



TRAFFIC CONGESTION PREDICTION THROUGH DEEP LEARNING

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ABSTRACT

Congestion in cities has become an increasingly severe concern across the planet, affecting progress and people's everyday lives. It also happens in India's medium and large areas, posing a threat to the nation's growth. Humans may learn from the governance and administration of urban traffic systems that traffic congestion can be mitigated or reduced if we could somehow predict traffic congestion that will happen in just few moments or which have already transpired in a few seconds and apply timely, appropriate traffic mitigation strategies. As a result, traffic congestion forecasting is critical for enhancing energy effectiveness and reliability of the transportation system. For this purpose a number of different approaches on this topic have been evaluated and detailed in this survey article. This has allowed the effective realization of our approach for a traffic congestion prediction system that will be detailed in the subsequent editions of this research article.

KEYWORDS: Traffic Congestion, Artificial Neural Networks, Decision Making, Segregation, Machine learning, Labelling, Smart City, Traffic Management.

I. INTRODUCTION

With something like the fast increase of the urbanization, there are an increasing number of metropolitan automobiles on the road. The advanced growth of cities is accelerating. The metropolitan traffic is growing increasingly convoluted, and traffic congestion in cities is developing particularly prominent. One of them is overcrowding on the roads. When traffic problems arises in metropolitan areas, if it is not addressed promptly, it will result in more congested regions and, in extreme cases, traffic immobility. The first step in addressing congestion problems is to minimize it from occurring in the first place. As a result, developing an efficient current traffic prediction facilitates the development of focused preventative actions and early warnings.

Time is the utmost important commodity in today's hyper society. The ability to organize your time well is vital for accomplishment. A traffic junction is one of the locations that will be several times throughout the day yet will be unable to handle. A traffic signal with a defined frequency in a junction might provide a few vacant lanes while also packed sections. International and domestic experts have made significant headway in conducting prediction studies in order

to anticipate the challenge of traffic congestion. Time series approach, parametric regression model, and artificial neural approach have all been deployed to roadway traffic congestion forecasting by academics from many professions and domains.

One of the primary issues that we confront in our daily lives is congestion. The existing signalized intersections design is a conceptual model that is unable to respond to traffic variations. The stationary program operates on a pre-programmed timer, which might also result in longer signal wait times. Throughout rush periods, particular sectors see higher bottleneck, while others experience less overcrowding. Because the stationary timer mechanism does not compensate for the increasing congestion, motorists on the crowded route must wait longer than required.

Inside the sector with reduced road congestion, however, all of the automobiles evacuate even before green countdown ends, wasting signal timing. Emissions and increased fuel waste are two long-term effects of road congestion. The present service's flaws and challenges contribute to a smart, flexible, and real-time traffic management. The approach presented in the research is dynamic, using current traffic camera footage and calculating overcrowding for each individual lane. Each lane's bottleneck is analyzed, and the



signaling duration is assigned based on the saturation proportion.

Congestion is an outward sign of a traffic system that is not working properly. According to data, there are over a thousand instances of road congestion in small and medium sized cities per year, and the scenario is significantly much worse metropolitan regions, where delays can approach two hours if traffic is severe. The occurrence not only affects thousands of automobiles, but also results in significant financial loss. In a nutshell, the asymmetry among both traffic demands and availability is to blame for the poor performance of city transportation system.

So, whenever traffic jams occur, there is still an issue that requires additional in-depth study, namely, how can they recognize the congestion condition as quickly and efficiently as possible and distribute the information to commuting operators, allowing us to disperse the clogged traffic flow more rapidly? Congestion is a serious issue that occurs on highways and causes traffic to be congested. This is a really aggravating occurrence that we come across in our daily lives while commuting on roadways. Overload cannot be alleviated just by the construction of infrastructure, overpasses, or increased road bandwidth. For freight forwarding, it is required to regulate traffic sequences with an integrated process.

These strategies have a positive impact on traffic bottleneck forecasting and may be used to create a quick and accurate prediction models. The majority of these techniques involve predicting and analyzing travel demand factors. The management of traffic congestion should indeed be centered on mitigation, which means being able to forecast the major shift of the traffic condition in a small amount of time relying on existing traffic flow statistics and providing insight into potential congestion. Current traffic congestion investigation has primarily concentrated on predicting traffic congestion characteristics such as volume of traffic and typical vehicle velocity, as well as determining the prevailing congestion. There is a demand for a paradigm for traffic congestion forecasting and visualization that can take into account the majority of traffic congestion attributes and forecast potential traffic congestion.

This literature survey paper segregates the section 2 for the evaluation of the past work in the configuration of a literature survey, and finally, section 3 provides the conclusion and the future work.

II. RELATED WORKS

L. Xu et al. [1] offer a deep learning short-term traffic flow prediction approach based on vehicle lane change behavior recognition, which can forecast the future change trend of traffic volume based on the vehicle lane change behavior picture. The deep sort algorithm is utilized as the target tracking model in this research. Deepsort algorithm is an enhancement to the sort algorithm, which is based on tracking by detection technique. To handle the correlation of

frame by frame data, the Sort algorithm employs the Kalman filter, and the Hungary algorithm is utilized for association measurement. In particular, the Kalman filter can anticipate the target's location at present based on the target's position at the previous time, and the Hungarian algorithm can determine if a target in the current frame is the same as a target in the previous frame. In comparison to previous research, this technique takes lane shifting behavior of cars into account components of short-term traffic flow prediction and builds a prediction model of short-term traffic flow change trend, which achieves high forecast accuracy and has some practical utility.

D. -H. Shin et al. proposed to use an LSTM-based traffic congestion prediction approach with compensation for missing temporal and geographical data [2]. Outliers and missing values in the traffic data impacted the prediction outcomes, according to the experimental results. Outliers were deleted to improve model performance, and the data were pre-processed with geographical and temporal trends and pattern data. LSTM was used as a prediction model. It is based on the RNN paradigm and addresses the issue of long-term reliance. In the LSTM model, the output of a hidden layer is used as an input for another hidden layer. Because the model takes into account sequential or temporal elements, it may be used to learn time-series features from traffic data.

P. Jiang et al. presents a data-driven traffic congestion prediction and detection system. There are three sections to the model. First, the authors employ clustering algorithms and a tiny bit of manual involvement to construct training data sets and train the model based on historical data with the defined features, which are referred to as new features. Second, as one of the most significant aspects of their algorithm, they present a short-term prediction model to estimate traffic flow [3]. SRBDP stands for Self-Related, Basis series, Deviation series, and Prediction, and it is the name of the forecast model. To anticipate traffic flow, this model uses a forecasting algorithm. Finally, they conducted trials on an actual data set to evaluate the algorithm's reasonableness.

A. E. Essien et al. suggested a deep learning framework that makes use of the LSTM's sequential learning capabilities as well as the convolutional neural network's scalability and performance. Using a Convolutional LSTM architecture, the suggested method uses a two-stage approach for multi-step network-wide traffic flow prediction [4]. The first stage includes employing a method known as recurrent quantification analysis (RQA) to encode the incoming traffic flow signals into pictures that indicate the spatiotemporal correlation in connection roads. The spatiotemporal dimension of network traffic data is kept in this fashion. A deep learning architecture with three ConvLSTM layers and a fully-connected layer is utilized in the second stage. The suggested model was validated using data from the California Transportation Management System's real-time traffic network.



M. M. Chowdhury et al. proposed a multi-agent coordination system-based method for anticipating traffic congestion. A road agent at each intersection uses a circular model to interact with its neighboring road agents in strategies to adapt to and anticipate traffic congestion in the short and long term. The authors map urban traffic networks into the circular model for road congestion predictions since they have a road agent installed [5]. The primary difference between the developed framework and existing models is that it would construct the current traffic table for each lane of each intersection after a defined period. Time series analysis was used to assess the developed framework, which was shown to be extremely efficient with both big and little quantities of data.

I. Loumiotis et al. [6] use intelligent agents to offer an innovative way to traffic congestion. These intelligent agents will gather, store, and interpret road traffic information to forecast future traffic flow, allowing road authorities to take preemptive steps, such as modifying the traffic signal approach, and individuals to utilize other paths to their destination. Specifically, the intelligent agents will use artificial neural networks to anticipate the next speed on the road as an indicator of traffic congestion. Artificial neural networks have been frequently employed in the literature to solve nonlinear issues, and their nonlinear features make them an excellent choice for road traffic. The suggested scheme's functioning is evaluated and confirmed utilizing real data gathered by a vehicle detection system (VDS) along the Attica Tollway in Athens, Greece.

S. -S. Kim, et al. developed the weight modeling approach for spatial modeling of the road network using the path distance metric to estimate future traffic. The key benefit of the introduced technique is its ability to give accurate traffic forecasts by reflecting urban network connection information with numerous limitations and employing a diffusion-based model [7]. The authors tested DCRNN-Path on a real-world urban network and found that it outperformed the four baselines. This research has shown that diffusion-depend deep learning techniques combined with the suggested spatial model are potential solutions for traffic prediction that represent the features of urban networks.

A. Rao et al. demonstrated a dynamic traffic signal system. To process the video, the system employs Image Processing techniques such as background removal and edge recognition [8]. The system also included a clustering-based prediction engine capable of forecasting congestion depending on prior observed patterns. The image processing technique, in conjunction with the prediction mechanism, converts each frame into a value known as the congestion percentage. The framework is built on Raspberry Pi 0 Ws and utilizes the OpenCV library for image processing. As the congestion changes, the system demonstrates its adaptability and dynamic nature. The suggested solution is low-cost and may be applied on a broad scale. The aforementioned system has the

advantage of being less expensive than other sensor-based traffic systems.

T. Sun et al. [9] utilize Ningbo City taxi trajectory data to propose a strategy that depends on the hidden Markov model and the speed of the upstream links to anticipate the congestion trend in the busy traffic zone. First, taxi trajectory data is analyzed and trained. Then, create a state transition matrix to replicate the random change of congestion patterns in a congested area. Simultaneously, evaluate the impact of the upstream traffic situation while constructing the observation probability matrix. Finally, the authors use the above two matrices and the HMM model to forecast the congestion pattern in the busy traffic zone.

The prospect of using CCTV images to anticipate traffic was investigated by W. D. Sunindyo and he created a CCTV footage processing system and experimented with prediction methods utilizing various variables gathered from that footage. The analysis of CCTV material yielded 91.3 percent accuracy in vehicle counts. The author was also able to determine the vehicle's speed, although using a pixel-per-frame measuring unit. The best prediction model achieved an RMSE score of 1.88, indicating that the model prediction is accurate up to 1.88 vehicles relative to real data [10]. The trained model developed in this research may also be utilized to create a smart traffic control system.

For the prediction and visualization of traffic congestion, a novel framework called MF-TCPV is developed by L. Li et al., which is separated into three layers: raw data layer, data processing layer, and data presentation layer. For congestion evaluation parameter prediction in the data processing layer, a deep prediction model is presented which depends on deep learning and machine learning dubbed long short-term memory networks integrated relevance vector machine which depends on spark parallelization [11]. The LSTM-SPRVM prediction findings are utilized to split traffic congestion into six levels using Fuzzy Comprehensive Evaluation. The entropy approach is used to determine the weight of each traffic congestion aspect. The authors built up a cache database and designed the Data Visualization of traffic congestion prediction in the data presentation layer. Based on real data from Whitemud Drive in Canada, the authors validate the performance of MF-TCPV.

To categories road congestion levels, the Road-Condition-based Congestion Prediction System (RCPS) is proposed by F. -R. Huang et al.. The RCPS employs a camera drone to collect traffic data and then applies deep learning to forecast future congestion levels. The RCPS divides traffic congestion into four levels. The RCPS' performance has been verified by extensive field testing [12]. An APP to display the projected road congestion level has also been developed to make it easier for drivers to acquire the congestion forecast. The RCPS forecast is fairly accurate, and it can be utilized in the actual world, according to experimental data. The RCPS-designed APP allows users to quickly view congestion level predictions.



N. Ranjan et al. provide a method for predicting traffic congestion that can learn both geographical and temporal correlations between sequences of historical picture data. The authors include the LSTM network between the convolutional encoder and decoder in the suggested architecture. The convolutional encoder first turns the sequence of the input picture into low-resolution latent state sequences [13]. The LSTM network then learns the time series representation from the sequences, and the convolutional decoder finally returns the latent state to its original resolution. Because of the incorporation of convolutional, downsampling, and upsampling layers, the suggested model may be applied to large-scale traffic prediction issues while keeping trainability on resource-constrained devices.

III. CONCLUSION AND FUTURE SCOPE

Traffic in metropolitan areas is becoming a more serious problem all over the world, impacting development and people's everyday routines. It also occurs in India's moderate and major cities, posing a serious concern to the country's economic development. People might very well start understanding from the administration and management of metropolitan vehicular networks that road congestion can be ameliorated or significantly lowered when we can anticipate traffic congestion that would occur in a matter of seconds or which has already occurred in a couple of moments and implement punctually, relevant traffic prevention measures. As a consequence, traffic congestion predictions is crucial for improving the transport platform's fuel efficiency and dependability. This survey study has assessed and documented a number of diverse strategies to this problem for this goal. This has enabled us to successfully implement our concept for a traffic congestion predictive model, which utilizes Artificial Neural Networks and Decision Making that will be outlined in future versions of this research paper.

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