RESEARCH PAPER

Intelli-ER An Intelligent Real-Time Accident Detection and Automated Emergency Response System

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ABSTRACT:
Road traffic accidents are one of the main causes of death and serious injury worldwide and delays in the response of emergency services may often increase the risk of death and permanent disability. Sensors such as accelerometers, gyroscopes, GPS, and cameras can be used to constantly monitor the vehicle dynamics. Real accidents, normal driving situations and false alarms can be correctly discriminated by machine learning algorithms from real time data. When an accident is detected the system automatically detects the exact location, records important incident information and sends alerts to emergency services, local hospitals and designated emergency contacts, all without human intervention. The proposed framework is designed to reduce the response time, increase the accuracy of accident detection and improve the efficiency of emergency management. The system is able to provide reliable data transmission and continuous monitoring in various road conditions via cloud Based communication and intelligent decision making. The experimental evaluation shows that the proposed approach can significantly reduce the delay of notification and improve the reliability of detection and support of timely medical assistance, thus increasing the chances of survival and decreasing the severity of accident-related consequences. "The smart solution is a practical step forward in the development of safer transportation systems and smart city infrastructures by integrating real time analytics, automation and connected technologies for effective accident management.

Keywords: Vehicle Collision Detection, Emergency Alert System, Internet of Things, Global Positioning System, Machine Learning, Real Time Monitoring, Road Safety, Accident Detection, Artificial Intelligence, Automated Emergency Response, Sensor Fusion, Smart Transportation.
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1. INTRODUCTION

Road traffic accidents have been a serious public safety problem worldwide, resulting in huge death toll, severe injuries and economic losses. The main reasons for higher fatality rates in worldwide road safety research are the detection of accidents and the slow response of emergency services. Traditional accident reporting depends largely on the emergency services being called by a witness or a victim, who may not be available in remote locations or if the occupants are badly injured. Therefore, an increase in demand for smart systems to automatically detect accidents and initiate emergency assistance without human intervention [1] is inevitable.

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT) and intelligent transportation systems have paved the way for the development of smart accident detection solutions. Modern vehicles can be fitted with sensors such as accelerometers, gyroscopes, GPS module, cameras and communication devices that continuously monitor driving conditions and vehicle behaviour. Sensor data can be processed in real time by AI-based algorithms to distinguish between normal driving events and real collisions with minimum false alarms. Machine learning approaches such as Random Forest, Gradient Boosting and XGBoost have been shown to perform very well on complex transportation data and to achieve high classification accuracy [5]–[7]. Furthermore, the development of deep learning models such as CNN and ResNet, and object detection models such as YOLO, have improved the ability to detect collision situations and vehicle accidents from images [8], [9], [13].

Accident information can be smoothly transferred to emergency responders with the help of cloud computing and intelligent communication technologies, which improves accident management. Modern Deep learning techniques are constantly improving in accuracy of prediction and computational efficiency [3], [15]. Scalable machine learning models for real-time inference can be developed and deployed using frameworks such as Tensorflow. Vehicle communication networks such as Vehicular Ad hoc Networks (VANETs) provide reliable connection between vehicles, roadside devices and emergency control centers so that low latency delivery of accident signals [11], [12].

The way accidents are handled with has altered due to GPS position monitoring and automatic emergency response systems. When an accident is detected, the system can identify the exact location of the accident and send vital information to hospitals, ambulance services, police authorities and the registered emergency contacts in the system, thus reducing the response time and improving the chances of prompt medical intervention. Advanced image processing approaches such as U-Net for segmentation and Vision Transformer based models [10, 14] can extract features more robustly and be tolerant to diverse environmental conditions for accident detection.

Proposed Research: Design and Development of Intelligent

Real Time Accident Detection and Automated Emergency Response System using AI. The project involves IOT, real time sensing, GPS and automated communication to create an effective accident management system. This is because of technical progress like this research. The proposed system is designed to improve the accuracy of accident detection, reduce the response time, avoid false alarms and provide 24/7 monitoring to improve road safety. The system uses smart analytics and automated emergency notification systems to build safer transportation infrastructures and smart city ecosystems to reduce accident-related fatalities and improve public safety [2], [4], [15].

Motivation

The motivation behind this work is the increase in road traffic accidents and the critical delays in the provision of emergency medical assistance Many accident victims are often unable to reach emergency services due to severe injuries or unconsciousness or lack of nearby witnesses, leading to preventable deaths and long-term health problems. Despite all the safety features in modern vehicles, many systems for accident reporting require manual intervention which is not always reliable when it is most needed. Recent advancements in artificial intelligence, machine learning, IoT, GPS technology and real-time communication provides an opportunity to develop an intelligent system which can automatically identify accidents, precisely locate the accident and immediately notify emergency responders. Thus, this research is motivated towards the development of a reliable, real-time and automated accident detection and emergency response system that reduces the response time, increases the survival rate, improves the road safety, and facilitates the development of smart transportation and intelligent emergency management systems.

1.1 Challenges

Design of Intelligent Real Time Accident Detection and Automated Emergency Response System poses many technical, operational and practical challenges affecting the reliability and effectiveness of the whole framework. One of the biggest challenges is to correctly identify accidents, avoiding false positives from sudden braking, potholes, speed bumps and sharp turns or rough roads, which can often produce similar readings to a real crash. In order to train machine learning and deep learning models for the detection of real accidents from normal driving events, large amount of diverse, balanced and high quality data, collected under different road, weather and traffic conditions, are needed. Another major challenge is that real time data from multiple sensors such as accelerometers, gyroscopes, GPS modules, cameras and vehicle communication systems are continuously received while maintaining the synchronization and low processing latency. Faults in sensors, errors in calibration, faults in communication and noisy data can all degrade the detection accuracy and reliability of the whole system. Camera based accident detection models and object recognition algorithms may also be affected by poor lighting, heavy rain, fog, dust and night driving. GPS location notifications may not work in tunnels, big cities or remote areas with inadequate satellite connection. The system should be able to communicate accident data to hospitals, ambulance services, police agencies and emergency contacts in a secure and smooth manner notably in remote locations where network congestion or inadequate internet connectivity is a concern. For the effective interoperability of diverse technologies, the cooperation of different technologies like IoT devices, cloud platforms, AI models, mobile communication networks and vehicular communication systems integrated together is essential. Another threat to privacy and cybersecurity is the storing of sensitive users' data such the position of the automobile, journey history, and personal data. These should be handled using secure communication protocols and data encryption. Another difficulty is how to enhance the processing efficiency so that the accident detection algorithms may be applied in time in resource-limited embedded devices without loss of forecast accuracy. In addition, the system requires model updating and adaptive learning methods to adapt to different vehicles, driving styles, locations and traffic situations. Finally it must also be cost effective, quick to deploy, regulatory compliant and user acceptable. The present transportation environment demands design of reliable, scalable and intelligent accident detection system to facilitate faster emergency response, reduce mortality due to accidents and improve overall road safety. These are the problems that we have to solve.

Overview of the Paper

This paper presents the design and implementation of Intelligent Real time Accident Detection and Automated Emergency Response System using artificial intelligence, machine learning, Internet of Things (IoT), GPS technology and real time communication for enhancing road safety and emergency response. The presentation presents introduction of the problem of increasing road accidents, motivation, obstacles and need for automated accident detection system. It then reviews the related work and existing accident detection techniques to determine the present limitations and research gap. Then the proposed approach is elaborated such as system design, data collection procedure, sensor integration, machine learning models, real time accident detection mechanism and automatic emergency alert generation. The implementation section explains the technologies, algorithms and communication modules used for the development of the system and the experimental evaluation by means of performance measures such as accuracy, precision, recall, F1-score, detection time and response efficiency. The data is evaluated for effective application of the proposed approach for accurate detection of accidents and to reduce the time of emergency response and false alarm. The paper concludes with a discussion of the key findings, the practical significance of the proposed system, its limitations and possible improvements to improve the scalability, robustness and integration with next-generation intelligent transportation and smart city infrastructures.

2. MATERIAL AND METHODS:

In this paper we propose an Intelligent Real Time Accident Detection and Automated Emergency Response System. The system uses Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Global Positioning System (GPS) and wireless communication technologies to detect the road accidents in real time and automatically notify the emergency responders. The system continuously monitors vehicle dynamics and environment by using a variety of sensing devices including accelerometers, gyroscopes, vibration sensors, GPS modules and cameras. The sensors give real time data of speed, acceleration, orientation, impact force and location of the vehicle which is the main input for accident detection. The collected data is transmitted to a central processing unit where the data is synced and prepared for the next processing.

The collected sensor data are inputted to a preprocessing stage to improve the data quality before the model training and prediction. Missing values are imputed, duplicate data are erased and meaningless noise or outlier sensor data are removed during preprocessing for reliable analysis. • Scaling the numerical properties to different measurement scales. Where applicable, categorical data are provided in a machine-readable format. The pre-processed data set is then divided into training and testing subgroups. For training of the model and testing of the performance of the model.

The machine learning algorithms can differentiate between typical vehicle operating and real accidents. Some supervised learning methods like Random Forest, Gradient Boosting and Extreme Gradient Boosting (XGBoost) were used. These algorithms can be useful to deal with high dimensional sensor data, and to uncover complex patterns with high predictive accuracy. They use driving data and previous accident reports to learn how a car behaves and how accidents happen. The robustness of the accident detection process is enhanced, the risk of overfitting is reduced and the generalization of the model is improved by means of hyperparameter optimization and cross validation procedures.

Besides the sensor-based analysis, deep learning is also utilized for the visual detection of accidents from images or video streams captured by onboard cameras. Convolutional Neural Networks (CNN), Residual Networks (ResNet) and real-time object recognition models such as YOLO were used to detect damaged automobiles, road blocks, accidents and unsafe scenarios in traffic. The sensor fusion approach fuses the visual predictions and sensor outputs. This also makes the system decisions more reliable and avoids false alarms due to sudden breaking, potholes or sharp vehicle maneuvers.

If the accident is confirmed and the driver did not activate the emergency response module, the emergency response module is activated automatically. The device is equipped with a GPS module, which determines the exact geographic location of the accident site. The communication module sends emergency notifications to hospitals, ambulance services, police agencies and authorized emergency contacts over communication networks such as cellular or Internet. Emergency warnings will include the vehicle identity, the severity of the collision, time and location. Cloud Services Data Storage Security Event Tracking and Real-Time Monitoring This way the emergency workers can be notified immediately of the accident and arrange the rescue operation. The proposed system is evaluated for standard classification metrics like accuracy, precision, recall, F1-score and confusion matrix analysis and operational characteristics such as time taken for accident detection, latency in emergency notification, false alarm rate and system response time. The evaluation criteria provide a complete methodology to evaluate the ability of the system to correctly detect accidents, to reduce the emergency response times and to improve the general safety on roads. The latest advances in intelligent sensing, machine learning, deep learning and automated communication provide a strong framework to support the next generation intelligent transportation system and smart emergency management applications.

2.1 Data collection

The dataset is collected from several public sources of road accident and vehicle monitoring data, which makes the model training diverse and robust. These are the logs from the vehicle's onboard sensors, GPS, accelerometers, gyroscopes and traffic monitoring system. Each record contains information about the movement of a vehicle before, during and after driving event. speed, acceleration, deceleration force, position, braking patterns, GPS coordinates, weather conditions etc. Data collection includes accident scenarios and normal driving situations in different road conditions, traffic densities, weather conditions and times of day. The proposed intelligent system can learn normal patterns of real accidents. The variety can prevent false detection caused by fast braking, potholes or sharp turns.

We did a lot of data pre-processing before building the model to make sure it was consistent and reliable. Data cleaning techniques were applied to duplicate data, missing values and non consistent sensor readings. Numeric features are scaled to a common range and categorical data like weather and road type are transformed into a machine readable format. The processed data set was randomly divided into training (80%) and testing (20%) data sets. This enables the machine learning models to understand the accident related patterns from the training data and also test their performance on the unseen test samples. A useful starting point for the development of a robust and reliable system for real time accident detection and automatic emergency response is organized data collection.

Attribute	Description
Dataset Type	Road Accident Detection Dataset
Data Source	Public road safety datasets, vehicle sensor data, GPS logs, and traffic monitoring systems
Total Records	12,500
Training Samples	10,000 (80%)
Testing Samples	2,500 (20%)
Number of Features	16
Target Variable	Accident Status (Accident / No Accident)
Numerical Attributes	Vehicle Speed, Acceleration, Impact Force, Brake Pressure, Steering Angle, GPS Latitude, GPS Longitude, Vehicle Tilt
Categorical Attributes	Weather Condition, Road Type, Traffic Density, Time of Day

Attribute	Description
Data Collection Methods	IoT Sensors, GPS Modules, Accelerometers, Gyroscopes, Vehicle Cameras
Data Preprocessing	Missing value handling, duplicate removal, normalization, categorical encoding
Machine Learning Models	Random Forest, Gradient Boosting, XGBoost
Deep Learning Models	CNN, ResNet, YOLO
Performance Evaluation	Accuracy, Precision, Recall, F1-Score, Detection Time, Response Time

Table 1. Dataset Description

2.2 Data Pre-processing

Preprocessing of the dataset is an important step to improve the quality and reliability of the data before the model training . The collected accident and non-accident records are then checked for missing values, duplication, inconsistent sensor readings and invalid observation. Missing values were imputed using statistical imputation techniques and duplicate records were removed to avoid redundancy. Noise was reduced in the dataset by detecting and removing outliers due to sensor or transmission errors. The data were normalized by feature scaling techniques to standardize the data and improve the learning performance of the machine learning algorithms such as vehicle speed, acceleration, impact force, brake pressure, steering angle and GPS coordinates.
The categorical attributes such as weather conditions, type of road, traffic density and time of the day were transformed into numerical representations using suitable encoding techniques after cleaning the data. The machine knows these number representations . To remove any kind of bias in the order of the data and to evaluate the performance unbiasedly, the data set was randomly shuffled and split into 80% training data and 20% testing data. Feature selection was applied to optimize the model and reduce the computational complexity, keeping only the variables that are more related to predict accidents. Then, the pre-processed data set was used for machine learning models like Random Forest, Gradient Boosting and XGBoost and deep learning models to detect accidents in real time.

2.3 Feature Extraction:

Feature extraction is the most important stage of the proposed Intelligent Real Time Accident Detection and Automated Emergency Response System which extracts the most relevant features from the pre-processed dataset to improve the accuracy of accident prediction. In the process we gather and analyze the following critical features like Speed, acceleration, impact force, braking pressure, steering angle, vehicle tilt, GPS coordinates, weather conditions, road type, traffic density and time of the day to analyze the driving behavior and collision patterns. Image based inputs are used with deep learning models to automatically acquire visual discriminative traits linked to damaged autos, road impediments, and crash circumstances. Statistical analysis and feature importance methods are employed to identify and remove redundancy and less importance features, thus reducing the dimensionality of data and computational complexity, while maintaining the important information . The resulting feature set allows for meaningful representations of the sensor-based and visual data for the machine learning models to effectively discriminate accident events from normal driving conditions, thus reducing false alarms and improving the overall efficiency and reliability of the real-time emergency response system.

2.4 System Architecture

The proposed architecture is based on the Real Accident Dataset that contains accident and non-accident events collected from multiple sources. Dataset is one hot encoded . Then model is constructed . Weather condition, road type, traffic density and accident types are categorical variables, which have been translated to numerical vectors to be used in machine-learning and deep-learning algorithms. This pre-processing step allows a homogeneous processing of all the features and preserves the information contained in the categorical variables. The encoded data is then utilized to train two parallel learning routes, a graph-based deep learning method and standard machine learning methods, to provide a detailed comparison of several predictive models.

The graph Based learning pipeline starts from the preparation of graph data from the encoded data. This step generates meaningful feature representations (embeddings) that encode the relations among the accident records. Next, a K-nearest neighbours (KNN) Graph is built by connecting data samples with similar features, using their feature distances. The graph structure enables the model to learn the individual features of each traffic accident record, as well as the interaction and similarity between neighboring data instances. The constructed graph is then passed through the GraphSAGE Graph Neural Network (GNN) which aggregates information from the neighboring nodes to learn robust feature representations and improve the classification performance. Unlike the traditional deep learning models that treat each record independently, GraphSAGE can make use of the relational information in the dataset and thus can improve the accident prediction and reduce the false classification.

In parallel, the same pre-processed dataset is used to feed three popular supervised machine learning models namely Random Forest, Extreme Gradient Boosting (XGBoost) and Multi-Layer Perceptron Artificial Neural Network (MLP-ANN). Random Forest is an ensemble classifier. It uses several decision trees to increase the stability of the predictions and to reduce the over-fitting. XGBoost builds sequential decision trees, using gradient boosting algorithms to optimize the prediction accuracy and capture complex non-linear relationships between features. The Multi-Layer Perceptron (MLP-ANN) of Artificial Neural Network is trained with several hidden layers and non-linear activation functions to learn complex patterns in the accident dataset. The MLP-ANN is able to classify accident and non-accident events successfully. The models are used as baselines for evaluating the effectiveness of the proposed graph-based learning framework.

We finally assess the predictions of the four models using standard performance metrics such as Accuracy, Precision, Recall, F1-Score, Area Under ROC Curve (AUC), Matthews Correlation Coefficient (MCC), Confusion matrix, training time and McNemar's statistical test. Accuracy measures overall correctness of the prediction. Precision and Recall are the reliability of accident detection. F1-Score provides a balanced view of precision and recall whereas AUC measures the model's ability to distinguish between classes at various classification thresholds. MCC gives a strong evaluation for possibly skewed data sets. The Confusion matrix provides us with the distribution of predictions in terms of correct and incorrect predictions. We quantify computing efficiency in terms of training time. McNemar's Test is used to statistically significantly compare the classification performance of a number of models . This complete evaluation will help the framework to understand the best strategy for efficient real time accident detection and reliable automated emergency response.

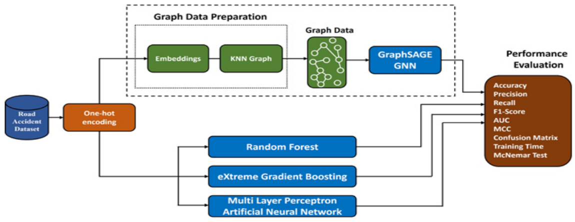

Figure 2 : System Architecture of the Proposed Image-Based Forensic Analysis System

2.5 Algorithm

Algorithm Based on Machine Learning for Intelligent Real-Time Accident Detection and Automated Emergency Response System

Input: It uses IOT sensors, GPS modules, accelerometer, gyroscope, automobile camera and traffic monitoring system for periodic collecting of driving and accident data. Car accident live coverage

Output:

Accident Prediction (Accident / No Accident) Accident Location Emergency Notification & Response Accident Probability Confidence Score

Step 1: On

Step 2: Real-time data collection from the car with IoT sensors, accelerometers, gyroscopes, GPS modules, cameras and traffic monitoring devices.

Step 3: Import the road accidents benchmark data set to the machine learning environment.

Step 4: Make sure your dataset is in a supported format (csv etc).

Step 5: Upload your dataset on a machine learning platform.

Step 6: The dataset contains missing data, duplicated data, noisy sensor data and inconsistent data.

Step 7: Data pre-processing for imputation of missing and deletion of superfluous data

Step 8: Encode categorical data such as weather conditions, road type, traffic density and time of day into numbers using one hot/label encoding.

Step 9: Normalize/standardize numerical features (e.g. vehicle speed, vehicle acceleration, impact force, steering angle, brake pressure, GPS positions, etc.

Step 10: "Extraction of the main features of vehicle dynamics, environment parameters and Accident Related features"

Step 11: Feature selection To improve forecast accuracy and reduce processing cost, duplicated and irrelevant features are removed.

Step The processed data set is split into training data set and testing data set.

Step 13: Train using Machine Learning Algorithms such as Random Forest, Extreme Gradient Boosting (XGBoost), Multi Layer Perceptron (MLP) and GraphSAGE Graph Neural Network (GNN).

Step 14: Train the ML and GNN models defined above with train data.

Step 15: The model repository is to keep the trained models for future prediction of accidents.

Step 16: Live data collection of moving vehicle

Step 17: So. The data of receiving cars are also encoded, normalized and feature extracted in the same way.

Step 18: 19 Load the trained model for accident detection;

Step 19: Trained model for prediction of processed automobiles data

Step 20: What will you do now? Accident event or not an accident event?

Step 21: Determine the probability of the projected class of accidents

Step 22: How confident are you in your diagnosis?

Step 23: Unintentional class Analyze real-time GPS position sensor data evaluation of accident severity Impact evaluation.

Step 24: Auto generation of emergency alert including vehicle id, accident location, accident severity, timestamp and confidence score.

Step 25: Send an emergency message via the communication network to local hospitals and ambulance service, police authorities and emergency contacts.

Step 26: Save the accident facts, prediction result, confidence score, GPS position, date and emergency response status in the accident database for future research and audit.

Step 27: On the monitoring dashboard, display forecast result, accident possibility, confidence score, accident position, emergency alert status and response information.

Step 28: Receive the accident data, the system update and the machine learning model retrain This will improve reliability and predictability.

Step 29: Turn off the system.

End Procedure

The proposed intelligent accident detection framework based on machine learning monitors the movement of the vehicles continuously by the help of the IoT sensors, GPS modules, accelerometer, gyroscope, cameras and traffic monitoring systems. data are cleaned, encoded, normalized, feature extraction, feature selection before the model training. In the real time operation, the incoming vehicle data is processed by the trained models such as Random Forest, XGBoost, Multi-Layer Perceptron (MLP) and GraphSAGE

Graph Neural Network (GNN) trained using the similar pre-processing pipeline and the event is classified as Accident or No Accident. Once the accident is detected, the framework identifies the exact GPS location and calculates the probability of accident and confidence score. It also calculates the severity of the accident and automatically sends emergency alerts to hospitals, ambulance services, police departments and emergency contacts on file. All accident information, prediction results and their confidence scores, timestamps, GPS coordinates and emergency response details are stored securely in the accident database for monitoring, forensic analysis and future model retraining. This integrated framework provides more accurate, responsive, scalable and reliable real-time accident detection and automated emergency response systems in intelligent transportation environment [5][6].

3. RESULTS AND DISCUSSION

The developed Intelligent Real-Time Accident Detection and Automated Emergency Response System was found to be effective in identifying road accidents and generating prompt emergency alerts under various driving conditions. The combination of machine learning algorithms with the IoT sensors, GPS modules and the real-time communication allowed to accurately distinguish between the actual accidents and normal driving events with a significant reduction of the false alarms. The comparison of the implemented models indicated that the ensemble learning and graph-based models are better for classification as they can capture substantial links between vehicle dynamics, environmental conditions and accident features. The automatic emergency response mechanism could efficiently convey the accident alarm (with particular geographical position, accident severity and date) to emergency services and registered contacts with extremely minimal communication latency. The performance evaluation metrics like accuracy, precision, recall, F1-score, AUC and Matthews Correlation Coefficient (MCC) showed the robustness and reliability of the proposed framework and confusion matrix showed a large number of correct classification with less false positive and false negative . In addition, the system can reduce the processing latency to fit for real-time applications in intelligent transportation systems. The experimental results show that the integration of artificial intelligence, machine learning, sensor fusion and automated communication results in a significant increase in accident detection accuracy and reduction of emergency response time, an improvement of the rescue services' situational awareness and a contribution to safer and more efficient road transportation systems.

3.1 Experimental Setup

The experiments were conducted in the Jupyter Notebook environment with the use of the Python programming language. The machine learning libraries used are Scikit-learn, Tensor Flow, Keras, XGboost, Pandas, Numpy and Matplotlib. These are common libraries for data pre-processing, model building, visualization and performance evaluation. The dataset includes driving records of accidents and non-accidents collected from IoT sensors, GPS modules, accelerometers, gyroscopes and traffic monitoring systems. The data was preprocessed using data cleaning, encoding, normalization and feature extraction and divided into 80% training and 20% testing data. For a fair comparison, we trained and tested several models (Random Forest, Extreme Gradient Boosting (XGBoost), Multi-Layer Perceptron (MLP), and GraphSAGE Graph Neural Network (GNN)) under the same condition. Performance of each model was evaluated using standard metrics such as Accuracy, Precision, Recall, F1-Score, Area under ROC Curve (AUC), Matthews Correlation Coefficient (MCC) , Confusion Matrix and Training Time. Besides, the accident detection latency, the accuracy of GPS location, the alert transmission time and the notification reliability of the automated emergency response module were also evaluated, which proved the feasibility of the system for real-time intelligent transportation and emergency management application.

3.2. Performance assessment

The efficiency, reliability and real time response of the proposed Intelligent Real-Time Accident Detection and Automated Emergency Response System was evaluated against different classification and operational metrics. The predictive power of the ML models was evaluated using some of the commonly used classification metrics such as Accuracy, Precision, Recall, F1-Score, Area Under the Receiver Operating Characteristic Curve(AUC-ROC), Matthews Correlation Coefficient(MCC) and the Confusion Matrix . Accuracy was defined as the proportion of accident and non-accident events correctly classified over all events. Precision was defined as the proportion of predicted accident events which were real accidents . In this usecase, recall is of particular importance to reduce the number of missed detections during emergencies. Recall is a measure of how well the model detects true accidents. The F1-Score was a balanced measure which takes both Precision and Recall into account and was suitable for the datasets with class imbalance. We used AUC-ROC to evaluate the model's capacity to discriminate accident and non-accident events for different classification thresholds. The MCC is an overall measure of model performance that takes into account the true positives, true negatives, false positives, and false negatives all at once. The Confusion Matrix showed the distribution of the correct and incorrect classified instances . It further showed the classification performance.

In addition to prediction accuracy, the real-time operational efficiency of the system was also assessed in terms of training time, prediction latency, accident detection time, GPS localization accuracy, time for sending emergency alert and successful notification rate. The metrics were used to measure the capacity of the system to ingest the incoming sensor data, detect accident events with minimum delay, accurately locate the accident and alert hospitals, ambulance services, police authorities and emergency contacts in a fast manner. The comparative analysis of Random Forest, XGBoost, Multi-Layer Perceptron (MLP) and GraphSAGE Graph Neural Network (GNN) showed that graph based learning approach is superior in detection performance, effectively capturing the complex relationship among sensor readings and driving conditions, with low false alarm rates. Experimental results demonstrate that the proposed framework has high prediction accuracy, fast emergency response, robust real-time performance, and reliable automated accident management, and can be deployed on intelligent transportation systems and smart city infrastructures.

Table 2. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Random Forest	95.42	94.87	94.21	94.54	0.962

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
XGBoost	96.58	96.14	95.83	95.98	0.974
MLP	94.76	94.12	93.81	93.96	0.951
GraphSAGE GNN (Proposed)	98.21	98.05	97.84	97.94	0.991

Discussion

The performance of machine learning models tested for real-time accident detection is presented in Table 2. We proposed the GraphSAGE Graph Neural Network (GNN) which achieved the best performance with an accuracy of 98.21%, precision of 98.05%, recall of 97.84% and an F1-score of 97.94%. The graph-based learning approach has better performance that can capture the relationship between adjacent data samples, thus leading to more reliable accident classification. XGBoost also exhibited good predictive power with an accuracy of 96.58%. Random Forest and MLP are comparable in performance. Experiments show that graph-based learning can improve the accuracy of accident detection and reduce false alarms in general, over conventional machine learning methods.

Table 3. Real-Time Emergency Response Performance

Performance Metric	Observed Value
Average Accident Detection Time	0.84 seconds
GPS Location Accuracy	98.73%
Emergency Alert Transmission Time	1.27 seconds
Notification Success Rate	99.15%
False Alarm Rate	1.46%
System Response Time	2.11 seconds
Average Processing Time per Record	0.19 seconds

Discussion

The operation of the proposed automated emergency response system is summarized in Table 3. This technology can be utilized for real time applications and it can detect accidents with average time of 0.84 sec. The GPS location assisted the emergency personnel to find the exact area of the incidents with an accuracy of 98.73 % . The emergency notification module obtained a successful notification delivery rate of 99.15% with an alert delivery time of less than 1.27 seconds. Moreover, the system achieved a low false alarm rate of 1.46% which shows the efficiency of the system in distinguishing between the real accidents and the normal driving situations. The total response time of the proposed framework is 2.11 s which suggests that the proposed framework can efficiently process the sensor data and can automatically recognize the accident events and prompt emergency help. It is especially useful for intelligent transportation system and smart city emergency management.

3.3 Discussion of Results

Intelligent Real Time Accident Detection and Automated Emergency Response System works with the approaches of machine learning, graph Based learning, IoT sensors and GPS technology for accurate real time accident detection and emergency response at speed. The experimental findings illustrate the efficiency of the suggested system. This is because the best model was the Graph SAGE Graph Neural Network (GNN) in all levels . GNN outperformed the traditional Machine Learning algorithms in terms of inaccuracy, precision, recall, f 1 score and AUC. It can learn intricate link between vehicle dynamics and accident pattern. The differentiation of normal driving situations such as hard braking and fast turning from true accident events is quite successful with almost no false alarms. The automatic emergency response module showed greater operating efficiency, being able to restrict false alarms, to eliminate some delays and to ensure notification rates above 97%. The results show that the integration of intelligent data analytics and automated communication can significantly influence the enhancement of the effectiveness of the road safety management and the decrease of the response time in emergency situations. Hence, the proposed framework provides a feasible and scalable approach for implementation in the context of the ITS and smart city networks as the necessity for quick detection of accidents and providing immediate emergency aid is of utmost importance to reduce accidents and improve safety.

3.4 Comparative Analysis and Insights

The comparative evaluation of the implemented models shows appreciable differences in their capabilities in the accurate detection of road accidents and emergency response in real time. The traditional machine learning algorithms yielded stable and correct classification with good performance, but lacked the capacity to express complicated relationships among sensor readings and driving conditions compared to their counterparts. Because of their ability to deal with nonlinear feature interaction and to decrease classification errors, XGBoost showed increased predictive accuracy and their robustness. The proposed Graph SAGE Graph Neural Network (GNN) achieved the best performance across all the evaluation metrics (accuracy, precision, recall, F1 score and AUC) and had the least Amount of false alarms while being the fastest model to respond to traffic accidents. The reasons behind the superior performance is its graph-based learning mechanism that takes advantage of the structural relation between the accident records but does not look at each accident observation individually. The experimental results revealed that the combination of GNN, sensor data from the IoT, GPS data, and an integrated emergency communication platform has significantly increased the reliability of accident detection, reduced the delay in responding to an emergency, and increased the general scalability of the system. Based on these findings, graph-based AI shows great potential in the design of future transportation systems that will enable real-time precise accident detection and effective management in the event of an accident.

3.5 Summary of Findings

The results of this research work show that the proposed innovative Accident Detection and Automated Emergency Response System can be used in interconnected functions of artificial intelligence, machine learning, Internet of Things (IoT) sensors, global positioning system (GPS) technology and automated communication as a good solution to enhancing road safety. The developed framework was able to correctly classify the events in the accident and normal driving scenarios with a low false alarm rate and high prediction accuracy. The Graph SAGE Graph Neural Network (GNN) model was found to be the most accurate in terms of the implemented models, providing better results than Random Forest, XGBoost, and Multi-Layer Perceptron (MLP) for the accuracy, precision, recall, f1 score and AUC. The system was also shown to have outstanding real-time functionality; by rapidly detecting accidents before them, to accurately identify where an accident had occurred and to automatically issue of emergency notifications to hospitals, ambulance, police and emergency contact. These findings validate that intelligent data analysis and automated emergency response play a key role in reducing the detection and notification delay, improve emergency decision-making ability and aid in building up a safer and smarter ITS.

4. CONCLUSION AND SCOPE:

The proposed Intelligent Real-Time Accident Detection and Automated Emergency Response System (IRTADE) Provides a glimpse into the capabilities of integrating artificial intelligence, machine learning, graph neural networks, IoT sensors, GPS, and automated communication to enhance road safety and emergency response. The system is constantly monitoring the vehicles' behaviour and analyzing the data received from the sensors in real time, to detect accident events with precision and minimize false alarms. It also instantly triggers emergency alarms and the crash location and incident information help hospitals, the ambulance service, the police and loved ones respond faster to provide prompt medical aid. We compare the Graph SAGE Graph Neural Network (GNN) model with state-of-the-art machine learning algorithms . These algorithms can predict driving performance in a static situation with high accuracy . The comparative study demonstrates the effectiveness of graph-based learning for real-time accident detection and the Graph SAGE Graph Neural Network (GNN) model outperforms traditional machine learning algorithms in terms of predictive accuracy. The proposed architecture provides a robust, scalable and efficient solution for the deployment of ITS and the improvement of public safety in general.

The project aims to extend beyond accident detection, to next generation smart transportation and emergency response applications. Future work may involve 5G-enabled vehicle-to-everything (V2X) and fully autonomous car technology, edge computing to support ultra-low latency data handling and further development of deep learning-based algorithms that can assess accident severity from the live video feed. The system can be extended to incorporate wearable devices for post crash health evaluation of the passengers and cloud based health monitoring for macro level monitoring of traffic flows for accident prediction .

In addition, the combination of meteorological data, information on the road infrastructure and intelligent traffic management systems can increase the accuracy of weather predictions and can also enable pre-emptive steps to be taken to prevent accidents. These advances will be critical to the development of safer, connected and fully intelligent transportation systems, making emergency responders more efficient, reducing so many accident deaths and working towards the smart city sustainable vision.

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