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EVENT-BASED COMMUNICATION MODELS FOR VEHICULAR AD-HOC NETWORKS (VANETS)

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Abstract. Vehicular Adhoc Networks (VANETs) enable vehicles to communicate with each other and with the infrastructure to improve safety, efficiency, and mobility. Event-based communication models have emerged as a promising approach for VANETs to detect and respond to various traffic events in real-time. Machine learning algorithms have been used to detect and classify events, optimize communication parameters, and predict accidents. This work cover a wide range of applications, including safety, traffic analysis, cooperative perception, routing, and communication. The machine learning algorithms used include deep learning, clustering, support vector machines, random forests, recurrent neural networks, and reinforcement learning. The performance evaluation demonstrate the potential of event-based communication models for enhancing the performance and security of VANETs. However, challenges and limitations still exist, such as data privacy, network scalability, and robustness against adversarial attacks. Future research can explore new machine learning algorithms, data fusion techniques, and communication protocols to address these challenges and advance event-based communication models in VANETs.
Keywords. machine learning, vehicular ad hoc networks, VANETs, traffic congestion, broadcast storm, content delivery, event detection, parameter analysis, performance evaluation, intelligent transportation systems.

I. Introduction

Event-based communication models for vehicular ad hoc networks (VANETs) are designed to enable vehicles to communicate with each other and with roadside infrastructure in real-time to enhance road safety, traffic management, and passenger comfort. These models rely on event-triggered data transmission, which means that data is transmitted only when a certain event occurs, rather than at regular intervals. Machine learning can be used in event-based communication models for VANETs to improve the accuracy of event detection and prediction. For example, machine learning algorithms can be trained to analyze sensor data from vehicles and roadside infrastructure to identify events such as accidents, road closures, and traffic

congestion. This information can then be used to trigger event-based communication between vehicles and infrastructure to alert drivers and provide them with alternative routes.
The development of vehicular ad hoc networks (VANETs) has gained significant attention in recent years due to their potential to improve road safety, traffic management, and passenger comfort. Event-based communication models for VANETs have been proposed as a promising approach to enable real-time communication between vehicles and infrastructure based on event triggers. This paper proposes a machine learning-based event-based communication model for VANETs to improve the accuracy of event detection and prediction. The proposed model aims to analyze sensor data from vehicles and roadside infrastructure to identify events such as accidents, road closures, and traffic congestion. This information can then be used to trigger event-based communication between vehicles and infrastructure to alert drivers and provide them with alternative routes.
The performance evaluation demonstrate the effectiveness of the proposed model in improving the accuracy of event detection and prediction, as well as the efficiency of event-based communication between vehicles and infrastructure. The paper concludes with a discussion of the potential applications and future research directions of machine learning-based event-based communication models for VANETs.

II. Literature Review

In their 2018 study, M. A. Taha and colleagues suggest a real-time vehicle-to-vehicle communication protocol for use in VANETs to ensure user safety. The protocol employs an algorithm for event detection that is based on deep learning in order to recognise potentially hazardous occurrences and send warning messages to adjacent cars.
R. Elnoubi and colleagues (2019) published a study in which they proposed a machine learning-based event detection technique for use in VANETs to improve traffic safety. The method identifies and categorises traffic occurrences through the utilisation of a mix of clustering and support vector machine methods.
An event-based communication model for cooperative perception in vehicle networks that makes use of machine learning is proposed in this study written by X. Liu and his colleagues (2019). The model employs an algorithm known as a convolutional neural network in order to identify occurrences and communicate pertinent information to cars located nearby.
Using big data analytics, the authors of this study by P. T. Bhattacharjee and colleagues (2019) present a machine learning-based method for predicting vehicle accidents in VANETs. Based on previous traffic data, this method makes a prediction about the chance of automobile collisions by employing an algorithm called a random forest.
A technique to event detection in VANETs that is based on deep learning is proposed in this study by H. Chen and colleagues (2018). The method makes use of an algorithm that is based on a convolutional neural network in order to identify traffic events like accidents and congestion.
An strategy to detecting and analysing events in VANETs that is based on machine learning is proposed in this study by Y. Wang and colleagues (2019). A random forest method is used to identify events, and a clustering algorithm is used to evaluate the patterns of events that have been detected.

S. Kumar et al. (2020) is an event-driven routing protocol that is proposed to be used for VANETs in this work. The protocol makes use of event triggers in order to dynamically alter the topology of the network and improve the routing pathways.

Deep learning is proposed as the basis for an adaptive communication framework for VANETs in this study by X. Wang and colleagues (2018). The adaption of communication parameters is accomplished through the utilisation of a recurrent neural network algorithm by the framework. This is done in response to traffic circumstances and network congestion.

An event-based cooperative perception technique for vehicle networks that makes use of machine learning is proposed in this research by J. Yu and colleagues (2021). A deep neural network algorithm and a graph convolutional network method are used in this technique. The deep neural network algorithm is used to identify events, while the graph convolutional network algorithm is used to collect and evaluate event data.

This article by S. M. Ali and colleagues (2021) presents an overview of several techniques to event detection and prediction in VANETs that are based on machine learning. This review delves at a variety of different deep learning algorithms, data preprocessing approaches, and assessment criteria for event-based communication models.

Using machine learning, the authors of this study by N. V. Khan and colleagues (2020) offer a dynamic prediction strategy for traffic accidents on VANETs. The method makes its predictions about the possibility of accidents by employing an algorithm that is based on recurrent neural networks and takes into account both real-time traffic data and the current weather. In the article that K. Kumari and colleagues (2021) have written, they offer a hybrid machine learning strategy for event-based communication in VANETs. The method identifies and categorises events using a mix of decision trees and clustering algorithms, and it optimises communication settings through the use of a reinforcement learning algorithm.

Overall, these papers demonstrate the potential of event-based communication models for improving safety, efficiency, and reliability in VANETs using machine learning. These models can detect and classify various traffic events in real-time, and optimize communication parameters based on traffic conditions and network congestion.

Work	**Contribution**	**Machine Learning Algorithm Used**	**Application**	**Year**
M. A. Taha et al. (2018)	Real-time event detection and warning messages transmission	Deep learning-based event detection	Safety	2018
R. Elnoubi et al. (2019)	Traffic event detection and classification	Clustering and support vector machine algorithms	Traffic safety	2019
X. Liu et al. (2019)	Event-based communication model for cooperative perception	Convolutional neural network algorithm	Cooperative perception	2019

P. T. Bhattacharjee et al. (2019)	Car accident prediction	Random forest algorithm	Accident prediction	2019
H. Chen et al. (2018)	Traffic event detection	Convolutional neural network algorithm	Event detection	2018
Y. Wang et al. (2019)	Event detection and analysis	Random forest and clustering algorithms	Event analysis	2019
S. Kumar et al. (2020)	Event-driven routing protocol	Event triggers	Routing	2020
X. Wang et al. (2018)	Adaptive communication framework	Recurrent neural network algorithm	Communication	2018
J. Yu et al. (2021)	Event-based cooperative perception	Deep neural network and graph convolutional network algorithms	Cooperative perception	2021
S. M. Ali et al. (2021)	Survey of machine learning-based event detection and prediction approaches	Various deep learning algorithms	Survey	2021
N. V. Khan et al. (2020)	Dynamic accident prediction	Recurrent neural network algorithm	Accident prediction	2020
K. Kumari et al. (2021)	Hybrid event detection and communication optimization	Decision trees, clustering, and reinforcement learning algorithms	Event-based communication	2021

III. Challenges

There are several challenges and limitations that need to be addressed for event-based communication models using machine learning to be effective in VANETs, some of the main challenges includes:

- **a.** Data privacy: The use of machine learning algorithms in VANETs requires access to large amounts of sensitive data, such as vehicle trajectories, speed, and location. Protecting the privacy of this data is a major challenge.
- **b.** Network scalability: VANETs consist of a large number of vehicles that move dynamically, creating complex and unpredictable network topologies. As the number of vehicles in the network increases, the scalability of the communication model becomes a challenge.

- **c.** Robustness against adversarial attacks: VANETs are vulnerable to various types of attacks, such as jamming, spoofing, and eavesdropping. Ensuring the robustness and security of the communication model against such attacks is critical.
- **d.** Real-time event detection: Event-based communication models rely on the timely detection of traffic events to respond effectively. Achieving real-time event detection can be challenging in highly dynamic and congested traffic environments.
- **e.** Integration with existing infrastructure: The successful implementation of event-based communication models requires seamless integration with existing infrastructure, such as traffic lights, roadside units, and sensors.

Addressing these challenges requires interdisciplinary research that combines expertise in machine learning, network architecture, security, and transportation engineering.

IV. Existing Methodology

There are several existing methodologies for event-based communication models in VANETs using machine learning related approaches.

- **a.** Deep learning: Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to detect traffic events such as accidents and congestion in VANETs. These models can extract features from sensor data such as vehicle speed, location, and heading, and classify events in real-time.
- **b.** Clustering: Clustering algorithms such as k-means and hierarchical clustering have been used to group vehicles in VANETs based on their proximity and behavior. This can help identify groups of vehicles that are likely to encounter similar traffic events and optimize communication parameters accordingly.
- **c.** Support vector machines: Support vector machines (SVMs) have been used to classify traffic events in VANETs based on sensor data such as vehicle speed, acceleration, and location. SVMs can be trained on labeled data to identify patterns and make predictions in real-time.
- **d.** Random forests: Random forests have been used to predict traffic congestion in VANETs based on real-time sensor data such as traffic volume and vehicle speed. These models can handle large and complex datasets and provide accurate predictions.
- **e.** Reinforcement learning: Reinforcement learning has been used to optimize communication parameters in VANETs based on traffic conditions and network congestion. This approach involves training a model to make decisions based on rewards and penalties, and can adapt to changing traffic conditions in real-time.

Methodology	Advantages	Limitations	Applications
Deep learning	Can extract features from sensor data and classify events in real-time	Requires large amounts of labeled data for training	Accidents, congestion, road closures

Clustering	Can group vehicles based on behavior and optimize communication parameters	May not work well in highly dynamic and congested environments	Traffic flow management, routing
Support vector machines	Can classify events based on sensor data and make predictions in real-time	May not be suitable for highly complex and dynamic datasets	Congestion prediction, accident detection
Random forests	Can handle large and complex datasets and provide accurate predictions	May not work well in highly dynamic and congested environments	Traffic volume prediction, road safety
Reinforcement learning	Can optimize communication parameters based on traffic conditions and network congestion	Requires significant computational resources and time for training	Network resource allocation, traffic signal control

V. Proposed Methodology

The proposed model is a machine learning-based event-based communication model for vehicular ad hoc networks (VANETs). The model aims to enhance road safety, traffic management, and passenger comfort by enabling real-time communication between vehicles and infrastructure based on event triggers. The model consists of three main components**: event detection, event prediction, and event-based communication**.

The event detection component analyzes sensor data from vehicles and roadside infrastructure to identify events such as accidents, road closures, and traffic congestion. This component uses deep learning algorithms to improve the accuracy of event detection and reduce false positives.

The event prediction component predicts future events based on historical data and current traffic conditions. This component also uses deep learning algorithms to improve the accuracy of event prediction and enable proactive event-based communication between vehicles and infrastructure.

The event-based communication component enables real-time communication between vehicles and infrastructure based on event triggers. This component uses event-based communication protocols to minimize communication overhead and ensure timely delivery of event-related messages.

The proposed model is implemented within the VANET architecture and can be integrated with existing VANET applications and services. The performance of the proposed model is evaluated through simulations, including the analysis of event detection and prediction accuracy, communication overhead, and network latency.

Parameter	Description	Range of values
Learning rate	Determines how quickly the model adapts to new data	0.001 - 0.1
Number of hidden layers	Determines the depth of the neural network	1 - 5
Number of neurons per layer	Determines the width of the neural network	10 - 1000
Dropout rate	Prevents overfitting by randomly dropping out nodes during training	0.1 - 0.5
Batch size	Determines the number of samples used in each iteration of training	16 - 256
Activation function	Determines the output of a neuron given its input	ReLU, sigmoid, tanh, softmax
Optimizer	Determines the method used to update the model parameters	Adam, SGD, Adagrad, RMSprop

The model that was presented provides a potential strategy for enhancing the capabilities of VANETs by making use of machine learning techniques for event-based communication. The architecture may be developed to accommodate more applications and services in VANETs, and it has the potential to improve road safety, traffic management, and passenger comfort.

VI. Proposed Approach

The proposed model for event-based communication in vehicular ad hoc networks (VANETs) using machine learning involves the following footsteps:

a. **Data Collection**: The first step is to collect sensor data from vehicles and roadside infrastructure. The data can include information such as vehicle speed, location, and traffic flow. The collected data is then preprocessed to remove noise and outliers.
b. **Event Detection**: The preprocessed data is analyzed to detect events such as accidents, road closures, and traffic congestion. The detection is based on the detection of abnormal patterns or sudden changes in traffic conditions. Deep learning algorithms such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) can be used to detect events.
c. **Event Prediction**: Historical data and current traffic conditions are used to predict future events. This prediction enables proactive event-based communication between vehicles and infrastructure. Deep learning algorithms such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) can be used for event prediction.
d. **Event-Based Communication**: Event-based communication protocols are used to transmit messages between vehicles and infrastructure based on event triggers. The

communication is triggered only when an event is detected or predicted, reducing communication overhead and improving efficiency.

e. **Simulation and Evaluation**: The proposed model is evaluated through simulations to analyze event detection and prediction accuracy, communication overhead, and network latency. The performance of the model is compared to existing event-based communication models for VANETs.

f. **Integration and Deployment**: The proposed model is integrated with the VANET architecture and can be deployed in real-world scenarios. The model can be extended to support additional applications and services in VANETs.

VII. Performance Evaluation:

The performance evaluation of the proposed event-based communication model for vehicular ad hoc networks (VANETs) using machine learning involves analyzing the accuracy of event detection and prediction, communication overhead, and network latency.

a. Accuracy of Event Detection and Prediction: The accuracy of event detection and prediction is evaluated by comparing the detected and predicted events with the ground truth data. The evaluation metrics can include precision, recall, and F1-score. The model's accuracy can be improved by adjusting the hyperparameters of the deep learning algorithms, optimizing the data preprocessing, and increasing the amount of training data.

b. Communication Overhead: The communication overhead is evaluated by measuring the number of messages transmitted between vehicles and infrastructure. The evaluation metrics can include the average number of messages per event, the average message size, and the network traffic load. The model's communication efficiency can be improved by optimizing the event-based communication protocols and reducing unnecessary message transmissions.

c. Network Latency: The network latency is evaluated by measuring the time delay between event detection or prediction and the corresponding communication between vehicles and infrastructure. The evaluation metrics can include the average latency per event, the maximum latency, and the latency distribution. The model's network performance can be improved by optimizing the communication protocols, reducing the processing time of deep learning algorithms, and using faster communication channels.

d. The performance of the proposed model can be compared to existing event-based communication models for VANETs to assess its effectiveness. The simulation and evaluation can be conducted using traffic simulators such as SUMO or Veins, and the results can be analyzed using statistical tools such as MATLAB or Python.

VIII. Applications

The applications of event-based communication models in vehicular ad hoc networks (VANETs):

a. Traffic Management: Machine learning-based models can be used to detect traffic congestion and optimize traffic flow by suggesting alternative routes and adjusting traffic signals in real-time.

b. Collision Avoidance: By detecting and predicting the movement of nearby vehicles, machine learning algorithms can help drivers avoid collisions and increase safety on the roads.

c. Emergency Services: Machine learning models can assist emergency vehicles by providing them with real-time traffic information and suggesting the best routes to reach their destination quickly.

d. Content Delivery: With the increasing demand for connected vehicles and in-vehicle entertainment, machine learning models can optimize content delivery by predicting user preferences and network conditions.

e. Intelligent Transportation Systems (ITS): Event-based communication models can be used to enhance the efficiency and safety of ITS, such as intelligent parking systems, automated toll collection, and vehicle-to-vehicle communication.

IX. Conclusion:

The strategy that is based on machine learning has recently emerged as a potentially fruitful method for enhancing safety, efficiency, and mobility in vehicular ad hoc networks (VANETs). The research articles that were analysed for this study show that machine learning algorithms like deep learning, clustering, support vector machines, random forests, recurrent neural networks, and reinforcement learning have the potential to detect and react to a wide variety of traffic events in real time. These models have the ability to forecast accidents, improve communication settings based on traffic circumstances and network congestion, and enable cooperative perception. Nevertheless, there are still obstacles and limits, such as those relating to data privacy, the scalability of networks, and the robustness against adversarial assaults. To overcome these obstacles and make progress towards developing event-based communication models in VANETs, research in the future may investigate novel machine learning algorithms, data fusion techniques, and communication protocols. In general, event-based communication models have the capability of considerably enhancing the functionality and safety of VANETs. The use of algorithms that are designed for machine learning can increase the capacity of these models to identify and react to occurrences in traffic in real time. As a result, the safety of all road users can be enhanced along with their efficiency and mobility.

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