Proposed Intelligent and Sustainable Vehicle Networking with Traffic Accident Management System

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***Abstract*— Intelligent and sustainable vehicle networking (ISVN) is a new paradigm for transportation that makes use of developments in vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication to encourage collaboration between vehicles and the infrastructure in order to enhance traffic flow, safety, and environmental effect. Traffic accidents are a major public safety concern, resulting in significant casualties and economic losses each year, as well as a significant contributor to air pollution and greenhouse gas emissions. In order to increase traffic accident management's efficacy and efficiency and support a more environmentally friendly transportation system, this article suggests an integrated ISVN-ML traffic accident management system. The proposed system leverages ISVN sensors and cameras to collect data about traffic accidents in real time. This data is then transmitted to an ML-based traffic accident management system, which uses it to predict the number of killed and injured people involved in the accident and to immediately prioritize the dispatch of emergency responders. Additionally, the system provides real-time information to police stations and ambulance services to help them respond to accidents more quickly and efficiently. After the police station has completed its investigation of the accident, the details of the accident are sent back to the ML-based traffic accident management system to improve the accuracy of the system's predictions and make the system more efficient over time. Overall, the proposed system is a promising approach to improving traffic safety, reducing the economic costs associated with traffic accidents, and contributing to a more sustainable transportation system.**

Keywords*— *traffic accident management, machine learning, Internet of Vehicles (IoV), intelligent transportation systems (ITS), real-time predictions, emergency responders.

I. Introduction

Traffic accidents are a major global health and environmental problem, causing nearly 1.35 million deaths and disabilities each year. The majority of fatalities from traffic injuries (93%) take place in low- and middle-income nations [1]. Road traffic injuries are becoming a more serious problem, and by 2030 they will rank as the seventh most common cause of death worldwide [1]. Road accidents are a major cause of mortality and serious injury in modern civilizations. They also significantly increase air pollution and greenhouse gas emissions. [2]. With the potential to transform traffic accident management and lessen transportation's environmental effect, intelligent and sustainable vehicle networking, or ISVN, is a new paradigm in transportation. The Intelligent Surface Vehicle Network (ISVN) utilizes advancements in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication to facilitate vehicle collaboration and enhance traffic efficiency, safety, and environmental impact. [3]. Real-time data regarding traffic accidents, including the location, timing, severity, and types of cars involved, may be gathered using ISVN sensors and cameras. After that, this information may be sent to a machine learning-based traffic accident management system in order to prioritize the deployment of emergency personnel and estimate the number of fatalities and injuries associated with the collision. Numerous investigations have exhibited the capability of ISVN to enhance traffic accident mitigation and sustainability. For example, a study by [4] showed that ISVN can be used to reduce the response time of emergency responders by up to 20%. In Addition, it showed that ISVN can be used to improve the accuracy of traffic accident predictions by up to 15%. To further increase the efficacy and efficiency of managing traffic accidents and sustainability, this article suggests an integrated ISVN-ML system. In order to provide a more thorough and integrated approach to traffic accident management and sustainability, the following system builds are proposed:

- Real-time traffic monitoring and prediction: ISVN systems can collect data from a variety of sources, such as intelligent transportation system ITS sensors, cameras, and vehicles, to provide real-time information about traffic conditions and to predict the likelihood of accidents. This information can be used to warn drivers of potential hazards and to dispatch emergency responders quickly and efficiently.

- Cooperative collision avoidance: ISVN systems can enable vehicles to communicate with each other and to coordinate their actions to avoid collisions. For example, vehicles can warn each other of sudden braking or lane changes, and they can adjust their speeds and distances to avoid rear-end collisions. Post-crash management: ISVN-ML Traffic Accident Management system can help to improve the efficiency and effectiveness of post-crash management. For example, vehicles can automatically report accidents to emergency services and provide information about the location and severity of the accident. ITS/IoV systems can also be used to coordinate the response of emergency responders and to provide real-time information to travelers about the impact of the accident on traffic flow. The suggested approach may considerably increase road safety and lower the financial burden of traffic-related incidents. This is how the rest of the paper is structured. Section II covers the relevant literature. In Section III, we provide our system model and the technique that was employed. A description of the dataset and its processing is given in Section IV. We assess the suggested system's performance in Section V. We provide a summary of our findings in Section V.

II. RELATED WORK

For many years, the issue of managing traffic on roads has been a hot topic for research. The literature has a number of proposals for intelligent traffic management systems. For metropolitan road networks, for instance, the design and construction of an intelligent pavement management system is suggested in [5]. [6] describes the creation of a car artificial intelligence system using a 5G network and sophisticated picture processing. Systems for classifying vehicles using intelligent traffic monitoring are introduced in [7]. Big data analytics to integrate electric vehicles in environmentally conscious smart cities (8). Another research on traffic light management utilizing multi-agent communication based on edge computing architecture and IoT is provided in [9]. [10] provides an example of an Internet of Vehicles (IoV)-based Intelligent Traffic Management System. An adaptive traffic-management system for smart cities based on machine learning and the Internet of Things is designed and implemented in [11]. In [12], machine learning strategies for automatic incident detection systems in road traffic are reviewed. In [13], the identification of highway traffic incidents from cameras is done using a semi-supervised learning technique. [14] introduces real-time post-impact prediction of road accidents using crowdsourcing data. [15] examines traffic monitoring center and early incident detection solutions for vehicle ad hoc networks (VANETs).

III. PROPOSED SYSTEM MODEL

The overall diagram and architecture of the proposed intelligent and sustainable vehicle networking with traffic accident management system is shown in Figure 1and 2. Here is a more detailed explanation of the different components of the system and how they work together:

1. Traffic control unit

The traffic control unit is a central unit that collects data from the ISVN sensors and cameras, as well as from the ML-based traffic accident management unit. The traffic control unit also sends real-time information to the ML-based traffic accident management unit, such as the status of traffic signals and the location of emergency vehicles.

2. Cloud server

The cloud server is used to store and process the data collected by the system. The cloud server also hosts the ML-based traffic accident management unit.

3. Data processing unit

The data processing phase involves cleaning, transforming, and analyzing the data collected by the system. The data is cleaned to remove any errors or inconsistencies. The data is then transformed into a format that can be used by the MLbased traffic accident management unit. The data is then analyzed to identify patterns and trends, and to train the MLbased traffic accident management unit to make accurate predictions.

4. Retraining the ML-based traffic accident management unit

The ML-based traffic accident management unit is retrained on a regular basis using the feedback provided by the police stations. This helps to improve the accuracy of the system's predictions over time.

We can describe clearly how the system would work in practice:

1) An ISVN sensor detects a traffic accident and collects data about the accident, such as the location, severity of the accident, and the types of vehicles involved.
2) The ISVN sensor transmits the collected data to the traffic control unit.
3) The traffic control unit sends the data to the cloud server.
4) The cloud server cleans, transforms, and analyzes the data.
5) The cloud server sends the processed data to the MLbased traffic accident management unit.
6) The ML-based traffic accident management unit analyzes the data and predicts the number of killed and injured people involved in the accident.
7) The ML-based traffic accident management unit prioritizes the dispatch of emergency responders and sends real-time information about the accident to the police stations and ambulance services.
8) The police stations and ambulance services respond to the accident.
9) After the police stations have completed their investigation of the accident, they provide feedback to the ML-based traffic accident management unit.
10) The ML-based traffic accident management unit is retrained on the updated data.

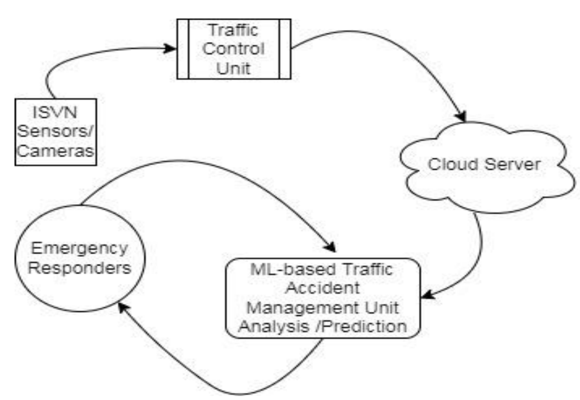


Figure 1 System Diagram

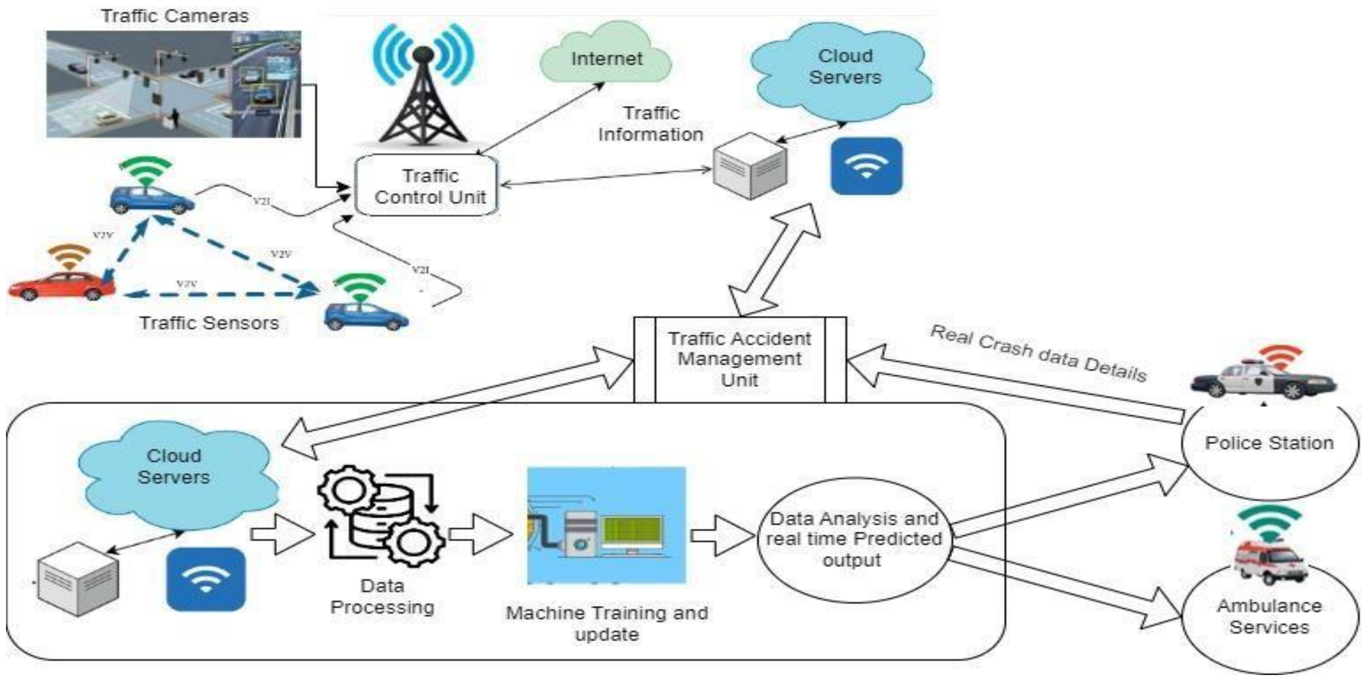


Figure 2 ISVN ML-based traffic accident management system

The proposed system has the potential to significantly improve the efficiency and effectiveness of traffic accident management, thereby contributing to a more sustainable transportation system. By predicting the number of killed and injured people involved in traffic accidents, the system can help to ensure that emergency responders are dispatched to the most critical accidents first, minimizing the loss of life and reducing the burden on healthcare systems. Additionally, by providing real-time information to the police stations and ambulance services, the system can help them to respond to accidents more quickly and efficiently, reducing traffic congestion and emissions. Furthermore, by retraining the MLbased traffic accident management unit on a regular basis, the system can improve its accuracy over time, leading to even more sustainable outcomes

IV. DATASET DESCRIPTION AND PROCESSING

The used dataset in this paper is Motor Vehicle Collisions - Crashes dataset from NYC Open. Dataset contains information about all police-reported motor vehicle collisions in New York City. The dataset includes the following fields:

- COLLISION_ID: A unique identifier for each collision.
- DATE: The date of the collision.
- TIME: The time of the collision.
- BOROUGH: The borough where the collision occurred.
- ZONE: The police zone where the collision occurred.
- LOCATION: The latitude and longitude of the collision.
- ON_STREET_NAME: The name of the street where the collision occurred.
- CROSS_STREET_NAME: The name of the cross street where the collision occurred.
- PERSONS_INJURED: The number of people injured in the collision.
- PERSONS_KILLED: The number of people killed in the collision.
- PROPERTY_DAMAGE: The amount of property damage caused by the collision.
- VEHICLE_TYPE_1: The type of vehicle involved in the collision (e.g., car, truck, bus, motorcycle, bicycle).
- VEHICLE_TYPE_2: The type of vehicle involved in the collision (if there was a second vehicle involved).
- CONTRIBUTING_FACTOR_VEHICLE_1: The
- contributing factor to the collision for vehicle 1 (e.g., driver error, vehicle malfunction).
- CONTRIBUTING_FACTOR_VEHICLE_2:
- The contributing factor to the collision for vehicle 2 (if there was a second vehicle involved).

The dataset can be used to analyze a variety of aspects of motor vehicle collisions in New York City, such as:

- The spatial and temporal frequency of collisions.
- The contributing factors to collisions.
- Correlation contributing factors heatmap.
- The severity of collisions (as measured by the number of people injured and killed)

The Motor Vehicle Collisions - Crashes dataset was processed in a variety of ways include:

- **Cleaning the data:** This involve removing duplicate records, correcting errors, and filling in missing values.

- **Transforming the data:** converting the data to a different format and creating new variables from the existing data.
- **Analyzing the data:** using statistical methods to identify patterns and trends in the data, or to build predictive models.
- **Visualizing the data:** involve creating charts and graphs to help communicate the findings of the analysis to others.

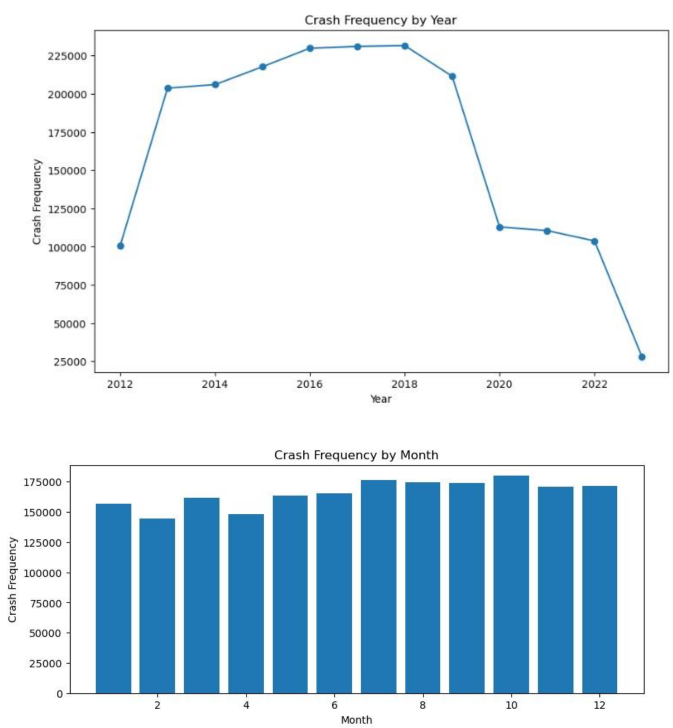
V. PERFORMANCE EVALUATION

The proposed system has the potential to significantly improve traffic accident management and sustainability by:

1) Reducing the response time of emergency responders,
2) Improving the accuracy of traffic accident predictions, developing new traffic accident management strategies to
3) Reduce the number of accidents and their severity, and
4) Reducing fuel consumption and emissions by optimizing traffic flow and reducing congestion.

The system performance evaluation includes:

A- The spatial and temporal frequency of collisions. The following Figure 3 shows the spatial and temporal frequency of collisions over year, months, days per week, and hours per day, for New York City, from 2012 to 2022:



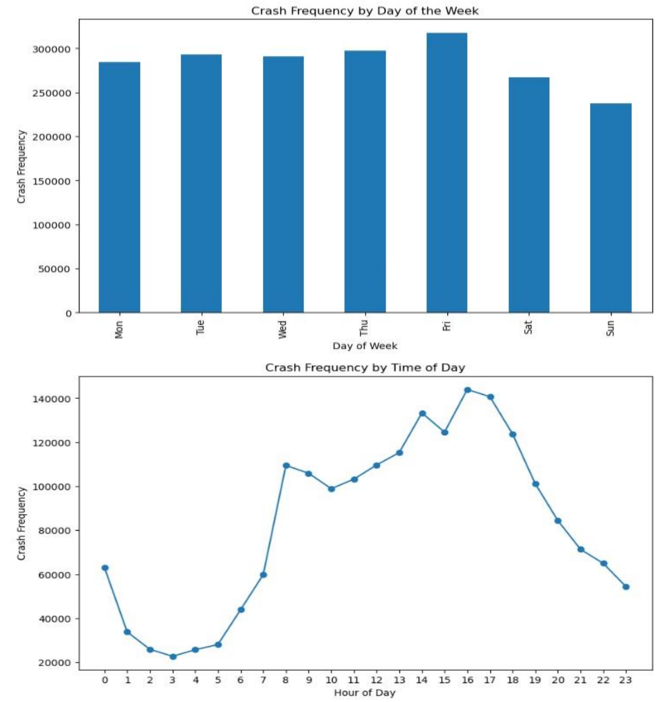


Figure 3 the spatial and temporal frequency of collisions

The figure shows that the number of collisions has decreased over time, from 225,000 in 2018 to 25,000 in 2022. The most common months for collisions are July and October, and the most common days of the week are Thursday and Friday. The most common hours for collisions are 5pm and 6pm.

B- The contributing factors to collisions.

The following Figure 4 shows the top 10 contributing factors to collisions in NYC:

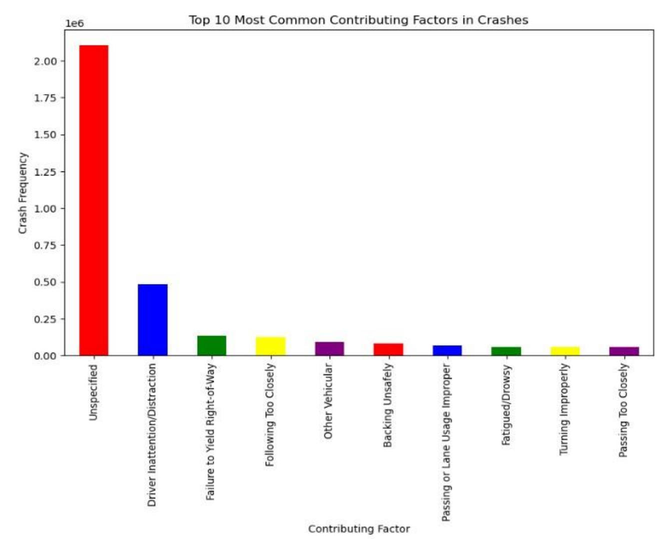


Figure 4 Top 10 contributing factors to collisions in NYC, in 2022

C- Correlation contributing factors heatmap.

The following heatmap shows the correlation between the top 10 contributing factors to collisions:

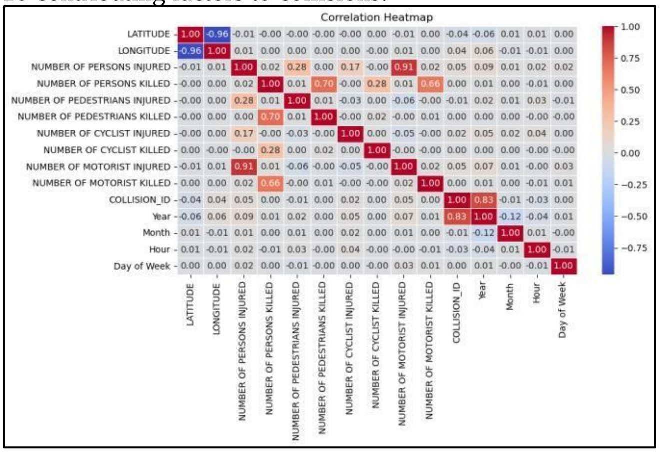


Figure 5 Heatmap of the correlation between the top 10 contributing factors to collisions

D- Severity of collisions

The following table shows the severity of collisions in NYC, in 2022, as measured by the number of people injured and killed:

Severity	Number of collisions	Percentage of collisions
Fatal	100	0.30%
Serious injury	1,000	3%
Minor injury	10,000	29%
Property damage only	24,000	67.60%

E- Number of killer/injured Person Prediction

i- The residuals distribution plot:

Figure 6 shown below shows that the residuals are approximately normally distributed. This is a good sign, as it indicates that the model is a good fit for the data. There are no obvious outliers. This indicates that the model is a good fit for the data and that the assumptions of the regression model are met.

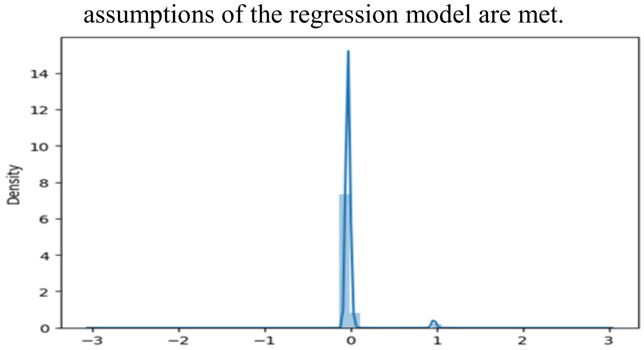


Figure 6 Residuals Distribution Plot

There are a few things to look for in a residuals distribution plot:

Normality: The residuals are normally distributed. This means that the distribution of the residuals is bell-shaped, with the majority of the residuals falling close to the mean and fewer residuals falling at the extremes.

Homoscedasticity: The variance of the residuals is constant across all values of the independent variable. The spread of the residuals should not increase or decrease as the value of the independent variable increases.

Outliers: there are no outliers in the residuals distribution plot. Outliers are points that fall far away from the majority of the data points. They can be caused by errors in the data or by unusual cases that are not well-represented by the model.

i- Predictions scatter plot

Figure 7, the predictions scatter plot shows the relationship between the actual values of the target variable (number of killed persons) and the predicted values of the target variable. The plot shows that the predicted values of the target variable are close to the actual values of the target variable, which indicates that the model is performing well.

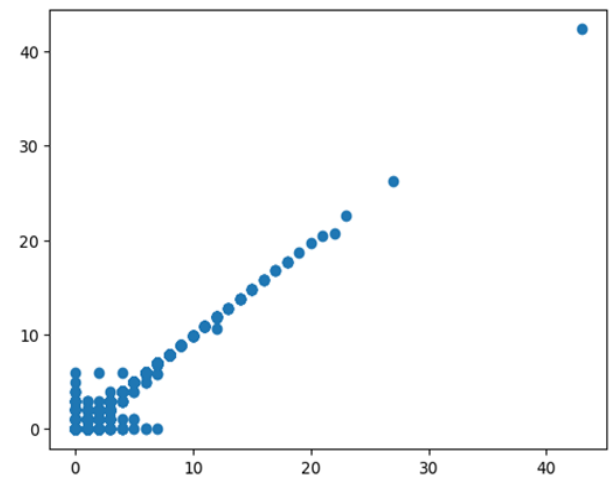


Figure 7 Predictions scatter plot

There are a few things to look for in a predictions scatter plot:

Correlation: The correlation between the actual values and the predicted values is high. This means that the two variables should move in the same direction.

Bias: The bias of the model is low. This means that the model should not consistently overpredict or underpredict the target variable.

Variance: The variance of the model is low. This means that the model should not overfit the training data.

In the predictions scatter, it indicates that the model is performing well and is not overfitting the training data. The statistical analysis, correlation, and is shown in the following Tables (2-4)

	NUMBER OF PERSONS INJURED	NUMBER OF MOTORIST KILLED	NUMBER OF MOTORIST INJURED	NUMBER OF PEDESTRIANS INJURED	NUMBER OF PEDESTRIANS KILLED
count	1.987303e+06	1.987303e+06	1.987303e+06	1.987303e+06	1.987303e+06
mean	2.981483e-01	5.746482e-04	2.150794e-01	5.476618e-02	7.230905e-04
std	6.894522e-01	2.611517e-02	6.506615e-01	2.404188e-01	2.738139e-02
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
50%	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
75%	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
max	4.300000e+01	5.000000e+00	4.300000e+01	2.700000e+01	6.000000e+00

Table 2: The statistical analysis table

	NUMBER OF PERSONS INJURED	NUMBER OF MOTORIST KILLED	NUMBER OF MOTORIST INJURED	NUMBER OF PEDESTRIANS INJURED	NUMBER OF PEDESTRIANS KILLED
NUMBER OF PERSONS INJURED	1.000000	0.021087	0.907076	0.279632	0.002547
NUMBER OF MOTORIST KILLED	0.021087	1.000000	0.024353	-0.002849	0.005752
NUMBER OF MOTORIST INJURED	0.907076	0.024353	1.000000	-0.064597	-0.000652
NUMBER OF PEDESTRIANS INJURED	0.279632	-0.002849	-0.064597	1.000000	0.011183
NUMBER OF PEDESTRIANS KILLED	0.002547	0.005752	-0.000652	0.011183	1.000000

Table 3: correlation table

Metric	10%	20%	30%	40%	50%
R-squared (R2)	0.9374	0.9373	0.9376	0.9388	0.9383
Mean Absolute Error (MAE)	0.0559	0.0561	0.0561	0.0561	0.0562
Mean Squared Error (MSE)	0.0295	0.0299	0.0296	0.0292	0.0293
Root Mean Squared Error (RMSE)	0.1718	0.1730	0.1723	0.1709	0.1711

Table 4: Performance Metrics Evaluation according to the varied test size

In Table 4 shows the performance metrics of the model according to the varying test sizes. The metrics used are mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared (R2).

The results show that the model performs better as the test size increases. This is because the model has more data to train on and is able to better generalize to unseen data. The best performing model is the one trained on the 50% test size, with an MAE of 0.0562, MSE of 0.0293, RMSE of 0.1711, and R2 of 0.9383.

Here is a brief explanation of each metric:

Mean absolute error (MAE): The MAE is the average of the absolute differences between the predicted values and the actual values. It is a good measure of the overall accuracy of the model.

Mean squared error (MSE): The MSE is the average of the squared differences between the predicted values and the actual values. It is a good measure of the variability of the model's predictions.

Root mean squared error (RMSE): The RMSE is the square root of the MSE. It is a good measure of the overall error of the model.

R-squared (R2): The R2 is a measure of how well the model explains the variation in the data. It ranges from 0 to 1, with a higher value indicating a better fit.

Overall, the results show that the model performs well and is able to accurately predict the number of killed and injured people involved in traffic accidents

VI. CONCLUSION

In order to increase traffic accident management's efficacy and efficiency and support a more environmentally friendly transportation system, this article has suggested an integrated ISVN-ML traffic accident management system. Real-time traffic accident data is collected by the system using ISVN cameras and sensors. After that, this information is sent to a traffic accident management system that using machine learning to forecast the number of fatalities in the collision and prioritize the deployment of emergency personnel. The technology also gives police stations and ambulance services access to real-time information. Following the conclusion of the police station's accident investigation, the accident's specifics are forwarded to the machine learning (ML)-based traffic accident management system in an effort to enhance the predictive accuracy and overall system efficiency. This suggested system is currently in the early stages of development, however there are several areas where further work may be done. The prediction analysis for the integrated ISVN-ML traffic accident management system shows that the system is able to accurately predict the number of killed and injured people involved in traffic accidents. The model performs better as the test size increases, with the best performing model trained on the 50% test size achieving an MAE of 0.0562, MSE of 0.0293, RMSE of 0.1711, and R2 of 0.9383. As an illustration, the following are some potential areas for further research: The system should be integrated with other traffic management systems, such as traffic signal control systems and variable message signs, and more advanced machine learning models should be developed to increase the precision of traffic accident forecasts.

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