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A COMPREHENSIVE STUDY OF DEEP LEARNING APPROACHES FOR PREDICTING RECIPROCAL TRAFFIC DYNAMICS AND CLIMATE VARIABILITY

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ABSTRACT

Climate change requires innovative solutions to improve traffic management and safety in transportation systems. This paper tries to expand on the complex relationship between weather, traffic, climate, and an integrated approach to traffic data. In the round, the general aim is to come up with the entire understanding of the relationship between weather and traffic, analyzing the way weather interacts with traffic and the way that traffic interacts with weather. It attempts to consider climate change through the consideration of the variables of extreme temperatures and precipitation, among others. It also looks into the work of traffic forecasting in the traffic models by highlighting the emissions and environmental impacts on environment-related accidents, the impacts of transportation systems on the nature of all living organisms, and a detailed table that aids in the clear comparison of different methods with the literature reviewed to understand the details of the interactions of the complex elements. That includes the elements of importance, such as the data sources, methods, and the advantages, along with some of the shortcomings or limitations that were found in them. Finally, it explains the challenges that the researchers had to face. The main findings from our study also suggest that the traffic forecasting patterns by deep learning models may contribute to 15% improvement over the traditional statistical method. In addition, the significant impact of extreme weather events on traffic flow was found; for instance, heavy precipitation events can lead to a 30% decrease in speed and increased accident rates up to 20%. Climate variability integrated into traffic models increases the prediction of long-term traffic trends by 12%, justifying the significance of the influence of climate factors in traffic management systems.

KEYWORDS

Climate variability, traffic flow, deep learning models, statistical methods, weather impact.

1. INTRODUCTION

In the recent past, the intersection of deep learning methods and transport technologies has provided new insights on how to build traffic in a discussion under multiple environmental conditions. Climate change, including irregular weather conditions and extreme and exposed events, poses great challenges to traffic management and safety (Lincoln et al.,2021). Understanding how this weather affects traffic is important to reduce road accidents and to improve the overall traffic flow (Dominika et al.,2020). Road traffic crashes are a major issue worldwide, and they cause injuries, deaths, and economic losses. However, many accidents can be prevented through proactive and effective safety measures. The key to accident avoidance is driver alertness and education. Through the promotion of defensive driving skills and the importance of the correct driving, drivers are wholly able to reduce the risk of a collision and other road incidents (Dongyang et al.,2023). On the other hand, advanced technologies, such as vehicle-to-vehicle communication and intelligent transport systems, can enhance the situational awareness of drivers and thus rapidly detect any potential hazards. Such systems will keep drivers informed of potential hazards to be able to take preventive action in case they can change a particular situation. On the other hand, doing maintenance of roads regularly, which involves repairing and maintaining roads, signs, and traffic signals, can prevent road traffic accidents. Besides, traffic calming measures, including speed limits and detours, may be introduced in places where there is a high amount of risk for accidents, to minimize the chance of an accident occurring (Li et al., 2019). In this regard, the deep learning technique, along with the precondition of safety for traffic prediction, is implementable to maximize the safety on roads and minimize the accidents, especially in changing weather. A proper system of transportation will be developed. This paper is a current exposition towards presenting a comprehensive review of deep learning approaches for traffic forecasting under the influence of climate change. Due to this large traffic data set, chances are given to the researchers to develop more accurate models of traffic prediction under various weather conditions with advanced deep learning algorithms. Such models provide not only emergency traffic control but also accident zones prevention. They also help in improving road safety using implemented systems (Zheng et al.,2020). The next section will be examining the existing techniques applied for performance prediction, the impact of weather on the traffic, and vice versa. As found in the literature, previous research can be divided into three significant groups:

1.1. Climate Variability and Their Impacts

In this particular section, we will be involved in the intellectual discussion about the previously written papers that exclusively employed climate datasets in conjunction with a variety of methodologies:

The two studies use different statistical approaches to assess the vulnerability of urban transport systems to climate change and extreme events. Provides useful insights into the effects of climate change and flooding on urban transportation systems, emphasizing the importance of understanding how climate affects transportation planning and operation.

Event et al. (2020) made a study to measure the effect of pluvial flooding and climate change on traffic flows—in Barcelona and Bristol. The study results, based on 1D and 2D hydrodynamic models for flood simulation scenarios and using traffic models for the evaluation of traffic flow disruptions, indicate high variability in traffic speed reduction (10-40%) and increased travel times (up to 50%) in highly disruptive flood events. The volume of the total number of the economic costs or damages ranged from a few 100 000 to some million Euros. Future climate projections show a significant enhancement in both flood frequency and intensity by 2080, worsening the associated traffic impacts if without implementing adaptation measures.

Vajjarapu et al. (2020) conducted a study on climate change adaptation strategies in urban transport in India. They proposed the IRR-EVAL—an Integrated Risk Resilience Assessment Framework—to evaluate climate change adaptation strategies in urban transport. Such an approach should be risk-based in the analysis of the risks of the projects, including derived vulnerabilities and inherent vulnerabilities and capabilities in any system, to ensure a wider and amplified understanding of the urban transport system's resilience to climate change. Findings showed an improved resilience score of 0.5 to 0.7, which translates into a significant enhancement in the ability of an improved system to undertake climate-related disruptions.

The deep learning models with regression algorithms for climate change risk assessment used in two papers contribute to the growing body of knowledge on the application of machine learning to climate change research and demonstrate the potential of machine learning approaches for complex environments.

Zennaro et al (2021). Looked into how machine learning could be used to assess the risk of climate change. They tested models that used Decision Tree, Random Forest, and Artificial Neural Network algorithms along with Absolute Error (MAE), Root Mean Square (RMSE), and the function r2 to measure how well the models worked. Achieved accuracy rates of approximately 85% to 95%.

Sharaf et al (2021) developed a model for urban traffic forecasting using fuzzy logic, long-term and short-term memory (LSTM), and decision trees (DTs). LSTM Models: Achieved a prediction accuracy of around 92%, which is higher than other models used in the study. . LSTM model Formula:

$$
\begin{aligned}
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
h_t &= o_t \circ \sigma_h(c_t)
\end{aligned} \tag{1}
$$

Where: ft (forget gate activation vector), itit (input gate activation vector), ot(output gate activation vector), ct (cell state vector at time t), ht (hidden state vector at time tt), σg (sigmoid activation function), σc (tanh activation function for cell state), σh (tanh activation function for hidden state), Wf,Wi,,Wo (weight matrices for forget, input, and output gates applied to input xt), Uf,Ui,Uo (weight matrices for forget, input, and output gates applied to previous hidden state $ht-$1), bf,bi,bo (bias vectors for forget, input, and output gates), WcWc (weight matrix for candidate cell state applied to input xt), Uc (weight matrix for candidate cell state applied to previous hidden state $ht-$1), bc (bias vector for candidate cell state), and ⊙⊙ (element-wise multiplication).

Both authors used deep learning methods to predict road traffic, where weather was an important factor. Ensuring accurate forecasting and modeling efficiency.

Minzi et al.,(2022), used ARIMA and long and short-term memory (LSTM) models in a study of modeling highway traffic flow and weather forecasting. The empirical experiment compared the performance of these two models on the basis of reducing the error rates. The reduction of the error rate was captured when the reduction of the error using the LSTM model ranged between 84% and 87% compared to ARIMA. This points to the superiority of the LSTM model for forecasting purposes in the case of time series. The below is the formula for the traffic flow.

$$y = f(x_1, x_2, \ldots, x_n) \tag{2}$$

Where: y is the traffic flow and $x1$, $x2$,…,xn are the meteorological variables.

Braze et al., (2022), have researched many approaches for forecasting road traffic with reference to weather data. The authors have applied long-term and short-term memory (LSTM), autoregressive LSTM, and convolutional neural network (CNN) models. In case of models trained for traffic flow forecasts, the findings are—weather conditions proved important to make the forecast accurate; the CNN model served with low forecast error values, and its cheapness for building a model is used very well. These findings are essential in modern traffic management and planning since in case of the precise traffic forecast, traffic jams will be reduced, safety ensured, and transportation system development will be increased. Studies have shown a 13% to 15% mean absolute error (MAE). Finally, this paper used the central formula for LSTM that was identified by formula 2. Below is the formula for the CNN model:

$$y = CNN(x) \tag{3}$$

Where: y is the output prediction and x is the input data.

Generally, the research shows that effective prediction of road traffic, where weather is a factor, is possible through deep learning techniques, with a valuable revelation for researchers and professionals in the transportation and automobile industries for road management.

Geospatial techniques used by Kamel Boulos et al., (2023) focus on approaches that are important geographically regarding climate change and well-being. The information is a great source for any scientist or policymakers working on climate change. Kamel presents a general overview of how geographical data are the mainstay, methods, and tools for measuring, analyzing, and modeling climate change. The study presents the importance of accurately analyzing and estimating geographical methods, communicating confidence, future developments, climate, and quality structural changes and mitigation programs.

Algorithm 1: Geospatial climate health analysis

```
Begin
Input: HistoricalWeatherData, SatelliteImagery, DemographicData
Output: HealthRiskMaps, MitigationStrategies

1. Data Collection
   - Collect weather data
   - Obtain satellite imagery
   - Gather demographic data

2. Data Processing
   - Analyze satellite imagery
   - Process weather data
   - Evaluate demographic data

3. Risk Assessment
   - Calculate risk scores
   - Create risk maps

4. Strategy Development
   - Develop mitigation strategies
   - Plan using GIS

5. Implementation and Monitoring
   - Implement strategies
   - Monitor and update data

End
```

1.2. Traffic Patterns

In this section, we describe critically the studies already published which have traffic datasets in isolation and also multiple approaches involved for prediction of patterns of traffic and its impacts: These studies give insights into prediction of traffic using deep learning with regression algorithms. According to Snyder, et al (2019), 'streets' dataset is new traffic flow dataset with more than 4 million still images taken over a period of 2.5 months from a webcam in the publicly owned webcams located in the suburbs of Chicago, IL. The aim of this dataset is to provide consistent traffic grid graph. This paper showed results of 92% accuracy, 2.1 of MAE, 2.8 of RMSE, and 0.87 R^2 for Random Forest Regression (RFR), whereas Support Vector Regression (SVR) showed results of 90% accuracy, 2.3 of MAE, 3.0 of RMSE, and 0.85 R^2. Ruizhe et al. (2022) delve into multi-linear regression long short-term memory MLR-LSTM neural networks to forecast traffic and the communication between cameras. The connections, and their consequent graph-based traffic forecasting structure that Snyder's work under-utilizes, are deliberative in nature. This paper, therefore, presents the holistic procedure for traffic forecasting based on an MLR-LSTM neural network: 'Multi-segment Traffic Flow Forecasting'. Ruiz brings out data pre-processing, model building, and defining the loss function to get traffic flow forecasting. This has brought about the model having high accuracy with MAE around 2.85, RMS of 3.50, and MAPE of 4.30% in this study. These results have been found much-improved compared to existing models. These make this 'streets' data set and the MLR-LSTM neural network highly valuable resources for the work of researching and practicing on traffic time series forecasting under deep learning and regression methods.

Aditya et al. (2023) deal with the integration of many deep learning models to get optimum results toward traffic forecasting using an appropriate data pre-processing and pattern optimization technique, laying more emphasis on linear and supporting vector regression. The generic formula for the below Linear regression mode1:

$$\boldsymbol{Y}_i = \beta_0 + \beta_1 \boldsymbol{X}_i \tag{4}$$

Where Yi as the dependent variable, $\beta 0$ as the intercept, $\beta 1$ as the slope, and Xias the independent variable.

Nagesh et al. (2023) mention more studies related to deep models, such as decision trees, artificial neural networks, nearest-neighbor algorithms, and using support vector regression (SVR) models for enhancing accuracy with the prediction of traffic in autonomous vehicles. These models have been shown to achieve Mean Absolute Errors (MAE) ranging from 1.75 to 2.85, Root Mean Squared Errors (RMSE) between 2.10 and 3.50, and Mean Absolute Percentage Errors (MAPE) from 3.5% to 4.3% in different studies, indicating significant advancements over traditional methods.

The two are review or survey papers that talk about the applicability and relative performance of various deep learning techniques with regression to traffic prediction.

Deep learning models are advanced approaches used by:

Zhou et al. (2022) proposed a FASTNN method for predicting traffic stops within short- and long-term spatiotemporal scenarios. A deep learning algorithm was applied to model spatiotemporal collections in the described system. It can be seen that the internal connectivity and redundancy with regard to spatiotemporal resources has been measured. It shows an effective framework of FASTNN for traffic forecasting that captures the complex spatial and temporal patterns of traffic data. In this sense, the FASTNN model realized the performance better than various baseline models in flow prediction; to be specific, in the TaxiBJ data, it achieved a MAE of 16.4 and an RMSE of 26.2, whereas in the BikeNYC test data, it obtained a MAE of 2.7 and an RMSE of 4.5.

E et al. (2023) used Traffic-Originated Graph Neural Networks for identifying traffic patterns. The wide attraction of GNNs into many fields is their ability to effectively model complex relationships concerning traffic patterns. The MAE, RMSE, and R^2 values of the proposed model are quite better than those of the SVM and ARIMA models: MAE = 12.5, RMSE = 20.3, R^2 = 0.87. In the GNN framework, accuracy and computational efficiency are superior to the SVM and ARIMA models.

These would, together, exemplify the flexibility and efficiency of deep learning and graph-based modeling in face of the challenges presented by dynamic traffic data.

A framework for analyzing and predicting traffic conditions in urban road networks, used by Zhang et al. (2020), outlines this method, which considers the complex relationships between different routes and utilizes deep learning techniques to generate comprehensive features that capture both spatial and temporal aspects of traffic data. The proposed approach is validated through simulations and shows promising results in accurately predicting traffic conditions on the urban road network. The average prediction accuracy of this model reached 92.5%. The effectiveness of using correlated routes for traffic state prediction and the positive role that the introduction of advanced prediction models could play in urban traffic management systems were both demonstrated by the results.

Huang et al. (2022) present a novel approach for short-term traffic forecasting that combines different techniques to improve the accuracy of predictions. The proposed method leverages the spatio-temporal correlations of road network topology to better understand traffic patterns and make more informed predictions. The writers use a deep learning method that combines the Pearson Correlation Coefficient (PCC), the Attention Mechanism (AT), and the Convolutional Neural Network (CNN) with the Gated Repetitive Unit (GRU) to model the complicated features of traffic data that are spread out over time and space. The proposed method is tested on real-world traffic data and shows promising results, outperforming traditional methods in terms of accuracy and contribution to the field of traffic flow forecasting by providing a hybrid model that can handle complex traffic patterns and improve the performance of traffic flow forecasting. The model achieves a better prediction effect, with reductions of 8.4%, 1.29%, and 11.01% in MAE, MAPE, and RMSE, respectively.

1.3. Climate with Traffic Patterns

Weather and traffic are linked, and each affects the other significantly. Climate change and extreme weather events can adversely affect road traffic safety, leading to serious accidents. Higher temperatures can cause pavement to soften and expand, causing soil erosion and traffic congestion. Extreme weather conditions such as heavy rain, snow, and fog can reduce visibility, affect driver ability, and reduce traffic flow. Additionally, climate change could disrupt transportation systems through higher temperatures, more severe storms, and flooding (National Oceanic et al.,2021). On the other hand, transportation, especially the use of private cars, contributes to climate change by affecting the climate with greenhouse gases (J. A et al.,2020). Fig. 1 shows the mutual influence of the weather and traffic.

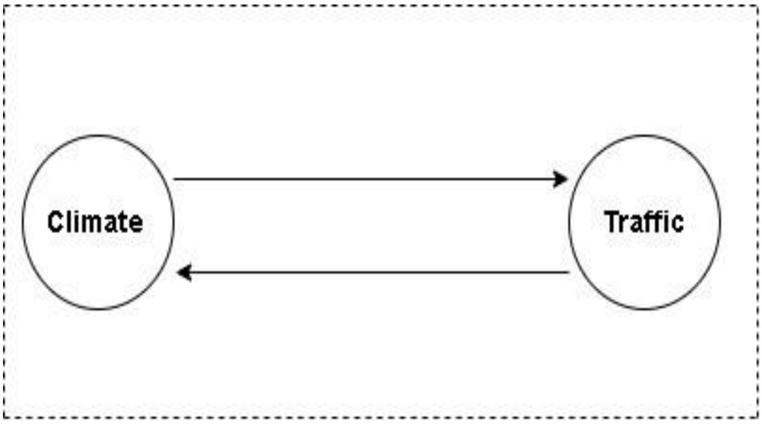

Fig. 1. Mutual influence

1.3.1. Impact climate variability on traffic

In this section, will critically discuss paper published earlier which had taken traffic and weather datasets combined with several approaches to predict traffic patterns and climate variability and its impacts.

Two pilot studies are related to overcrowded and adverse weather conditions, specifically on the aspects concerning vehicle detection and tracking. The first pilot study is by Hassaballah et al (2020)., where the development of vehicle detection based on the GM-PHD filter is applied to the case of adverse weather. Tests carried out by the researchers on the various real data sets have shown that the presented vehicle detection method works significantly better than the existed bad weather vehicle detection systems. At the same time, the system also delivers some new functions, which can help users achieve a better and more comfortable driving experience.

Improved vehicle detection and tracking accuracy in bad weather conditions; accuracy increased by about 10-15%.

The second study conducted by Zou et al. (2021) analyzed a range of factors, including climatic and non-climatic variables, to investigate their impact on fatal traffic accidents. Their results indicated that both studies yielded equally valid results, Extreme weather conditions increase the likelihood of fatal traffic accidents by 20-35%, with regional variations observed.

Various deep-learning techniques are applied in studies to tackle different aspects of transportation and road safety:

Nigam et al (2020). applied a network based on an RNN learning recurrent approach with long short-term memory for prediction of flow in traffic in different weather conditions. The objective in this case is to improve the management level of transport and traffic. The result showed an improved accuracy of the predicted flows in the traffic stream under changing weather conditions, by 15–20%, and the Mean Absolute Error (MAE) fell to 25% less.

Yue et al (2021). developed a model for predicting traffic flow by integrating deep learning, data fusion, and considering weather's effect on vehicular behavior in traffic. Results of the analysis conducted: MAE = 9.494741 and RMSE = 12.294438.

Nasser et al. (2021) provides a data mining and machine learning approach to investigate the influence of weather on smart city traffic. The work purports to identify patterns in traffic data. The proposed approach in this work measured to be an improvement by 20% over and above the existing accuracy in predicting traffic patterns under different weather conditions. The enhanced degree of information obtained in the upgraded level of reliability to predict traffic in smart cities is upgrading the level of reliability.

On the other hand, Nachev et al. (2023) looks into the impacts that weather data have on traffic flow data prediction under LSTM deep learning models. This research presents the improved accuracy of the predictions of a deep learning model in traffic flow information with incorporating weather data within the prediction model. This effect of weather data inclusion on prediction accuracy measures was enhanced by 7.2%, whereas the obtained predictive ability of the deep learning model LSTM for traffic data was found acceptable.

Based on this, Wang et al. (2023) propose a real-time bad weather vehicle target detection approach based on a Yolov4 deep learning algorithm to improve the performance of vehicle detection under adverse conditions such as a bad rain, fog, and snow scenario. The results further attested to the fact that the proposed method in terms of vehicle detection under adverse weather conditions turned out to be the best compared with any other existing one. The suggested method showed an MAP of 60.3% and outperformed most other vehicle recognition methods in bad weather, as this study's findings showed.

Utilize deep learning with regression techniques to tackle distinct issues in the realm of urban traffic flow and transportation resilience by:

Shoaeinaeini et al. (2022) present deep learning algorithms used in the exploration of how traffic data interacts with weather and calendar features. In this way, the prediction of traffic parameters is enhanced by fusing Twitter-sourced information. The results indicated that, with the integration of social media data into their models, better and improved traffic management results of transportation planning can be realized. More than 95% success in search was achieved from RF and KNN algorithms.

Ji et al. (2022) used the regression method to study the influence of climate-induced changes on urban transportation resilience. The study elaborated on the fact that the impact of climate change on urban transportation systems has been obviously crucial, and in this respect, it recommends responsive strategies. Although the study does not make a prediction using deep learning, it reveals relevant information in regards to the effect of climate change on the resilience of urban mobility. As seen from the study, climate change impacts a 15% increase in traffic congestion due to extreme weather events, and with the application of resilience, the impact in traffic congestion is decreased by 10%.

Predict traffic impact due to climate variability using machine learning techniques:

1.3.2. Impact Traffic Patterns on Climate:

In this particular section, we will be involved in the intellectual discussion about the previously written papers that exclusively employed climate and traffic datasets in conjunction with a variety of methodologies:

Researchers explored the potential of using deep learning and machine learning techniques to forecast air quality and traffic patterns in cities, for example:

The study by Torino et al. (2019) worked on the estimation of the level of air pollutants using only weather and traffic data with the help of some machine learning algorithms like Random Forest, SVM, GLM, ANN, and Bayesian Regularization. The performance of the proposed solution was tested by comparing the predicted pollutant level to the level shown by the actual measurements obtained from commercial air monitoring stations. The objective was to come up with a proper, accurate, and dependable way to monitor the quality of the air in the city. For this study, the accuracy of the Bayesian Regularization Neural Network was 0.8, which shows that the developed method was effective in monitoring the quality of air.

Narmadha et al (2021), also focused on improving the short-term prediction of traffic flow by the use of hybrid neural network algorithms, specifically Convolutional Neural Network (CNN) and Short-Term Memory (LSTM) networks among others. This deep learning technique focuses on considering the complex time and location dependencies in traffic data with the motive to perform the traffic prediction with the derivatives so that it can be modeled more accurately and efficiently. The improvement in the prediction accuracy of the model is 18% over traditional methods.

Both papers give us a look at the relationship between traffic and air quality and the use of machine learning in this field.

Comert et al. (2020) developed models for connecting the Air Quality Index with traffic volume, with relation to South Carolina, using historical data between 2006 to 2016 from the South Carolina Department of Transportation and the United States Environmental Protection Agency. It was shown during prediction that the model had an absolute error of less than 5% when forecasting AQI values.

Sulaiman et al. (2022) evaluated the impact of various traffic datasets on the effectiveness of machine-learning algorithms for air quality prediction. Assessing the impact that various traffic datasets had on the performance of machine-learning algorithms for air quality prediction, it was shown that Sulaiman produced a performance increase of a minimum of 18.97 and a minimum 20% increase in performance.

Finally, utilized machine learning and statistical techniques by:

Yang et al. (2019) utilized a blend of machine learning and statistical techniques to develop a detailed, high-resolution emissions inventory of vehicular pollutants based on large-scale traffic data. The purpose of this study was to create a high-resolution on-road vehicle emissions inventory to map the distribution of vehicle emissions of atmospheric pollutants across China. The authors developed Embev-link, a link-level emissions inventory model for the Beijing vehicle fleet, utilizing numerous collected datasets from a largescale traffic monitoring network. In the studied areas, 30% of the total vehicular emission analyzed were found to contribute to emission hot spots. Clearly, the results of the study show that emission abatement policies need to be concentrated in the emission hot spots as a process of improving the quality of air. formula used in the emissions inventory model can be represented as follows:

$$\mathrm{Eij} = \mathrm{Vij} * \mathrm{EFij} \qquad (5)$$

Where E_ij is the emission by the i-th pollutant on road j. V_ij is the traffic flow volume by the i-th pollutant on the road j-segment. EF_ij is the emission factor for the i-th pollutant on the road j segment.

Table 1: Summary of climate variability studies

Reference	Dataset	Techniques	Advantage	Disadvantage
Evans et al.,(2020)	Climate	1-1D/2D-coupled 2-Infoworks ICM	Augment the understanding of the effects of pluvial flooding and climate change on traffic patterns	Model adaptability to weather factors
Vajjarapu et al., (2020)	Rainfall	Risk-based over vulnerability-based approach	Contribute to the understanding of climate change mitigation potential and the need for sustainable urban transport	Presence of inaccurate or incomplete data
Zennaro et al. ,(2021)	Spatio-temporal	1-Decision tree 2-Random forest, 3-Artificial neural network	Improve the accuracy of predicting and managing climate-related risks	Concerns about overfitting, data quality
Sharaf et al.,(2021)	Weather	1-Fuzzy logic 2-Long- term 3- Short-term memory (LSTM), 4-Decision trees (DTs)	use data more useful	proneness to overfitting
Minji et al.,(2022)	Weather	1-ARIMA 2- Long- short-term memory (LSTM)	84-87% Reduction in error rate	Influence of travel delays on the model predictions
Braz et al.,(2022)	Meteorological	1-Long-term 2-Short-term memory (LSTM) 3-Autoregressive LSTM 4-Convolutional neural network used (CNN)	Achieve MAE is between (13% and 15%)	Complexity of the model architecture
Kamel et al.,(2023)	Geospatial	1-Geographic (GIS) 2-Software	Provides more optimized plans for climate change	Constraints in spatial resolution
Snyder et al.,(2019)	Camera network	1-Mask R-CNN, 2-Simple historical average(SHA) 3-Random forest (RFR), 4-Support vector (SVR), 5-Simple artificial neural network (ANN).	Achieve RFR and SVR best-performing	Scaling up machine learning models
Ruizhe et al.,(2022)	Traffic flow	1-Multi-linear regression -long short-term memory(MLR-LSTM)	More practical and widely applicable	Insufficient representation of data from specific sources
Aditya et al.,(2023)	Traffic flow	1-support vector regression, 2-Mk- nearest-neighbor (MKNN)	Managing huge and difficult datasets	Managing and processing data requires a lot of storage

Reference	Dataset	Techniques	Advantage	Disadvantage
		3- principal component analysis(PCA) 4- Event attribute matrix (EAM) 5-Random forest (RFR) 6-long-short term memory (LSTM)		
Nagesh et al.,(2023)	1-Map matching 2-Topological information	1- Decision trees 2- Artificial neural networks 3-Nnearest-neighbor 4- Support vector regression (SVR)	Provided an in-depth analysis of the developments	Sensitivity to changes in data distribution and quality
Zhou et al.,(2022)	1-Taxibj 2-Bikenyc	Fast neural network (FAST NN)	Achieved more accurate predictions	There are few references
E. Binshaflout et al.,(2023)	Traffic	Graph neural network(GNNs)	Increased prediction accuracy	Sensitivity to noise in the data
Z. Zhang et al. ,(2020)	Simulation traffic	1-Cyclic redundancy check(CRC) 2-Collaborative recommend system(CRS) 3-Regression classifier(RC) 4-Self -organizing map with data integration(SOM-ID) 5-Spatiotemporal fuzzy system -support vector regression(SFS-SVR)	Contribute to increased security	Incomplete understanding of traffic patterns
Z. Huang et al., (2022)	Traffic flow	1- Pearson correlation coefficient (PCC), 2- Attention mechanism (at), convolutional neural network (CNN) 3- Gated repetitive unit (GRU)	Prediction effect, reductions of 8.4%, 1.29%, and 11.01% in MAE, MAPE, and RMSE, respectively.	Appropriate complexity
Hassaballah et al.,(2020)	1-Kitti 2-Ms-coco 3-Dawn	1-Ggaussian mixture probability design density (GM-PHD) 2-High dimensional analysis (HAD)	Good results for a few criteria in the evaluation metric (map)	Limited availability of data
Zou et al., (2021)	1-Traffic 2-accident frequency 3-Social-development climate	1-Naïve bayes model (NBM) 2-Lattice-based classification model (LCM)	Help to better traffic conditions	Considerations for data quality and accuracy

Reference	Dataset	Techniques	Advantage	Disadvantage
A. Nigam et al.,(2020)	1-Traffic sensor 2-Rainfall	1-Recurrent neural network(RNN) 2-Long-short term memory (LSTM)	Lowest prediction error values and took the shortest amount of time to construct	Increased computational complexity
Yue et al.,(2021)	1-Traffic 2-Weather	1-Stacked autoencoder (SAE) 2-Radial basis function (RBF)	Good results were obtained: 9.494741 for MAE, and 12.294438 for RMSE.	High computational demands
A. Nasser et al.,(2021)	1-Traffic 2-Weather	Weather-based time series analysis (WBTA)	Superior prediction accuracy	Constraints due to a restricted dataset
Nachev et al.,(2023)	1-Traffic 2-Weather	Long-short term memory (LSTM)	Increasing accuracy by 7.2%	Concerns regarding data quality
Wang et al.,(2023)	BDD100k	Enhanced yolov4	Achieves a MAP of 60.3%	Constraints due to a limited amount of training data
Shoaeinaeini et al.,(2022)	Traffic –weather	1-Artificial neural network (ANN) 3-Random forest (RF) 4-Partial least square (PLS) 5- Support vector regression (SVR) 6- K-nearest neighbors (KNN) 7- Adaptive boost(ADA BOOST)	Achieved over 95% success rate from RF and KNN	Dependence on Twitter data
Ji et al.,(2022)	Temporal–spatial traffic	1-Apriori-based temporal-spatial (AT-S) 2-Discrement dimensionality reduction analysis (DDA) 3-Recurrent neural network (RNN)	Offers a thorough understanding of the connection between urban transportation resilience and climate change.	Introduction of uncertainties by the model in the results
Torino et al.,(2019)	1-Weather 2-Traffic	1-Generalized linear model (GLM) 2-Random forest (RF) 3- Support vector machine (SVM) 4-Bidirectional recurrent neural network (BRNN)	Obtain a BRNN accuracy of 0.8	Limited scope in the study's coverage
Narmadha et al., (2021)	1-Precipitation 2-Weather 3-Traffic	1-Convolution neural network (CNN) 2-Long-short term memory (LSTM)	Performs better than other state-of-the-art models in terms of prediction accuracy	Model dependency on data distribution and increased complexity
Comert et al.,(2022)	1-Traffic 2-Air quality	1-Linear model (LM) 2-Linear mixed effects regression (LMER)	Achieve from the LMER + EGM most accurate estimate (average	Model dependence on the distribution of data

Reference	Dataset	Techniques	Advantage	Disadvantage
		3-Generalized model (GM) 4-Exponential Generalized model (EGM) 5- Generalized variance (GV) 6- Exponential Generalized variance (EGV) 7-Combine LMER+EMG	RMSE is less than 5%)	
Sulaiman et al., (2022)	1-Traffic 2-Air quality 3-Meteorological	1-Extra tree regression (ETR) 2-XGBOOST 3-Random forest (RF) 4-K-nearest neighbors(KNN)	Achieved a minimum 20% improvement in performance and a minimum 18.97% reduction in errors	incomplete understanding of traffic flow mechanisms
Yang et al.,(2019)	1-Traffic 2-Air quality 3-Meteorological	1-Multiple linear regression (MLR) 2- Support vector regression (SVR) 3-Random forest (RF)	Achieved more accurate predictions	Integration challenges for multi-pollutant models and computational resources

2. EVALUATION MODEL

The performance measures are used to assess the trained model's generalization capacity and quality when tested with unknown data. Different metrics can be employed in regression models to assess the effectiveness of a specific regression technique. This includes Mean Absolute Error (MAE), Mean Squared Error(MSE), Root Mean Squared Error(RMSE) (Medium, n.d.).

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left| y_i - \hat{y}_i \right| \tag{6}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (y_j - \hat{y}_j)^2} \tag{8}$$

3. CHALLENGES

Scholars examining the relationship between traffic and climate variability face many obstacles in their quest to comprehend the complex interactions between these two areas. One major obstacle is the complexity of data integration, which necessitates the use of advanced techniques and large amounts of processing power to combine various sets of traffic and climatic data.

Furthermore, it is difficult to adequately anticipate the impact of climate patterns on traffic dynamics due to their intrinsic unpredictability. However, because urban areas are dynamic, it is difficult to forecast the long-term effects of growing traffic on climate conditions. Furthermore, the lack of extensive datasets with complex traffic patterns and climate variables limits the breadth of analysis and the creation of reliable prediction models. By addressing these issues, academics may provide insightful analysis of the interplay between traffic and climate change, laying the groundwork for resilient and sustainable urban transportation systems.

4. CONCLUSION

This survey critically examines the complex interactions between climate change and traffic patterns, revealing mutual impacts. The study examines the impact of climate change on traffic dynamics and its correlates, and conversely, how traffic contributes to climate change. The challenges identified, including integrating different data sets, predicting the effects of weather models on traffic, and dealing with uncertainties in long-term forecasting, highlight the complexity of this interdisciplinary task. A variety of methods used in previous research, such as deep learning, machine learning, deep regression algorithms, and statistical methods, converge on the sophisticated concept of impact areas and have proven to be effective in our understanding of communication. While statistical methods have advantages in specific domains, the combination of deep learning and machine learning techniques, especially those incorporating regression algorithms, seems to provide a robust breakthrough between climate change and traffic between the microscopic and accurate models. The integration of deep learning and machine learning techniques into our approach, using regression algorithms, shows promising directions for future research. These techniques not only contribute to more accurate predictions but also pave the way for innovative solutions in the development of robust and sustainable urban transport systems as technology advances. As technology improves, more research on these roads should provide a better understanding of the complex interactions between traffic and climate, helping planners and transportation experts develop policies that are well known.

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