

A Survey on Traffic Flow Prediction with Deep Learning Algorithms on Big Data

J. Swami Naik, N. Kasiviswanath, K. Ishthaq Ahamed, S. Raghunath Reddy

Abstract— Correct and very much planned activity stream data is vital for the fruitful arrangement of astute transportation frameworks. In the course of the most recent couple of years, activity information have been report, and we have truly entered the period of huge information for transportation. Existing movement stream expectation strategies for the most part utilize shallow activity forecast models and square measure as yet frustrating for a few genuine world applications. The objective of the smart transportation framework (ITS) is utilizing the correspondence framework to entirely consolidate the vehicle arrangement of individuals, vehicles and street. Propelled movement control framework and dynamic activity the executives framework are required to give real time activity stream data. The conventional movement stream show is named the activity stream state variables (velocity, thickness and stream) with the correction of your time and area. Traffic stream examination is essential research idea in the transportation framework. Deep Learning is a type of machine learning used to anticipate movement flow. This circumstance moves us to take the activity stream expectation issue dependent on profound design models with enormous activity information.

Keywords—Traffic flow prediction, Deep learning, Learning algorithms, Intelligent transportation system, Artificial neural network.

I. INTRODUCTION

Movement data, for example, stream, volume, speed, inhabitation, travel time, thickness, vehicle classification, emission level and so on [31] along street systems is imperative for arranging, control and the executives of transport systems. With the fast increasing urbanization and activity request, transportation issues are getting to be essential issue wherever on the planet. Foundation development is restricted in light of the size, space requirements and as a result of absence of arranging, innovation. So the answer for this basic issue is to plan shrewd frameworks to give creative and more brilliant administrations to the vehicle clients. One such application is movement stream forecast on transient premise which makes the vehicle clients to be better educated and makes the vehicle arrange more intelligent, more secure and all the more coordinated. According to a most recent study roughly 60 percent of individuals will live in urban communities by 2050 and as a result, millions of autos will keep running on

the streets prompting a basic strain on the knowledge transportation framework. Huge volume of activity information is recorded by canny transportation framework under every single climate condition. The recorded information is broke down to help with foreseeing moderate moving movement. Since no model exists that gives a 100 percent effectiveness in foreseeing movement stream, further research has been done with the end goal to build the precision in rush hour gridlock expectation. The present framework uses shallow methods to anticipate movement stream which is regarded wasteful. profound learning calculation will be connected to see profound activity examples and make for more precise forecasts [10].

II. TRAFFIC DATA MANAGEMENT

Activity Big information term is being connected to vast informational indexes which can't be prepared by customary information handling methods. The gigantic learning space is developing horribly rapidly because of with truth development of innovation with cell phones, keen sensors, and so on it is a considerable measure of less demanding as of now to assemble expansive amount of data, which should be prepared. Bigdata typically has various measurements and this make it substantially more hard to process since information the preparing multifaceted nature develops quickly with dimensionality increment. The approach of Big Data has activated problematic changes in numerous fields including Intelligent Transportation Systems (ITS). The rising associated advancements made around worldwide computerized gadgets have opened exceptional chances to upgrade the execution of the ITS.

Activity gigantic information holds numerous attributes, for example, worldly relationship, spatial correlation, historical connection, and multistate. Hua-pu Lu, Zhi-yuan Sun et al [15] considers the technique for continuous movement stream state ID and forecast dependent on huge information driven hypothesis. Activity huge information holds a few attributes, for example, transient relationship, spatial connection, verifiable relationship, and multistate. Activity stream state measurement, the premise of movement stream state identification, is accomplished by a SAGA-FCM (simulated strengthening hereditary calculation based fluffy cmeans) based activity bunching model. Thinking about straightforward estimation and prescient precision, a bilevel streamlining model for provincial activity stream relationship examination is built up to anticipate movement

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J. Swami Naik, Research Scholar, JNTUA, Ananthapuramu, Andhra Pradesh, India. (swaminaikcse@gmail.com)

Dr. N. Kasiviswanath, Professor & Head, CSE Department, G. Pulla Reddy Engineering College (Autonomous), Kurnool, Andhra Pradesh, India. (hodcse@gprec.ac.in)

K. Ishthaq Ahamed, Associate Professor, CSE Department, G. Pulla Reddy Engineering College (Autonomous), Kurnool, Andhra Pradesh, India. (ishthaq@gmail.com)

S. Raghunath Reddy, Assistant Professor, CSE Department, G. Pulla Reddy Engineering College (Autonomous), Kurnool, Andhra Pradesh, India (raghunath.gprec@gmail.com)

stream parameters dependent on fleeting spatial-chronicled connection. A two phase display for remedy coefficients streamlining is accelerative to rearrange the bilevel advancement model. The first stage show is made to ascertain the amount of worldly spatial-chronicled relationship variables. The second stage demonstrate is blessing to compute fundamental model detailing of local movement stream correlation. Dawei Chen proposes an upgraded expectation calculation of outspread premise work neural system dependent on a demonstrated fake honey bee state (ABC) algorithmic program with in the colossal information atmosphere. To confirm the effectiveness of this calculation inside the tremendous learning environment, apply it to Lozi and Tent disorganized time arrangement and estimated activity stream me arrangement, and after that contrast it and K-closest neighbor demonstrate, spiral premise work (RBF) neural system show, enhanced back engendering neural system model, and RBF neural system dependent on a cloud hereditary calculation model [4]. Some Applications are, Traffic Analysis, Traffic Prediction, Traffic Forecasting, Breakdown Flow Prediction and Predicting Freeway work zone Delays.

Traffic flow prediction:

Activity stream forecast is a critical component of movement displaying, task, and the executives. Precise realtime activity stream forecast can (1) propose data and direction for street clients to improve their movement choices and to lessen expenses and (2) assist specialists with creative movement the executives procedures to lighten blockage. With the arrangement of high goals activity learning from wise transportation frameworks (ITS), traffic stream expectation has been dynamically self - tended to abuse information driven approaches. In this respect, movement stream Prediction could be a ststic drawback to gauge the stream tally at a future time upheld the data gathered over past periods from at least one perception areas.

There are two different ways of movement stream forecast

1. Transient Traffic stream Prediction
2. Long Term Traffic Flow Prediction

Chengcheng Xu et al [20], planned to build up a basic and compelling half and half model for guaging activity volume that consolidates ARIMA and the Genetic Programming (GP) models. The ARIMA show was utilized to display the direct segment of the activity stream time series. Then the general professional model was connected to catch the non-straight segment by demonstrating the residuals from the ARIMA model. The mixture models were fitted for four distinctive time-collections: 5, 10, 15, and 20 min. The results demonstrated that the cross breed models had higher prophetic execution than using exclusively ARIMA show for different conglomeration time interims underneath run of the mill conditions. Selvaraj Vasantha Kumar was proposed an expectation conspire dependent on Kalman separating strategy (KFT) and assessment requires just restricted information data. Only past 2 days stream perceptions has been used in the Prediction topic created abuse KFT for foreseeing consequent day stream esteems with a coveted precision. Movement stream expectation utilizing both

notable and constant information upon the arrival of intrigue was likewise endeavored. Promising outcomes were acquired with mean total extent blunder (MAPE) of ten among discoverd and forseen streams And this implies the nature of the arranged forecast subject for activity stream anticipation in ITS applications [1].

III. ANN TO PREDICT TRAFFIC FLOW PREDICTION

Because of the arbitrary and nonlinear attributes of movement stream, it's troublesome to beat the constarints of parametric models. Nonparametric machine learning techniques have moved toward becoming bit by bit popular. Non Parametric methodology is the most acclaimed and right now utilized in research. Artificial neural systems (NN) have been commonly utilized for this drawback, which might be believed to be the last example of machine learning application in rush hour gridlock designing.

Smith and Demetsky built up a NN demonstrate that was contrasted and customary expectation systems and their outcomes guide that the NN beats elective models all through pinnacle crest conditions. Dougherty et al. contemplated back-engendering neural system (BPNN) for the expectation of movement flow, speed, and inhabitanace and in this way the outcomes demonstrate some promise. Since at that point, NN approaches have regularly been utilized for activity stream forecasting. In addition several half and half NN models are wanted to enhance performance. Other nonparametric models have additionally been considered, for example, closest neighbor (NN) models and bolster vector relapse [9].

Felix Kunde Alexander Hartenstein et al [17]. Execute an idea of encouraging sensor information to an Artificial Neural Network (ANN). We train the ANN with various spatial and worldly burglaries to locate an ideal setup for a whole city. They have dealt with a sensor organize that is appropriated over a whole city and got the best outcomes when they included estimations from all sensors. Counting arrangement data improved the forecast just barely. After work with RNNs, it ought to be more noteworthy for time arrangement examination since they support to learn short and long groupings.

Vedat TOPUZ et al. [11] arranged totally unique fake neural system (ANN) models for anticipating the hourly movement flow. Because the movement framework is a troublesome and movable framework that includes a people's action, the activity stream state has high arbitrariness and vulnerability. The customary movement stream figure techniques, for example, Kalman filter, Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA) and so forth had been unable to fulfill the interest of the gauge accuracy that was expanding in apply (CHEN and MA, 2009) On the other hand, counterfeit neural systems (ANNs) have been connected to a substantial number of issues in view of their non-straight framework demonstrating ability by mental aptitude exploitation gathered information.

Amid the most recent decade ANNs have been connected broadly to forecast of the activity data.[1] Compared the speculation execution of the diverse ANN models like Multi-Layer Perceptron (MLP), Radial Basis Function Network (RBF), Elman persistent Neural Networks (ERNN) and Non-direct vehicle Regressive and exogeneous input (NARX) type. Wusheng HU, Yuanlin LIU, LI et al.[13] chose BP neural system demonstrate in which the movement stream distinction was taken as the info parameter, connected the idea of dynamic moving expectation to extend another short term activity stream forecast method. Then exploitation the specific perception information of activity stream given the model structure, thought and figuring ventures of this new method. The results demonstrate this strategy is achievability, unwavering quality, and of some useful value. Kang Kai, Han Jinfeng et al[16]. Proposes relate degree ideal asset benefit procedure that upheld matrix registering pool model, manufactures an activity stream forecast show dependent on framework technique, and predicts the movement by utilizing hereditary calculation dependent on higher-arrange summed up neural systems. In the rush hour gridlock stream forecast process, the ideal asset benefit method on the possibility of network figuring pool display is utilized to mechanically ask for the best equipment beneath the present remaining in rush hour gridlock data stage to play out the expectation, with the end goal to improve the administration quality and effectiveness. At the point when various clients ask for movement estimating in the meantime, the ideal asset administration can meet the necessities of constant activity figures. The model of hereditary calculation dependent on the higher-arrange summed up neural systems is worked to anticipate activity stream finally.

Kranti Kumar, M. Parida et al[14]. applies Artificial Neural Network (ANN) for brief term forecast of activity stream utilizing past movement data. The display joins activity volume, speed, thickness, time and day of week as information factors. Speed of every class of vehicles was considered independently as info factors in divergence to past investigations announced in writing that consider normal speed of joined movement stream.

Profound Learning Based Traffic Flow Prediction Deep learning is a type of machine discovering that can be seen as a settled various leveled demonstrate which incorporates customary neural networks. Deep-learning is progressively being perceived as a fundamental instrument for man-made brainpower explore, with applications in a few zones. Profound learning calculations can be generally ordered into four kinds: Deep Neural Network (DNN), Convolution Neural Network (CNN), Recurrent Neural Network (RNN) and Q-learning. With the brisk advancement of ITS, it is conceivable to gain admittance to tremendous measure of activity information and multisource ecological data. However, each the regular steady and measurement models will in general frame presumptions to overlook extra controlling variables, because of the shallow engineering and failure to manage enormous information and additionally wasteful preparing techniques.

The profound learning method, a sort of machine learning, has been very much grown as of late to address this issue. Profound learning has a few points of interest in

example acknowledgment and arrangement. For activity stream forecast, Huang et al. proposed a profound conviction arrange (DBN) architecture for perform multiple tasks learning and trials results demonstrate that the DBN may come through with respect to five hitter EnhanceNet over alternate calculations. Another technique utilized a stacked autoencoder show (SAE) to execute expectation considering expressly the spatial and worldly connections. These papers are the signs in applying deep learning in rush hour gridlock stream prediction. Furthermore, to catch the time arrangement attributes in the preparation and forecast, another profound learning model is presented as the intermittent neural system (RNN), which is intended to manage time arrangement information expectation issue. As far as activity information, a period arrangement information, the RNN can utilize memory cells to spare the transient data from past time interims. A standout amongst the most popular RNN is the long transient memory (LSTM) show, which can consequently alter some hyper parameters and can catch the long fleeting choices of the PC record.

Deep Learning Methods To Predict Traffic Flow Nicholas G. Polson created of an engineering [5] that joins a straight model that is fitted utilizing 'l regularization and a succession of tanh layers. The test of foreseeing movement streams are the sharp non linearities on account of advances between free stream, breakdown, recuperation and congestion. We demonstrate that profound learning models can catch these nonlinear spatio-worldly impacts. The principal layer recognizes spatiotemporal relations among indicators and elective layers display nonlinear relations.

Hongsuk Yi, HeeJin Jung et al[10]. proposed a profound learning neural-arrange dependent on TensorFlow™ is proposed for the expectation activity stream conditions, exploitation timeframe movement information. There is no exploration has connected the TensorFlow™ profound learning neural system model to the estimation of activity conditions. The recommended managed display is prepared by a profound learning calculation, which utilizes genuine activity information gathered each five minutes. Xiaolei Ma, Zhuang Dai et al[19] proposed a convolutional neural system (CNN)- based strategy that learn traffic as pictures and predicts huge scale, organize wide movement speed with a high exactness. Spatiotemporal activity elements are changed over to pictures depicting the reality relations of movement stream by means of a two dimensional time-space framework.

A CNN is connected to the picture following two continuous advances: conceptual movement include extraction and system wide activity speed expectation. The CNN can prepare the model in a reasonable time and, along these lines, is appropriate for extensive scale transportation systems [19]. Yuanfang Chen, Falin Chen et al. proposes a profound learning based for the most part forecast algorithmic rule, DeepTFP, to on the whole anticipate the activity stream on each and each movement street of a town. This calculation utilizes three profound leftover neural systems to demonstrate fleeting closeness, period, and

pattern properties of activity flow. Each lingering neural system comprises of a part of remaining convolutional units. DeepTFP totals the yields of the three residual neural systems to streamline the parameters of a statistical expectation model. They utilized portable time genuine information from the transportation framework. The proposed DeepTFP outflanks the Long Short-Term Memory (LSTM) [18].

Hongxin Shao et al [8], discovered the use of Long Short-Term Memory Networks (LSTMs) in short-term movement stream expectation. As a profound learning approach, LSTMs can take in more conceptual portrayals in the non-direct activity stream information. The key component of catching long haul conditions in a successive information additionally settles on it an appropriate decision in rush hour gridlock expectation. Tests on genuine movement informational collections demonstrate a decent execution of model.

Hongsuk Yiet.al [3] a deep-learning neural-arrange dependent on TensorFlow is proposed for the expectation movement stream conditions, utilizing ongoing activity information. The proposed administered display is prepared by a profound learning calculation, which utilizes genuine movement information collected at regular intervals. Results show that the model's exactness rate is around 99%. Haiyang Yu et al [24]. Propose a system framework representation procedure which will hold the fine-scale structure of a transportation vast activity speeds are renewed into a progression of static pictures and contribution to a novel profound plan, in particular, spatiotemporal intermittent convolutional systems (SRCNs), for movement gauging. The proposed SRCNs acquire the upsides of profound convolutional neural systems (DCNNs) and long momentary memory (LSTM) neural systems. The spatial conditions of system wide activity can be caught by DCNNs, and the transient elements can be learned by LSTMs. Yisheng Lv, a novel profound learning-based movement stream expectation strategy is proposed, which considers the spatial and worldly relationships innately.

A stacked car vehicle encoder demonstrate is utilized to be told conventional movement stream options, And its prepared in an exceedingly covetous layer insightful fashion. To the most straightforward of our information, this is the first occasion when that a profound engineering model is connected exploitation car vehicle encoders as building squares to speak to activity stream alternatives for expectation. Also, tests exhibit that the anticipated system for movement stream expectation has unrivaled execution [26].

Yaguang Li et al [27]. Proposed Graph Convolutional Recurrent Neural Network to consolidate both spatial and temporal dependency in rush hour gridlock stream. They further coordinate the encoder-decoder system and planned testing to enhance long haul estimating. At the point when assessed on true street network traffic data, their approach can precisely catch spatiotemporal relationships and consistently outperforms best in class baselines by 12% - 15%. Li Li, Xiaonan Su et al [28]. introduce a numerous progression strategy to process the crude "Big Data" into time arrangement for regression and causality investigation. They utilized the Granger causality to characterize

the potential reliance among data, and deliver a much dense arrangement of times series who are additionally very needy. Next, they conveyed a decay calculation to separate daily-comparable pattern and non-stationary blasts parts from the activity stream time series yielded by the Granger test. The deterioration results are then treated by two rounds of Lasso regression: the standard Lasso strategy, strong Lasso technique. The acquired causal reliance diagram uncovers the connection between the structure of street systems and the relationships among movement time series. All these revelations are helpful for building better activity stream expectation models. Different Factors with Deep Learning (Rainfall, Weather) Nowadays different factors, for example, climates and precipitation are utilized to anticipate with profound learning and considered as a multisource input. Concerning the effect of precipitation, there is general agreement that it essentially influences movement stream attributes and prompts blockage and mishaps. Without an exhaustive comprehension of the climate impact on movement stream, activity the executives specialists can't consider pertinent factors in related operational approaches to enhance activity productivity and wellbeing. For precipitation incorporated activity stream expectation utilizing machine learning techniques, Dunne and Ghosh consolidated stationary wavelet change and BPNN to build up an indicator that could pick between a dry model and a wet model contingent upon whether precipitation is normal in the forecast hour. The outcomes demonstrate that precipitation coordinated indicator could enhance the expectation precision amid precipitation occasions. Profound learning devices give a promising method to fuse the effects of precipitation in rush hour gridlock stream expectation.

Yuhan Jia et al. [2] present the profound conviction arrange (DBN) and long transient memory (LSTM) to anticipate urban movement stream thinking about the effect of precipitation. The precipitation coordinated DBN and LSTM can take in the highlights of activity stream under different precipitation situations. Trial results show that, with the thought of extra precipitation factor, the profound learning indicators have preferable exactness over existing indicators and furthermore yield enhancements over the first profound learning models without precipitation input. Furthermore, the LSTM can outflank the DBN to catch the time arrangement attributes of activity stream data. Arief Koesdwiady et al [21]. Utilized whether conditions for activity stream expectation. In particular, severe climate conditions may have uncommon effect on movement time and activity stream. It has two destinations: first, to explore a relationship between's climate parameters and activity stream, and to enhance movement stream expectation by proposing a novel all encompassing engineering. It consolidates: 1) profound conviction systems for activity and climate expectation and, 2) decision-level information combination plan to upgrade forecast precision utilizing climate conditions. The late development of new innovations, for example, sensor systems, cell phones, and

new ideal models, for example, publicly supporting interpersonal organizations has initiated significant changes in the way movement the board will be done later on.

Clever Transportation frameworks serves to explorers achieve their goal at an expected time. Savvy urban communities have sent most recent advances to fulfill the requirements of voyagers through proficient route [30]. It can possibly help street clients settle on better travel choices, mitigate movement blockage, decrease carbon emanations, and enhance activity task effectiveness [26]. Constant movement stream expectation goes for assessing foreseen activity stream state at a future time. Traffic stream estimation and gauging intends to comprehend and create street systems foreefficient mobility. To distinguishing and break down important spatio-transient investigation and information digging concepts and strategies for short-term urban street movement stream forecast. Foresee the movement with continuous information enhances exactness. Some of the real applications are, Application of probe vehicle data for a real time prediction and short term on a freeway. Neural networks for real time traffic signal control. Network state estimation and prediction for real time traffic management.

IV. RESEARCH CHALLENGES AND ISSUES

With regards to movement expectations, relating the portrayals of information vectors to the central properties of activity stream is a testing issue which should be contemplated [5]. CNN is connected to the picture following two continuous advances: unique activity include extraction and system wide activity speed forecast. In particular, CNN would first be able to separate unique movement highlights from a transportation arrange. Other models, for example, the mix of CNN and LSTM NN, would be an intriguing endeavor [20].

Extra factors, for example, the climate, get-togethers, can consider further with movement control. In request to test the heartiness of the proposed model, more information in various urban areas are required to approve the regular variety impact on the forecast accuracy. Moreover, the preparation productivity can be likewise improved by advancing pre-preparing strategies, which may decrease the quantity of emphases while accomplishing more exact results. Another charming exploration heading is to create novel transportation arrange portrayal approaches. By disposing of the blank locales with no roadway organize, the computational weight of preparing SRCNs ought to be greatly diminished [25].

V. CONCLUSIONS

In this paper, a concise outline of movement stream expectation is presented. With over a time of broad research, there has been a colossal advancement and application exercises in the information mining with profound learning space for forestalling activity flow. There are many testing research issues to foresee and gauge activity spill out of both spatial and fleeting information. Parametric and non-parametric strategies are utilized to foresee. Additionally profound learning is a quickest technique to foresee activity

stream with exactness. Still need different techniques and components to foresee with security.

REFERENCES

Journal papers

1. Selvaraj Vasantha Kumar, Traffic Flow Prediction using Kalman Filtering Technique, Elsevier, 2017.
2. Yuhua Jia, Jianping Wu, and Ming Xu, Traffic Flow Prediction with Rainfall Impact Using a Deep Learning Method, Journal of Advanced Transportation, 2017.
3. Hongsuk Yi, HeeJin Jung, Sanghoon Bae, Deep Neural Networks for Traffic Flow Prediction, IEEE, 2017.
4. Dawei Chen, Research on Traffic Flow Prediction in the Big Data Environment Based on the Improved RBF Neural Network. IEEE Transactions on Industrial Informatics, 2017.
5. Nicholas G. Polson, Deep Learning for Short-Term Traffic Flow Prediction, arXiv, 2017.
6. Minal Deshpande, Performance Improvement of Traffic Flow Prediction Model using Combination of Support Vector Machine and Rough Set, International Journal of Computer Applications, 2017.
7. Xian Yao Ling, Xinxin Feng, Zhonghui Chen, Yiwen Xu, Haifeng Zheng, Short-term Traffic Flow Prediction with Optimized Multi-kernel Support Vector Machine. IEEE congress on Evolutionary Computation. 2017.
8. Hongxin Shao, Boon-Hee Soong, Traffic flow prediction with Long Short-Term Memory Networks (LSTMs), IEEE, 2016.
9. Yuhua Jia, Jianping Wu, and Ming Xu, Traffic Flow Prediction with Rainfall Impact Using a Deep Learning Method, Journal of Advanced Transportation, 2017.
10. Sivabalaji Manoharan, Short Term Traffic Flow Prediction Using Deep Learning Approach, National College of Ireland, 2016.
11. Vedat TOPUZ, Hourly Traffic Flow Predictions by Different ANN Models, www.intechopen.com, 2010.
12. Wenhao Huang, Haikun Hong, Man Li, Weisong Hu, Guojie Song, Kunqing Xie, Deep Architecture for Traffic Flow Prediction, Springer, 2013.
13. Wusheng Hu, Yuanlin Liu, The short-term traffic flow prediction based on neural network, IEEE, 2010.
14. Kranti Kumara *, M. Paridab, V.K. Katiyar, Short term traffic flow prediction for a non-urban highway using Artificial Neural Network, Elsevier, 2013.
15. Hua-pu Lu, Zhi-yuan Sun, and Wen-cong Qu, Big Data-Driven Based Real-Time Traffic Flow State Identification and Prediction, Hindawi, 2015.
16. Kang kai, Hanjinfeng, Short-term traffic flow prediction based on grid computing pool model, IEEE, 2010.
17. Felix Kunde Alexander Hartenstein Stephan Pieper Petra Sauer, Traffic prediction using a Deep Learning paradigm, CEUR-WS.org, 2017.
18. Yuanfang Chen, Falin Chen, Yizhi Ren, Ting Wu, Ye Yao, DeepTFP: Mobile Time Series Data Analytics based Traffic Flow Prediction, arXiv:1710.01695, 2017.
19. Xiaolei Ma, Zhuang Dai, Zhengbing He, Jihui Ma, Yong Wang and Yunpeng Wang, Learning Traffic as Images: A Deep Convolutional Neural Network for Large-Scale Transportation Network Speed Prediction, Sensors, 2017.
20. Chengcheng Xu, & Wei Wang, Short-term traffic flow prediction using a methodology based on autoregressive integrated moving average and genetic programming, Transport, 2016.

21. AriefKoesdwiady, RidhaSoua, and FakhriKarray, Improving Traffic Flow Prediction With Weather Information in Connected Cars: A Deep Learning Approach, IEEE Transactions on Vehicular Technology, 2015.
22. Qiang Shang, Ciyun Lin, ZhaoshengYang, Qichun Bing, Xiyang Zhou, A Hybrid Short-Term Traffic Flow Prediction Model Based on Singular Spectrum Analysis and Kernel Extreme Learning Machine, 2016.PLOSONE,journal.pone.
23. Zhiyuan Ma andGuangchunLuo, Dijiang Huang, Short Term Traffic Flow Prediction Based on On-line Sequential Extreme Learning Machine, International Conference on Advanced Computational Intelligence,2016.
24. Haiyang Yu, Zhihai Wu, Shuqin Wang, Yunpeng Wang and Xiaolei Ma, Spatiotemporal Recurrent Convolutional Networks for Traffic Prediction in Transportation Networks, sensors, 2017.
25. YishengLv,YanjieDuan,Wenwen Kang,Zhengxi Li, Fei-Yue Wang,Traffic Flow Prediction With Big Data: A Deep Learning Approach,IEEE Transactions on intelligent Transportation Systems,2015.

ABOUT AUTHORS:

1. J.Swami Naik received M.Tech in Computer Science and Engineering from Indian Institute of Technology,Guwahati in 2003.Pursuing Ph.D in JNTUA,Anantapuramu as a external research scholar,Working as associate preofessor in G.Pullareddy engineering college,kurnool.his research interest includes big data analytics.
2. Dr. N.Kasiviswanth received Ph.D from rayalaseema university in 2010.He is head & professor of CSE department in G.pullareddy engineering college.He is having 24 years of teaching and research experience.his research interest includes computer networks.
3. K.Isthaq Ahamed,received M,Tech from Indian school of mines, Dhanbad.He is working as associate professor in g.pullareddy engineering college,kurnool.His area of research is neural networks and artificial intelligence systems.
4. S.Raghunath reddy received M.Tech from JNTUA,Anantapuramu.He is working as assiatnt professor in g.pullareddy engineering college,kurnool.His research area is cloud computing and big data.