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Heterogeneous Spatiotemporal Graph based Deep Convolutional Neural Network for Pattern Mining and Outlier Detection

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Abstract - *There is a general increase in the incidence of increased morbidity and mortality of road traffic accidents around the world, but the majority of the morbidity occurs in underdeveloped nations. This research conducts a spatial and temporal analysis of the incidence of road traffic accidents along the Indian Expressway, in order to enable the researcher to identify prominent accident spots on the road, as well as identify accident prevailing time in order to see whether there is a correlation. Statistical records were checked for this research. Using a regression statistical tool, the collected data was analyzed and theories were evaluated. Based on the results, it can be concluded that human, mechanical, and environmental characteristics are the most important factors that cause road traffic crashes in the study area. The research recommends that traffic rules and regulations be strictly enforced to correct erring drivers, and that the administration and affected organization take road construction and maintenance more seriously, with proper diversion in the event of road construction.*

Key Words: **Dynamic Temporal Attention, Dynamic Spatial Attention, Late Fusion, Accident Anticipation, Autonomous Vehicle**

1.INTRODUCTION

Traffic incidents have a wide and expanding detrimental influence on both traffic systems and the quality of social activities as the number of vehicles on the road increases and cities expand. In intelligent transportation systems, traffic safety management plays a critical role. Traffic safety management is a vast field of study in which it is critical to examine and forecast the impact of traffic events [1]. If the impact of an occurrence is accurately foreseen, traffic incident management can be utilized to reduce economic losses. In transportation science, research on traffic incidents has mostly focused on driver behaviors and physical models. At the microscopic level, cellular transmission modeling has been used to mimic the genesis and dissipation of traffic jams [2].

Driving characteristics such as lane change, acceleration, and deceleration are all taken into account in this model. Car-following models, on the other hand, depict how drivers follow each other in the traffic stream to better replicate the congestion and dissipation generated by traffic events. To attain exact findings, these tiny models focus on conventional road features such as junctions, highways, and rectangular grid networks [3]. Macroscopic network traffic simulation models based on kinematic wave theory, on the other hand, have recently been developed to simulate and anticipate diverse traffic behaviors, such as accidents on vast road networks. Despite the thorough findings acquired using these technologies, the lengthy computation periods have rendered them unsuitable for use in Traffic Incident Management. Furthermore, these microscopic approaches have limited spatial transferability and cannot be used in real-world road networks [4].

Although spatial-temporal data analysis is still in early development, with even the most fundamental difficulties unaddressed, various patterns can be obtained using trajectories, and techniques and algorithms that should be implemented to accomplish so. It's important to be aware of them from the beginning of the research. It's also important to realize that many of these issues are still unaddressed. Some of the general research concerns that must be addressed include interdisciplinary and spatial discretion issues, data characteristics, and minimum research effort. Our major research focus depends on pattern mining and outlier detection based on data analytics for public safety, traffic, and transportation, as well as earth and environmental monitoring [5].

Time, on the other hand, is one-dimensional and can only move in one direction. This makes it difficult to evaluate the results of Spatiotemporal research. Another issue is data classification, which can have a substantial impact on the patterns seen in the data. When it comes to the modifiable areal unit problem, the results vary substantially depending on whether space is measured in states, zip codes, or census tracts, and time is defined in years, days, or minutes. This is an issue that has existed for quite some time. The identical inquiry may provide completely different results if other spatial/temporal criteria were used [6].

2. Literature Survey

Due to a rapid growth in geographical and temporal statistics as a result of broad collecting of network and location aware decisions, geographic and temporal data analysis approaches are in great demand. Most of the time, these enormous spatial-temporal data sets hide potentially surprising and helpful discoveries. Geotemporal analysis has various challenges, yet it has potential applications in a variety of sectors and research areas. Transportation networks are becoming more complex and interconnected, necessitating a deeper understanding of the stochasticity and uncertainty of spatiotemporal network variables like demand, flow, and speed.

The traffic categorization was first established by W. Wei et al. in [1]. They divided traffic into homogeneous and heterogeneous types, as well as congested and non-congested modes. They also create clusters to increase the MorphAn scatterplot's spatiotemporal quality. They did this by looking at case studies of three expressways on Beijing's ring road. With a spatiotemporal scatter plot, they were able to classify urban traffic conditions and traffic conditions. Pre-classification and Spatiotemporal clustering were used to produce clustering once more.

In [2,] L. Wangh et al. reported the computation of traffic index urban road networks using floating automobiles from traffic. The road network was rebuilt using a grid approach. They used a grid approach to show traffic movement. Their technique helped traffic management by distinguishing congested locations with the usage of urban networks. They intended to employ an approach that included data preprocessing, a map grid, traffic extraction, and a traffic performance index visualization. In the form of a grid model, they obtained the traffic ratio indicator and traffic index result.

In [3,] Liyan Lui et al. used temporal and spatial aggregation of traffic data to extract critical regions and generated readable traffic flow maps, while using the topic model to capture latent semantic information. They suggested an interactive topic modelling system with a variety of interactive features that allows users to examine data at various degrees of depth. Then, using Spatiotemporal graphs and interactive topic modelling, they created and constructed an interactive visual analytics prototype system. Two case studies using real-world traffic data in Hangzhou were used to illustrate the system's practicality and validity.

In [6], Yoichiro Iwasaki et al. described a method for identifying vehicle locations and movements using thermal pictures captured by an infrared thermography camera. Even in poor visibility circumstances like snow and dense fog, the infrared thermography camera provides excellent contrast images. Based on the standard deviations of pixel values in the time direction of Spatiotemporal pictures, their suggested method defined the area of moving vehicles. They also used a pattern recognition technique that employs Haar-like characteristics per frame of the photos to specify vehicle placements.

Xu Wang et al. [14] used a large cellular usage dataset comprising 1.5 million users and 5,929 cell towers in a major Chinese metropolis to analyse cellular traffic. They discovered extensive Spatiotemporal dependence even among far-flung cell towers, which had hitherto been neglected. They suggested an unique breakdown of in-cell and inter-cell data traffic, as well as a graph-based deep learning technique to accurate cellular traffic prediction, to clearly identify and successfully simulate the Spatiotemporal dependence of urban cellular traffic. Their technology regularly outperforms the state-of-the-art time-series based approach, as evidenced by their experimental findings.

3. Design Methodology

3.1 Traffic Dataset and Preprocessing

In this section, we analyze to make a comprehensive research on the collected heterogeneous spatial-temporal data, later formalizing the dataset according to our need for data handling and model preparation. In this research, we used large-scale heterogeneous data considering all factors related to traffic accidents, flow, and management collected from the cities of India. Our heterogeneous dataset can be purely categorized into five significant categories as shown below :

A. Data on traffic Accidents

This dataset basically includes the timestamps and locations of traffic incidents which were gathered on a hourly based from 2014 to 2018. The site of an accident is closely connected to the urban transportation system, implying that current traffic analyses based on neural network that ignore the spatial connections between road segments that are not acceptable.

B. GPS data from taxis

This dataset basically includes the timestamps and locations of GPS based taxis which were recorded in every five minutes which were based from 2014 to 2018. Additionally, the data contained speed of each vehicle with their GPS activity.

C. Point of Interest GIS Data

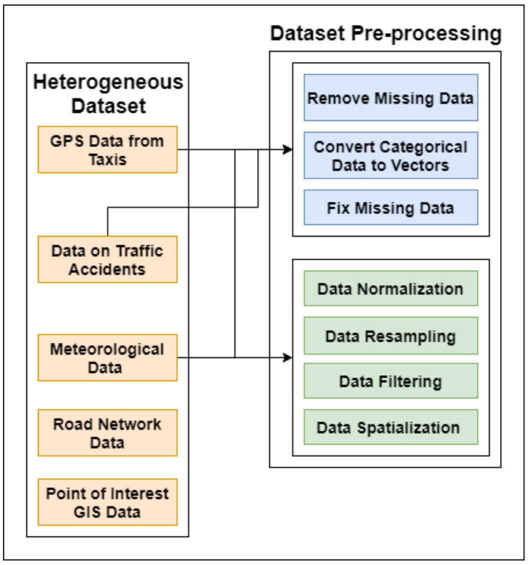
This dataset basically includes the specific physical location which someone may find interesting. This includes 500,000 POI including information of each POI along with their name, location and category.

D. Data from the Meteorological Service

We scour the weather underground for meteorological data. The data was collected hourly between August 1, 2018 and October 31, 2018. This dataset covers meteorological data such as temperature, weather patterns, as well as the link between traffic accident frequency, temperature, and other weather conditions. According to the findings, high temperatures and more severe weather conditions are more likely to result in frequent traffic accidents.

E. Data on the Road Network

Data from major Indian city's road networks is also utilized. The statistics provide essential data on the metropolitan road network, such as the name of each road, the number of points on each road, road intersection sites, and road lengths.



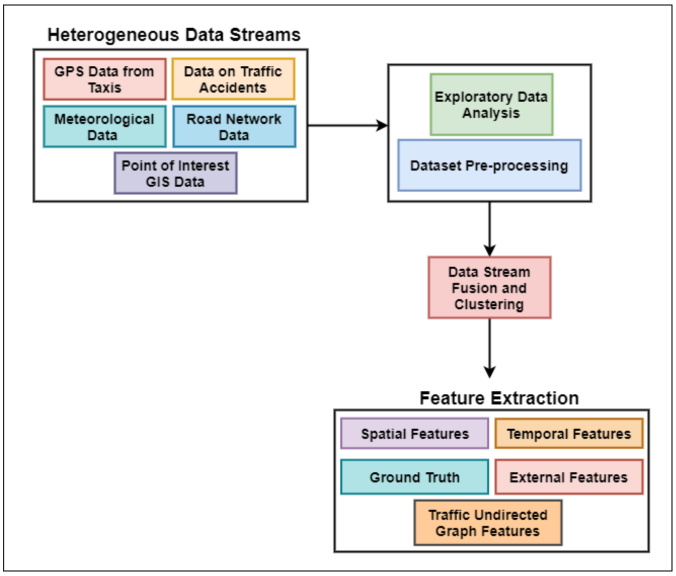
[Figure I: Heterogeneous Spatiotemporal Dataset Preprocessing]

Several preprocessing techniques have been performed on the heterogeneous dataset for making the dataset compatible for the system working and input. For the GPS data from taxis, data on traffic accidents and meteorological data, we remove missing data columns, convert categorical data to vectors and fix missing data columns. Additionally for meteorological data, we perform data normalization, data resampling, data filtering and data spatialization for handling the data streams and making fusion for a single stream input.

For the point of interest GIS data and data on the road network, undirected graph is defined representing the urban traffic conditions and road segment management represented by the vectors $G = (V, \eta, A)$ where G represents the undirected graph, V represents the urban road network, η represents the connectivity between the point of interest and road segments and A represents the is the adjacency matrix of the traffic network G. If the road segments are connected to each other the adjacency matrix is set to 1 else set to 0.

3.2 Feature Extraction

An overview to feature extraction is provided in this section, which include generating vectors through road network as well as the extraction of other types of features. Three kinds of impact variables have been identified from the heterogeneous dataset : geographical aspects, temporal features, and external characteristics. Each characteristic feature is described in detail in this section, including how it is generated.



[Figure II : Feature Extraction from Heterogeneous Dataset]

A. Heterogeneous Spatial Traffic Features

In addition to road structural features and POI distribution (X_i^p), the spatial features (X_i^S) include local spatial features of each road segment that have direct or indirect influence on the probability of traffic accidents. Traffic accidents are more likely to occur on roads with more difficult circumstances, where X_i^S indicates the characteristic of road structure for each road segment V_i. In order to determine the route's geographical location, we average the locations of points on each road section. A number of road-structure-related attributes, such as length and total number of points, may then be retrieved from each road segment.

Traffic accident risk is believed to be indirectly affected by the local surroundings of each road segment, as shown by the POI distribution X_i^p of each road segment V_i. There is an increased chance of traffic accidents on roads with leisure facilities or parking lots nearby, as opposed to routes with calm parks nearby. When predicting traffic accidents, we use POI data and extract POI features since it is a good way to capture the road segment characteristics.

$$X_i^{spatial} = X_i^S + X_i^p$$

B. Road Network Heterogeneous Graph Features

Each crossroad $\mathbf{G' = (\gamma', \varepsilon')}$ is represented by a set of nodes (intersection points), while the edges (road segments) connecting them are represented by a set of edges (road segments). So, roads should be considered as nodes in the network if we're trying to anticipate traffic accidents at the road level. As a result, the ith node $\boldsymbol{\gamma i} \subseteq \boldsymbol{\gamma}$ corresponds to the ith edge $\mathbf{e'} \in \boldsymbol{\varepsilon'}$. Then it becomes necessary to form the edge set $\mathbf{e'}$, which is created when road segments $\boldsymbol{\gamma i} \subseteq \boldsymbol{\gamma}$ and $\boldsymbol{\gamma j} \subseteq \boldsymbol{\gamma}$ are joined by junction in $\boldsymbol{\gamma'}$ represented as :

$$\boldsymbol{\varepsilon} = \{(\gamma i, \gamma j) : \gamma i, \gamma j \in \gamma \cap (\exists\ e' \in \varepsilon' \text{ such that } \gamma i \wedge \gamma j = e')\}$$

C. Heterogeneous Temporal Traffic Features

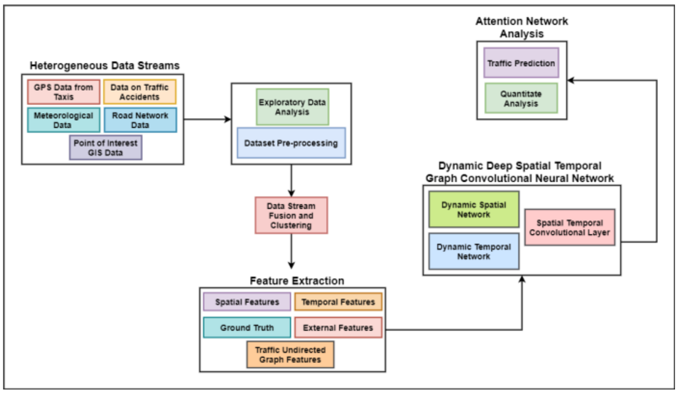
Since the historical traffic conditions of each road segment can be reflected by this temporal characteristic ($X_i^{temporal} = X_i^{v,t}$), it can have a temporal influence on the probability of a traffic collision. A traffic accident's likelihood is inversely proportional to the speed of the traffic flow, according to common sense. The average speed of each road segment in each time slot represented by $X_i^{v,t}$ is then calculated. To visit each road section step by step would be costly and impractical since taxi data is so huge. This is accomplished by first dividing each time slot's traffic flow into grids of equal size, and then calculating the average taxi speed in each grid. In the next step, we assign a traffic flow speed characteristic for each route based on its location in a grid. A road segment's traffic speed is governed by its grid location. Each grid is a $d \times d$ square. For the modification of each road segment's scope, we have d. Each hour corresponds to a temporal feature dimension.

D. Heterogeneous External Traffic Features

Beyond spatial and temporal characteristics, external variables also have a role in determining the likelihood of a traffic collision occurring Meteorological features and calendar features make up the external factors examined in this article. We don't use the subscript to distinguish between roads because all roads have the same timestamp for identifying exterior characteristics. Since severe weather can increase the likelihood of traffic accidents, meteorological factors can have a significant impact on traffic accidents. And hence, eight meteorological parameters are taken into account: weather type, temperature, dew point and humidity; pressure; wind speed, wind direction, and perceived temperature; with 15 values each for the weather type and wind direction, these elements are category attributes; the rest are numerical attributes. As an example, we use one-hot encoding to represent the kind of weather and the direction of wind.

3.4 Network Architecture

Heterogeneous Spatial-Temporal Graph based Deep Convolutional Network for Early Anticipation of Traffic Flow Accidents is one of the finest study areas since we can apply advanced models that leverage traffic flow variables on both a spatial and temporal basis to make traffic forecasting more accurate. To simplify the model structure and estimate technique while yet providing high forecasting results, the Graph-based Deep Convolutional Structure was designed. Spatial-temporal traffic flow forecasting models are used in empirical studies, with specific focus dedicated to the methodologies of feature selection and extraction.



[Figure III : Architecture for Heterogeneous Spatial-Temporal Graph based Deep Convolutional Network]

Temporal correlations and spatial correlations must be taken into consideration in the analysis of Spatiotemporal data. Spatiotemporal objects have continuous and discrete changes in spatial and non-spatial features, as well as the effect of adjacent Spatiotemporal objects that are collocated. This adds substantial complexity to the data analysis process. Spatial-temporal data is a combination of spatial and temporal representations of data. These qualities comprise non-spatiotemporal, spatial, and temporal properties. They are divided into three categories: Spatial and temporal characteristics are used to describe things that do not have context. Objects have spatial characteristics that determine their positions, extents, and forms. Timestamps and duration of processes denote spatial object (vector) or field as temporal characteristics (raster layers).

Data from the road network is used to create the traffic network. Then, for each road segment, features from heterogeneous data (such as road networks, taxi GPS data, weather data, traffic accident records, and POIs) are extracted. We divide extracted features into three categories because different features have different effects on the probability of future traffic accidents: spatial features that reflect the spatial local characteristics of road segments; temporal features that record the historical traffic conditions of each road segment; and external features that describe external influences.

To begin, DSTGCN examines several sorts of features for each training sample based on three components, the

Spatial Convolution Layer, the Spatiotemporal Convolution Layer, and the Embedding Layer, in order. This compact representation is input into a Fully Connected (FC) network to learn relationships between multiple characteristics and forecast the probability of future traffic accidents using the processed hidden features. Last but not least, real-world datasets are used to test the suggested model. Comparisons are made with both classical and current baselines, as well as the impact of different model characteristics and structures.

In order to build our model, we use three sorts of modules. When we represent spatial links between road segments with topological structure, we use graph convolutions to capture spatial correlations, as opposed to the FC layer, which is a simple linear transformation followed by an activation function. As a means of spreading spatial data, a graph convolution layer is used. Spatial Convolutional Layer can be described as follows :

$$h_{it}^{(l+1)} = \sigma\left(b^{l} + \sum_{j\epsilon N(i)} \frac{1}{Cij} h_{j}^{(l)} W^{l}\right)$$

where, $h_i^{(l+1)}$ is graph signal equivalent to $\mathbf{R}^F$, **N(i)** is neighbor set of node i, Cij is the product of square root of node edges which is $\sqrt{|\mathbf{N(i)}|}$.

This layer combines spatial information from road segments and their surroundings. As part of our model's initialization and training, we employ a batch normalization to enhance the model's resilience, as well as a Multi - layer perceptron to enhance its training speed.

While our model is initially set up using batch normalization to enhance robustness and speed up training, we also utilize the ReLU activation function to capture non-linearity correlation. To update the signal at each node, a conventional convolution layer in time is used to merge the nearby data in successive time slots, while the graph convolution operations collect neighboring data in spatial dimension. Temporal Convolutional Layer can be described as follows :

$$H_{ik}^{(l+1)} = \sigma\left(b_f^{(l)} + \sum_{k=0} \frac{1}{Cik} H_{ik}^{(l)} * W^{l}\right)$$

the cross-correlation operator * is valid in this case, k, which is the k^{th} channel of the input signal $H_{ik}^{(l+1)}$ at the layer level l. With a stride of l and zero padding of l, the convolution kernel size is 3x1. The ReLU activation function to capture non-linearity correlation can be denoted by :

$$H^{external} = ReLU(BN(H_{ik}^{(l)} * W^{\alpha}))$$

We fuse the spatial, temporal and external features and fuse them with a multi-view perspective in mind, as well as to predict future mishaps. A spatial convolution block is composed of several spatial convolution layers. In order to cope with the problem of vanishing/exploding gradients, the residual learning framework is adopted.

$$H_{it}^{spatial} + H_{ik}^{temporal} + H^{external} = h_{it}^{(l+1)} = \sigma\left(b^{l} + \sum_{j\epsilon N(i)} \frac{1}{Cij} h_{j}^{(l)} W^{l}\right) + H_{ik}^{(l+1)} = \sigma\left(b_f^{(l)} + \sum_{k=0} \frac{1}{Cik} H_{ik}^{(l)} * W^{l}\right) + ReLU(BN(H_{ik}^{(l)} * W^{\alpha}))$$

Improving the mobility, safety and reliability of the transportation systems after implementation, we will get to know how properly we can manage the uncontrolled traffic flow, prevent accidents flow, abnormal activities on road and traffic.

4. RESULT AND DISCUSSION

As a first step, we offer a strategy for dealing with sparse data called under-sampling. Finally, the model configurations are tested. Last but not least, we describe the assessment measures and baselines that will be used to compare the proposed model. Only a tiny percentage of roads suffer traffic accidents at any one moment. As a result of a lack of positive samples, the model would likely provide all-zero outcomes, resulting in an unacceptable performance. An under-sampling approach is used to tackle the problem of sparse samples. Every accident report begins with a road location and is followed by a road network based on the location and the road's k-hop neighbors. Then, we extract spatial, temporal, and external characteristics of the route and its k-hop neighbors.

It is possible to generate a graph of the road's K-hop neighbors, including their characteristics, by following the procedures outlined above. In the end, we gather positive samples after considering all traffic accidents. We next randomly choose a route where no traffic accidents occurred during the specified time period and extract the information as described above to create a negative sample of the road in question. A last step in the under-sampling process would be to stop when the positive samples outnumber the negative samples by an equal amount. Our model predicts if there will be a traffic collision in the target road segment based on the extracted spatial, temporal, and external characteristics of the target road segment and its k-hop neighbors. If accidents have occurred there, we record the ground truth with 1, otherwise 0.

Table 1: Effects of different features on prediction performance

Feature	RMSE	PCC	Precision	Recall	F1-Score	AUC
w/o x^s	0.3673	0.7050	0.7996	0.8765	0.8362	0.8283
w/o x^t	0.3589	0.7162	0.7973	0.8829	0.8370	0.8283
w/o x^e	0.3621	0.7030	0.7942	0.8809	0.8352	0.8261
x^{s+t+e}	**0.3439**	**0.7445**	**0.8213**	**0.8968**	**0.8573**	**0.8508**

Table 2 : Effects of different features on prediction performance

Structure	RMSE	PCC	Precision	Recall	F1-Score	AUC
w/o S	0.3716	0.6948	0.7876	0.8825	0.8322	0.8221
w/o ST	0.3525	0.7280	0.8028	0.8884	0.8432	0.8349
w/o E	0.3550	0.7180	0.8019	0.8936	0.8452	0.8363
DSTGCN	**0.3439**	**0.7445**	**0.8213**	**0.8968**	**0.8573**	**0.8508**

In order to forecast the road's k-hop neighbor, a produced training sample comprising the road's spatial, temporal, and external characteristics must be used. Instead of feeding graph-structure data containing topological information into baselines, we process the graph topology structure as follows. As an example, for spatial and temporal aspects, we averaged the related information from both the projected route and its k-hop neighbor, allowing us to get two vectors of spatial and temporal data correspondingly. If you want your k-hop neighbor to be predicted, you'll need a training sample that includes the road's spatial and temporal features, as well as its exterior attributes. This is an alternative of feeding graph-structure data including topological information into baselines. Our geographical and temporal dimensions, for example, were averaged using information from both the predicted path and its K-hop neighbor.

Nodes participating in testing data have been counted at 1234251, 178414 and 350851, respectively. As one longitude or latitude degree equates to 111 km, thus 222 meters is roughly equivalent to 0.002 longitude or latitude degree, d is set to 222 meters in order to determine traffic flow speed. The model works best when 10-hop neighbour are taken into account. To test this hypothesis in the trials, we set k equal to 10, i.e. we evaluate the impact of 10-hop neighbour of each route. To train our model, 70% of the data is utilized as a training set, and 10% as a validation set. As a result, 20 percent of the remaining 20 percent will be used as a test group. Cross-validation was ruled out due to the huge dataset, therefore we opted for the hold-out technique. There are numerous train-test splits required for cross-validation which would require more time and processing resources to perform than the hold-out approach. Using the same approach for all the models, we divided the training data into training, validation, and testing sets to ensure a fair comparison. Z-score is also used to standardize the input data before it is analyzed.

Table 3 : Feature Analysis and statistics for heterogeneous model

R^2	Adj R^2	C_p	BIC	Pop	w/o x^s	w/o x^s	w/o x^s
0.60	0.59	6.00	-1809.31	0.67	-190.57	19.37[a]	0.22
0.60	0.59	6.00	-1812.34	0.52	-136.56	25.23	0.14
0.59	0.59	6.00	-1796.86	0.41	-100.30	24.64	0.10
0.61	0.61	6.00	-1900.70	0.30	-68.96	18.14	0.06
0.59	0.59	6.00	-1782.06	0.18	-40.04	10.99	0.04
0.45	0.45	6.00	-1169.35	0.06	-22.93	-7.29	0.04
0.43	0.43	4.02	-1120.11	0.59	-49.12	-54.92	0.14
0.47	0.47	4.16	-1262.46	0.61	-95.27	-109.00	0.27

Then, we compute the evaluation metrics based on the remaining characteristics in order to examine the influence of different features on model performance. A model's performance would suffer if certain aspects were removed, as we could observe. External qualities like weather and calendars are provided by external features. Spatial attributes include building distributions and road structures, while temporal characteristics include dynamic changes in traffic flow. Assuming that all of the characteristics are inputs, the suggested model would be able to uncover hidden influencing variables. Model performance is studied by manually removing the external characteristics spatial, spatiotemporal, and embedding layers. When using DDSTGCN, spatial layers are used to express the effect of geographic information, spatiotemporal layers are used for dynamic changes in temporal information, and auxiliary information is embedded in an embedded layer to provide a seamless interface. They all work together to provide the greatest results. An explanation of the above experimental results.

We run each model ten times in a row to eliminate the possibility of unexpected outcomes. After 150 epochs of training, the models with the greatest performance on validation sets are selected for testing and further refinement. Our measurements are summarized using the mean and standard deviation. There is a very tiny variation in the standard deviation of LR, LASSO or SVM, which is why we indicate them as 0. Summary of the results may be made. Primarily because it uses a kernel technique to identify the optimum line separator gap, SVM outperforms LR and LASSO in terms of learning complicated nonlinear functions. DT outperforms other conventional machine learning models in the majority of measures because it is better at identifying more essential characteristics relevant to traffic accidents and less susceptible to noise in the inputs than other models. The deep learning models outperform the traditional machine learning models, demonstrating the capacity of deep architectures to represent complicated connections. And the standard deviations of deep learning models are within a narrow range, demonstrating their stability.

5. CONCLUSION AND FUTURE WORK

Here, we looked at the topic of traffic accidents and developed a unique spatiotemporal graph-based model for predicting the probability of future traffic accidents. As a result of this aim, a large amount of data was collected and important characteristics were retrieved. It has three main parts: the Spatial-temporal layer was used to capture both spatiotemporal connections and temporal dependencies in temporal characteristics. To learn meaningful and dense representations of external characteristics, the embedding layer was used. A comparison of the proposed model to current techniques was carried out using real-world datasets. The suggested approach may be used to alert individuals of possible risks in advance and help them pick safer travel routes.

We are improving the results of this research by analyzing latest models, increasing model accuracy and performing a comparative analysis of algorithms for boosting performance. We implement this research on dataset based on foreign dataset. After implementation, we will get to know uncontrolled traffic flow, prevent accidents, predict traffic jams, proper and correct navigation factors, abnormal activities on road and traffic. We use the new methodology based on a hybrid approach to improve the reliability and sustainability of large-scale networks through improving both recurrent and non-recurrent traffic conditions. We detect abnormal events on road traffic to prevent accidental cases, road traffic management, structural management, prediction of traffic flow.

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