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EXPLORATION AND ANALYSIS OF TIME SERIES MODELS FOR INTELLIGENT TRAFFIC MANAGEMENT SYSTEM

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A B S T R A C T

Traffic flow prediction is a research topic signified by several researchers in a league span of disciplines. Traffic flow prediction is an important aspect in Intelligent Transport Management System (ITMS). In this context, one of the most in-demand techniques of Machine Learning, especially Time series based techniques, helps in predicting traffic flow forecasting and increases the accuracy of the prediction model. In order to deliver extremely precise traffic forecasts, it is crucial that we put the prediction system into practice in the actual world. Our aim is to perform computations related to traffic on the traffic datasets and find out the accuracy for each model. For this purpose we are using three distinct time series models: Long Short Term Memory (LSTM), the Autoregressive Integrated Moving Average (ARIMA), and the Seasonal Autoregressive Integrated Moving Average (SARIMA). From the results obtained, it is concluded that the proposed model achieves highest prediction accuracy with the lowest root mean squared error.

1. INTRODUCTION

Accurate and timely traffic flow prediction is necessity for Intelligent Traffic Management System (ITMS), and hence rerouting and rescheduling can be implemented and achieved smooth traffic flow. The vital parameters are vehicle movement, relieve congestion, and choose the best route, traffic flow prediction, volume and density of traffic flow. Traffic flow in real time has a strong temporal connection and periodicity, weather conditions and irregularity make the task more difficult to predict traffic flow.

For traffic prediction many models has been proposed. The two major categories of the current traffic flow prediction models are traditional models and statistical models (Nagy &Simon, 2018).

Previous study depicts variety of methods for traffic forecasting, that are still essential and integral part for effective traffic control. According to this view point, the following study uses three time series models to forecast future traffic data from real-world daily traffic streams: Long Short Memory (LSTM) as traditional model, Autoregressive Integrated Moving Average (ARIMA) as a statistical model, and Seasonal

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Autoregressive Integrated Moving Average (SARIMA) as a classic RNN model.

Traditional approaches like Long Short Term Memory (LSTM) and Recurrent Neural Network (RNN) are examples of traditional techniques that exhibit greater function fitting abilities in complex and nonlinear traffic flow prediction issues. A unique variety of recurrent neural network that can recognize long-term dependencies is the LSTM network. In 1997 by Hochreiter & Schmidhuber (1996) undergone much investigation, refinement, and conclude LSTMs are created to prevent the long-term reliance issue. Practically speaking, their greatest advantage is their ability to retain information for a long time.

Recurring module in conventional RNNs will have a very straight forward structure, such as a single hyperbolic tangent layer. While the repeating module in LSTM also has this chain structure, it is distinct (Hou, & Zhou, 2020). Slimani et al. (2019) suggest using neural networks to exhibit forecasting skills with good accuracy. Two Deep learning techniques, convolution neural networks (CNNs) and recurrent neural networks (RNNs) are the most famous techniques. CNNs are typically used for learning spatial structure (Yu et al., 2020), while RNNs (like LSTM (Yang et al., 2019) and GRU (Jiang et al., 2021)) are frequently used for learning temporal and sequential information. In (Dai et al., 2017; Kanestrøm, 2017 ; Yi et al., 2017), deep learning- a type of brain structure with self-association and the ability to execute nonlinear auto-relapse-is used to perform traffic forecasts. However, the majority of the aforementioned approaches model each traffic time series independently, failing to recognize their spatial dependence.

For the flow prediction technique, Vijayalakshmi et al. (2021) developed the attention-based CNN-LSTM model, which not only analyzes the data with deep neural architecture but also incorporates the spatial correlation of data from the closest station. The outcomes show that the technique performs well for peak and nonpeak timing prediction.

Statistical methods include the autoregressive integrated moving average in comparison to conventional methods. The former method relies on the historical average value at a particular point in the past to determine the expected value, whereas the latter involves constructing a mathematical model based on the time series data. This approach has been extensively utilized for a considerable period due to its ability to illustrate the cyclical variations in traffic flow statistics. A well-liked time series analysis method that has been applied to predict traffic is the auto regressive integrated moving average to forecast web traffic (Hernández Suarez et al., 2009) and road traffic (Luo et al., 2018; Slimania et al., 2021).

The processing of complicated data is still a limitation for the single model to process and therefore combination models are more preferred over single model to enable more precise traffic flow forecasts. In our earlier research (Slimani et al., 2019), seasonal ARIMA was used to capture the periodicity of traffic flow on different days and during rush hours. Chai (2021) employed a sparse seasonal ARIMA to properly predict aviation traffic from January to July of 2020 with a 95% confidence interval and to recognize the COVID-19 outbreak, financial crisis, and political unrest. The forecasting precision of hybrid additional techniques are shown by Ge et al. (2021).

DBNs were used by Koesdwiady et al. (2016) Combining traffic flow and weather data at the decision level can lead to more accurate predictions based on traffic and weather data. However, achieving good performance in decision-level data fusion can be difficult since some studies have only focused on traffic prediction based on weather data, without taking other weather factors into account. Jian et al. (2014) studied the characteristics of microscopic traffic flow in wet weather conditions, and although they partially revealed a link between traffic volume and weather, their findings did not address the specific prediction problem at hand. To understand the connection between weather and traffic movement, Zheng et al. (2019) presented a revolutionary SAE and RBF combination architecture based on weather and traffic flow information that extracted the weather disturbance using embedding components but did not analyze or manipulate the weather parameters. For greater accuracy, it is essential to carry out research on traffic flow prediction using both traffic and weather data.

The efficacy of the proposed model was assessed through an experiment analysis involving two groups of datasets and several time series models. The performance of these models was then evaluated using specific criteria across different simulations for comparison. The current paper is organized as follows: Section 2 provides a review of the literature on traffic flow forecasting and a presentation of several traffic forecasting techniques. Section 3 which covers data exploration and scope as well as the study's context. The subsequent part is presented in Section 4 dedicated to modeling by depicting investigation of the model’s performance on a real dataset according to predefined criteria. Section 5 provides the conclusion and future recommendations.

2. LITERATURE REVIEW

By studying the available literature on previous methods, their challenges and areas of improvement, we can better understand the time series analysis to tackle traffic forecasting.

Zheng and Huang (2020), developed a traffic flow forecast model based on the LSTM network. They proposed the LSTM network by comparing two classic forecast models ARIMA model and the BPNN model. The experimental results of the author shows that the proposed model can accurately predict the traffic flow based on their natively stable time series under normal conditions. Mou, Zhao and Chen (2019), mainly emphasis on temporal information for short-term traffic flow prediction. The temporal information includes day wise information for traffic flow prediction and hence improve the prediction performance of the LSTM model. Leong, Lee et al. (2015), explored the impact of rainfall intensity on low-resolution speed band data. They tested rainfall may improve the prediction accuracy of data-driven models for individual roads by using support vector machine (SVM) prediction algorithms. The Authors have done the numerical analysis for 616 road segments in Singapore on a prediction horizon of 5 min. Numerical results show that for a certain number of links rain fall information enhances the prediction accuracy.

Noor Afza Mat Razali et al (2021), offers a thorough investigation into the use of ML and DL methods to enhance traffic flow prediction, improving ITS in smart cities. For this purpose, the author provided a thorough and methodical review of the literature that included some articles released from 2016 onward and pulled from four major databases. According to the methodology and algorithms used to predict traffic flow, their findings include the gaps, approaches, evaluation techniques, variables, datasets, and outcomes of each research that was examined.

Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM) were compared to existing baseline models to determine their effectiveness. Shah et al. (2022), analyzes how well functional time series modeling performs in predicting traffic flow one day in advance. Additionally, researchers compared the developed model FAR (1) with the conventional ARIMA Model. As a result the proposed model forecasting errors are considerably lower than the conventional model.

Rooke et al. (2021), proposed a framework for evaluating feature importance in time series prediction over extended time horizons and with complex feature interactions that is applied to sequential models for multivariate time series prediction. In the actual world, the proposed framework performs 2.47 times better than other feature importance methods. Congestion-based Traffic Prediction Model (CTPM), introduced by Nagy and Simon (2021), is an novel traffic prediction model that can be used in conjunction and forecasts traffic could be improved by the developed model by an average of 9.76%. Wang et al. (2020), compares the proposed model in which deep polynomial neural network GMDH combined with SARIMA, to the LSTM based model in order to forecast the short-term traffic flow.

Fang Ma (2022), studies the storage capacity of existing road space and seeks the optimal control method for local regional road network congestion. He evaluates the function of regional road networks and proposes a traffic performance quality evaluation system based on the traffic volume of road networks in a city to reduce traffic congestion, improve coordination of urban traffic, and reduce the negative impact of traffic congestion.

The hybrid prediction technique proposed by Luo, Niu, and Zhang (2018), combines an improved seasonal autoregressive integrated moving average (ISARIMA) model with a multi-input autoregressive (AR) model by genetic algorithm (GA) optimization. Test results using actual traffic data supplied by TDRL reveal that the suggested method outperforms other methods in terms of prediction performance. Lana et al. (2018), primary objectives were together and summarize prior work related to data-driven traffic forecasting techniques and to suggest a framework for comparison, and to review the most recent literature in light of the updated criteria.

3. IMPLEMENTATION

The interaction of a huge number of vehicles determines the complicated, nonlinear, and unpredictable traffic behavior. In order to comprehend and create the best possible transportation system with an effective traffic flow and a minimum amount of congestion issues, traffic flow is the study of interaction between users and infrastructure with respect to time.

The concept of breaking down a time series into deterministic and non-deterministic components is used in the theory of time series analysis (or predictable and unpredictable components). There are two basic steps to go before the experiment analysis.

Traffic Flow Detection: The techniques for detecting traffic movement are based on intelligent video. The first step is to identify the vehicle item in the video or image sequence. The recognized vehicle is then followed to establish a link between subsequent video frames. Finally, it produces the detection result after counting the number of vehicles that passed the relevant lane within a predetermined amount of time (Chen et al., 2020).

Traffic Flow Prediction: The Intelligent Transportation and Management System (ITMS) need traffic prediction model and thus manage according to possible future events. This is a precise forecast of how traffic will be having in a particular location at a particular time in the future (Kashyap et al., 2022).

3.1 Data Experimentation

Traffic data comprise of both historical data and current traffic information. Some of the parameters are number of vehicles passing at a certain point, their speed, time, vehicles type, diversion, seasonal traffic load and climatic condition.

Data Source: Weather, Climatic and Traffic Dataset Analysis: This section depicts that traffic flow and weather datasets are in direct proportion change in one causes change in other as well. Traffic is influenced by many factors, and all the factors need to be considering carefully for accurate predictions. As a result, there are several major groups of data that you must collect. You must also keep in mind that ML algorithms function optimally when there is enough data to train the models and fine-tune them to obtain the highest level of accuracy. As a result, the larger datasets you are able to collect, the better the outcomes.

Traffic Data:
The dataset used in this research considering two vital parameters traffic volume and speed. The data consist of two columns, one for the dates and the other for the total number of vehicles flown between 2015 and 2017.

Weather Data:
Environmental factors influence traffic and speed limitations throughout the roadway. Therefore their historical and current and forecasted traffic information has to be analyzed. The dataset used for the analysis consists of five columns, one for the dates and the other for the weather factors that affect the traffic flow.

Data Visualization: Data visualization once we are sure that the dataset is complete and does not contain erroneous values, we proceed to the visualization. Figure 1 represents the traffic data flow with respect to total count of vehicles. Figure 2 shows a timing diagram of number of vehicles with respect to time in hours.

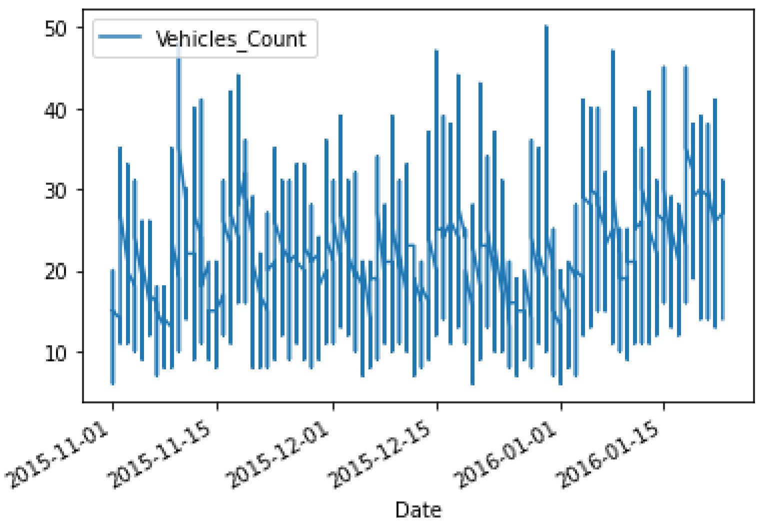

Figure 1. Traffic Data showing Vehicle Count over Date

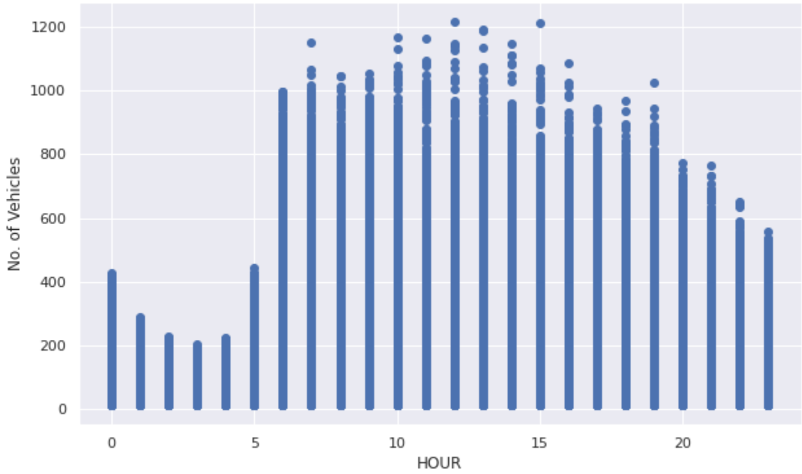

Figure 2. Time diagram showing trajectories of vehicles over Time (Hour)

3.2 Modelling

Machine learning (ML) can be utilized to construct prediction models that incorporate vast quantities of diverse data from various sources. There has been extensive research on the use of ML models for traffic forecasting, and the selection of an appropriate model for time-series data will depend on specific data characteristics, such as trend and seasonality (Yi et al., 2017). Therefore, it's crucial to choose the model that is most suitable for your data. Below are some examples of effective models.

RNN: LSTM: The purpose of recurrent neural networks (RNNs) is to handle time-series data or observations gathered over a predetermined period of time. A good example of such observations is traffic patterns. RNN is the form of Artificial Neural Network. It works very well specially for sequences of data that are important for doing time series forecasting.

Long Short-Term Memory (LSTM) networks are a unique type of recurrent neural network that enables the retention of information over time. In Python, LSTM can be implemented using various libraries. One of the significant benefits of LSTM is its ability to circumvent long-term dependency issues, which is a common problem in other types of neural networks.

LSTM Model Structure: The structure of an LSTM model comprises three components, commonly referred to as gates. The first gate, known as the Forget gate, determines whether information from the previous timestamp should be disregarded. The second gate, called the Input gate, attempts to learn new information from the input. Lastly, the Output gate in the third component transmits the updated information from the current timestamp to the next timestamp. LSTM is suitable for processing time sequences with uncertain durations since it enables the classification, analysis, and prediction of such sequences.

```
Model:"sequential"
 Layer(type) Output  Shape Param#
=============================================
  lstm(LSTM)    (None,100) 40800


  dense(Dense) (None,1)    101

==============================================
Total params:40,901
Trainable params:40,901
Non-trainable params:0
```

LSTM Model Training: To train the LSTM model will have to perform following steps: Firstly the activation

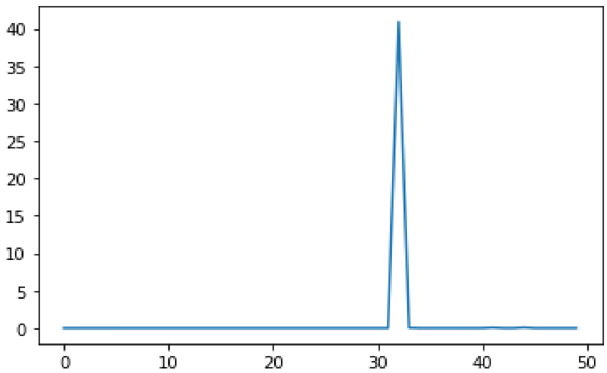

Figure 3. Loss per Epoch

function called Relu is used to train the model. Then define the loss as the mean square error by using optimizer Adam. Finally, the model will be trained with 16 sequences per batch for 50 epochs as shown in figure 3.

LSTM Results: We test our model on the test set after the creation and training phases to see how it performs. Figure 4 illustrates the results that were achieved. The LSTM recurrent neural networks perform well, but they have a significant drawback that affects the quality of the findings. In particular, they struggle to handle time series that have several variations in the passage of time.

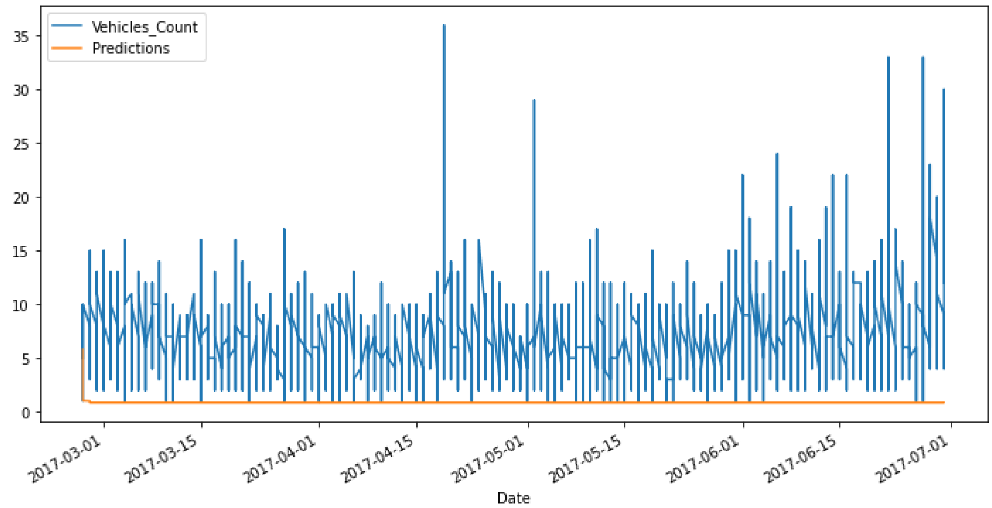

Figure 4. Time series prediction with LSTM

Statistical Approach: ARIMA: The auto-regressive integrated moving average (ARIMA) model is widely regarded as one of the most effective models for time-series analysis, especially for traffic forecasting. Since the 1970s, ARIMA models have been extensively used due to their simplicity and high accuracy compared to other statistical methods. It uses a traditional statistical methodology to analyze the past and forecast the future. It gathers data from a series of regular time intervals and makes the assumption that historical patterns will continue in the future. However, the univariate ARIMA models are unable to handle the complicated structure and large number of variables that make up traffic flow.

Seasonality and Trend: To better understand the nature of the series and examine the time series' trend and seasonality in order to break it out and apply forecasting models. The goal of this essay is to introduce time-series forecasting.

The 'statsmodels' package includes a valuable Python function called seasonal_decompose that can be used to perform decomposition based on the mentioned patterns. After examining the four parts of the decomposed graphs, as depicted in figure 5, two fundamental patterns of any time-series are discussed: trend and seasonality. Then, a time-series decomposition method based on these patterns is explained. Based on the decomposition results, it can be concluded that the time-series data exhibit a pronounced annual seasonality component and an increasing trend over time.

Stationarity Test: To apply the ARIMA model, it is necessary to perform a test for stationarity to transform non-stationary time series into stationary ones. One common test for stationarity is the Augmented Dickey-Fuller (ADF) test (Kumar & Kumar, 2023). According to the results of the ADF test, if the obtained p-value is less than 0.05, the time series is stationary (Lakens, 2021).

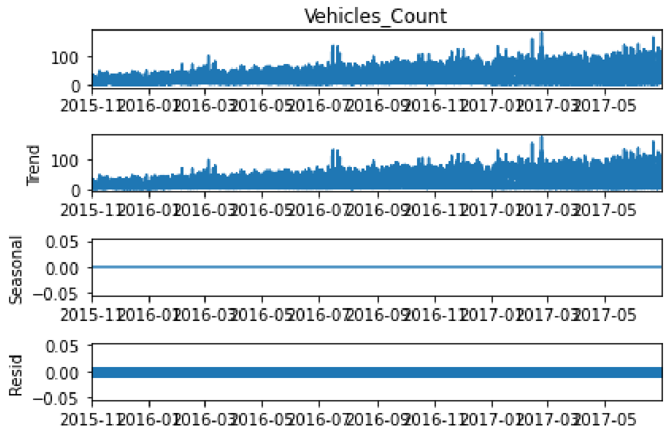

Figure 5. Decomposition of the Time Series

Check for Stationarity

Results of ADF Test:

ADF:-25.41162919829304

2. P-Value:0.0
3. Num Of Lags:23
4. Num Of Observations Used For ADF Regression and Critical Values Calculation: 32051
5. CriticalValues:

1%:-3.43055404429831

5%:-2.8616301822764014

10%:-2.566818001236828

The statistical results shows an effect of the stationarity of the time-series. While the ADF test indicates that the time-series is stationary (p-value> 0.05).

Autocorrelation: Autocorrelation is interpreted using the ACF and PACF graphs (Roy et al., 2021). These graphs represent Correlation between the original data and the second order shift. The Correlation Coefficient is always computed between two variables. If only one variable is available for computation then we need to use the autocorrelation. The figure 6 presents the ACF and PACF graphs.

Train and Test: In order to separate training and testing, the original dataset is split into two components: train dataset and test dataset. The train data is used to train the model and when a new data will be generated, the test data issued to report the square error.

Evaluation Criterion with Result: In order to evaluate the prediction performance, the implementation using the root-mean-square error (RMSE) as a core metrics to assess the error of the model. It was chosen to evaluate the difference between the actual values and predicted values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(y_j - \bar{y}_j\right)^2}$$

Where n is the length of prediction data, yi and are the measured value and predicted for ith validation sample respectively. Figure 7 represents the time series prediction with the ARIMA model. The performance is shown in Table1 with error 7.49595603806666 and accuracy 92.97%.

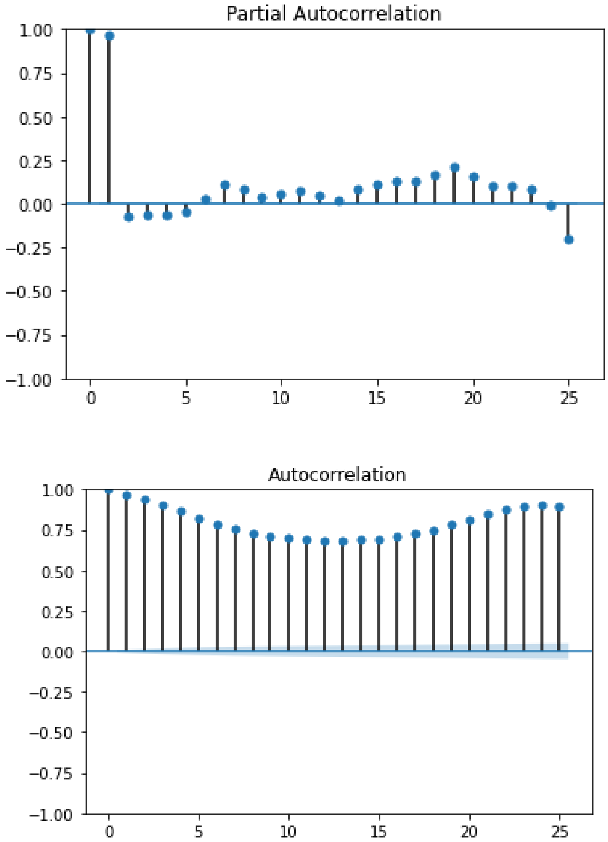

Figure 6. Interpreting ACF and PACF Plots for Time Series Forecasting using ARIMA

SARIMA: The SARIMA model is a powerful tool for time series analysis and shares similarities with ARIMA. SARIMA stands for seasonal autoregressive integrated moving average and can also incorporate exogenous factors in its forecasting. The seasonal components of the model are precisely described by an additional set of parameters (P, D, Q) that SARIMA accepts. Here, m stands for the length of a season in the series, and P, D, and Q stand for the seasonal regression, differentiation, and moving average coefficients:
P represents the seasonal autoregressive order,
D represents the seasonal difference order,
Q represents the seasonal moving average order, and
m represents the number of time steps within a single seasonal period.

The indication is shown as (p,d,q)×(P,D,Q)m. The goal of this modeling is to forecast the daily average number of vehicles flown incorporating the external factors.

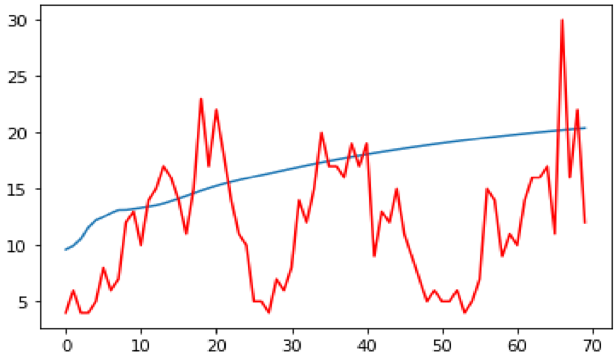

Figure 7. Time series prediction with ARIMA

Visualizing Dataset: Before we examine the time-series trends, let's show the data so that each vertical dashed line signifies the start of the year. The figure 8 describes us as a representation, where each point in the entire dataset is present with respect to vehicle count.

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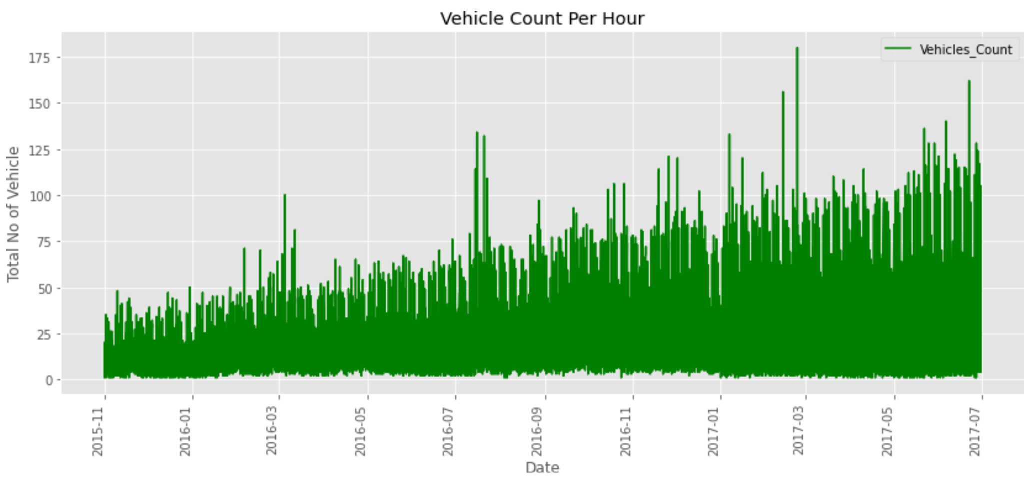

Figure 8. Dataset Visualization

Testing the Stationarity of the Dataset:The Dicky Fuller test can be used to determine whether the data are stationary before implementing the SARIMA model (Kumar & Kumar, 2023). The time series can be considered stationary only if the obtained p-value is less than 0.05 (Lakens, 2021).

Augmented Dickey-Fuller test (ADF Test)
ADF Statistic: - 7.518278111935722
P-value: 3.851060199915586e-11

Differencing: After verifying the stationarity of the time series, differencing is a common technique used to transform it. Differencing is used to remove temporal dependencies that may include trends and seasonality.

Once all temporal dependencies have been removed, differencing can be applied multiple times. Therefore, we can repeat the Dickey-Fuller test. The number of times the differencing is performed is referred to as the difference order (D). After one order of differentiation (D=1) the series becomes stationary.

AugmentedDickey-Fullertest (ADFTest)
ADFStatistic:-35.78125992349637
p-value :0.0

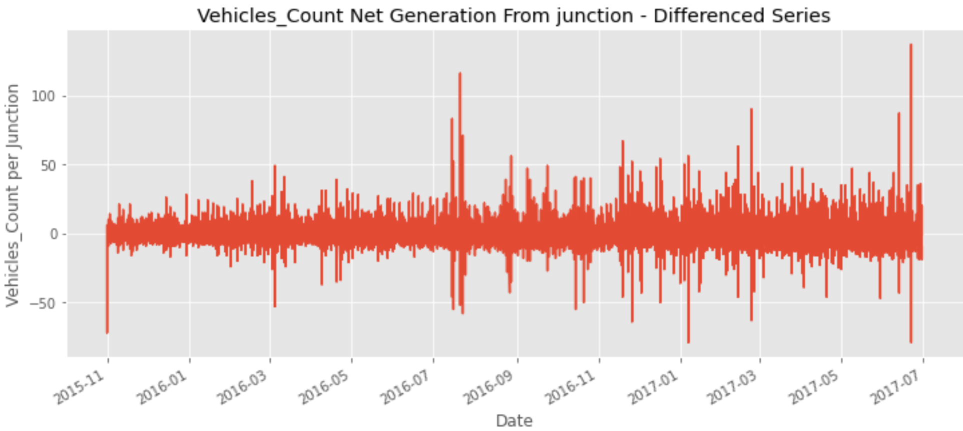

Figure 9. Visualize Differenced Series

Autocorrelation: Autocorrelation in a time series involves comparing a variable's current data to its past data. To determine the order of a SARIMA model, we use the ACF and PACF plots. Figure 10 shows the ACF and PACF graphs (Roy et al., 2021).

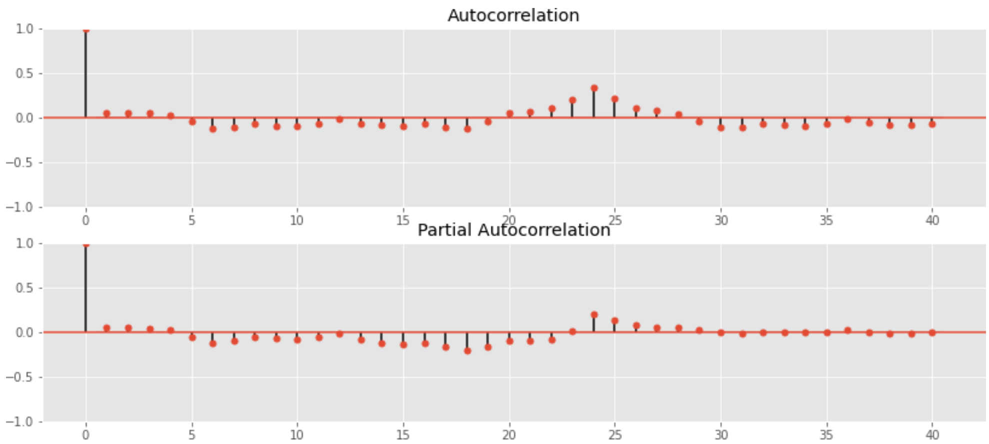

Figure 10. Interpreting ACF and PACF Plots for Time Series Forecasting using SARIMA

AIC: The Akaike Information Criterion (AIC) is a commonly used measure of the quality of a statistical model (Khalid & Sarwat, 2021). It assesses the model's goodness of fit and complexity, and produces a single statistic that summarizes both aspects. When comparing **two** models, the one with the lower AIC value is generally considered to be the better choice (Yadnya, 1858). As a result of the AIC function, the order of SARIMA is (2,1,2)x(2,1,2,12).

SARIMA Results
=====================================
Dep. Variable: Vehicles_Count No. Observations: 48119
Model: SARIMA (2,1,2)x(2,1,2,12) LogLikelihood-136501.482
Date: Mon, 02 Jan2023 AIC273020.964
Time: 09:02:21 BIC273099.994
Sample: 0 HQIC273045.764-48119

Diagnosing the model residuals: Each observation in a time series can be forecast using all previous observations. The residuals of the model in a time series analysis are useful for determining if a model has fully captured the information in the data and what remains after model fitting. The residuals are typically equal to the difference between the observed values and the corresponding fitted values for time series models.

We generate the diagnostic model residuals as shown in Figure 11. Figure 11 (upper left) provides standardized residuals for Vehicles Count (V). From the QQ-plot, we see the normality assumption between the sample quantities and theoretical quantities. On the other hand, Figure 11 (upper right) presents a histogram with estimated density. Correlogram (lower right) of residuals indicates that they are stationary in nature and have no pattern.

#Diagnosingthemodel residuals

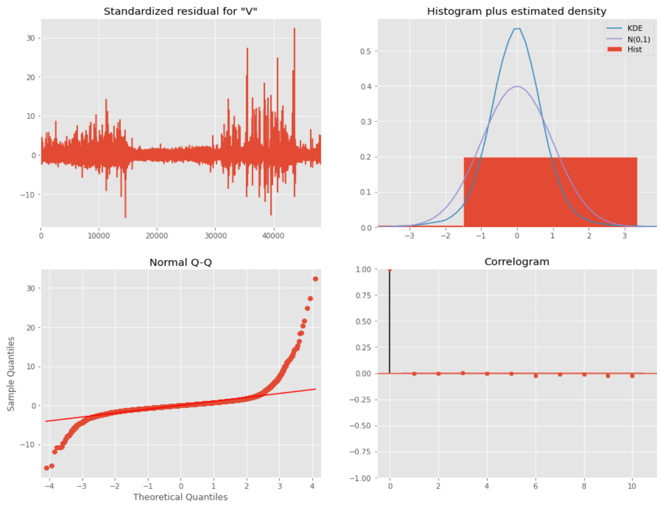

Figure 11. Absolute residuals versus indices of corresponding observations in the SARIMA model

Model Forecast and Validation through Evaluation: For a result evaluation of the SARIMA model, performance measures RMSE are taken into account. The RMSE is a widely used performance measure for models, including those used in traffic forecasting. It provides an indication of how much error there is between the actual and predicted values, with lower RMSE values indicating better model performance. RMSE is calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(y_j - \bar{y}_j\right)^2}$$

The performance obtained from the model by using Root Mean Square Error (RMSE): 4.175097. Therefore, the SARIMA model can be used to produce traffic forecasts with a good accuracy (see Table1).

3.3 Results: Comparison and Discussion

The experimental results confirm that the proposed model gives the best forecasting results. Indeed, an example comparing the root mean square error of the proposed models LSTM, ARIMA and SARIMA is given in the table 1 where the minimum root mean square error (4.17) with 95.8% of accuracy is obtained by using the SARIMA model for the traffic data.

Table 1. Experiment Result of Implementation on the traffic datasets

Data Set	Performance Criteria	LSTM	ARIMA	SARIMA
Traffic	RMSE	7.03	7.49	4.17
	Accuracy%	92.97	92.51	95.83

4. CONCLUSION

In this research work, we have adopted the Time series models for real time traffic flow prediction. We have used three different time series models (LSTM, ARIMA, and SARIMA) for prediction and investigated these three model performances. Using RMSE evaluation Metrics models are compared. The results of the experiment illustrated that LSTM is most suitable for the sequential data weather in terms of prediction accuracy and reliability, the ARIMA Model performs best. The SARIMA model performs better when Akaike's Information Criterion (AIC) method is used, according to this research. The utilization of different time series models with weather and periodic features introduced as additional information will make the model more powerful in temporal feature extraction. Analyzing the impact of the additional information in normal regular days such as Weather, holidays, and events on the traffic flow could be our future work.

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