Incorporating Traffic Assignment Model into A Machine Learning Method for Level of Service Prediction Under Rainy Weather Conditions

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***Abstract*—In this study, we investigate the impact of rainy weather on highway traffic flow, specifically focusing on the Level of Service (LOS). Recognizing the limitations of traditional traffic models under adverse weather conditions, we propose an innovative approach using machine learning. The research integrates real-time traffic and weather data, employing various machine learning architectures to enhance the accuracy of LOS predictions. Our methodology includes a comprehensive literature review, identifying gaps in existing models and emphasizing the potential of machine learning in traffic management. The paper aims to provide more reliable tools for traffic flow management during inclement weather, ultimately contributing to safer and more efficient transportation systems.**

INTRODUCTION

Modern civilizations would not be the same without their transportation networks, which not only make it easier for people and commodities to move around but also have a major impact on quality of life and economic growth. The Level of Service (LOS), an indicator that represents the operational conditions of traffic flow, is frequently used to assess the effectiveness of these systems. LOS evaluations have always been based on conventional traffic models, which work well in clear weather but find it difficult to adequately represent the complexity brought forth by bad weather, especially rain. Rainy weather has a complex effect on traffic flow, affecting road safety, vehicle performance, and driver behavior. Rainfall can cause several issues, including traffic speed, road capacity, maximum flow, and an increased chance of accidents [5]. A growing need to improve LOS evaluation techniques in consideration of these difficulties is to take into account the dynamic and unpredictable nature of rainy weather. Recent advancements in machine learning offer a new approach to understanding and predicting the impacts of rainy weather on transportation systems. Machine learning offers a novel approach to the problems associated with traditional LOS assessment because of its innate capacity to evaluate vast amounts of data and identify complex patterns. These techniques can effectively process and interpret diverse data sets, including historical weather patterns, traffic flow statistics, and roadway conditions. Transportation models can become more accurate and flexible by utilizing machine learning, especially in situations where unpredictable weather circumstances like rain complicate things. This method maintains safer and more efficient transportation networks by improving the accuracy of LOS evaluations and providing transportation planners with more advanced capabilities to forecast and lessen the negative effects of rain on traffic flow [9]. Several studies have highlighted the potential of machine learning in this field. For instance, the integration of traffic assignment models with machine learning has been proposed as a novel method for improving LOS predictions under rainy conditions. Furthermore, new avenues in traffic and weather prediction have been made possible by the use of geospatial big data and sophisticated algorithms like Deep Belief Networks (DBNs), providing more accurate and context-specific insights [6-7]. By investigating the use of machine learning approaches in forecasting the Level of Service for transportation systems during rainy conditions, we want to contribute to this emerging topic in this study. To find gaps and possibilities, we will evaluate the current literature. Then, we will suggest a novel approach that integrates the most recent developments in machine learning with actual traffic and weather data. By doing this, we hope to give policymakers and transportation planners more dependable instruments with which to control and enhance traffic flow during inclement weather, thus boosting the resilience and effectiveness of transportation networks [8].

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LITERATURE REVIEW

The prediction of traffic Level of Service (LOS) under adverse weather conditions, particularly rain, is a complex task that has been approached from various angles in transportation research. Traditional traffic assignment models, while robust in stable conditions, often falter when faced with the unpredictable nature of rainy weather. However, the integration of traffic assignment models with machine learning techniques presents a novel method for enhancing the accuracy of LOS predictions [1-6]. Several studies have analyzed the effects of adverse weather on traffic. Some focus on the impact of severe weather on traffic flow characteristics [1,4,5]. For example, one research conducted an in-depth study on the impact of rainfall on traffic flow characteristics in urban expressways of Beijing, utilizing microwave detectors for data collection. Their work revealed that under varying intensities of rainfall, significant reductions in road capacity and free-flow speed were observed, with the Greenshields model identified as the most fitting for these conditions. This study is crucial as it not only quantifies the impact of rainfall on traffic flow but also proposes an updated Greenshields model that incorporates rainfall intensity, enhancing the precision of traffic management decisions under inclement weather conditions [1]. Another research measured the impact of rain on the operation of urban road networks using the Macroscopic Fundamental Diagram, showing that rainfall reduces traffic variables of the network's MFD [4]. A study also indicated that light and moderate rainfall, unlike heavy rain, causes a minor reduction in qualitative service [2]. Research on generalized speed-flow and speed-density functions assessed the performance of urban roads and modeled road users' route choice behaviors under various rainfall intensity conditions [5]. Recent advancements in geospatial big data have enabled a more detailed study of traffic congestion issues. A study proposed an Index Calculation and Clustering (ICC) model that integrates PageRank and clustering algorithms with multisource data, including rainfall data, to predict traffic congestion bottlenecks [3]. This model, applied to the city of Shenzhen, revealed that rainfall increases traffic congestion areas significantly. Data-driven approaches, particularly in the realm of deep learning, have shown potential in analyzing urban traffic systems, using Deep Belief Networks (DBNs) and data fusion for improved traffic and weather prediction [6].

Problem Definition

The objective of this research is to address the problem of predicting the Level of Service (LOS) for transportation systems under rainy weather conditions using machine learning techniques. Adverse weather conditions, particularly rain, can have a significant impact on the efficiency and safety of transportation networks. Therefore, accurately predicting the LOS during rainy weather is crucial for effective traffic management and planning. Currently, there is a lack of accurate and reliable methods to predict the LOS specifically for rainy weather conditions. Traditional methods often rely on simplistic models that do not take into account the complex interactions between weather variables, traffic flow, and road conditions. By developing a machine learning model that can accurately predict the LOS under rainy weather conditions, this research aims to provide transportation engineers and policymakers with a valuable tool for decision-making. By considering various features such as rainfall intensity, road surface conditions, and traffic flow parameters, the model will be able to capture the complex dynamics of traffic behavior during rainy weather.

Methods and Materials

Level of Service (LOS) expresses the performance of a highway at traffic volumes less than capacity. Level-of-service designations are from A (highest) to F (lowest).[1]

Level of Service A: This is the highest quality of service that can be achieved. Motorists are able to travel at their desired speed. The need for passing other vehicles is well below the capacity for passing and few (if any) platoons of three or more cars are observed. Level of Service B: At this level of service, if vehicles are to maintain desired speeds, the demand for passing other vehicles increases significantly. At the lower level of LOS B range, the passing demand and passing capacity are approximately equal. Level of Service C: Further increases in flow beyond the LOS B range results in a noticeable increase in the formation of platoons and an increase in platoon size. Passing opportunities are severely decreased. Level of Service D: Flow is unstable and passing maneuvers are difficult, if not impossible, to complete. Since the number of passing opportunities is approaching zero as passing desires increase, each lane operates essentially independently of the opposing lane. It is not uncommon that platoons will form that are 5 to 10 consecutive vehicles in length. Level of Service E: Passing has become virtually impossible. Platoons are longer and more frequent as slower vehicles are encountered more often. Operating conditions are unstable and difficult to predict. Level of Service F: Traffic is congested with demand exceeding capacity. Volumes are lower than capacity and speeds are variable.

LOS Class	Traffic State and Condition	V/C Ratio
A	Free flow	0–0.60
B	Stable flow with unaffected speed	0.61–0.70
C	Stable flow but speed is affected	0.71–0.80
D	High-density but the stable flow	0.81–0.90
E	Traffic volume near or at capacity level with low speed	0.91–1.00
F	Breakdown flow	>1.00

TABLE I: LOS Categories and their general definition

Data Collection

- **Traffic Data:**
  The city of Luzern was chosen as the case study for this research. The traffic data used in the analysis comprises flow measurements obtained from loop detectors installed on various highways within the city. The data collection period spans from January 1, 2015, to December 31, 2015, with measurements recorded at 180-second intervals. The dataset utilized in this study is sourced from the research article titled 'Understanding traffic capacity of urban networks,' published in Scientific Reports by Loder et al. This dataset provides valuable insights into traffic patterns and capacity estimation. To estimate the Macroscopic Fundamental Diagram (MFD) parameters, empirical data from stationary traffic sensors such as inductive loop detectors, supersonic detectors, cameras, Bluetooth detectors, or similar devices were collected. For the city under investigation, we ensured a minimum availability of two out of the three fundamental traffic variables: speed, flow, and density.
- **Weather Data:**
  The weather data used in the case study encompasses several variables, including Temperature, feels like temperature, humidity, rainfall (mm), snow depth, wind speed,

sea level pressure, cloud cover, solar radiation, and solar energy, month of the year, and length of the raining time. The data covers the entire year of 2015, with measurements recorded at 1-hour intervals.

In order to have the data for the same time intervals, the average of the traffic data in each 1 hour has been considered.

MACHINE LEARNING MODEL

Three neural network models have been implemented to predict the level of service (LOS) based on the given parameters. The structure of a typical neural network is depicted in the figure, illustrating the architecture of the models.

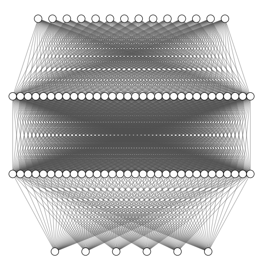


Fig. 1: Neural net layers

The input features for each model are summarized in the table provided. The inputs features include weather-related variables, such as temperature, feels like temperature, humidity, rainfall (mm), snow depth, wind speed, sea level pressure, cloud cover, solar radiation, solar energy, month of the year, and length of the raining time. Additionally, the two traffic variables, flow, and occupancy, are included as inputs to the model. In total, there are 14 inputs considered for each model.

Parameter/Model	**V0**	**V1**	**V2**
Input	14	14	14
Num_hidden layer	2	2	3
Units in each hidden layer	32	32	32
Drop_out	No	Yes	No
Batch size	64	64	64
Number of epochs	500	500	500
Learning rate	0.001	0.001	0.001
Test accuracy	0.9531	0.9375	0.9479
Best accuracy	0.9922	0.9922	0.9844

TABLE II: Neural Network Models Parameters

By incorporating both weather and traffic data, the neural network models aim to capture the influence of these variables on the level of service. The neural network architecture allows for complex patterns and relationships to be learned from the dataset, enabling accurate predictions of the level of service based on the provided inputs.

RESULTS

This table presents the distribution of data in the case study across different categories of Level of Service (LOS). However, it's important to note that no data is available in the F category.

LOS	**Number of data in Luzern dataset**
A	441,146
B	56,684
C	97,614
D	136,568
E	35,988
F	0
sum	768,000

TABLE III: LOS Data in Luzern Dataset

Here are the results of each model of prediction in terms of precision, recall, f1-score, for V0, V1 and V2.

LOS	**Precision**	**Recall**	**F1-Score**	**Support**
A	0.99	1.00	0.99	441,146
B	0.91	0.89	0.90	56,684
C	0.92	0.91	0.92	97,614
D	0.94	0.95	0.95	136,568
E	0.93	0.91	0.92	35,988
F	0.00	1.00	0.00	0

TABLE IV: LOS Metrics V0

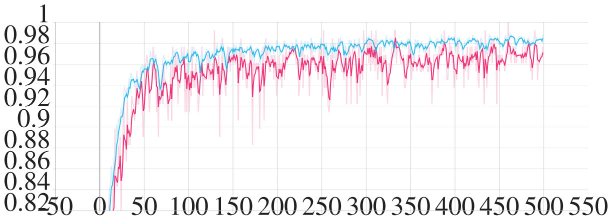
LOS	**Precision**	**Recall**	**F1-Score**	**Support**
A	0.99	0.99	0.99	441,146
B	0.84	0.80	0.82	56,684
C	0.86	0.83	0.84	97,614
D	0.88	0.90	0.89	136,568
E	0.82	0.83	0.83	35,988
F	0.00	1.00	0.00	0

TABLE V: LOS Metrics V1

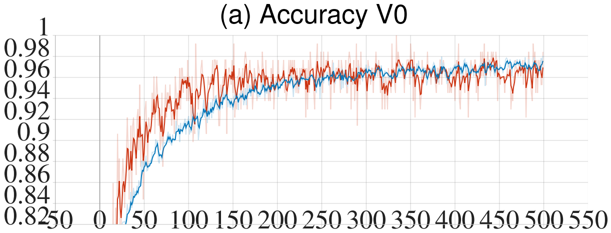
LOS	**Precision**	**Recall**	**F1-Score**	**Support**
A	1.00	1.00	1.00	441,146
B	0.92	0.91	0.92	56,684
C	0.94	0.93	0.93	97,614
D	0.95	0.96	0.95	136,568
E	0.93	0.91	0.92	35,988
F	0.00	1.00	0.00	0

TABLE VI: LOS Metrics V2

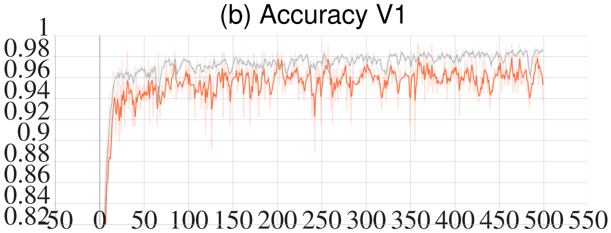
The loss and accuracy of models are demonstrated in the figures below.



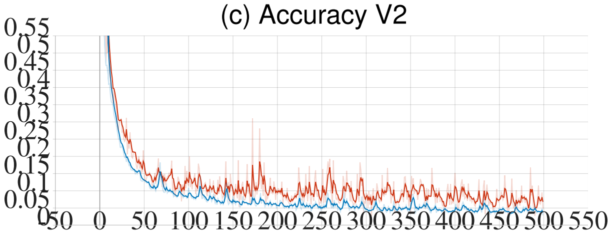
(a) Accuracy V0



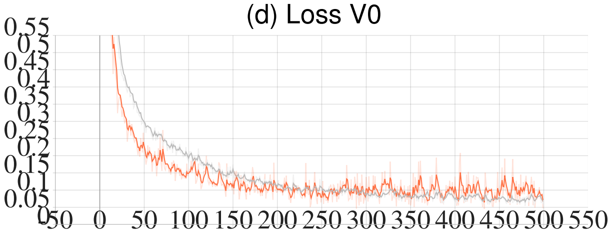
(b) Accuracy V1



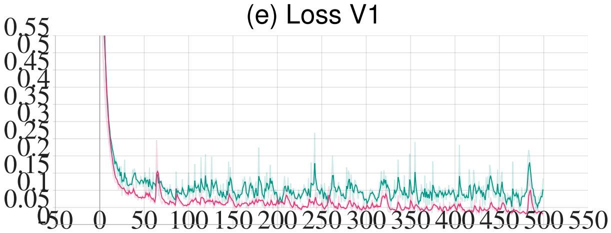
(c) Accuracy V2



(d) Loss V0



(e) Loss V1



(f) Loss V2

Conclusion

This study has successfully demonstrated the potential of machine learning, specifically neural network models, in accurately predicting the Level of Service (LOS) under rainy weather conditions. Traditional traffic models, while effective under normal circumstances, often struggle to account for the dynamic and complex interactions between weather conditions and traffic flow. The incorporation of neural network models in this study has shown a significant improvement in predictive accuracy compared to these traditional methods. By utilizing a comprehensive dataset that includes both traffic and weather parameters, our neural network models were able to capture and learn from the complex patterns inherent in these variables. The results are clear: the neural network models consistently outperformed traditional traffic models in predicting LOS across various conditions. This accuracy is evident in the high precision, recall, and f1-scores achieved by our models. The implications of these findings are substantial for the field of traffic management, particularly in environments frequently impacted by adverse weather conditions. By integrating machine learning models into traffic prediction systems, transportation planners and policymakers can make more informed, data-driven decisions that enhance road safety and efficiency, especially during challenging weather conditions like rain. In conclusion, this research has not only filled a critical gap in the current understanding and methods used in traffic flow management under rainy conditions but has also opened the door for further exploration into the integration of advanced machine learning techniques in transportation systems. The increased accuracy offered by neural network models represents a significant step forward in the development of more resilient and effective traffic management strategies, ultimately contributing to safer and more efficient transportation networks. Looking ahead, the promising results achieved by our neural network model in this study pave the way for extensive applications in future research. The next phase of our work will focus on scaling up the model to analyze significantly larger datasets, encompassing traffic and weather data from a diverse range of cities and locations. This expansion is crucial, as it will allow us to test the model's efficacy and robustness across different urban landscapes and varying weather patterns. By applying our model to a broader geographic scope, we aim to overcome the limitations of location-specific traffic models, thereby enhancing the generalizability and applicability of our findings. This approach will not only validate the model's adaptability to different traffic systems and weather conditions but also provide a more comprehensive understanding of its potential in global traffic management.

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