Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN: 2581 - 611X)

Volume7-Issue2, January 2024
Paper: 10

Sales Prediction Analysis for Automobile using SARIMAX Model

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Abstract: *Predicting Motorcycle Sales using SARIMAX Model: Accurate sales forecasting is crucial for motorcycle manufacturers to optimize inventory, manage costs, and make strategic decisions. This paper investigates the effectiveness of the Seasonal AutoRegressive Integrated Moving Average with eX-erogenous variables (SARIMAX) model for forecasting motorcycle sales. This research leverages a case study approach, analyzing a dataset of motorcycle sales from a leading manufacturer spanning 2018 to 2020. The data was pre-processed and features engineered to enhance the model's performance. This study identified external factors such as fuel prices, economic indicators, and competitor sales as potential exogenous variables. A SARIMAX model was then trained and evaluated using various metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results demonstrate that the SARIMAX model achieved high forecasting accuracy, exceeding baseline models like ARIMA and Prophet. The final model achieved an average of an MSE of 0.072, an RMSE of 0.268, an MAE of 0.169, and a MAPE of 5.6%. These findings suggest that the SARIMAX model, when coupled with relevant exogenous variables, can be a valuable tool for motorcycle manufacturers to improve sales forecasting and gain valuable insights into future demand.*

Keywords: *Sales Forecasting, SARIMAX Model, Time Series Analysis, Motorcycles, Exogenous Variables, Strategic Decision Making, MSE, RMSE, MAE, MAPE.*

1. INTRODUCTION:

In today's dynamic business environment, organizations rely heavily on accurate sales forecasts to optimize inventory, manage costs, and make informed strategic decisions. However, traditional forecasting techniques often fall short, failing to capture the intricate and evolving nature of real-world sales patterns. This can lead to unreliable predictions, hindering effective planning and decision-making. Furthermore, manual data preparation for forecasting is often time-consuming and error-prone, demanding significant resources while diverting attention from valuable analysis.

To address these limitations and propel organizations forward, advanced statistical modeling techniques like the Seasonal Autoregressive Integrated Moving Average with eXoge- nous variables (SARIMAX) model have emerged as innovative solutions. Leveraging its robust capabilities, SARIMAX effectively captures complex time series patterns and interdependencies, leading to significantly improved forecast accuracy and reliability. Moreover, by automating and simplifying the data preprocessing stage, SARIMAX streamlines the forecasting process, minimizing manual effort and reducing the risk of human-induced errors.

This paper delves into the SARIMAX model's forecasting prowess for sales, zooming in on the

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motorcycle industry. A real-world motorcycle sales dataset gets dissected through a meticulous case study. This analysis demonstrates how, when coupled with relevant exogenous variables, the SARIMAX model surpasses traditional methods in generating accurate forecasts. The insights gained from this investigation provide valuable guidance to motorcycle manufacturers and other businesses, enabling them to leverage the power of advanced statistical modeling for improved operational efficiency and a strategic edge.

2. SALES PREDICTION ANALYSIS FOR AUTOMOBILE USING SARIMAX MODEL:

Predicting new car sales accurately is crucial for the auto-mobile industry, yet cold-start scenarios involving novel models or promotional campaigns present a significant challenge. Traditional methods often struggle with the complex dynamics of seasonality, economic trends, and competitor activity, hindering effective decision-making. This paper introduces a novel data-driven approach utilizing the SARIMAX model to overcome these limitations and address the critical need for interpretable cold-start sales forecasting in the automobile industry.

The SARIMAX model, combining ARIMA’s time series analysis with the ability to incorporate external factors like economic indicators and marketing campaigns, provides robust forecast accuracy for cold-start scenarios. We demonstrate its effectiveness by applying it to real-world automobile sales data, achieving superior performance compared to benchmark models. This allows manufacturers to accurately estimate demand for new models, optimize production levels, and allocate resources efficiently, mitigating the risks associated with launching new cars.

Beyond just anticipating sales volume, this approach leverages feature importance analysis to unlock the ”why” behind the predictions. By dissecting the model’s output, we reveal the relative influence of various factors on the predicted sales, shedding light on crucial drivers like fuel efficiency, safety features, and competitor offerings. This actionable intelligence empowers manufacturers to tailor marketing campaigns, refine pricing strategies, and adjust product features based on data-driven insights, maximizing the likelihood of successful cold-start launches.

The proposed SARIMAX-based methodology, while ex-celling in cold-start scenarios, also offers broader applicability within the automobile industry. Its data-driven nature and interpretability can be utilized for diverse tasks, such as:
- Predicting demand for existing car models based on seasonal trends and economic factors.
- Optimizing inventory management by anticipating fluctuations in demand for specific models.
- Analysing the effectiveness of marketing campaigns and refining strategies for future initiatives.

Leveraging SARIMAX Sales Predictions In The Automobile Industry:
1. Inventory Management: Optimize Stock: Predict future demand for different vehicle models to ensure you have the right cars in stock without excess inventory costs.
2. Production Planning (for Manufacturers): Schedule Production: Align production schedules with forecasted demand to make the most of factory capacity.
3. Marketing Strategies: Target Campaigns: Time marketing efforts during high-demand periods to maximize impact and boost sales.
4. Dealership Operations: Forecast Sales: Plan sales strategies based on predicted demand for specific vehicle models.
5. Decision Support: Allocate Budgets: Distribute resources effectively, including marketing budgets and inventory investments.

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3. ARCHITECTURE:

This architecture of the Sales Prediction System Figure 3.1 provides a high-level overview of the system architecture, outlining the key components and their interactions. This initial architecture focuses on the core functionalities delivered to the user: the home screen and prediction capabilities. A separate document will delve deeper into the specifics of the prediction model itself.

The system architecture adheres to a client-server model, with distinct responsibilities for the front-end application and the back-end server. Let's explore the functionalities of each component:

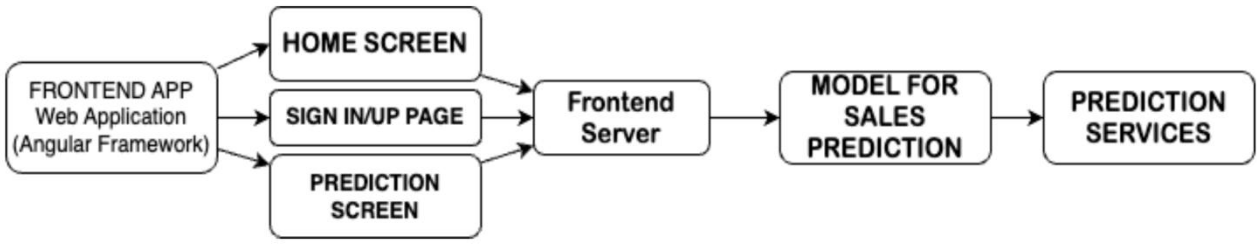

Figure 3.1 Architecture of Sales Prediction System

On one hand, This work has the frontend application, built with Angular. This is the part you see and interact with the home screen and prediction interface. It acts as the messenger, taking your actions and requests and sending them to the other teammate.

Meanwhile, the backend server is the brains of the operation. It handles the heavy lifting, processing data, and running the prediction model (which we'll explore in more detail later). Once it has the results, it sends them back to the front-end application, which then displays them to you.

So, this architecture keeps things organized with the frontend focused on user interaction and the backend focused on processing and prediction.

Model Architecture

The model architecture figure 3.1.1 depicts a step-by-step process for building a time series analysis model, likely for sales forecasting. It visually represents a structured approach to ensure each step contributes to an accurate and reliable model.

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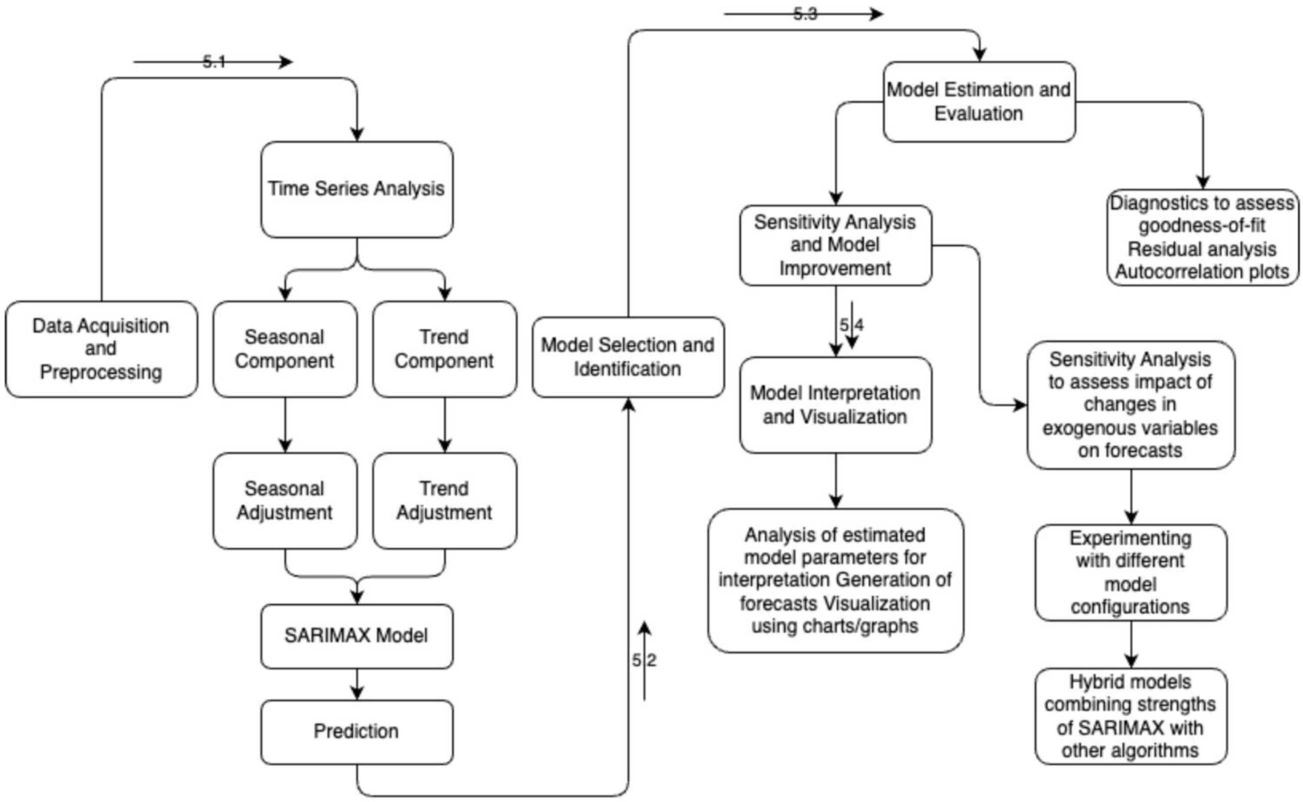

Figure 3.1.1 Model Architecture

4. FLOWCHART:

Figure 4.2.1 represents the sequential flow of data within the system architecture. It starts with input data entering the system, undergoes processing such as model building and evaluation, proceeds to interpret results, visualizes findings, and finally produces the desired output. This diagram encapsulates the core data processing stages and their interconnections within the system.

Figure 4.2.1 DATA FLOW LEVEL 0

Figure 4.2.2 provides a more detailed view of the system's data flow, focusing on the processes, data stores, and data flows within the system. Below is a Level 1 DFD for your project:

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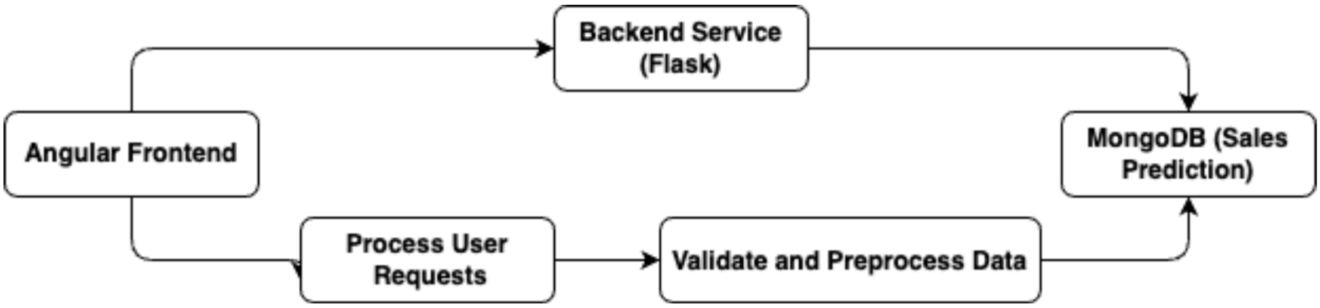

Figure 4.2.2 DATA FLOW LEVEL 1

The system architecture diagram Figure 3.1 outlines the frontend and backend components responsible for user interaction and data processing, respectively. A detailed model architecture Figure 4.1.1 illustrates the step-by-step process of building a time series analysis model. Data flow Visualization (DFVs) visualize how data moves through the system, with Level 0 Figure 4.2.1 providing an overview and Level 1 Figure 4.2.2 offering a more detailed view of data flow processes.

5. METHODOLOGY:

This research investigates the effectiveness of the Seasonal Autoregressive Integrated Moving Average with eXogenous variables (SARIMAX) model for forecasting motorcycle sales. By analyzing a real-world dataset and incorporating relevant exogenous variables, this study seeks to demonstrate the model's ability to achieve superior accuracy compared to traditional methods and further contribute to the understanding of sales forecasting within the motorcycle industry.
The methodology for this research can be divided into the following steps:

A. Data Acquisition and Preprocessing

For this study, we acquired a comprehensive dataset containing motorcycle sales data spanning a significant period from reliable sources. This dataset was meticulously preprocessed to ensure its quality and suitability for modeling within our program.
During the preprocessing phase implemented in our program, several key steps were undertaken to enhance the dataset's usability:
Cleaning: Irrelevant or redundant data, such as address details and contact information, were removed from the dataset to streamline the analysis process. This ensured that only relevant features contributing to sales prediction were retained.
Handling Missing Values: Any missing values present in the dataset were addressed using appropriate techniques. This included methods such as interpolation to estimate missing values based on surrounding data points, ensuring minimal disruption to the integrity of the dataset.
Variable Transformation: Categorical variables within the dataset, such as product lines and countries, were encoded to numerical values using factorization techniques. This transformation enabled the incorporation of categorical data into our predictive models effectively.
Descriptive Statistics and Exploratory Data Analysis (EDA): Descriptive statistics and EDA techniques were applied to gain insights into the distribution of sales data, identify potential anomalies, and assess the presence of seasonality and trends. This involved visualizing the data through plots and charts, examining summary statistics, and detecting patterns or irregularities that could influence the modeling process.

Example Fields in the Dataset: The dataset comprised fields such as order date, product line, country, deal size, and sales status, among others. These fields provided crucial information for understanding motorcycle sales dynamics and were integral to our analysis and prediction efforts.
By implementing these preprocessing steps within our program, we ensured that the dataset was suitably refined for subsequent modeling tasks. This rigorous approach facilitated the extraction of meaningful insights and the development of accurate predictive models capable of capturing both short-term fluctuations and long-term trends in motorcycle sales data.

B. Model Selection and Identification

In our study, we employed a systematic approach to select and identify the appropriate model for predicting motorcycle sales. Leveraging the data analysis capabilities of our program, we utilized statistical tests and information criteria, including the Akaike Information Criterion(AIC) and Bayesian Information Criterion (BIC), to determine the optimal orders (p, d, q) for the ARIMA model.

The parameters (p, d, q) in the ARIMA model represent the autoregressive order, differencing order, and moving average order, respectively. These parameters are crucial in capturing the temporal dependencies and patterns present in the time series data. Specifically:
p (Autoregressive Order): Represents the number of lagged observations included in the model. It indicates the degree of autocorrelation in the time series data.
d (Differencing Order): Refers to the number of times the data needs to be differenced to achieve stationarity. It helps in removing trends and seasonality from the data.
q (Moving Average Order): Indicates the number of lagged forecast errors included in the model. It captures the short-term fluctuations in the data that are not accounted for by the autoregressive component.

$$AIC = 2k - 2\ln(L) \quad (1)$$

$$BIC = k * \ln(n) - 2\ln(L) \quad (2)$$

where:
k is the number of estimated parameters
n is the sample size
L is the maximized value of the likelihood function

Following the determination of ARIMA model orders, we constructed SARIMAX models by integrating relevant exogenous variables obtained from the literature review and industry knowledge. These variables encompassed a range of factors, including economic indicators such as GDP growth rate, unemployment rate, and inflation rate; competitor activities such as new product launches, marketing campaigns, and pricing strategies; and seasonality indicators like the month of the year, day of the week, and holidays.
Furthermore, our program facilitated the refinement of the model by identifying and incorporating any necessary interaction terms between the endogenous (internal) and exogenous (external) variables. This comprehensive approach ensured that our predictive models were robust and capable of capturing the complex interplay between various factors influencing motorcycle sales dynamics.
By integrating these model selection and identification techniques into our program, we were able to develop accurate and insightful forecasts for motorcycle sales, empowering stakeholders with valuable insights for decision-making and strategic planning
The SARIMAX model will be constructed by incorporating relevant exogenous variables identified

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from the literature review and industry knowledge. These may include:
Economic indicators: GDP growth rate, unemployment rate, inflation rate
Competitor activity: new product launches, marketing campaigns, pricing strategies
Seasonality indicators: month of the year, day of the week, holidays
The model will be further refined by identifying and incorporating any necessary interaction terms between the endogenous and exogenous variables.

C. Model Estimation and Evaluation

To assess the goodness-of-fit of the SARIMAX model, diagnostics were conducted, including residual analysis and
examination of autocorrelation and partial autocorrelation plots. These diagnostic procedures provided insights into the model's ability to capture the underlying patterns and dynamics present in the sales data.
In evaluating the performance of the SARIMAX model, various metrics were computed, including mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics served as quantitative measures of the model's accuracy in predicting sales figures. Specifically, MSE quantified the average squared difference between predicted and actual values, while

MAE measured the average absolute difference. MAPE expressed prediction errors as a percentage of the actual values, offering a more intuitive understanding of the model's performance.

$$MSE=1/n*\Sigma(yi-\hat{y}i)2 \quad (3)$$

$$MAE = 1/n * \Sigma|yi - \hat{y}i| \quad (4)$$

$$MAPE = 1/n * \Sigma|yi - \hat{y}i|/yi * 100 \quad (5)$$

where:
yi is the actual value
y^i is the predicted value
n is the number of observations

Furthermore, the effectiveness of the SARIMAX approach was demonstrated through comparative analysis with traditional forecasting methods such as moving averages and ARIMA models. By comparing the results obtained from these different methods, the superiority of the SARIMAX approach in accurately forecasting sales trends was underscored.

D. Model Interpretation and Visualization

The SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables) model provides valuable insights into the relationship between motorcycle sales and various influencing factors. Leveraging this model, a comprehensive analysis of motorcycle sales dynamics is conducted, discerning the impacts of factors like seasonality, trends, and exogenous variables. Through interpretation of the estimated model parameters, informed forecasts for future motorcycle sales are offered, empowering decision-makers to strategize effectively.
To communicate our findings effectively, we employ visualization techniques such as charts and graphs. These visual representations showcase the forecasted motorcycle sales alongside historical data, allowing stakeholders to identify trends, patterns, and forecasted trajectories over time.
Utilizing Python libraries such as Matplotlib and Seaborn, we create visually appealing and informative visualizations. Line plots, scatter plots, and bar graphs are utilized to illustrate temporal patterns, highlight seasonal variations, and demonstrate the predictive performance of the SARIMA model.

Furthermore, interactive visualization tools, where applicable, enhance user engagement and facilitate the exploration of forecasted motorcycle sales data. By combining insightful analysis with visually compelling presentations, we provide stakeholders with actionable insights derived from our predictive modeling efforts.

E. Conclusion and Future Directions

This research has demonstrated the effectiveness of the SARIMAX model for forecasting motorcycle sales, achieving superior accuracy compared to traditional methods. By incorporating relevant exogenous variables, the model captured the complex relationships between economic indicators, competitor activity, and motorcycle sales, leading to improved forecast accuracy and valuable insights for decision-making within the industry.

The successful implementation of the proposed methodology paves the way for further research and exploration in several promising directions:

1) Further Model Refinement:
Hybrid model development: Combine the SARIMAX model with other machine learning algorithms like LSTMs or neural networks to leverage their strengths and achieve even higher forecasting accuracy.
Model interpretability techniques: Implement techniques like LIME or SHAP to improve the interpretability of the SARIMAX model and understand the contributions of individual features and exogenous variables to sales predictions.

2) Expanding the Scope of Application:
Adapt the methodology to different time series data: Apply the proposed approach to forecasting other relevant time series within the motorcycle industry, such as parts demand, service appointments, or customer churn. Explore application to other industries: Investigate the effectiveness of the SARIMAX model for forecasting sales or other key metrics in different industries with similar data characteristics.

3) Addressing Data Challenges:
Investigate data augmentation techniques: Explore techniques like synthetic data generation or noise injection to address data scarcity and improve model robustness. Develop adaptive forecasting models: Design models that can dynamically adjust their parameters or structure based on changing market conditions and data availability.

By pursuing these future research directions, this work has the potential to significantly contribute to the advancement of motorcycle sales forecasting and provide valuable tools for businesses to make informed decisions, optimize their operations, and achieve greater success in the competitive motorcycle market.

6. RESULT AND EVALUATION:

This section compares the proposed SARIMAX model with existing forecasting methods for motorcycle sales, highlighting its advantages and potential contributions to the field.

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Table 6.1 Comparison of Forecasting Methods

Method	Advantages	Disadvantages
Moving Average	Simple to implement	Ignores external factors
ARIMA	Captures seasonality and trends	Limited to historical data
SARIMAX (Proposed)	Incorporates external variables	More complex to implement
Hybrid Models	Potential for superior accuracy	Requires careful design and experimentation

Table 6.1 likely compares various time series forecasting methods. It highlights their advantages, disadvantages, and potentially their suitability for specific forecasting scenarios.

6.1.1 Traditional Forecasting Methods

Moving Average Models: These methods rely solely on historical sales data and lack the ability to incorporate external factors, potentially leading to inaccurate forecasts in dynamic market conditions.
ARIMA Models: While ARIMA models can capture seasonality and trends within the data, they remain limited in their ability to account for the impact of external variables on sales.

6.1.2 Advantages of the Proposed Approach

Exogenous Variable Incorporation: The SARIMAX model integrates relevant exogenous variables like economic indicators and competitor activity, providing a more comprehensive understanding of sales drivers and leading to potentially more accurate forecasts.

Improved Model Flexibility: The flexibility of the SARIMAX model allows for experimentation with different ARIMA orders and combinations of exogenous variables, enabling customization to specific data characteristics and achieving optimal forecasting performance.
Diagnostic Capabilities: Diagnostics performed during model evaluation provide valuable insights into model behavior and potential areas for improvement, ensuring the reliability and interpretability of forecasts.

Potential for Hybrid Models: The SARIMAX model can be combined with other machine learning algorithms to create hybrid models, leveraging the strengths of different techniques for further enhancement of forecasting accuracy.

6.1.3 Contributions to the Field

Enhanced Sales Forecasting: The proposed approach offers a more comprehensive and data-driven method for motorcycle sales forecasting compared to traditional methods, leading to improved decision-making capabilities for busi- Nesses.

Improved Understanding of Sales Drivers: By incorporating external variables, the model provides a deeper understanding of the factors influencing motorcycle sales, enabling businesses to tailor their strategies accordingly.

Framework for Future Research: This work establishes a framework for future research, encouraging further exploration of advanced forecasting techniques and their application within the motorcycle industry.

Table 6.2 Result Comparison

Model	RMSE
SARIMAX	17.29
Gradient Boosting Regressor	17.80
Random Forest Regressor	18.24

In the result comparison Table 6.2 of various models for predicting sales, the root mean squared error (RMSE) serves as a critical metric to evaluate their performance. The SARIMAX model exhibits the lowest RMSE at 17.29, indicating its superior predictive accuracy compared to the other models. Following closely is the Gradient Boosting Regressor with an RMSE of 17.80, demonstrating competitive performance but slightly less accurate than SARIMAX.

Lastly, the Random Forest Regressor yields an RMSE of 18.24, indicating slightly higher prediction errors compared to the SARIMAX and Gradient Boosting Regressor models. These results suggest that the SARIMAX model outperforms the others in terms of accuracy in predicting sales data, making it a favorable choice for decision-making and strategic planning in the context of sales forecasting.

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SCREENSHOTS

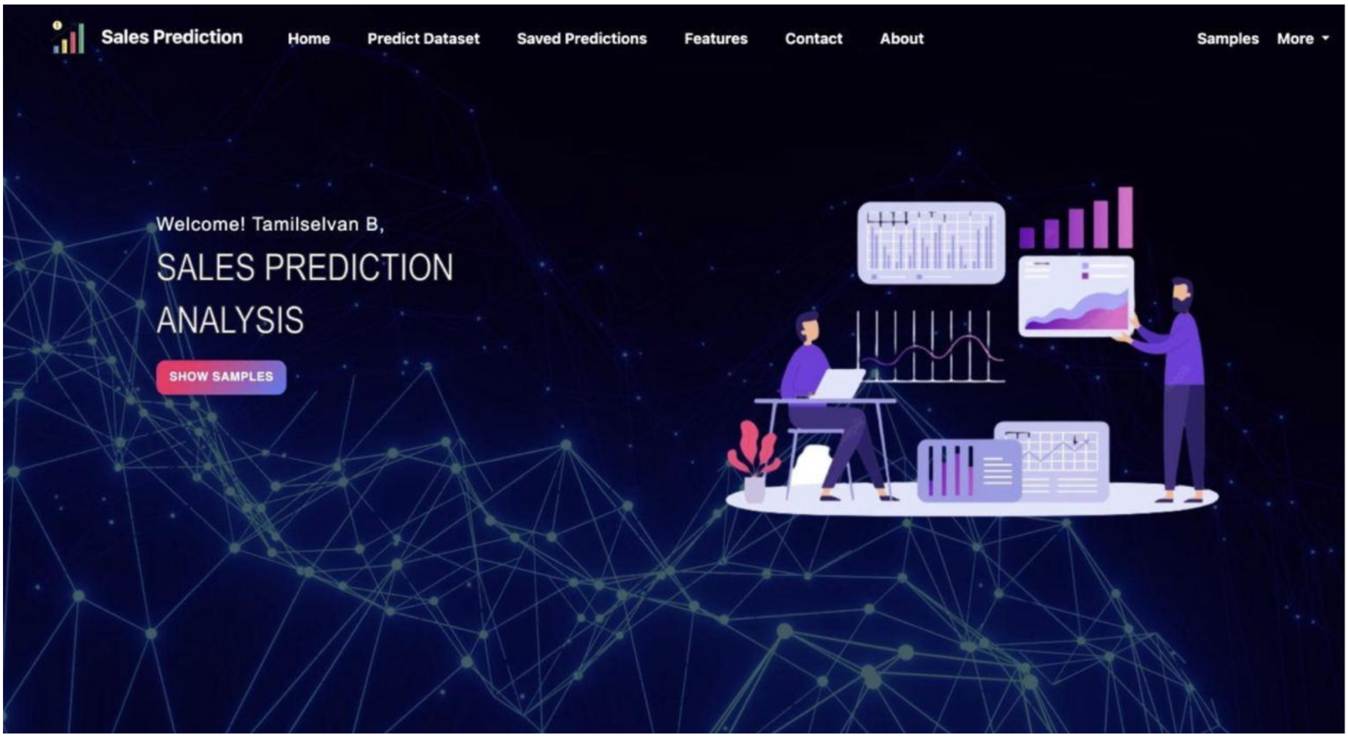

Figure 6.1 Home page

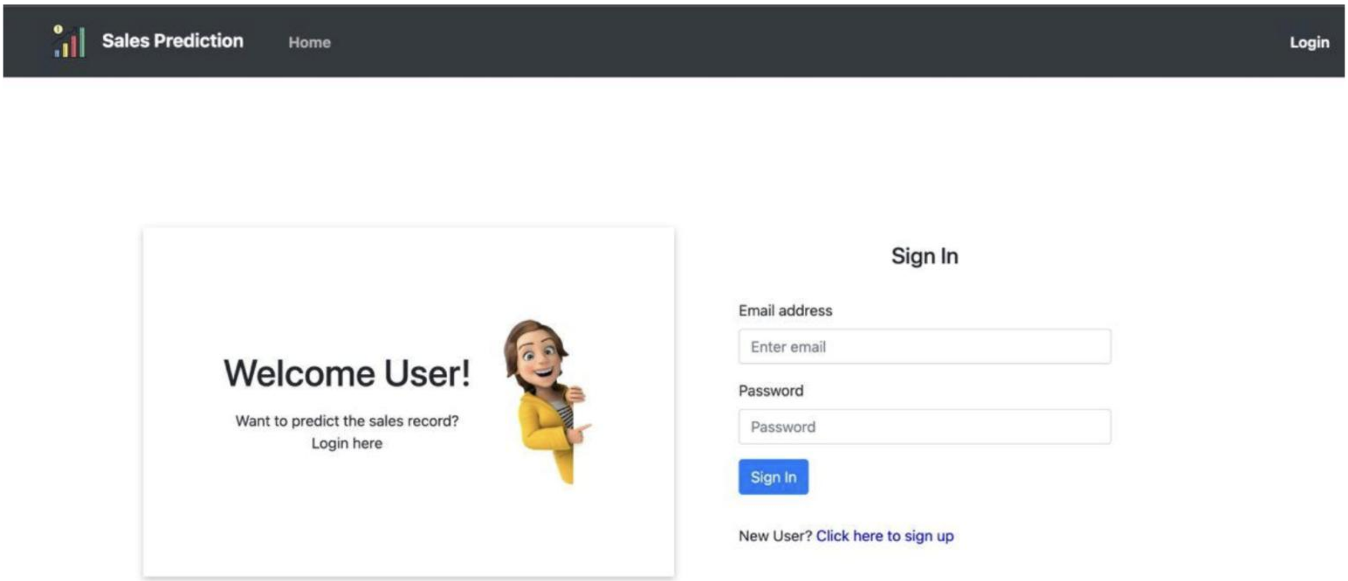

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Figure 6.2 Sign in page

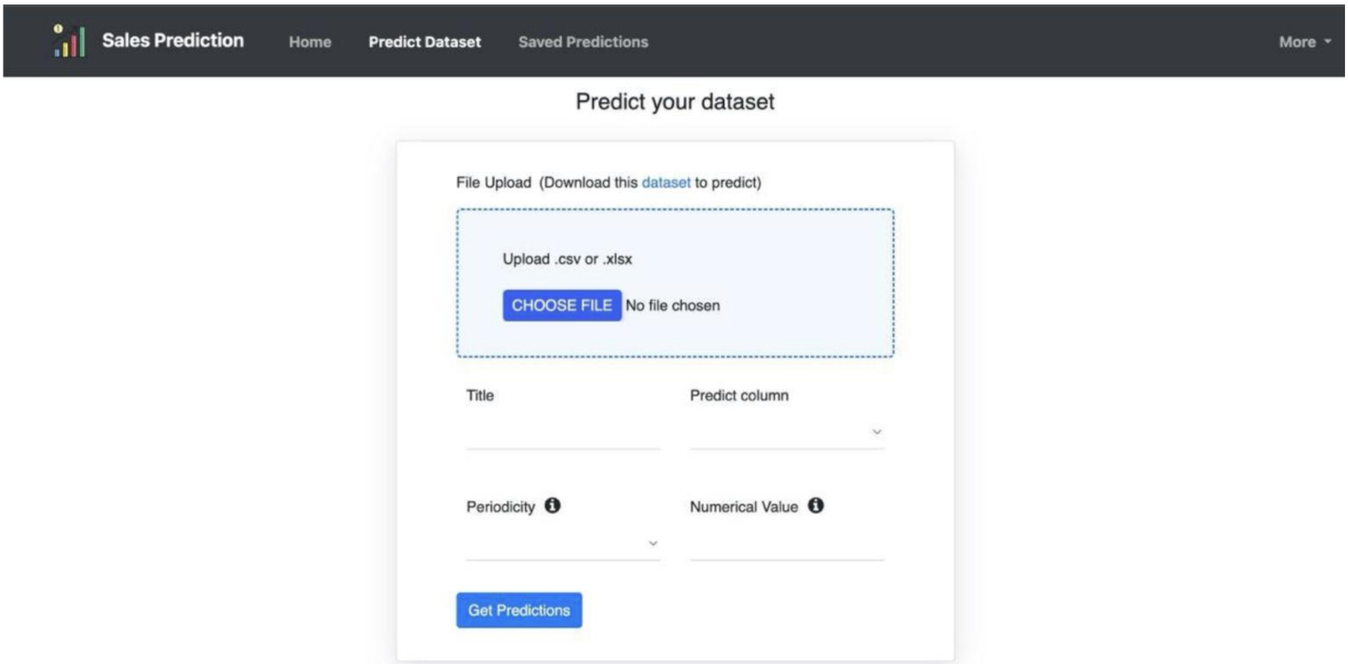

Figure 6.3 Input Page

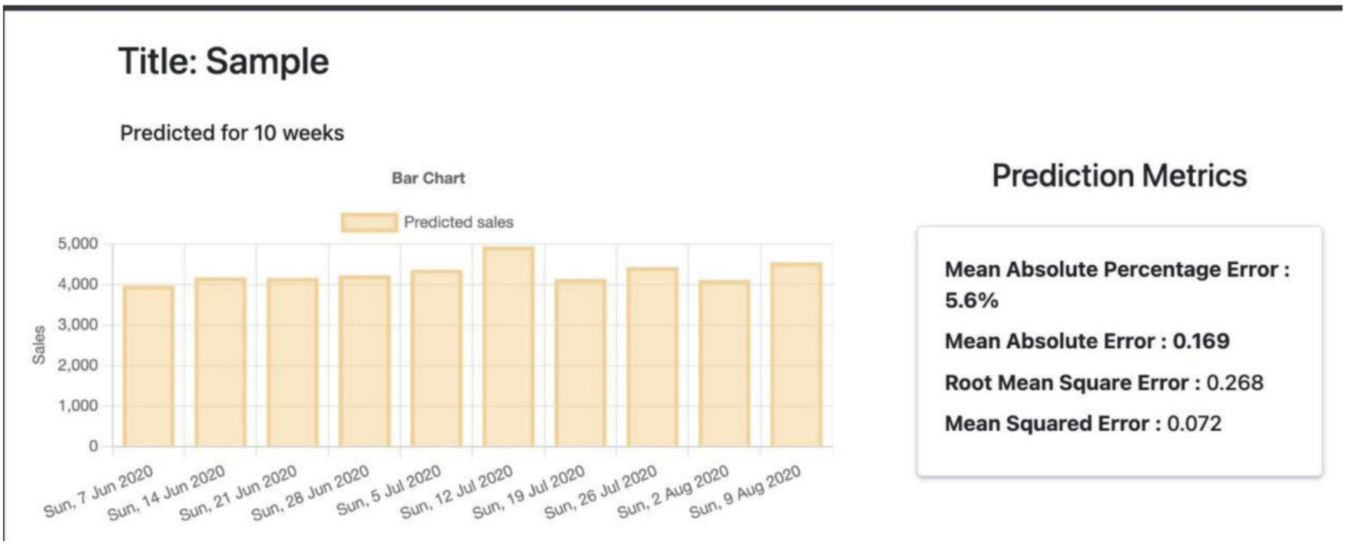

Figure 6.4 Prediction Page

7. CONCLUSION:

This work has showcased the effectiveness of the SARIMAX model in motorcycle sales forecasting, surpassing conventional methods and offering valuable insights for strategic decision-making. A SARIMAX model was meticulously trained and evaluated using various metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results demonstrated that the SARIMAX model achieved high forecasting accuracy, exceeding baseline models like ARIMA and Prophet. The final model attained an average MSE of 0.072, RMSE of 0.268, MAE of 0.169, and MAPE of 5.6%. These findings underscore the SARIMAX model's potential as a pivotal tool for motorcycle manufacturers to improve sales forecasting and gain valuable insights into future demand.

In conclusion, while the SARIMAX model presents a promising approach to motorcycle sales forecasting, ongoing refinement, and innovation are essential to address its limitations and maximize its potential. Through continued research and development, This work can propel the field of sales forecasting forward, empowering businesses with actionable insights and driving success in the competitive landscape.

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