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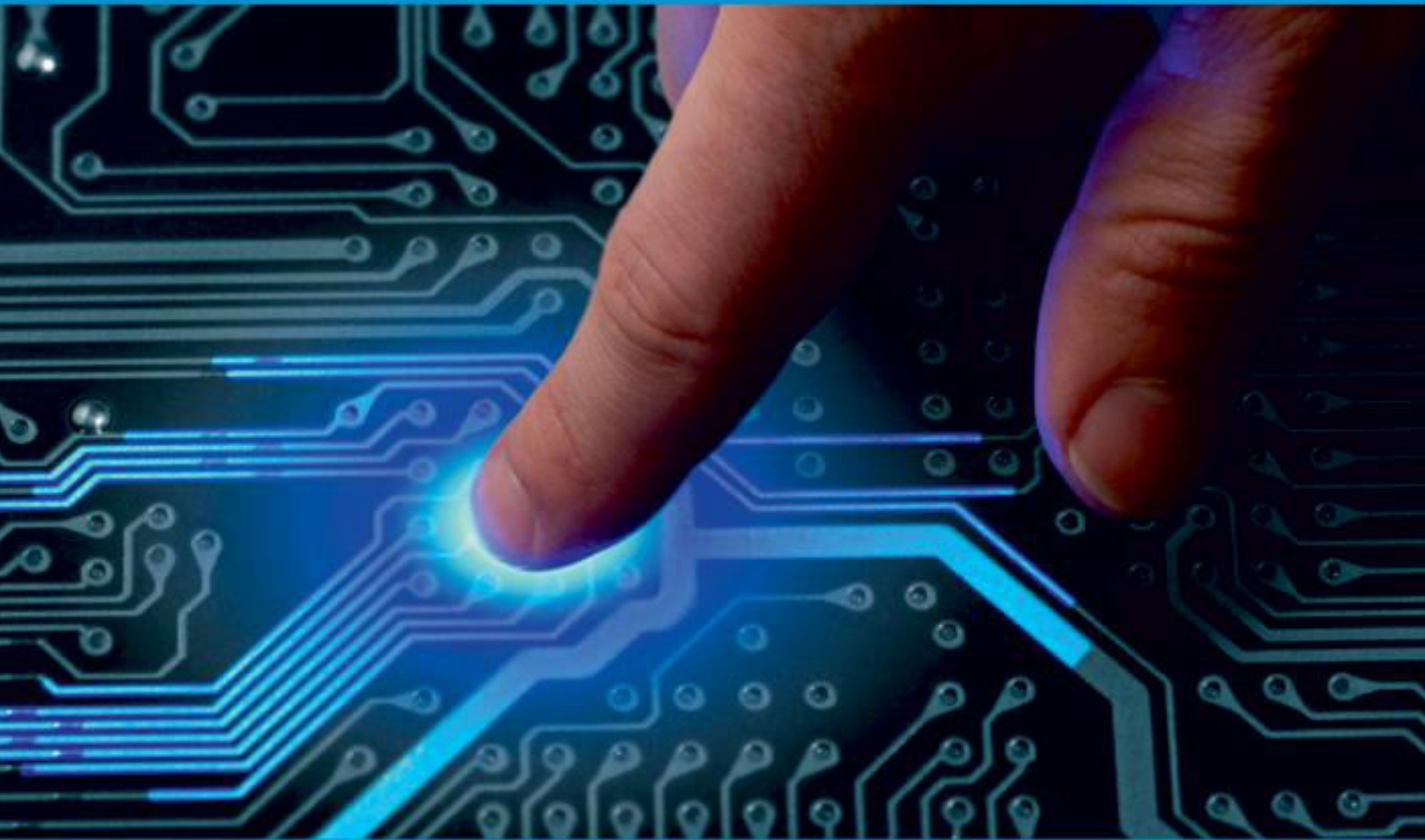

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Traffic Prediction Using Holt-Winter and ARIMA Algorithms

Jyothirmai Bavirisetty[1], Kalisetty Himasri[2], Kakani Shanmukha Manoj[3], Kethavath Anusha[4], P.J.Jyothi[5]

B. Tech Students, Department of CSE, Vasireddy Venkatadri Institute of Technology, Guntur, Andhra Pradesh, India[1,2,3,4]

Associate Professor, Department of CSE, Vasireddy Venkatadri Institute of Technology, Guntur, Andhra Pradesh, India[5]

ABSTRACT: Traffic is susceptible to external and internal factors such as traffic migration, and high population, and due to these factors, the actual traffic is non-linear and is a challenging task and is used to analyze using a statistical model for future prediction. In this paper, we investigated and evaluated the performance of different statistical prediction models for the traffic and showed a significant improvement in prediction. A Stochastic Lagrangian traffic model is proposed to capture the transition into traffic congestion. To design the model, motor vehicles are separated by cells, and only the first and last cars in each cell are investigated. Flexible data collection is performed by adjusting the test cell size according to the prediction variation from the stochastic model. Initially, a set of best hyper-parameters for the corresponding prediction model is identified by analyzing the traffic characteristics. Then, we performed a comparative performance analysis among AutoRegressive Integrated Moving Average (ARIMA) and Holt-Winter. We will train Holt-winter and ARIMA algorithms using 80 percent of the training dataset and then we test the accuracy of the algorithms using the remaining 20 percent of testing data. The algorithm that produces the highest accuracy when trained on the data will be considered the best model for the traffic prediction.

KEYWORDS: Holt-Winter, ARIMA, Stochastic Lagrangian, traffic congestion.

I. INTRODUCTION

Over the past two decades, the growing need for short-term forecasting of road limits embedded in the system of intelligent real-time traffic systems has led to the creation of a large number of forecasting algorithms. Apart from this, there is currently no clear idea about the various requirements involved in modeling. This field of study was evaluated by dividing the process of constructing short-term forecasting algorithms into three key categories: measurement, conceptual modeling process, and modeling process, which includes many decisions regarding appropriate method selection, input and output method used, and data quality. The critical dialogue clarifies several connections between the above and results in a logical flow that can be used as a framework for constructing temporary road forecast models. Among the statistical models developed to predict future values based on a historical database are the Autoregressive Integrated and Moving Averages (ARIMA) model. Proposed by Box & Jenkins, the model is suitable for describing stationary and non-stationary series. The methodology consists of fitting ARIMA models (p, d, q) to a data set. Where p is the number of terms of the autoregressive part (AR), d is the number of successive differences, and q is the number of terms of the moving average part (MA).

Holt winter's algorithm has wide areas of application. It is used in various business problems mainly because of two reasons one of which is its simple implementation approach and the other one is that the model will evolve as our business requirements change. Holt Winter's time series model is a very powerful prediction algorithm

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despite being one of the simplest models. It can handle the seasonality in the data set by just calculating the central value and then adding or multiplying it to the slope and seasonality, It just has to make sure to tune in the right set ofparameters, and viola, it has the best fitting model. Always remember to check the efficiency of the model using the MAPE (mean absolute percentage error) value or the RMSE(Root mean squared error) value, and the accuracy may depend on the business problem and the data set available to train and test the model.

II. RELATED WORK

The current system introduces a new analytical tool that predicts road traffic using a highway traffic model and investigates a data collection strategy that matches the quality of road information. A Stochastic Lagrangian traffic model is proposed to capture the transition into traffic congestion. To design the model, motor vehicles are separated by cells, and only the first and last cars in each cell are investigated. Flexible data collection is performed by adjusting the test cell size according to the prediction variation from the stochastic model. While collecting data on all vehicles in traffic is expensive and may not be, it is actually possible that the data test should be performed using a traffic flow model. Due to the size of the Lagrangian LWR model, it is easy to track traffic rather than one vehicle to measure.

Traffic Flow Model

The LWR model consists of a first-order partial differential equation derived from the conversation law and the fundamental diagram. LWR model performs well for modeling heavy traffic on the highway when drivers cannot do much but follow the flow. A stochastic partial differential equation (SPDE) model building on the classic LWR traffic flow model was then developed to improve the original LWR model.

III. PROPOSED SYSTEM

In the Proposed system, the two algorithms such as Holt-Winter and Arima are used and these are trained with the sample datasets, these models provide higher accuracy compared to the existing Stochastic Lagrangian model. The Holt-Winters forecasting algorithm allows users to smooth a time series and use that data to forecast areas of interest. Exponential smoothing is a way to smooth out data for presentations or to make forecasts. It's usually used for finance and economics. Real-world data like that of demand data in any industry generally has a lot of seasonality and trends. When forecasting demands in such cases requires models which will account for the trend and seasonality in the data as the decision made by the business is going to be based on the result of this model.For such cases, Holt winter's method is one of the many time series prediction methods which can be used for forecasting.ARIMA makes use of lagged moving averages to smooth time series data.They are widely used in technical analysis to forecast future security prices. It is widely used in demand forecasting, such as in determining future demand in food manufacturing. That is because the model provides managers with reliable guidelines in making decisions related to supply chains.

Advantages of Proposed System

1) Prediction can be done with a low figuring burden and high accuracy.

2) High prediction accuracy.

3) Very responsive.

4) High reliability.

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A. Time Series Forecasting Models

The use of the ARIMA and Holt-Winters exponential smoothing models to forecast traffic relied on their ability to predict time series data showing both trend and seasonal variation. The objective is to choose the best model for predicting the traffic.

ARIMA:

ARIMA model was proposed by Box and Jenkins and is also known as the Box-Jenkins methodology. This model predicts the future value based on the past values of the time series, that is, its own lagged values and the lagged forecast white noise. The time series needs to be stationary before applying the ARIMA model as it performs well when there is no correlation and dependency among the predictors. Total of three parameters, such as order of AR term (p), order of MA term (q), and the number of differencing to make the time series stationary (d) are required to design the ARIMA (p, q, d) model. We can express the ARIMA model mathematically as follows:

$$\Phi(L)^p \ \Delta^d y_t = \phi(L)^q \ \Delta^d \epsilon_t \qquad (1)$$

$$\Delta^d y_t = y_t^{d-1} - y_{t-1}^{d-1} \qquad (2)$$

Here, yt is the time series, and p, d, and q are referred to as the order of AR, I and MA components of the ARIMA model, Δd is an operator to make the yt stationary, and Φ(L) p id the lag polynomials of order p, and L is defined as the lag operator whereas Et is white noise.

Holt-Winter:

The Holt-Winters method is also known as Triple Exponential Smoothing, one of the popular algorithms designed for time-series forecasting. The first studies of Exponential Smoothing are back to Simeon Poisson; after him in 1956, Robert Brown introduced its forecasting application. This forecasting model is defined in three equations one for level (lt), one for trend (bt), and one for seasonality (st) and also forecasting equations with smoothing parameters α, β, and γ, respectively. Holt-Winters method has two variations, additive and multiplicative, that differ like the seasonal data values. We used an additive version of the Holt-Winter model for our experiment, and the equation can be defined as follows:

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$$

$$\hat{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)}$$

Here, m represents the seasonal period and Bi is the coefficient for the variable Xi, h is the forecast horizon and k is the integer part of (h-1)/m. The Holt-Winters forecasting algorithm allows users to smooth a time series and use that data to forecast areas of interest.

The Holt-Winters technique is made up of the following four forecasting techniques stacked one over the other: Weighted Averages: A weighted average is simply an average of n numbers where each number is given a certain weight and the denominator is the sum of those n weights. The weights are often assigned as per some weighing function. Common weighing functions are logarithmic, linear, quadratic, cubic, and exponential. Averaging as a time series forecasting technique has the property of smoothing out the variation in the historical values while calculating the forecast. By choosing a suitable weighing function, the forecaster determines which historical values should be given emphasis for calculating future values of the time series. Exponential Smoothing: The Exponential

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Smoothing (ES) technique forecasts the next value using a weighted average of all previous values where the weights decay exponentially from the most recent to the oldest historical value. When you use ES, you are making the crucial assumption that recent values of the time series are much more important to you than older values. The ES technique has two big shortcomings: It cannot be used when your data exhibits a trend and/or seasonal variations. Holt Exponential Smoothing: The Holt ES technique fixes one of the two shortcomings of the simple ES technique. Holt ES can be used to forecast time-series data that has a trend. But Holt ES fails in the presence of seasonal variations in the time series. Holt-Winters Exponential Smoothing: The Holt-Winters ES modifies the Holt ES technique so that it can be used in the presence of both trend and seasonality.

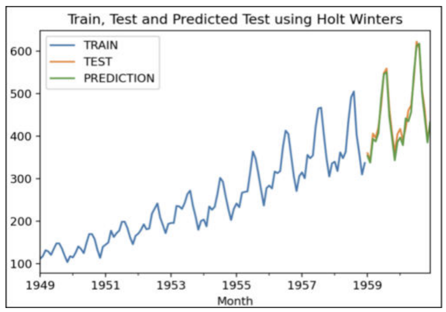

Fig. 1: Plotting of Train, test and predicted data using Holt-Winter

B. Time series decomposition

Some distinguishable patterns appear when we plot the data. The time series has an obvious multiplicative seasonality pattern, as well as an overall increasing trend. We can also visualize our data using a method called time-series decomposition. As its name suggests, time series decomposition allows us to decompose our time series into three distinct components: trend, seasonality, and noise. Trend: A trend exists when there is a long-term increase or decrease in the data. It does not have to be linear. Sometimes we will refer to a trend as “changing direction” when it might go from an increasing trend to a decreasing trend. Seasonal: A seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month). Seasonality always has a fixed and known period. Cycles: A cyclic pattern exists when data exhibit rises and falls that are not from the fixed period. Using time-series decomposition makes it easier to quickly identify a changing mean or variation in the data. These can be used to understand the structure of our time series. The intuition behind time-series decomposition is important, as many forecasting methods build upon this concept of structured decomposition to produce forecasts shown in fig. 2.

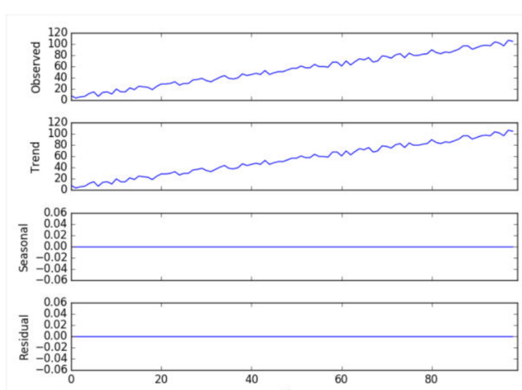

Fig. 2: Decomposed time series data

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IV. RESULT ANALYSIS

In this section, we first present the observation of time series decomposition plots obtained when converted from time series data to the seasonal data having different trends and seasonality. Then, we use the result of estimation and prediction to show the capability of the Holt-Winter and Arima Algorithms.

A. Time Series Decomposition Graphs for Holt-Winter and ARIMA

Time Series data is a set of observations on the values that a variable takes at different times. Such data may be collected at regular time intervals such as hourly, daily, weekly, monthly, quarterly, annually, etc.Time series decomposition involves thinking of a series as a combination of level, trend, seasonality, and noise components. Decomposition provides a useful abstract model for thinking about time series generally and for better understanding problems during time series analysis and forecasting.

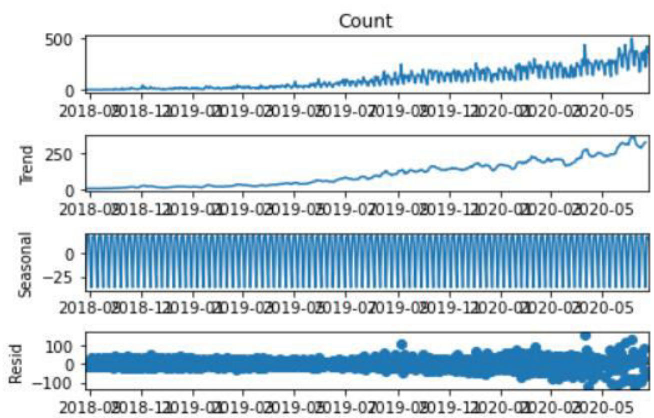

Fig. 3: Decomposed time series data in Holt-Winter

ARIMA Seasonal Graph

This algorithm is used when the seasonal method has regular trends and it is not used for irregular patterns. In this diagram, we plotted the training data, testing data, and the predicted data.

$$\text{ARIMA} \quad \underbrace{(p,d,q)}_{\substack{\uparrow \\ \text{Non-seasonal part} \\ \text{of the model}}} \quad \underbrace{(P,D,Q)_m}_{\substack{\uparrow \\ \text{Seasonal part of} \\ \text{of the model}}}$$

where m= number of observations per year. We use the uppercase notation for the seasonal parts of the model, and lowercase notation for the non-seasonal parts of the model.The seasonal part of the model consists of terms that are similar to the non-seasonal components of the model, but involve backshifts of the seasonal period. For example, an ARIMA(1,1,1)(1,1,1) model (without a constant) is for quarterly data (m=4), and can be written as

$$(1-\phi_1 B)\ (1-\Phi_1 B^4)(1-B)(1-B^4)y_t = (1+\theta_1 B)\ (1+\Theta_1 B^4)\varepsilon_t.$$

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The additional seasonal terms are simply multiplied by the non-seasonal terms.

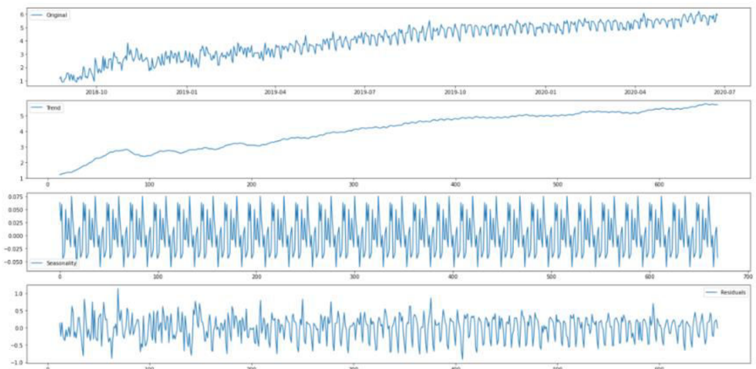

Fig. 4: Arima Seasonal Graph obtained by decomposing time series data

B. Holt-Winter Predicted Graph

The Holt-Winters set of rules is used for forecasting and It is a time-collection forecasting method. Time collection forecasting techniques are used to extract and examinerecords and records and signifyoutcomes to greaterappropriatelyexpect the destinyprimarilybasedtotally on ancientrecords and is shown in the fig. 5. For greaterrecordsapproximatelyrecordsfashion and sampleevaluation techniques, examine our article entitled, ` What Are Data Trends and Patterns, and How Do They Impact Business Decisions?` The Holt-Winters forecasting set of rulespermitscustomers to clean a time collection and use that records to forecast regions of interest. Exponential smoothing assigns exponentially reducing weights and values in opposition toancientrecords to lower the cost of the burden for the older records. In different words, greaterlatestancientrecords is assigned greater weight in forecasting than the older outcomes.

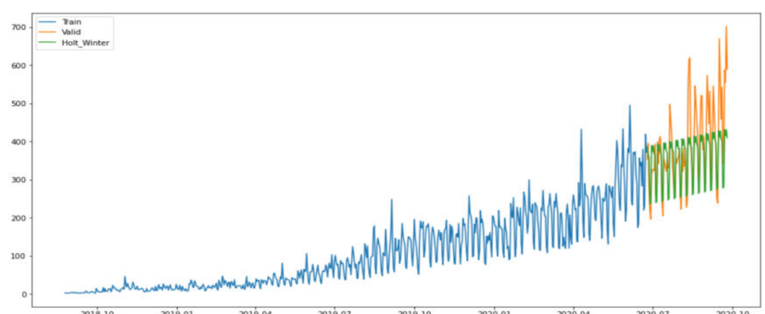

Fig. 5: Holt-Winter Predicted Graph using all the train, and tests data.

C.Arima Predicted Graph

Using this Algorithm, the diagram shows the plotting of the original values and the predicted values and the trend obtained is more accurate than that of Holt-Winter Algorithm. An autoregressive incorporatedtransferring average, or ARIMA, is a statistical evaluationversion that makes use of time-collectionfacts to bothhigherrecognize the facts set or to expectdestiny trends. A statistical version is autoregressive if it predicts destiny values primarily based totally on beyond values. For example, an ARIMA versionwould possiblybe searching for to expect a stock`s destinycostsprimarily based totally on its beyondoverall performance or forecast a company's profitsprimarily based

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totally on beyond periods.An autoregressive incorporated shifting commonversion is a shape of regression evaluation that gauges the energyof 1structured variable relative to differentconverting variables. The version`s intention is to be expectingdestiny securities or economicmarketplacemovementsthroug hanalyzing the variationsamong values withinside the collection as opposed to through real values.

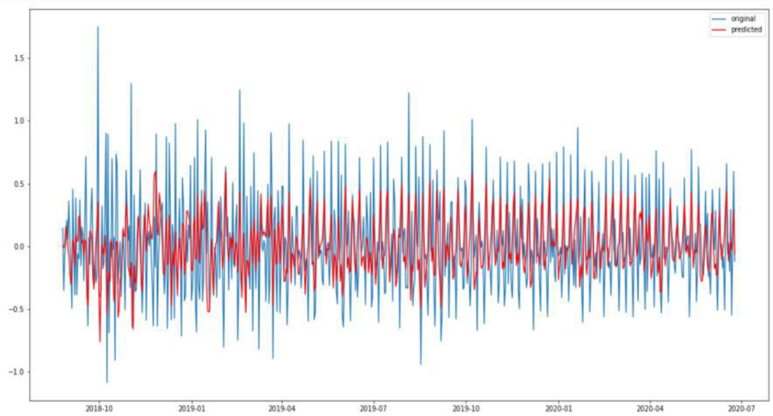

Fig. 6: Plotting of Original and Predicted data using ARIMA

V. CONCLUSION

In this survey, we have studied about existing traffic control solutions and how they can be improvised. The suggested model aims to be advantageous in managing traffic in a smart city. Based on prevailing and influential enactment, this project is highly useful. By using arima algorithm, this system will provide high-end performance in predicting the fastest route. As a result, superior services will be given to the citizens which will result in the satisfaction of all sectors of services. We propose a short-term operating system that is more efficient in terms of the flow pattern of routes and regression paths. We analyzed traffic congestion on two highways. Future traffic flow can be predicted using login details. Initially, we collected data to predict traffic flow and calculated traffic that occurred at subsequent stations. With details of the pattern and LWL model, we predict the flow of the road in the temple. The results show that pattern- based forecasting will be an effective way to predict traffic flow in major cities. This will be very helpful in predicting an unusual road situation in India. This function can be extended by looking at other important external factors such as weather conditions, road changes due to construction or road damage, and road events.

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BIOGRAPHY

P.J.Jyothi is an Associate Professor in department of Computer Science and Engineering, VasireddyVenkatadri Institute of Technology. She receivedMtech degree from ANU,India in 2009,BTech degree from JNTU, Hyderabad, India in 2006. She is currently pursuing the Ph.D. degree in the department ofBioInformatics, ANU, Andhra Pradesh, India. Her research interests include Machine Learning, Cloud Computing, Data Base Management Systems.

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