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FORECAST WEB TRAFFIC TIME SERIES USING ARIMA MODEL

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Abstract : Web traffic forecasting is a key topic since it has the potential to cause major problems with website functionality. Making predictions about future time series values is one of the most challenging problems, hence it has become a popular issue for research. As a result of the increased web traffic, the site may crash or load very slowly. Such disruptions may cause numerous disruptions for users, resulting in a lower user rating of the site and user migration to another site, which has an impact on the business. To predict online traffic, we created a forecasting model. The ARIMA model is used to forecast Web traffic time series. We used some of the information, such as the name of the page, the date it was seen, and the number of visits, to make more accurate predictions.

Keywords Web traffic prediction, ARIMA model, Time series forecasting, Data Collection and Feature Understanding.

1. INTRODUCTION

People who work for online service providers must know how much traffic a web server receives, since if they don't, clients may have waited too long and will abandon the site. This is a challenging endeavour, however, because it necessitates making precise predictions about how people will behave based on their randomness. In this post, we'll teach you how to create an architecture that leverages source data to forecast how many people will visit a specific page at a given time. Web applications process HTTP GET requests based on the website's response, media apps distribute content based on what the user wants, and so on. The length of the request will have a significant impact on how the end-user perceives the service's quality. Many users have abandoned platforms because they waited too long to respond. The response time, on the other hand, is the time it takes for an application to receive a request and respond to it. This is referred to as the response time. This is something that can't be taken away. The response time for web services is too long for clients to expect. Developers have figured out when the response time is excessively long, which is referred to as web congestion. For the problem, a time series with dates and page visits makes sense. The goal of this study is to create a forecasting model that can anticipate online traffic based on certain characteristics such as page name, visited date, and number of visits per page over the course of a year. As more people throughout the world have access to the internet, an increase in traffic to virtually all websites has become unavoidable. The increase in internet traffic could cause a plethora of problems, and the company that can best deal with the fluctuations in traffic will win.[7] As most people have encountered a crashed site or a very slow loading time for a website when there are a lot of people using it, such as when various shopping websites may crash just before festivals as more people try to log in than it was originally capable of, causing a lot of inconveniences for the users, and as most people have encountered a crashed site or a very slow loading time for a website when there are a lot of people using it, for example, when a number of ecommerce websites may go down right before a festival. As a result, users may give the site a worse rating and instead use another site, reducing their business. As a result, a traffic management strategy or plan should be established to reduce the risk of such calamities, which could put the company's existence in jeopardy. Until recently, such solutions were unnecessary because most servers could handle the increased traffic. However, the smartphone era has driven up demand for some websites to the point where firms have been unable to reply rapidly enough to maintain an inconsistent level of customer service.

2. LITERATURE SURVEY

The system successfully rebuilt the old model and introduced new features throughout the prediction model construction, resulting in higher model efficiency. New features were combined in various ways.
1)Use the median of the provided window length in each time series as an independent feature to capture weekly, monthly, quarterly, and yearly page popularity.
2)Median of medians of various time frame windows based on the golden ratio.
The study [1] analysed the acquired results and compared the ac curacies in various scenarios to establish the value of each attribute. We'll then try to figure out how to improve an existing model by tweaking parameters. The goal of the study was to develop the best time-series forecasting model that would allow us to estimate future traffic statistics when

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a large enough dataset was available. With this goal in mind, researchers began looking for predictive models that would allow them to estimate the value of data. However, after doing further research, we discovered that it was forecasting rather than prediction, so we concentrated on that. The study in [2] encountered so many timeseries forecasting models that it made our work both tiresome and enjoyable. The paper developed a time series forecasting technique for predicting internet traffic using historical data. Many forecasting techniques, such as ARIMA, are widely utilised in the literature, however they are most useful for time series that are linear in form. Neural networks, on the other hand, such as RNN, are particularly useful for forecasting nonlinear time series. The proposed method employs the Discrete Wavelet Transform, as well as a high pass and low pass filter, to generate linear and nonlinear components for the time series. ARIMA and RNN are clearly outperformed by the proposed approach [3]. The technology is very easy to use in data centres due to its simplicity. The research [4] proposed a novel technical approach to predicting the exit-link traffic pattern on campus networks. It also forecasts that if enough historical data is available, EPTS will have the following effect in network traffic forecasting. Forecasting Web Traffic Time Series

1)Using past network traffic data, estimate network exit-link traffic trends so that network resource planning can be planned ahead of time.

2)It is simple to implement and has a manageable computing complexity.

The impacts of the LSTM network, BPNN model, and ARIMA model on time series recorded at a single point are compared in the paper [5]. Under typical conditions, the proposed LSTM network can accurately anticipate traffic flow based on relatively steady time series. The traffic system on roadways, on the other hand, is stochastic and complex, and it is frequently influenced by unusual circumstances such as severe weather, traffic accidents, and huge events.

TITLE	**PUBLICATION AND AITHOR**	**TECHNICAL DETAILS**
Web Traffic Prediction of Wikipedia Pages	**2018**IEEE International Conference on Big Data (Big Data) [1] -Navyasree Petluri, Eyhab Al-Masri	During the construction of the prediction model, the system effectively rebuilt the current model and incorporated new features, resulting in increased model efficiency. New features were used in various combinations. 1) For capturing weekly, monthly, quarterly, and yearly page popularity, use the median of a defined window length in each time series as an independent feature. 2) Golden ratio-based median of medians of varied time frame windows. To determine the importance of each feature, the study analysed the obtained results and compared the accuracies in various scenarios. Next, we'll try to figure out how to tweak parameters in an existing model to get better outcomes.
Traffic Forecasting using Time-Series Analysis.	**2021** 6th International Conference on Inventive Computation Technologies (ICICT) [2] - Mohammmad Asifur Rahman Shuvo, Muhtadi Zubair Afsara Tahsin Purnota, Sarowar Hossain, Muhammad Iqbal Hossain	The goal of the study was to develop the best time-series forecasting model that would allow us to estimate future traffic statistics when a large enough dataset was available. With this goal in mind, researchers began looking for predictive models that would allow them to estimate the value of data. However, after doing further research, we discovered that it was forecasting rather than prediction, so we concentrated on that. We came across so many time-series forecasting models during our research that it made our task both laborious and enjoyable.

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Predicting Computer Network Traffic: A Time Series Forecasting Approach Using DWT, ARIMA and RNN	**2018** Eleventh International Conference on Contemporary Computing (IC3) [3] - Rishabh Madan, Partha Sarathi Mangipudi	The paper developed a time series forecasting technique for predicting internet traffic using historical data. Many forecasting approaches, such as ARIMA, are widely utilised in the literature for creating forecasts, however they are most useful for linear time series. Neural networks, on the other hand, such as RNN, are particularly useful for forecasting nonlinear time series. The proposed method employs the Discrete Wavelet Transform, as well as a high pass and low pass filter, to generate linear and nonlinear components for the time series. ARIMA and RNN are obviously outperformed by the proposed method. The technology is very easy to use in data centres due to its simplicity.
An Engineering Approach to Prediction of Network Traffic Based on Time-Series Model	**2009** International Joint Conference on Artificial Intelligence. [4] -Fu-Ke Shen, Wei Zhang, Pan Chang	The study proposes a new technical technique to predicting campus network exit-link traffic trends, and it forecasts that if enough historical data is available, EPTS can have a follow-on effect in network traffic forecasting. 1) To forecast network exit-link traffic trends using previous network traffic data in order to plan network resource allocation ahead of time. 2) It is simple to implement and has a manageable computing complexity.
Traffic Flow Forecast Through Time Series Analysis Based Deep Learning	**2020** IEEE Access [5] - Jianhu Zheng, Mingfang Huang	The effects of the LSTM network, the BPNN model, and the ARIMA model on a single-point time series are compared in this research. Under normal circumstances, the proposed LSTM network can reliably estimate traffic flow using a somewhat stable time series. The traffic system on roadways, on the other hand, is stochastic and complex, and it is frequently influenced by unusual circumstances such as severe weather, traffic accidents, and major events.

3. RELATED WORK

Over the years, experts have disregarded neural networks (NNs) as non-competitive, while NN enthusiasts have presented a slew of new and sophisticated NN architectures, many of which lack credible empirical assessments when compared to basic univariate statistical methods. This notion was supported by many time series prediction competitions, such as the M3, NN3, and NN5 competitions [18– 20]. As a result, NNs have been deemed unsuitable for forecasting. The historical low performance of NNs could be attributable to a number of issues, one of which is that individual time series were typically too short to be simulated using advanced approaches. Alternatively, the properties of the time series could have changed over time, resulting in lengthier time series with inadequate relevant data to fit a sophisticated model [7,8]. As a result, it's critical that when employing intricate ways to depict series, they're the proper length and come from a somewhat stable system. NNs are also frequently chastised for being closed systems. As a result, forecasting experts have always preferred to use more straightforward statistical procedures [9]. We do, however, live in a data-rich atmosphere right now. Businesses have amassed a vast amount of data over time that may be used to get important insight into their operations. Big data does not always imply that each time series contains a lot of information in the context of time series. Rather, they frequently imply that a given field has a huge number of interconnected time series. In this instance, univariate prediction algorithms that analyse each time series separately may not be reliable. Because a single model can learn from numerous comparable timeseries at the same time, they become inaccessible when dealing with big data sets. Furthermore, complex models like neural networks (NNs) benefit as much as possible from having access to vast amounts of data. Recurrent Neural Networks (RNN) play a role in this emerging topic of scientific interest in neural networks. With this new type of neural network that specialises in the sequence prediction problem [18], results never seen before in the field of language and time series analysis are starting to be realised.

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RNNs, on the other hand, have significant memory concerns that were addressed when the LSTM was introduced into the field of research. This new sort of RNN has a new internal memory in addition to the standard concealed state of RNNs (cell state). When training LSTMs, this makes it easier to avoid issues like vanishing or exploding gradients [19]. Because time series incorporate seasonality components, LSTM can be applied in a predictive setting. If a monthly time series has yearly seasonality, the value of the same exact month the previous year, for example, is more beneficial in predicting the value of the upcoming month. Suilin et al. did an outstanding job with the Kaggle challenge for estimating Wikipedia's site traffic, which used this notion. [20]. Despite the fact that this dataset has been frequently used to predict time series linked to internet traffic, it was not used in the creation of the LSTM with minimum data since the researchers think that other models, such as ARIMA, are more efficient in similar cases. The various driving data in this model are given different weights depending on how significant they are in contributing to the forecast at each time stage. To validate this model, the authors compared it to ARIMA, NARX RNN, Encoder Decoder, Attention RNN, Input Attention RNN, and the Dual Stage Attention RNN [22]. The model proposed by Qin et al. has recently been investigated. The authors claimed in [23] that their model can handle the fundamental features of spatial temporal series. In recent years, researchers have begun stacking RNN or LSTM to achieve the desired outcome in FTS challenges. However, we observed a gap in the literature when using FTS prediction models in time series with insufficient data [24]. Due to a gap in the state of the art in the prediction of time series with limited data, we proposed a supervised architecture based on LSTM that is trained through distributed data parallelism and follows the Downpour technique.

4. PROPOSED SYSTEM ARCHITECTURE

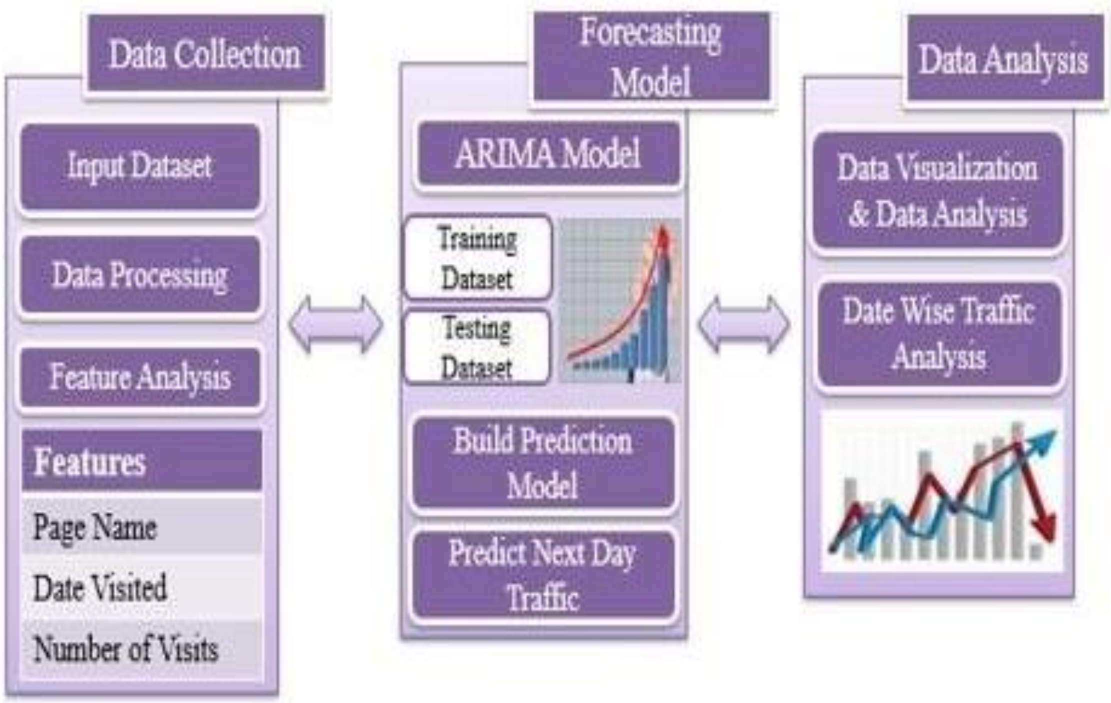

Figure 1: System Architecture

5. ARIMA MODEL

ARIMA (Auto regressive Integrated Moving Average model) is a statistical research technique that employs time series data to better comprehend or forecast future trends. An autoregressive integrated moving average model is a sort of regression analysis that assesses the strength of one dependent variable in relation to other changing variables. The model's goal is to predict future securities or financial market movements by analysing the differences between values in a series rather than the actual values. The complete model is as follows:

$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$

The differences series is denoted by yt' (it may have been differences more than once).

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Both lagged yt values and lagged errors are included in the "predictors" on the right-hand side.
ARIMA with p, d, and q is a standard notation in which integer values replace the parameters to denote the kind of ARIMA model utilised.
The parameters are as follows:
1. p - the auto regressive part's order
2. d- the degree to which the first difference is involved
3. q - the moving average part's order

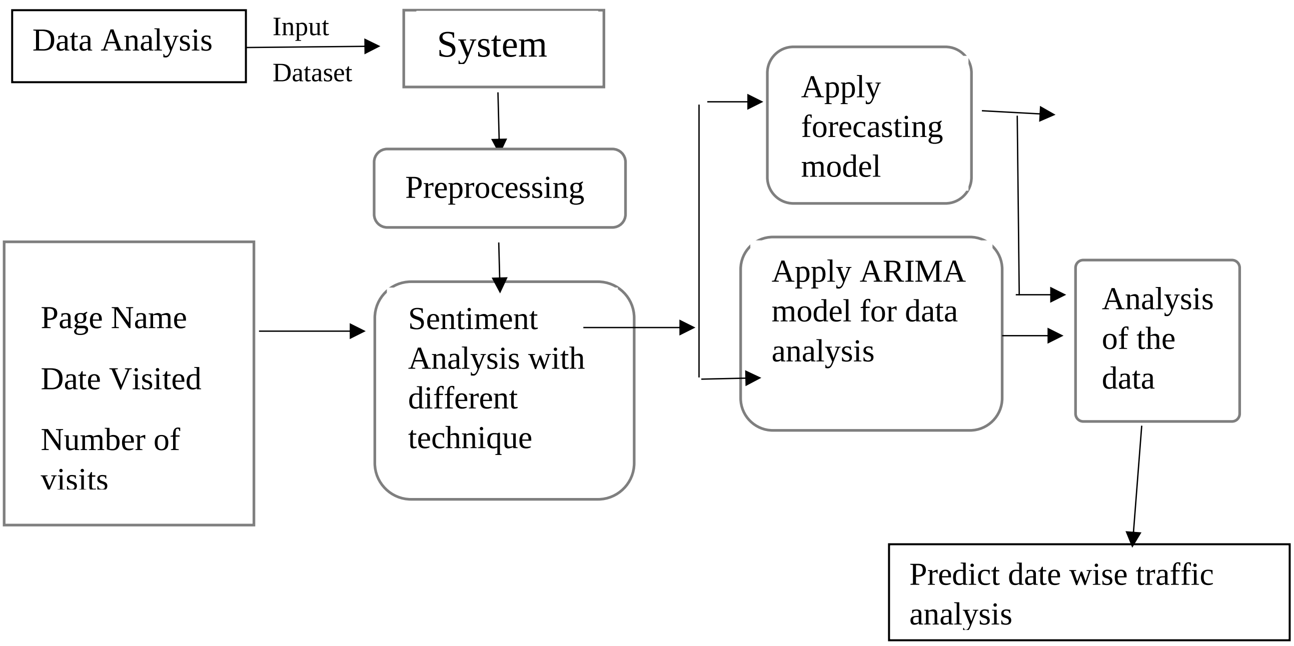

Figure 2: DFD Level 2

5. RESULT AND EVALUATION

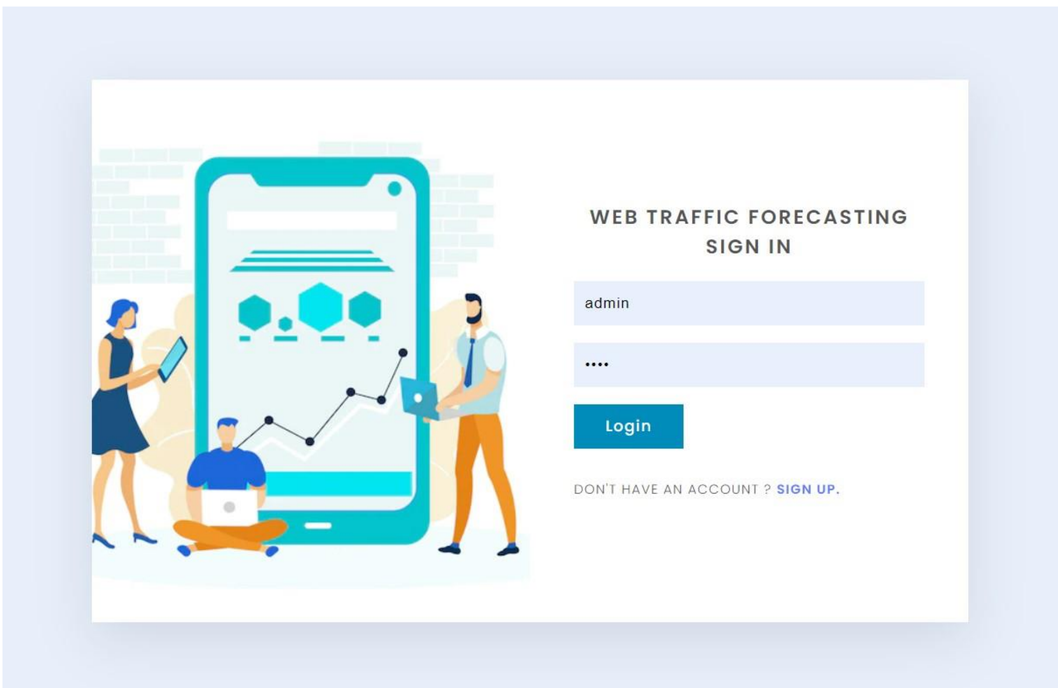

Figure 3: UI Home Page

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Figure 4: Load Dataset

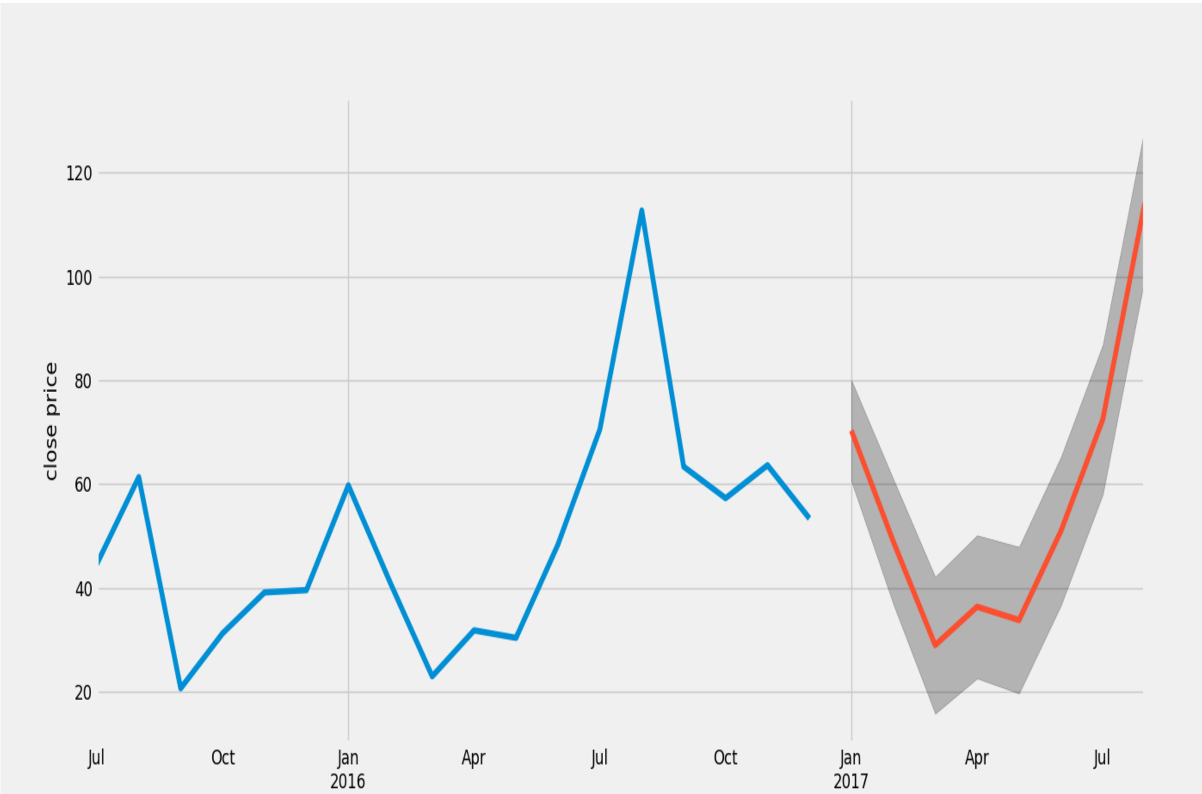

Figure 5.1: Result 1

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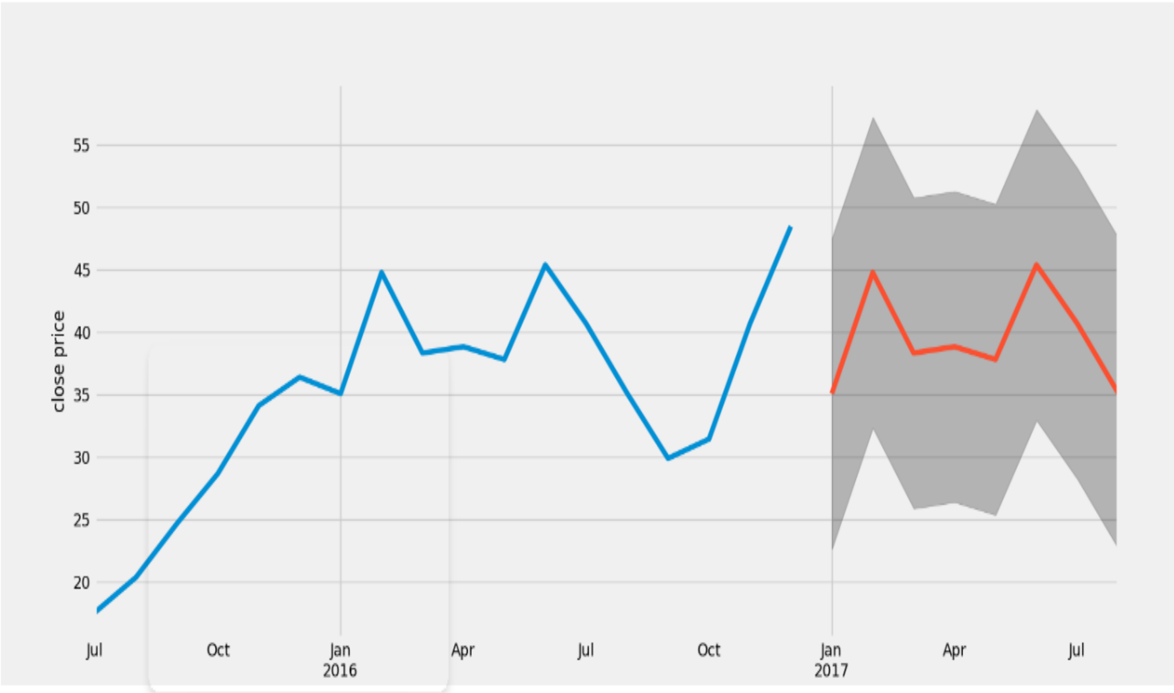

Figure 5.2: Result 2

TEST ID	TEST CASE NAME	TEST CASE DESCRIPTION	EXPECTED RESULT	ACTUAL RESULT
1	To verify login name and password	Enter valid login name and password	System should display the homepage	Same as expected
		Enter valid login name and password	System shows the error message	Same as expected
2	Data collection	The web traffic dataset is downloaded from the kaggle	Use pre-processing to clean the data	Same as expected
3	Feature extraction	Extract the feature from the data	Features for predicting the web traffic are extracted	Same as expected
4	Time series analysis	Find the underlying trends and patterns in the data	The pattern in time series data is observed	Interpret and integrate the pattern with other
5	Build prediction model	Model is trained using ARIMA	Predict the future web traffic	Same as expected

Table 1: Test Cases

Limitations
The server computer should be turned on at all times.

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6. CONCLUSION

The major goal of our study is to create a reliable forecasting model for predicting future traffic to Wikipedia pages. We utilise the ARIMA model on the Web Traffic Time Series Forecasting dataset to validate our prediction model. We used this model to train the data using variables like page name, visited date, and number of visits for pages over the course of a year to forecast future web traffic.

6.1 Future Scope

In the future, we'd like to improve our ability to spot hidden trends so that we can investigate how human behaviour influences online traffic more quickly. We'll look into the unsupervised model that has been utilised in other papers to improve our model.

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