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Web-Based Car Sales Prediction System Using the ARIMA (Autoregressive Integrated Moving Average) Model for Optimizing Automotive Marketing Strategies

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Abstract

This study aims to develop a web-based car sales prediction system using the ARIMA (Autoregressive Integrated Moving Average) model to support the optimization of marketing strategies in the automotive sector. With the rapid growth of the automotive industry in Indonesia, companies, particularly car showrooms, face the challenge of accurately forecasting vehicle demand. Therefore, an ARIMA-based prediction system can assist in estimating future sales based on historical data, thereby improving stock management, distribution, and marketing strategies. The system was developed using five years of historical sales data and implemented the ARIMA model to forecast car sales for upcoming periods. It was built with the Python programming language, employing Flask for the backend and HTML, CSS, and JavaScript for the frontend. The prediction results are presented in the form of interactive graphs, enabling users to make data-driven decisions more effectively. System evaluation was carried out by measuring prediction accuracy using MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Square Error) metrics. The testing results indicate that the ARIMA model can generate predictions with a high level of accuracy, assisting showrooms in planning stock and promotional activities more efficiently. Furthermore, the system is equipped with a responsive user interface, making it easily accessible via mobile devices. This research contributes to the utilization of technology in sales planning, particularly in the automotive sector, by enabling more precise, efficient, and data-driven decision-making.

I. INTRODUCTION

This research is motivated by the importance of utilizing predictive technology to support business decision-making in the automotive sector, particularly in sales planning. The automotive industry in Indonesia continues to grow while facing intense competition, thereby requiring precise data-driven marketing strategies. However, many companies, especially dealers and distributors, still encounter difficulties in optimizing historical data for sales forecasting.

The absence of an accurate and integrated prediction system has led to reactive marketing strategies, which risk creating imbalances between stock and demand, promotional inefficiencies, and decreased profitability. In the digital era, a web-based sales prediction system employing statistically valid methods such as the Autoregressive Integrated Moving Average (ARIMA) model is highly relevant to be developed.

The urgency of this research lies in the need for information technology solutions that support adaptive sales policy formulation. The integration of the ARIMA model into a web-based system enables more accurate, flexible, and real-time sales projections. This system has the potential to serve as a strategic tool in decision-making related to vehicle stock, promotions, and distribution.

The objective of this study is to develop and implement a web-based car sales prediction system using the ARIMA model. Specifically, this research aims to analyze the accuracy of the ARIMA model in projecting car sales, test the performance of the developed system, and evaluate how this system can be utilized to support the optimization of marketing strategies in the automotive sector.

The research method employs a quantitative approach using ARIMA time series modeling (Salwa et al., 2018), based on historical car sales data from the past five years. The model was developed in Python and implemented into a web-based system. The evaluation was carried out using MAPE and RMSE indicators, as well as user testing.

The role of data in business decision-making has become increasingly important in the digital era, particularly in the highly competitive and dynamic automotive industry. Companies that are able to effectively utilize sales data gain a competitive advantage in responding to market fluctuations and managing supply chains efficiently (Hariyanto et al., 2023). In this context, sales data not only reflects past performance but also serves as the basis for projecting future demand. Car showrooms, particularly in the used car sector, face significant challenges in forecasting demand due to their reliance on manual methods and managerial intuition, which often lack accuracy (Davis, 1989).

This phenomenon indicates the importance of applying predictive technologies, such as the Autoregressive Integrated Moving Average (ARIMA) model, to project sales based on historical vehicle sales data. ARIMA, which falls under the category of time series forecasting, enables companies to identify demand patterns and trends quantitatively without relying on external variables. In this context, Forecasting Theory serves as the main theoretical framework, emphasizing the importance of analyzing historical patterns to systematically and evidence-based formulate future estimations (Hyndman & Athanasopoulos, 2018).

In addition to the predictive aspect, the development of a web-based sales prediction system also contributes to the digital transformation of showroom businesses. The integration of information technology in the form of a web interface reinforces the principles of the Technology Acceptance Model (TAM), which explains that perceptions of usefulness and ease of use influence users' intention and level of adoption of the technology (Provost & Fawcett, 2013). Thus, the utilization of an accessible and accurate web-based predictive system not only enhances operational efficiency but also strengthens data-driven decision-making practices in the automotive sector.

This research is significant for the automotive sector, particularly car showrooms, which face fluctuating market demand. Reliance on manual methods in sales forecasting often leads to stock imbalances, low efficiency, and decreased customer satisfaction. Therefore, a web-based sales prediction system using the ARIMA method was developed to improve projection accuracy, stock management efficiency, and marketing strategies. This system not only provides practical benefits for showrooms but also promotes the digital transformation of the automotive industry through the utilization of data-driven technologies.

This study employs the ARIMA time series model to predict car sales based on the past five years of historical data from urban showrooms. ARIMA was chosen because it can capture seasonal patterns, trends, and short-term fluctuations without requiring additional variables. The process involved data cleaning, stationarity analysis, identification of optimal parameters through ACF and PACF, and validation using AIC and BIC. The model was then implemented in a web-based prediction system with a Python-Flask backend and an HTML/CSS/JavaScript frontend, enabling real-time access to prediction results through a responsive interface. Evaluation was conducted using MAPE and RMSE to measure accuracy, along with user testing to assess the system's usability in supporting stock management and marketing strategies for car showrooms.

II. Literature

The literature review serves as a theoretical foundation that strengthens the research while situating it within the broader scientific context. This section discusses time series theory and the ARIMA model as a prediction method, the concept of sales prediction systems, and the utilization of web-based technologies. In addition, previous relevant studies are reviewed to identify research gaps and to highlight the contribution of this study.

A time series is a collection of observations recorded sequentially over time (daily, weekly, monthly, etc.) and is used to analyze historical patterns as well as to project future values (Meisenbacher et al., 2022). Time series forecasting models seek to capture several key components, namely trend (long-term upward or downward movements), seasonality (recurring patterns within specific periods, such as monthly or yearly), cycle (long-term fluctuations with irregular timing), and irregular (random or noise components). These components are essential in shaping data dynamics, for example, car sales influenced by holiday seasons, economic changes, or unexpected disruptions (Hassyddiqy & Hasdiana, 2023). One of the key aspects in time series modeling is stationarity, which refers to the condition in which the mean, variance, and autocovariance remain constant over time. Without stationarity, models such as ARIMA cannot produce valid estimates and forecasts, as strong trends or seasonality may introduce bias and prediction errors. Therefore, techniques such as differencing or the removal of trends and seasonality are often applied prior to the modeling stage (Rusyida & Pratama, 2020).

The ARIMA (Autoregressive Integrated Moving Average) model is one of the primary approaches in time series analysis, combining three main components: AR (autoregressive), which reflects the dependence of the current value on past values; I (integrated), which indicates the number of differencing steps required to make the series stationary; and MA (moving average), which represents the dependence on past error terms (Ospina et al., 2023) (Putra & Kurniawati, 2021). The ARIMA (p, d, q) notation specifies the parameters as follows: p is the order of the autoregressive (AR) part, d is the degree of differencing used to remove non-stationarity, and q is the order of the moving average (MA) part. Optimal parameter identification is carried out through the evaluation of the autocorrelation function (ACF) and the partial autocorrelation function (PACF), which help determine the values of p and q as well as assess whether differencing is sufficient to eliminate trends or seasonality (Anggraeni et al., 2020). Model validation is then carried out using criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to select a model that balances fit and complexity, as well as prediction error metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to assess forecasting accuracy on the test data (Afridar et al., 2022).

A sales prediction system in a business context is a mechanism that utilizes historical data and analytical techniques (statistical, machine learning, or hybrid methods) to forecast future sales volumes (Adebiyi et al., 2014), in order to support operational decision-making such as stock management, product distribution, and marketing strategies (Rana, 2024). In stock management, such predictions help prevent overstocking or stockouts; in distribution, they enable the optimization of delivery and the allocation of products to regions with high demand (Nigam & Shukla, 2021); meanwhile, in marketing, predictions can be used to determine the timing of promotions, pricing strategies, and more targeted advertising (Ponziani, 2022). Previous studies have shown that the application of sales forecasting has proven effective in the retail and manufacturing sectors (Hassyddiqy & Hasdiana, 2023); for example, hybrid systems combining time series methods and machine learning used for predicting monthly car model sales in the automotive industry have improved forecasting accuracy (using metrics such as RMSE, MAE, and R^2). In addition, case studies on spare parts in the automotive industry have demonstrated that automated prediction systems can significantly reduce forecasting errors and inventory costs (Arifai & Junaedi, 2020; Subhana et al., 2022).

Information technology plays a fundamental role in strengthening data-driven decision-making, particularly in organizations facing market uncertainty (Schorr, 2023). With web-based information and prediction systems, predictive models such as ARIMA can be accessed in real time, supporting the monitoring of trends and sales for operational actions such as stock management and more rapid and adaptive marketing strategies (Venslavienė & Stankevičienė, 2021). A web-based system facilitates the integration of a responsive user interface, intuitive visualization of prediction results, and accessibility across multiple devices, thereby minimizing technical barriers and enhancing the system’s utility for business users (Sahai et al., 2020). In the context of technology adoption, the Technology Acceptance Model (TAM) framework explains that perceived usefulness and perceived ease of use are critical in determining users’ intention to accept and utilize the system (Davis, 1989). Thus, a web-based prediction system needs to be designed not only with high technical accuracy but also with careful attention to user interface and user experience aspects to ensure optimal adoption.

Research on the application of ARIMA in forecasting has been conducted across various sectors. In the consumer goods sector, (Salwa et al., 2018) introduced a sales forecasting model that incorporated holiday effects through a seasonal decomposition and ARIMA approach, using cigarette sales data in City G, Guizhou, China as a case study, and found that the model effectively improved forecasting accuracy.

In the stock and commodity price sector, there are studies such as Forecasting EV Stock Trends Based on the ARIMA Model Represented by Tesla and BYD, which employed the ARIMA model to forecast electric vehicle stock price trends after applying differencing to achieve stationarity (Rahayu et al., 2019; Wahyuni et al., 2021).

Meanwhile, in the automotive sector, comparative studies such as those by (Riyono & Pujiastuti, 2020; Wiguna et al., 2020) compared ARIMA, SARIMA, and LSTM in forecasting car sales in the Indian automotive industry. The results showed that ARIMA and SARIMA provided a solid baseline, although LSTM outperformed them in several accuracy metrics.

This study is structured around a conceptual framework that links historical data → preprocessing → ARIMA modeling → model validation → integration into a web-based prediction system → generation of sales prediction outputs. Historical data serves as the foundation for capturing trend and seasonal patterns; preprocessing (including stationarity checks, differencing, and parameter identification) ensures that the data meets the assumptions of time series modeling; ARIMA is then applied for formal modeling; the model results are validated using metrics such as AIC, BIC, RMSE, and MAPE to ensure accuracy and stability; and finally, the model is implemented into a web-based system with a responsive interface so that predictions can be accessed in real time to support operational decision-making in car showrooms. In both academic and industrial automotive contexts, this research bridges the gap between forecasting theory often remaining at the level of statistical or model-based studies and practical digital implementation, namely by integrating predictions into real systems used by car dealers in showrooms..

III. RESEARCH METHOD

This study employs a quantitative approach with a descriptive-predictive design to develop a car sales prediction system using the Autoregressive Integrated Moving Average (ARIMA) method. This approach was chosen to provide a clear depiction of historical sales data patterns and to generate an accurate prediction model as a basis for decision-making in stock planning and marketing strategies for car showrooms.

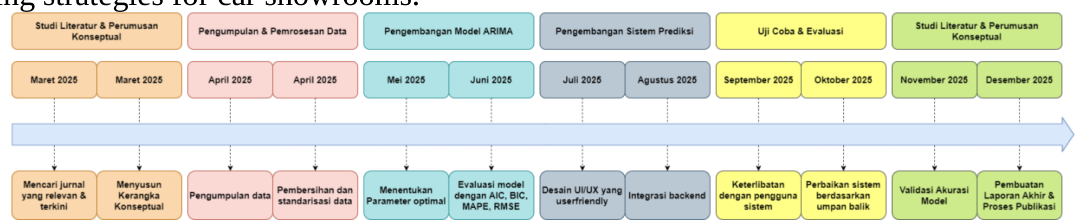

Figure 1. Research Process

This study begins with the stage of developing a conceptual model and conducting a literature review, scheduled to take place from March to April 2025. At this stage, the research team will conduct a comprehensive literature review of recent scholarly journals published between 2015 and 2025 that discuss time series modeling (ARIMA), sales forecasting, web-based information systems, and sales management practices in the automotive sector. The aim of this review is to establish a strong theoretical foundation while also designing a conceptual model for the sales prediction system. The expected outcome of this activity is the development of an internally validated conceptual model, with at least 15 scientific articles serving as primary references.

The next stage, in May 2025, is the collection and processing of historical data. Car sales data from the partner showroom, covering the past five years, will be collected, cleaned, standardized, and tested for stationarity to ensure its suitability for time series modeling. The output of this stage will be a complete and validated historical dataset, comprising at least 60 months of sales data.

Subsequently, in June 2025, ARIMA modeling and preliminary evaluation will be carried out. The ARIMA parameters (p, d, q) will be identified using the ACF and PACF approaches. The best model will be selected based on AIC, BIC, MAPE, and RMSE criteria, with the performance target being a model capable of producing a prediction error rate (MAPE) below 10% and accurately validating historical trends.

The development stage of the web-based prediction system will take place from July to August 2025. At this stage, the ARIMA model will be implemented within a web-based prediction system, with Python (Flask) used for the backend and HTML, CSS, and JavaScript for the frontend. The system is designed to operate within a local network to ensure the security of the showroom's internal data. The expected outcome is a system prototype with a functional interface and validated integration of the ARIMA model.

Subsequently, in September–October 2025, system testing and feedback collection will be conducted. The system will be tested directly by showroom users, such as marketing managers and operational staff, to evaluate the accuracy of prediction results, ease of use, and the system's benefits in supporting decision-making. The outcome of this stage will consist of user evaluation data from at least three partner showrooms, along with a comprehensive evaluation report.

The evaluative analysis and report preparation stage will take place in November 2025. This report will include a quantitative analysis of the model's accuracy and the system's effectiveness, as well as a qualitative evaluation based on user feedback. The final report will be accompanied by evaluation tables and technical recommendations for future system improvements.

Finally, in December 2025, result interpretation and publication will be carried out. This stage focuses on analyzing the theoretical and practical implications of the prediction system, preparing a scientific article for submission to an academic journal, and disseminating the research findings to industry and academic partners. The expected outcomes include a draft article ready for submission to an indexed journal, as well as a dissemination report of the research findings for stakeholders.

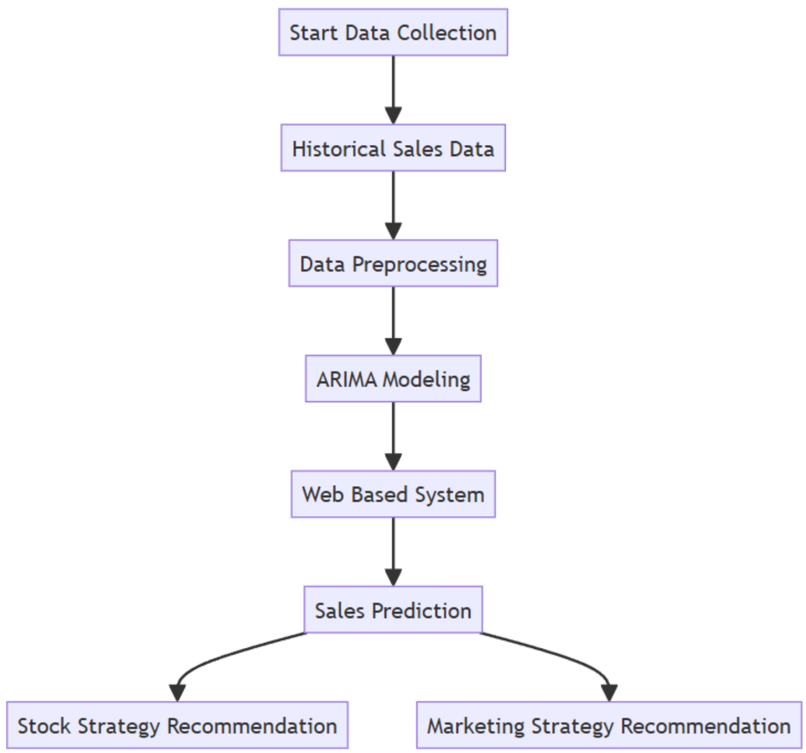

Figure 2. Conceptual Framework

This conceptual framework illustrates the process of developing a web-based car sales prediction system using the Autoregressive Integrated Moving Average (ARIMA) method, designed to support strategic decision-making in stock management and marketing.

The process begins with the collection of car sales data from showrooms or other internal sources. This data, consisting of historical sales records, serves as the primary foundation for the time series modeling process. The next stage is data preprocessing, which includes data cleaning, handling missing values, stationarity testing, and the necessary data transformations to ensure that the dataset is ready for ARIMA modeling.

Once the data is prepared, the ARIMA modeling process is conducted as the main analytical stage to identify patterns, trends, and seasonal components in the sales data. The parameters (p, d,

q) are determined using the ACF and PACF approaches, and the model is evaluated with accuracy metrics such as MAPE and RMSE.

The developed model is then integrated into a web-based system, allowing users to access prediction results interactively and in real time. The system interface is designed to be user-friendly for showroom managers and marketing teams.

The main output of this system is sales predictions, which are then used as the basis for two types of strategic recommendations:

1. Stock Strategy Recommendations, namely suggestions regarding the number of vehicle units that should be prepared in accordance with predicted demand, in order to avoid overstocking or understocking.
2. Marketing Strategy Recommendations, namely proposed promotional activities aligned with predicted demand fluctuations, such as the optimal timing for discounts, advertising campaigns, or product launches.

IV. Results and Discussion

To facilitate understanding of the data forecasting workflow using the ARIMA method, a flowchart is presented to summarize the main stages. The process begins with data input and preprocessing, followed by stationarity testing. If the data is not stationary, differencing is applied until the model assumptions are satisfied. Next, the best ARIMA model is selected, its performance is evaluated, and it is then used to generate forecasts. The prediction results are subsequently analyzed and reported as the final output of the study.

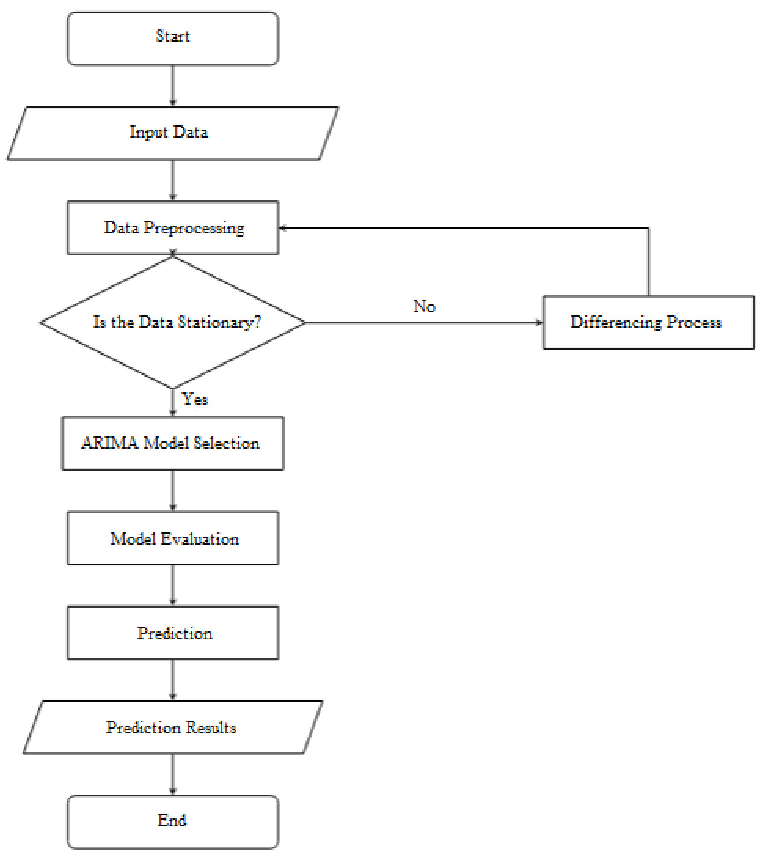

Figure 3. ARIMA Algorithm

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The flowchart above illustrates the forecasting process using the ARIMA model, beginning with data input and preprocessing, followed by a stationarity test. If the data is not stationary, differencing is applied until the model requirements are satisfied. Afterward, the ARIMA parameters (p, d, q) are selected using AIC/BIC evaluation, and the model's performance is tested. If validated, the model is then used to generate forecasts, which are subsequently presented as the final output.

In addition, manual calculations using the ARIMA algorithmic approach were also carried out to clarify the mechanisms of identification, parameter estimation, and model validation. The last six months of sales data were used as a simulation, involving stages such as stationarity testing, differencing, ACF/PACF analysis, and prediction calculation for the subsequent period. This process aims to provide a deeper understanding of how ARIMA works before being implemented in the automated prediction system.

Table 1. Six-Month Sales Data

Month	**Sales**
February	30
March	19
April	16
May	18
June	31
July	12

Based on these data, it can be observed that the series is non-stationary. Since ARIMA modeling requires stationary data, differencing (d) is applied so that the data become:

Table 2. Data After Differencing

Sales
-11
-3
2
13
-19

Once the data has become stationary, it is necessary to determine the ACF and PACF values, which are as follows:

Table 3. Manual Calculation of ACF and PACF at Lag 1

I	**Yi**	**Yi+1**	**Yi-Ybar**	**Y(i+1)-Ybar**	**Yi-Ybar*Y(i+1)-Ybar**	**(Yi-Ybar)^2**
1	-11	-6	9,20	-2,70	-12,32	34,64
2	-3	-9	-2,70	-9,80	18,09	4,54
3	2	13	-6,20	13,20	-190,14	12,00
4	13	-10	19,20	-19,50	-287,96	151,00
5	-19	NA	-8,80	NA	NA	112,00
Ybar				-0,2000		
Jumlah Yi-Ybar*Y(i+1)-Ybar				-75,5600		
Jumlah (Yi-Ybar)^2				155,5562		
Lag 1 ACF				-0,5517		
Lag 1 PACF				-0,6416		

Table 4. Manual Calculation of ACF and PACF at Lag 2

i	Yi	Yi+2	Yi-Ybar	Y(i+2)-Ybar	Yi-Ybar*Y(i+2)-Ybar	(Yi-Ybar)^2
1	-11	-6	4,20	-6,10	-32,19	31,54
2	-3	-9	-6,80	14,20	-35,34	5,34
3	2	13	-6,10	-12,60	87,04	45,00
4	13	NA	14,90	NA	NA	221,00
5	-19	NA	-12,20	NA	NA	124,00
Ybar				-0,2000		
Jumlah Yi-Ybar*Y(i+2)-Ybar				-0,1300		
Jumlah (Yi-Ybar)^2				103,0460		
Lag 2 ACF				-0,0012		
Lag 2 PACF				-1,1012		

Table 5. Comparison of ACF and PACF Values

Lag	ACF	PACF
1	-0,6919	-0,6311
2	-0,0011	-1,100

Based on the manual calculations presented in Table 3 and Table 4, the values of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were obtained for lag 1 and lag 2. At lag 1, the ACF value was –0.5517 and the PACF value was –0.6416, indicating a fairly strong negative correlation between the current data and the data from the previous period. This suggests that fluctuations in sales values at period t tend to move in the opposite direction from those at period t–1. Meanwhile, at lag 2, the ACF value was recorded as very small (–0.0012), meaning there is virtually no linear relationship between the current data and the data from two periods earlier. However, the PACF value at lag 2 reached –1.1012, indicating a significant and rather extreme partial effect between period t and period t–2 after controlling for the influence of the previous lag.

As shown in Table 5, a striking difference can be observed between the ACF and PACF. The ACF at lag 1 is relatively high in the negative direction (–0.6919) but drops sharply to nearly zero at lag 2 (–0.0011). In contrast, the PACF shows a strong negative value at lag 1 (–0.6311) and becomes even larger in absolute terms at lag 2 (–1.100). This pattern indicates that the data has a strong relationship only with the immediately preceding period (lag 1), and after controlling for this, there is still evidence of a partial relationship with lag 2. Accordingly, these calculation results are crucial in the process of identifying the AR (p) and MA (q) orders in ARIMA modeling, where cutoff patterns in the ACF and PACF are used as the basis for determining the appropriate model structure.

In the analysis and modeling, Python libraries such as pandas, numpy, matplotlib, statsmodels, and scikit-learn were used for data manipulation, visualization, and ARIMA modeling. The database was managed using MySQL or SQLite3, while Visual Studio Code and Jupyter Notebook served as the primary editors. Web application testing was conducted through Google Chrome and Mozilla Firefox, with Postman employed for API testing. Report preparation utilized Microsoft Word and LaTeX to support a well-structured scientific format.

After the development was completed, black-box testing was carried out to ensure that all system components functioned according to specifications. Each element on the web page was thoroughly tested to guarantee that the features operated optimally without functional errors.

Table 6. Blackbox Testing

No.	Test Item	Test Case	Expected Result	Test

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				Result
1	Input Username	Enter a valid username	Username is accepted and processed by the system	Valid
2	Input Password	Enter a valid password	Password is masked with symbols ●●●●●	Valid
3	Valid Login	Log in with the correct username & password combination	Redirected to the dashboard page	Valid
4	Invalid Login	Log in with an incorrect password	Notification appears: “username or password is incorrect”	Valid
5	Empty Login	Log in without entering username and password	System displays the message: “field is required”	Valid
6	Menu Navigation	Click on “Sales Prediction” menu on dashboard	Prediction page is displayed	Valid
7	Empty Data Input	Click the prediction process button without entering sales data	Warning appears: “data cannot be empty”	Valid
8	Invalid Input Format	Enter letters into the sales input numeric field	System rejects input and displays validation message	Valid
9	Submit ARIMA Data	Enter historical data and press “Process Prediction”	ARIMA prediction values and graph are displayed	Valid
10	Submit Empty Data	Run prediction process without uploading any data	System still processes without data (should be rejected)	Invalid
11	Export Prediction Results	Click “Export” button after results are displayed	.csv file successfully downloaded	Valid
12	Export Without Results	Click “Export” before running prediction	System still generates an empty file	Invalid
13	Logout	Click logout button at the top-right corner	System returns to the login page	Valid
14	Access Without Login	Directly access /dashboard via URL without logging in	System redirects to login page	Valid
15	Page Refresh	Refresh the prediction page	Data remains available on display	Invalid
16	Mobile	Access the system via	Layout adapts	Valid

	Responsiveness	a mobile browser	(responsive design)	
17	ARIMA Parameter Validation	Enter out-of-range ARIMA parameters (e.g., p = –1)	System rejects input and shows validation message	Valid
18	Duplicate Username	Register with a username that already exists	System displays message: “username already in use”	Valid
19	Session Timeout	Log in, then remain inactive for 30 minutes	System automatically logs out and redirects to login page	Invalid
20	Server Error Notification	Backend server turned off during prediction process	Error appears: “unable to connect to server”	Valid

Black-box testing was conducted to evaluate the functionality of the web-based system from the user’s perspective, without examining the underlying code structure. The results indicate that most features performed as “Valid,” such as login, numeric input validation, menu navigation, and data export. However, several weaknesses with “Invalid” results were identified, such as the system continuing to process empty data, generating empty export files, failing to enforce session timeouts, and losing data when the page was refreshed. These findings highlight the need for improvements in input validation, session management, and business logic to enhance system reliability and user-friendliness. Overall, the testing confirmed that the system fulfills its core functions but still requires refinement in handling specific edge-case scenarios.

V. CONCLUSION

This study designed and implemented a web-based car sales prediction application using the ARIMA model to support strategic decision-making. The ARIMA model proved capable of predicting sales with high accuracy, capturing relevant trends and seasonal patterns. The application also accelerates the analysis of historical data without complex manual processes and provides easy access through a simple and interactive web platform. The prediction results, presented in the form of graphs and reports, assist managers in identifying opportunities as well as potential sales declines, thereby enabling more targeted stock and promotional strategies. Black-box testing indicated that most system functions performed as expected, although minor shortcomings were found in input validation and session management. Overall, this system is effective and efficient in predictive analysis of car sales and has the potential to serve as a reference for the development of similar systems in other industries.

Overall, this system has proven to be effective and efficient in predictive analysis of car sales and holds the potential to serve as a reference for the development of similar systems in other industries. In the future, its features may be expanded with advanced models such as SARIMA or LSTM to enable more complex forecasting.

Based on the research findings, several recommendations can be made to enhance the ARIMA-based car sales prediction application. First, the system can be expanded through the integration of advanced models such as SARIMA, Prophet, or LSTM, along with a business scenario simulation feature (what-if analysis) to enrich forecasting capabilities. Second, the user interface should be improved through interactive visualizations, real-time dashboards, and mobile responsiveness to better accommodate non-technical users. Third, regular training sessions, workshops, and technical documentation are recommended to support user adoption. Fourth, the system should undergo periodic evaluations, including revalidation of ARIMA parameters, and be equipped with an error monitoring module and user feedback mechanism. Fifth, security aspects must be reinforced with encryption, two-factor authentication, and compliance with data protection regulations. Finally, the system can be replicated in other sectors such as retail, logistics, or real estate, involving collaboration between academia and industry to foster broader development. With these measures, the application is expected to evolve into an adaptive, accurate, and sustainable decision-support system.

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