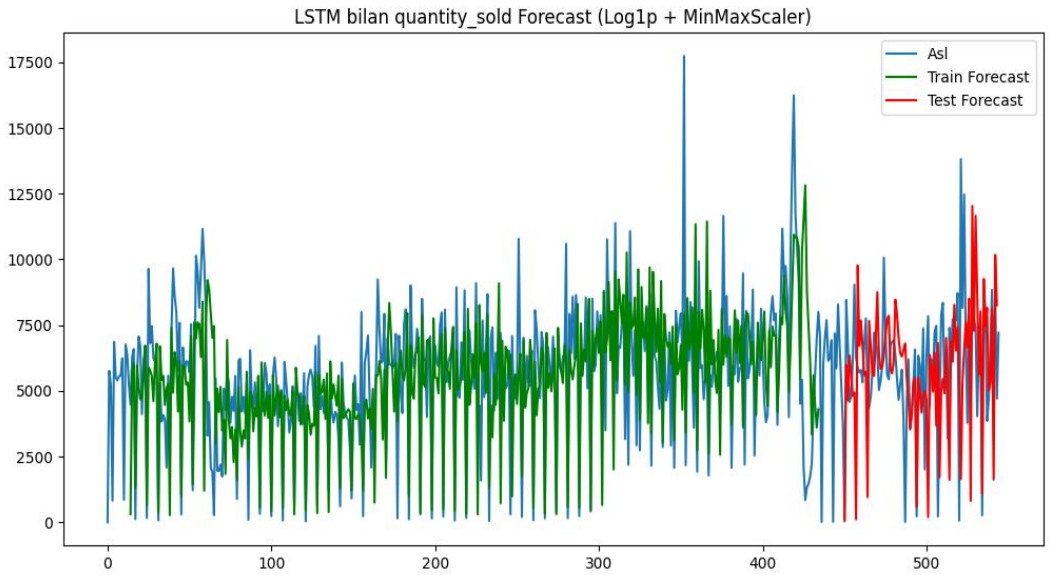

Figure 3. Results Obtained Using the LSTM Model

The final evaluation results of the time series models are summarized in Table 2. As shown in the table, the LSTM model outperformed all other models across all evaluation metrics. In particular, it exhibited significantly lower error rates and demonstrated a high degree of adaptability. In contrast, the ARIMA and SARIMA models resulted in comparatively higher error values, indicating their limited ability to accurately capture the complex dynamics present in real-world sales data. Therefore, this comparative analysis confirms that the LSTM model holds a clear advantage in forecasting based on time series data (Table 2).

Table-2. Final evaluation metrics of ARIMA, SARIMA, and LSTM models on the test dataset

Model	Test MSE	Test MAE	Test R^2
ARIMA	1.38	0.69	–0.3745
SARIMA	1.91	0.97	–0.9066
LSTM	0.02	0.06	–0.0853

Conclusion. This study analyzed the potential of time series and machine learning models to detect and forecast sales delays based on the sales data of a poultry product distribution company in Samarkand. Throughout the research, the mathematical foundations of ARIMA, SARIMA, and LSTM models were explored, applied to real-world sales data, and their results were comparatively evaluated.

The ARIMA model proved effective as a simple and interpretable solution for short-term forecasting. The SARIMA model delivered improved accuracy by accounting for weekly seasonal patterns observed in the sales data. The highest accuracy, however, was achieved with the LSTM model, which successfully captured complex and nonlinear dependencies across longer time intervals.

The results of the study suggest that statistical and deep learning models offer complementary approaches to identifying delay patterns. By employing time series-based models, companies can proactively forecast potential future delays and optimize their inventory management and logistics planning. This contributes to increased economic efficiency, timely satisfaction of customer demand, and strengthened competitiveness in the market.

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