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Street Traffic Forecasting: Ongoing Advances and New Challenges

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***Abstract*—**In metropolitan cities traffic congestion became a severe issue due to large scale multiple-layer road networks. The multifaceted nature, heterogeneity of traffic framework and the enormous information challenge have turned out to be generous troubles. The current transportation systems deal with these issues with the requirement of qualified overall prediction accuracy. Checking, foreseeing and understanding traffic conditions in any city is a vital issue for city arranging. More recently, the development of new technology for traffic data processing using big data for accurate traffic prediction has shifted the spotlight to data-driven procedures. Different researchers build traffic forecasting systems using big data analytics in order to prevent traffic congestion and accident issues. However, most of the researchers focus on the prediction of individual road segments or intersections instead of the multilayer roads. This paper is an attempt to review the different techniques used by numerous researchers for traffic forecasting using big data analytics. The ultimate goal of this work is to set an updated compilation of prior literature around traffic prediction models so as to motivate and guide future research on this vibrant field.

***Keywords*—**Traffic Forecasting system, Big Data Analytics, Smart Transport System (STS),

I. INTRODUCTION

Smart Transport System (STS) is made out of Advanced Transportation Information Service System (ATIS), Advanced Traffic Management System (ATMS) and so on. A dependable expectation of things to come traffic status dependent on the present traffic data is a standout amongst the most test issues for both ATIS and ATMS. In the investigation of urban transport framework, there are a few essential factors, for example, vehicle stream, normal speed, line length, travel time, vehicle thickness, etc. which describe the traffic state in numerous viewpoints. The traffic information is gathered from circle locators, floating car data (FCD), transport area data, vehicle tag distinguishing proof information and portable information. These traffic informational collections give information asset to related research work, yet then again rise a major test for substantial scale forecast.

With the acknowledgment of the help and modernization, urban areas are facing increasingly more traffic issues that need to be resolved. Blockage traffic isn't just spreading in more extensive zones yet in addition showing up in additional timeframes. So as to facilitate the jam trouble conveyed to our everyday life, look into on traffic including the traffic states investigation turns into a problem area. With the quick improvement of the national economy, the certainly major issue of urban congested roads turns out to be increasingly imperative for quite a while. Propelled traffic the executives and data frameworks (ATMIS) are progressively considered as necessary part methods has been centered on a few adaptations of artificial neural system (ANN) models. The paper is organized as follows, Section I contains the introduction of traffic forecasting in urban areas, Section II contains the related work about the traffic congestion forecasting using big data analytics, Section III contains some new challenges in traffic forecasting system using big data techniques, and finally Section IV concludes research work with future directions.

II. RELATED WORK

In this section, we describe the previous research works carried out by different researchers for traffic congestion forecasting using big data techniques:

Sch¨afer et al. (2002) utilized GPS-empowered vehicles to get continuous traffic data in various European urban communities. By considering clogged streets as those where the speed is beneath 10km/hr, the creators exhibit a representation of traffic conditions around the city can be utilized to identify clogged and blocked street portions. Firmly identified with assessing traffic conditions are acquiring precise evaluations of the movement time between two points in a city.

G¨uhnemann et al. (2004) use GPS information to build travel time and speed gauges for every street fragment, which are thusly used to evaluate discharge levels in various parts of the city. Their assessments are gotten by essentially averaging over the latest GPS sections; this is firmly identified with the chronicled methods gauge we look at our calculation against

Singliar and Hauskrecht (2007) contemplated two models for traffic thickness estimation: contingent autoregressive models and blend of Gaussian trees. This work was intended to work with a lot of traffic sensors set around the city, and not with GPS-prepared vehicles. The creators expect the Markov property for traffic streams: the condition of a street portion in the quick future is needy just on the condition of its prompt neighbors. We receive a comparative supposition in our development of a model.

Su and Yu (2007) utilized a Genetic Algorithm to choose the parameters of an SVM, prepared to anticipate momentary traffic conditions. Their strategy is intended to work with either traffic sensors or GPS-prepared vehicles. In any case, their exact assessment is very restricted and misses the mark concerning completely persuading the lector of their technique's common sense.

Wen et al. (2008) utilized GPS-prepared taxicabs to break down traffic clog changes around the Olympic Games in Beijing; note this is an ex post facto examination of traffic conditions.

Blandin et al. (2009) use kernel methods (Scholkopf and Smola, 2002) to acquire a non-direct gauge of movement times on "arterial " streets; the execution of this gauge is then enhanced through portion relapse.

Yuan and Zheng (2010) propose developing a chart whose hubs are tourist spots. Tourist spots are characterized as street portions much of the time navigated by cabs. They propose a technique to adaptively part multi-day into various time fragments, in view of the difference and entropy of the movement time between tourist spots. This outcome in a gauge of the dispersions of the movement times between milestones. The examination most applicable to this paper is those which endeavor to display or potentially foresee traffic conditions.

Lippi et al. (2010) use Markov logic networks to perform relational learning for traffic estimating on various synchronous areas, and at various strides later on. This work is likewise intended for managing a lot of traffic sensors around the city.

Herring et al. (2010) use Coupled Hidden Markov Models (Brand, 1997) for evaluating traffic conditions on blood vessel streets. They propose a refined model dependent on traffic hypothesis which yields great outcomes. All things considered, we contend that this sort of advancement is, as it were, "pointless excess". We profit by the coarse consistency of traffic stream amid the week to develop a model which yields great outcomes, without falling back on progressively complex, and computationally costly, techniques. One of the primary inspirations driving our work is the use of these outcomes in a constant setting, where computationally costly recommendations are unsatisfactory.

Yuan et al. (2011) used utilized both verifiable examples and continuous traffic to appraise traffic conditions. Be that as it may, the forecasts they give are between lots of "tourist spots" which is littler than the extent of the street organize. Albeit appropriate for some applications, (for example, ideal course arranging), the coarseness of their expectations makes them less appropriate for a point by point comprehension of a city's traffic elements.

Here is the summary of the presented cases:

Year	Author	Title	Research Methodology	Research Gap Analysis	Accuracy
2000	H. M. Zhang	RECURSIVE PREDICTION OF TRAFFIC CONDITIONS WITH NEURAL NETWORK MODELS	A recursive traffic flow prediction algorithm using artificial neural networks. The a system prediction model is specified based on the understanding of how disturbances in traffic flow are propagated, and the order of the model is determined by correlation analysis. The parameters of the model, on the other hand, can be obtained through nonlinear optimization.	The nonlinear nature of such models makes them good candidates for modeling complex nonlinear systems, but the performance of nonlinear models are also more sensitive to their parameters, and globally Optimal parameters are often difficult to obtain in practice. As a result, the potential of nonlinear neural network models may not be fully harnessed without doing numerous experiments	The linear model was able to achieve an average accuracy of about 98% of the target output

2007	H. Su, L. Zhang, and S. Yu	Short-term Traffic Flow Prediction Based on Incremental Support Vector Regression	A new short-term traffic flow prediction model and method based on incremental support vector regression (ISVR) are proposed, according to the data collected sequentially by the probe vehicle or loop detectors, which can update the prediction function in real time via incremental learning way. As a result, it is fitter for the real engineering application. The ISVR model was tested by using the I-880 database, and the result shows that this model is superior to the back-propagation neural network (BPNN) model	It produces more useless data in the training set and it causes more learning samples. Which it decreases the prediction rate.	The ISVR-based model gave higher accuracy than the BPNN-based model and reached a high value of EC fitting. Besides, the ISVR updated forecast function via an incremental learning algorithm, which was more suited for the practical application. 90%
2008	Antony Stathopoulos* & Loukas Dimitriou	Fuzzy Modeling Approach for Combined Forecasting of Urban Traffic Flow	A new, artificial intelligence (AI)-based approach is suggested for improving the accuracy of traffic predictions through suitably combining the forecasts derived from a set of individual predictors. This methodology utilizes a fuzzy rule-based system (FRBS), which is enlarged with a fitting metaheuristic (direct inquiry) procedure to robotize the tuning of the framework parameters inside an online versatile moving skyline structure. The proposed hybrid FRBS is used to nonlinearly combine traffic flow forecasts resulting from an online adaptive Kalman filter (KF) and an artificial neural network (ANN) model. The empirical results obtained from the model implementation into a real-world urban signalized arterial demonstrate the ability of the proposed approach to considerably overperform the given individual traffic predictors.	This system limited to only individual traffic predictor, the process of traffic flow from multiple relations needs to be estimated.	The performance of the three models (KF, ANN, and FRBS) for providing one-step-ahead out-of-sample forecasts of urban traffic flow is evaluated by using three different performance measures. The first two measures refer to the MARE and the Mean Square Relative Error (MSRE), which are commonly used in the literature of traffic flow forecasting. The third measure is the normalized error (NER), which is defined as the root mean square error (RMSE) divided by the standard deviation of the data. The accuracy rate is 92%
2011	Mr. Stephen Dunne, Dr. Bidisha Ghosh	TRAFFIC FLOW PREDICTIONS EMPLOYING NEURAL NETWORKS IN A NOVEL TRAFFIC FLOW REGIME SEPARATION TECHNIQUE	A new multivariate short-term traffic flow and speed prediction methodology are proposed in this paper where the traffic flow and speed observations from uncongested (or linear) and congested (or non-linear) regimes are regime-adjusted to ensure consistent system dynamics. The prediction methodology is developed using Artificial Neural Networks (ANN) algorithms in	This model produces more traffic prediction error and the error rate is more during identifying the objects, the classification of predicting the object rate is decreased due to the higher error rate	The 20 different ANN models with 4 different learning strategies were compared to identify which of the models produce the most accurate forecasts, and also whether an increase in prediction accuracy compromised the computational speed of the mode. 93%

			conjunction with adaptive learning rules. These learning rules demonstrate significantly improved accuracy and simultaneous reduction in computation times. Additionally, the paper attempts to identify the most suitable adaptive learning rule from a chosen pool of rules. The validation of the prediction methodology is performed using traffic data from multiple locations		
2012	Pablo Samuel Castro, Daqing Zhang, and Shijian L	Urban traffic modeling and prediction using large scale taxi GPS traces	Urban Traffic Modelling method to construct a model of traffic density based on large scale taxi traces. This model can be used to predict future traffic conditions and estimate the exact emissions on the city's air quality. We argue that considering traffic density on its own is insufficient for a deep understanding of the underlying traffic dynamics, and hence propose a novel method for automatically determining the capacity of each road segment.	This model doesn't indicate correlation amongst different road segments, this study failed to identify and prediction of objects for different road segments	Average Accuracy rate with vehicle speed is around 76%
201	C. Y	Ensemble learning	A generic method for large scale	This model didn't attempt to solve	Overall Homologous Accuracy

6	uan, D. Li, and Y. Xi,	based on urban traffic state prediction for coupling traffic network with large scale data	coupling urban traffic to forecast the future states of the overall network. In the preliminary stage, the features are extracted using the unsupervised method. Subsequently, an ensemble learning via matching the historical data and the current information is implemented to predict the traffic state transition. The data set for the experiment is composed of multiple layers of the road network	real traffic system in full detail	(OHA)= 78%
2016	Yuan Chengjue, Li Dewei, Xi Yugeng	Medium-term Prediction of Urban Traffic States Using Probability Tree	A probabilistic tree modeling framework for estimating the overall traffic states is proposed in this paper. Firstly, we extract several typical traffic states covering the overall characteristics. Secondly, the state predicting algorithm based on dynamic Variable-order Markov Model and Genetic Algorithm is developed, where different date attributes were evaluated separately. Finally, the prediction model using the probability tree with multiple prediction steps is verified. Experimental results using traffic speed data in Shanghai	The forecasting of urban traffic only depends on the probabilistic tree model, the probabilistic model only determines the traffic state, but it didn't identify the different object features	The average accuracy of the multi-step cluster prediction is all above 90%, which means the prediction algorithm could predict the multi-step traffic state quite well. The prediction becomes less effective as the prediction step turns longer, especially in some certain days, the accuracy is less than the average.

			demonstrate the high accuracy and efficiency of the proposed method		
2018	Fangzhou Sun, Abhishek Dubey, Jules White	DxNAT - Deep Neural Networks for Explaining Non-Recurring Traffic Congestion	DxNAT, a deep neural network model to identify non-recurring traffic congestion and explain its causes. To the best of our knowledge, our work is one of the first efforts to utilize deep learning techniques to study traffic congestion patterns and explain nonrecurring congestion using events. A convolutional neural network (CNN) is proposed to identify non-recurring traffic anomalies that are caused by events	This system has a limitation to identify the different traffic pattern and didn't consider different traffic features to identify the object	This model reaches an accuracy of 98.73 percent when identifying traffic congestion caused by football games

III. New and Revisited Challenges

An existing foundation of traffic anticipating writing and surveys present countless endeavors committed to handling prior difficulties. This area is expected to expand the extent of past inquiries and present the latest improvements in them. The most recent study in [1] exhibited a huge writing audit up to 2014 and assembled difficulties in ten worldwide classifications. The move to information-driven machine-learning methods that is additionally referenced in [1].

A. The Context of Forecasting A noteworthy increment in system forecasts is uncovered since past cutting edge, which considered it a challenge.A significant increase in network predictions is revealed since previous state of the art, which considered it a challenge.. Around 1 out of 20 of works analyzed in [1] had networkwide inclusion Since their survey, the extent has risen impressively. System wide expectations as a rule require the model to know the impact of encompassing street joins

B. *Long-term Prediction Horizons:-*Expanding the forecast skyline isn't generally viewed as a test. Numerous creators portray the corruption of expectations when this skyline is broadened [2], [3], [10], yet long haul forecasts can be valuable from the ATMS viewpoint [20], [21], or for booking in coordination arranging [18]. The relevance of long haul forecasts is asserted likewise for plainly visible system arranging [22] for framework improvement [23].

C. Exogenous Factors in Multi-Input Models:-The principle deterrents for precise long haul and even momentary forecast are factors that influence traffic yet are not part of its occasional conduct and give traffic its stochastic nature [1], [10], [11]: street works, occurrences, occasions, climate, vicinity to traffic influencing offices (parking areas, shopping zones, work/think about focuses), and date-book matters (bank occasions, ends of the week).

Despite the fact that occurrences or climate changes can happen any time and they can be hard to anticipate, other traffic influencing factors like street works or occasions are normally predictable. Nourishing these sort of contributions to information-driven expectation models can upgrade their execution, advancing the gave figures [13]. Foreseen by [10] in 2007, portability information sources and accessibility have been expanding from that point forward. This involves an opportunity and a test with respect to information combination and joining [1], [14], [18].

D. Data Ageing and Concept Drift in Data-driven Models
A move to information-driven methodologies is discernible in the latest writing about traffic factors estimating [14]. These models utilize expansive databases with ample records from which they learn and produce forecasts. As information augmentation expands, it is progressively plausible that learning removed from that information is less authentic; street systems are always showing signs of change, exceptionally in extensive urban zones**.**

The use of those streets is likewise factor inside significant lots of time, expanding in a flourishing city and declining in monetary emergencies influenced regions. On the off chance that an expectation demonstrates gains from a multi-year database, as [16], an adjustment in stream heading, a shut or new path, or an adjustment in utilization designs amid those years are conceivable, and relying upon the urban region displayed, they can be exceedingly plausible.

Responsive models that adjust to unforeseen momentary components, similar to mishaps, blockage circumstances or climate conditions, were proposed in [14]. An adjustment to long haul factors is plausible through information maturing. Overloading old estimations can be a credulous way to deal with give an overlooking component that gives a more noteworthy significance to current info estimations of the model [17].

Expectation models have encountered an impressive changeover. ARIMA models are in clear decrease, and just three of the examined examinations expound expectations with this sort of strategies. Despite everything, they are, however, regular models to contrast with.

E. Big Data and Architecture Implementation

The time of associated vehicles and detected streets is close, and lavish information is ending up progressively accessible to misuse. Cloud and parallel processing huge information ideal models can give the way to large scale reenactment, computationally modest whole system expectations, traffic profound learning and increasingly illustrative intensity of models. Usage of traffic estimating instruments in Big Data models likewise takes into account ongoing expectations dependent on a few kinds of information, taken from various open and not open sources in a successful way. By the by, critical work is required in this field; learning strategies should be parallelized to be equipped for mining pieces of bury related information without jeopardizing the quality of the predicted variable.

IV. CONCLUSION AND FUTURE SCOPE

Traffic factors have been an object of investigation and expectations for over 40 years. A few overviews have inspected the subject with various differentiating criteria and field test appraisals. The most important advancement in the field of traffic forecast as of late is identified with a move in the expectation demonstrating worldview.

Advances in information situated procedures and innovations, the blast of Big Data and machine learning, alongside developing accessibility of traffic-related information from copious sources have added to abandon time-arrangement investigation techniques and given a lift to information-driven models.

This move has constrained the latest analysts to spread out new skylines and difficulties for the field. This work has expected to accumulate and summarize past work, to propose a contrasting system and with audit latest writing concerning the refreshed criteria.

A lot of basic issues and difficulties is found in every past audit, with respect to forecasting degree and setting, most appropriate model determination, measurements for various models correlation, and hybridization of models to enhance execution. These perspectives stay appropriate, 30 years after the primary overview that uncovered them, and notwithstanding the move to information-driven demonstrating.

In addition, new issues and difficulties emerge in the light of this currently overall method for displaying. Gathering information from new sources includes intertwining distinctive sorts, and overseeing information conglomeration and goals are probably the latest difficulties proposed by writing surveys. Extra difficulties are presented in this work: expanding the expectation skyline, fusing exogenous components to models, and including information maturing instruments that enable models to adjust their figuring out how to changing conditions

Traffic factors forecast writing has been concentrated completely, so this audit has centered in late works. Refreshed reference criteria have been utilized to ponder new writing. In our investigation, the previously mentioned move to information-driven models is clear: the use of ARIMA and other time-arrangement examination strategies is diminishing, and first works with expectation skylines longer than an hour show up, establishing the frameworks for future work in this line.

Models with idea float or adaptive learning are likewise found in a little offer of the checked on works, yet the dynamic consolidation of models situated in extensive databases which introductory information changes in time and requires adjustment may encourage this system to be overwhelming. Exogenous variables are yet insufficiently presented in rush hour gridlock estimating models. Their comfort has been extraordinarily demonstrated when utilizing schedule and time of day data as model parameters, yet numerous other information is increasingly accessible consistently, which could help traffic forecast execution of future models.

REFERENCES

[1] E. I. Vlahogianni, M. G. Karlaftis, and J. C. Golias, "Short-term traffic forecasting: Where we are and where we're going," Transport. Res. Part C Emerging Technol., vol. 43, pp. 3–19, 2014
[2] B. Van Arem, H. R. Kirby, M. J. M. Van Der Vlist, and J. C. Whittaker, "Recent advances and applications in the field of short-term traffic forecasting," Int. J. Forecasting, vol. 13, no. 1, pp. 1–12, 1997.
[3] B. Van Arem, H. R. Kirby, M. J. M. Van Der Vlist, and J. C. Whittaker, "Recent advances and applications in the field of short-term traffic forecasting," Int. J. Forecasting, vol. 13, no. 1, pp. 1–12, 1997.
[4] E. I. Vlahogianni, J. C. Golias, and M. G. Karlaftis, "Short-term traffic forecasting: Overview of objectives and methods," Transport Rev., vol. 24, no. 5, pp. 533–557, 2004.
[5] .Ensemble Learning based Urban Traffic State Prediction for Coupling Traffic Network with Large Scale Data*
[6] Urban track modeling and prediction using large scale taxi GPS traces.
[7] DxNAT - Deep Neural Networks for Explaining Non-Recurring Traffic Congestion
[8] .Medium-term Prediction of Urban Traffic States Using Probability Tree
[9] .RECURSIVE PREDICTION OF TRAFFIC CONDITIONS WITH NEURAL NETWORK MODELS
[10] TRAFFIC FLOW PREDICTIONS EMPLOYING NEURAL NETWORKS IN A NOVEL TRAFFIC FLOW REGIME SEPARATION TECHNIQUE

[11] C. van Hinsbergen, J. van Lint, and F. Sanders, "Short term traffic prediction models," in Proc. 14th World Congress Intelligent Transportation Systems, Beijing, 2007.
[12] H. J. van Lint and C. P. van Hinsbergen, "Short-term traffic and travel time prediction models," Artif. Intell. Applicat. Crit. Transport. Issues, vol. 22, pp. 22–41, 2012.
[13] E. Bolshinsky and R. Freidman, "Traffic flow forecast survey," Technion—Israel Institute of Technology, Tech. Rep., 2012.
[14] E. I. Vlahogianni, M. G. Karlaftis, and J. C. Golias, "Short-term traffic forecasting: Where we are and where we're going," Transport. Res. Part C Emerging Technol., vol. 43, pp. 3–19, 2014.
[15] Z. Ma, G. Luo, and D. Huang, "Short term traffic flow prediction based on on-line sequential extreme learning machine," in Proc. 8th Int. Conf. Advanced Computational Intelligence, Chiang Mai, 2016, pp. 143–149.
[16] A. Wibisono, W. Jatmiko, H. A. Wisesa, B. Hardjono, and P. Mursanto, "Traffic big data prediction and visualization using fast incremental model trees-drift detection (FIMT-DD)," Knowledge-Based Syst., vol. 93, pp. 33–46, 2016.
[17] U. Mori, A. Mendiburu, M. Álvarez, and J. A. Lozano, "A review of travel time estimation and forecasting for advanced traveler information systems," Transportmetrica A Transport Sci., vol. 11, no. 2, pp. 119–157, 2015.
[18] N. E. Faouzi and L. A. Klein, "Data fusion for ITS: Techniques and research needs," Transport. Res. Proc., vol. 15, pp. 495–512, 2016.
[19] Short-term Traffic Flow Prediction Based on Incremental Support Vector Regression
[20] C. Lamboley, J. C. Santucci, and M. Danech-Pajouh, "24 or 48-hour advance traffic forecast in the urban and periurban environment: The example of Paris," in Proc. 4th World Congress Intelligent Transport Systems, Mobility for Everyone, Berlin, 1997.
[21] F. Jin and S. Sun, "Neural network multitask learning for traffic flow forecasting," in Proc. IEEE Int. Joint Conf. Neural Networks, Hong Kong, 2008, pp. 1897–1901.
[22] P. Næss and A. Strand, "Traffic forecasting at 'strategic', 'tactical' and 'operational' level," J. Crit. Realism, vol. 51, no. 2, pp. 41–48, 2015.
[23] K. Jha, N. Sinha, S. Arkatkar, and A. K. Sarkar, "A comparative study on the application of time series analysis for traffic forecasting in India: Prospects and limitations," Current Sci., vol. 110, no. 3, pp. 373–385, 2016.
[24] J. A. K. Suykens, J. Vandewalle, Least Square Support Vector Machine Classifiers, Neural Process Letter. 9 (1999): pp. 293-300
[25] J. H. Liu, J. P. Chen, S. Jiang, J. S. Cheng, Online LSSVM for function estimation and classification, Journal of University of Science and Technology Beijing. 10 (2003) 73-77
[26] C.H. Wu, C.C. Wei, M.H. Chang, et al. Travel time prediction with support vector regression. IEEE Transaction on Intelligent Transportation Systems, 2004, 5(12): pp. 276-281
[27] .Z.S. Yang, G.Y. Jiang. Theories and models of urban traffic guidance system based on high-order neural networks. Journal of Highway and Transportation Research and Development, 1998, 6: pp. 16-19
[28] C.Y. Zhang, G.H. Hu, T.Z. Xu. Traffic flow time series prediction based on LS-SVM. Journal of Yunnan University, 2004, 26: pp. 19-22
[29] Traffic Data Collection System Based on Floating Cars. Computer and Communications, 2006, 5(24): pp. 31-34

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