Deep Learning-Based Traffic Accident Prediction: An Investigative Study for Enhanced Road Safety

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Abstract

INTRODUCTION: Traffic accidents cause enormous loss of life as well as property, which is a global concern. Effective accident prediction is essential for raising road safety and reducing the effects of accidents. To increase traffic safety, a deep learning-based technique for predicting accidents was developed in this research study.

OBJECTIVES: It gathers a large amount of data on elements including weather, road features, volume of traffic, and past accident reports. The dataset goes through pre-processing, such as normalization, to ensure that the scales of the input characteristics are uniform. Normalizing the gathered dataset ensures consistent scaling for the input features during the data processing step. This process enables efficient model training and precise forecasting. In order to track and examine the movement patterns of automobiles, people, and other relevant entities, real-time tracking and monitoring technologies, such as the deep sort algorithm, are also employed.

METHODS: The model develops a thorough grasp of the traffic situation by incorporating this tracking data with the dataset. Convolutional Neural Networks (CNN), in particular, are utilized in this research for feature extraction and prediction. CNNs capture crucial road characteristics by extracting spatial features from images or spatial data. With its insights into improved road safety, this study advances the prediction of traffic accidents.

RESULTS: A safer transport infrastructure could result from the developed deep learning-based strategy, which has the potential to enable pre-emptive interventions, enhance traffic management, and eventually reduce the frequency and severity of traffic accidents.

CONCLUSION: The proposed CNN demonstrates superior accuracy when compared to the existing method.

1. Introduction

Cars have increasingly become a part of every home as a result of the ongoing development in people's living conditions and the growing number of urban highways. Without doubt, utilizing a car for daily transportation has become a necessity. The issues with controlling traffic are becoming more and more obvious in the context of the quick expansion of contemporary mobility due to the stark disagreements among individuals, cars, and roadways. Every year, numerous individuals lose their lives in road collisions [1]. The World Health Assembly has issued life-loss statistics that show that a staggering number of disasters happen every year all across the globe.

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A projected increase in tourist injuries and an immediate financial burden of forty-three billion dollars endanger both human life and asset integrity. One crucial area of roadway security study is anticipating changes in the fate of pedestrians and cyclists [2].

The structural features of the avenue, the volume of attendees, driver considerations, and the road's boundary all have a significant impact on the frequency of collisions. However, as the network of automobiles develops, vehicles would be able to communicate with one another as well as base stations, pedestrians, and other vehicles to exchange data. This allows the vehicle section to be strongly tracked and managed in the network's design surroundings.

With the advent of the big data era comes the realisation that complete, highly accurate data could simultaneously represent current events and forecast the future. Deep learning has made it possible for machines to mimic the way that human brains learn. Convolutional Neural Networks are a type of machine learning framework that deep learning controls [2,3]. The likelihood of unknown events might be determined as long as there is an adequate amount of data, and these sets of information are learned by algorithms.

When vehicular networks and deep learning are combined, it is simple to analyse and foresee the data that is gathered in real-time, such as driver insight, information about the state of the roads, information about the weather, etc., and deliver the expected findings to the vehicle in motion employing edge calculation.

Reminding the driver to modify their speed in a timely manner and to be aware of their surroundings will help to reduce the likelihood of collisions while driving. This study builds a traffic accident prediction structure combining a convolutional neural network and a recurrent neural network in order to accurately anticipate people's road accidents. It outlines how to create a road-based traffic accident forecasting system that solely depends on the system that has been suggested.

This article is structured in the following manner: The review of the literature is explained in Section 2, the suggested strategy is explained in Section 3, the findings and discussions are explained in Section 4, and the work is concluded with a list of references.

2. Literature Survey

Theofilatos et al. [4] employed real-time traffic data from metropolitan arterial routes along with random forest and Bayesian logistic regression models to examine the probability of crashes involving vehicles. In a more recent study [5], researchers contrasted a number of deep learning and machine learning approaches, including K-Nearest Neighbour (KNN), classification trees, Naive Bayes, Random Forests, Support Vector Machine (SVM), Shallow Neural Networks, and Deep Neural Networks (DNN). They discovered that the method using deep learning generated the best outcomes, while other, less sophisticated approaches, like Naive Bayes, only slightly underperformed.

An approach to estimating traffic accident danger by employing a Long-Short Term Memory (LSTM) framework was proposed by *Ren et al.* [6], where risk is characterised as the quantity of accidents in an area at some point in time.

Utilising information from the previous seven days, the tests involved predicting locations for the following seven days. ConvLSTM performed better in terms of accuracy in forecasting than all baselines. Additionally, the algorithm accurately anticipated accidents that happened in the case study on December 8, 2013, during a severe snowfall. Road accident forecasting has been the subject of recent research reviews by *Gutierrez-Osorio et al.* [7].

The investigators discovered that while combining a variety of data sources of information, neural networks and deep learning techniques demonstrated great precision and reliability. It is also important to note that methods for data mining are employed most frequently in automobile accident data analysis with the aim of discovering variables that affect an accident's severity. As stated by *Das et al.* [8], data mining techniques like methods for clustering, categorization, and mining association rules, in addition to identifying different accident-prone regions, is very beneficial in assessing the different pertinent variables that contribute to collisions on the road.

Finding accident locations is a crucial component and frequently the initial step in studies on highway security. The outcomes could be worse as a result of identification errors in hotspots. The different popular Hotspot Identification approaches have been compared by *Montella et al.* [9].

The experimental Bayes approach, one of the techniques, has been shown to be the most dependable and reliable technique, outperforming the other Hotspot identification methods. With the help of a clustering approach and the accident's geographic coordinates, Szénási and Csiba's study [10] offers a replacement to the conventional HSID procedures.

The DBSCAN technique enables the detection of hotspots with shorter lengths and high accident frequency. Low-density regions would also be removed by the method. The authors employ a variety of evaluation criteria to assess the algorithm's effectiveness. Accuracy, sensitivity, precision, specificity, and false-positive rate, or FPR, are frequently utilised measures; however, *Roshandel et al.* [11] observed that few research utilise all of these metrics in order to fully assess their mathematical models. The author contends that any forecasting system must be verified through a variety of indicators.

3. Problem Statement

Traffic collisions continue to be a serious problem on a global scale, resulting in enormous loss of life and assets. Accidents continue to be a major worry despite considerable improvements in transport infrastructure and road safety measures. The inability to precisely forecast when and where accidents are likely to happen is a major problem. Traditional methods for predicting accidents frequently rely on statistical models that take into account past accident data as well as fundamental elements like traffic volume and road conditions.

The complex linkages and dynamic character of the contributing components cannot be captured by these methodologies, despite the fact that they do offer some insights. Their prediction powers are therefore constrained, making it difficult to take proactive steps to reduce accidents and improve road safety. In order to solve this issue, it is necessary to investigate more sophisticated systems that can efficiently analyse and make utilisation of the enormous amounts of accessible data to properly anticipate traffic accidents.

The ability of deep learning, a kind of machine learning, to automatically discover and extract significant patterns from complex data, has demonstrated promise in a number of fields. The objective of the research is to investigate the implementation of deep learning techniques for traffic accident prediction, with the goal of creating more precise and trustworthy models that could enhance traffic safety procedures.

4. Proposed Framework

The suggested framework includes a standardised method for predicting traffic accidents that includes data processing through normalisation, feature extraction using CNN, and tracking and monitoring methods employing the deep sort algorithm. To achieve uniform scaling across the features, the acquired dataset first goes through data processing, including normalization, which renders accurate analysis and model training possible. The deep sort algorithm for tracking and monitoring is then incorporated into the framework, allowing for the real-time identification and tracking of pertinent things like automobiles and pedestrians.

For the succeeding feature extraction procedures, this tracking data is an invaluable input. In order to capture the sequential patterns and relationships that underlie traffic accidents, subsequently employed to remove temporal features from the pre-processed data. CNNs are employed simultaneously to extract spatial features from spatial data or images, enabling the model to develop and identify relevant road characteristics or visual clues related to accidents. The proposed strategy performs better than the outcomes of the current approaches. The suggested system's process is depicted in Figure 1.

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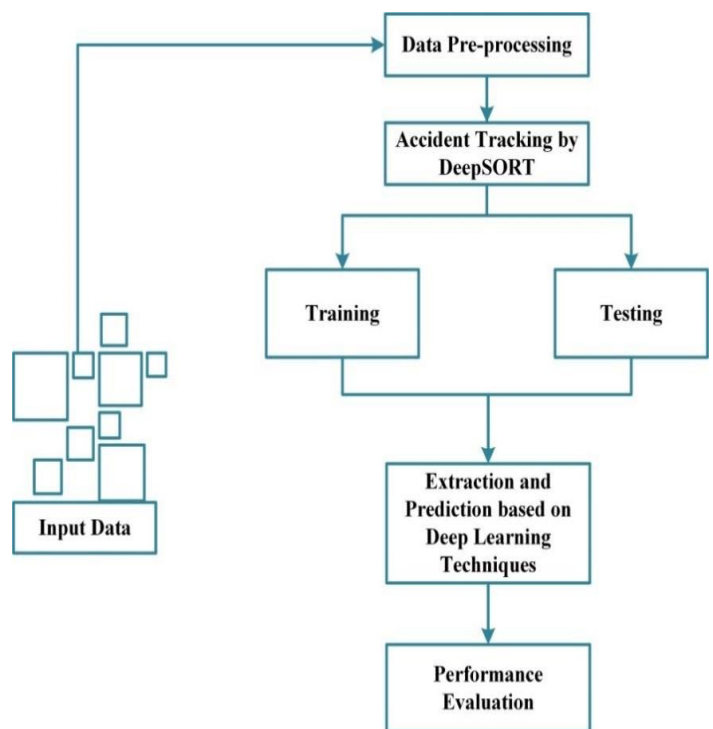

Figure 1. This Process flow of the proposed system

4.1 Data Collection

The important information pertaining to weather conditions, road parameters, vehicle information, and historical accident records is included in the proposed database for traffic accident prediction. It consists of structured tables that record

particular elements of the dataset, such as weather variables (temperature, precipitation, and visibility), road characteristics (road type, speed limit, signage), vehicle characteristics (vehicle type, age, and speed), and historical accident records (accident location, severity, contributing factors, and casualties). The database offers a thorough resource for examining the connections between these parameters and forecasting traffic accidents by integrating these diverse datasets. This collected data could assist with research projects, make it easier to create reliable accident prediction models, and provide information for initiatives to improve general road safety [12].

Table 1: Overview of the data collection [12]

Accident ID	Weather Condition	Road Characteristics	Time of day	Historical Accident Records
1	Clear	Straight road	Morning	0
2	Rainy	Curved road	Afternoon	1
3	Snowy	Intersection	Evening	2
4	Foggy	Highway	Night	3
5	Clear	Straight road	Morning	1
6	Rainy	Curved road	Afternoon	2
7	Snowy	Intersection	Evening	1
8	Foggy	Highway	Night	0
9	Rainy	Straight road	Morning	2
10	Snowy	Curved road	Afternoon	3

- **Accident ID:** A unique identifier for each accident.
- **Weather Condition:** Describes the weather condition at the time of the accident (e.g., clear, rainy, snowy, foggy).
- **Road Characteristics:** Describes the characteristics of the road where the accident occurred (e.g., straight road, curved road, intersection, highway).
- **Time of Day:** Indicates the time of day when the accident took place (e.g., morning, afternoon, evening, night).
- **Historical Accident Records:** Represents the number of previous accidents recorded at the same location.

4.2 Data Preprocessing

For categorization, the normalization type of pre-processing is essential. The input data should be normalized to speed up the learning process. Furthermore, to avoid numerical problems like accuracy loss due to arithmetic errors, some sort of data normalization may be necessary. Following initially outweighing features with originally lower ranges,

characteristics with initially big ranges would take over a gradient descent. Feature space normalization might be considered a kernel impression of pre-processing rather than, strictly speaking, a type of pre-processing because it is not introduced externally to the input matrices. In other words, by transforming the data into a usable plane, normalization is a distinct kernel mapping approach that simplifies calculations. Given the enormous amount of data points, the complex normalization algorithm requires an extended period for processing. The Min-Max normalization technique that was selected is fast and efficient.

By using Min-Max Normalisation, the real data m is translated straight into the required interval as given in equation (1) (max_{new}, min_{new}).

$$m = min_{new} + (max_{new} - min_{new}) * \left(\frac{m - min_x}{max_x - min_x} \right) \quad (1)$$

The method's advantage is that it maintains every connection among the data points precisely.

4.2.1 Missing value imputation

To handle missing values in the parameters of weather conditions, road characteristics, time of day, and historical accident records, various imputation techniques can be applied. For weather conditions and road characteristics, categorical features, missing values can be imputed using mode imputation, where the most frequent value is assigned. Time of day, another categorical feature, can also be imputed using mode imputation.

For the numerical feature of historical accident records, mean or median imputation can be used to fill in the missing values based on the central tendency of the data. By applying these imputation techniques, the missing values in the dataset can be addressed, ensuring a complete and usable dataset for subsequent analysis and modelling tasks.

4.3 Accident Tracking based on Deep sort

The IOU tracker makes the assumption that each component is monitored once every frame, with minimal to no lag time among identifications. Similar to this, when identifying an item in subsequent structures, the IOU estimates a greater overlapping value for an intersection across connections [29]. The IOU metric computation that serves as the foundation for this method is provided in the equation (2).

$$IOU(m, n) = \frac{K(z) \cap A(y)}{K(z) \cup A(y)} \quad (2)$$

The greatest IOU rating from Equation (1) is employed to track entities if the IOU tracker fails to exceed a predetermined threshold.

Considering the goal of this research is to monitor objects, cancelling traces that fail to meet a predetermined threshold time length and where zero observed objects exceed the necessary IOU threshold may enhance IOU efficiency. The effectiveness of training models for object detection ought to be given special attention because the IOU monitor depends heavily on how reliably object recognition classifiers identify items.

A very potent object tracker, the IOU could handle rates of motion of up to 50,000 frames per second and has a minimal computing expense. Users could skip images while still following the component due to the Kalman filter's predictive power. The detection system could accelerate up the procedure by discarding frames, and dropping lesser frames lowers the computational expense. Algorithm 1 illustrates the IOU tracking mechanism.

4.3.1. Deep Sort

In order to monitor numerous objects, Deep-Sort, a deep learning variant of the straightforward digital real-time tracker method blends view data with monitoring elements [13].

For monitoring, Deep Sort combines the Kalman filter and the Hungarian procedure. The Hungarian method utilizes a relational factor which estimates bounding box overlay to simplify frame-by-frame information linkages while Kalman filtering is applied to the picture's region.

After gathering movement and appearance data, a trained deep learning is employed.

By including deep learning, the detector acquires more resistance to object misses and occlusions while maintaining its capacity to operate fast and in real-time situations online. Six Wide Residual Blocks are deployed after the initial two layers of a big leftover system. A 128-dimensional global map of characteristics is produced in dense layer Ten.

Finally, the measure of hyper sphere accessibility suitability with the cosine arrival measure is discovered to have aggregate and l2 normalization features. To determine the minimal cosine difference among tracks and findings, the collected characteristics are employed. Through cascade pairing, the distance calculated by Mahalanobis is additionally used to find differences. As a whole, Deep sort is a highly flexible tracker that could compete in terms effectiveness with other state-of-the-art monitoring techniques.
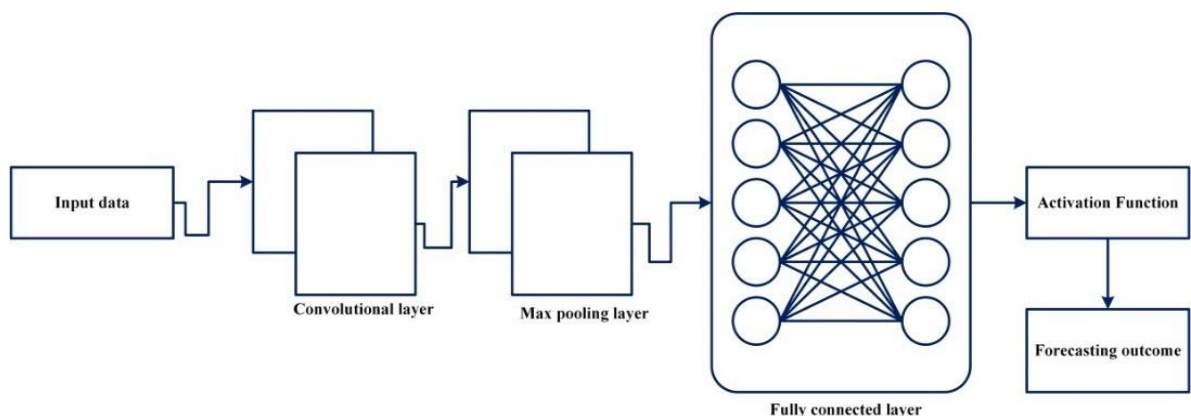

Figure 2. Architecture of CNN

The layer of convolution incorporates a number of kernels to produce the tensor type of characteristic transformations. These kernels organize the whole source using "stride(s)" and provide the resultant measurements that are integer sized. The specifications of source volumes for the layers of convolution gradually decrease after the striding procedure.

Zero padding is required to encircle a source volume with zeros for the purpose to preserve the dimensions of an intake volumes with minimal characteristics. The operation of the convolutional layer's functionality is explained as follows in equation (3):

$$K(u,v) = (I \times W)(x,y) = \sum \sum I(x+g, y+h)W(g,h) \tag{3}$$

In this formula, I stand for the input matrix, K for a two-dimensional filter with a size of g, h, and W for the output of a 2D characteristic map. $I * W$ Stands for the convolutional layer's operation. The ReLU

4.4 Feature extraction by deep learning

Although a CNN is a particular type of multi-layered perceptron, in contrast to deep learning architecture, simple neural networks are unable to learn intricate characteristics. In numerous applications, including image categorization, recognition of objects and evaluation of medical images, CNNs have revealed exceptional performance. The basic idea underlying a CNN is that it can take regional attributes out of the highest-level inputs and pass them to deeper layers for more sophisticated characteristics. A CNN is made up of three layers: pooling, fully connected and convolutional. The aforementioned layers and a standard CNN design are illustrated in Figure 2.

A layer is employed for enhancing nonlinearity in feature maps. ReLU computes activation by maintaining a zero-threshold input. The following is how it is stated mathematically in equation (4):

$$h(x) = max(0, x) \tag{4}$$

The pooling layer down samples a specific source dimensions to reduce the overall number of variables. The most often used method, maximum pooling, produces the highest values in an input region. The FC layer is used as a classifier to categorize input from the pooling and convolutional layers, respectively.

5. Result and Discussion

The study used Traffic accident dataset, which was contrasted to the CNN, SVM, and KNN neural network systems in order to confirm the detecting effectiveness of the CNN model suggested in this research.

The outcomes demonstrate that the Proposed CNN neural network model represents improved traffic accident recognition. The experimental results of the suggested system are displayed below.

5.1. Performance Evaluation

5.1.1. Accuracy

The proportion of data that were correctly categorised in relation to all the data is known as accuracy. Accuracy has been used as an evaluation parameter for traffic data categorization in order to gauge the efficacy of the learning processes. The Accuracy metric counts the total number of flows across all classes that were accurately detected. Accuracy is expressed in equation (5)

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{5}$$

5.1.2 Precision

The percentage of texts accurately categorised as belonging to a category relative to all texts properly categorised as belonging to that class is known as precision. Since it is sensitive to incorrect classification, precision is in fact a crucial factor in TC results. Additionally, incorrect categorisation produced less precise findings. Precision is expressed in equation (6)

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{6}$$

5.1.3 Recall

Recall is calculated by dividing the total quantity of texts that genuinely belonged to the class by the amount of data that were accurately allocated to the class. The number of texts that aren't assigned to a certain class is known as the true negative (T_{POS}). False negative (F_{Neg}) refers to the proportion of texts that are wrongly categorised into a particular class. False positives (F_{POS}) show how many data were mistakenly categorised for a particular class, while true positives (T_{POS}) show how many texts in a given class were correctly detected. Recall is expressed in equation (7)

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{7}$$

5.1.4. 1-Score

The F1-score measurement combines precision and recall. Precision and recall are used to calculate the F1-score measure that is symbolized in equation (8),

$$F1 - score = \frac{2 \times p \times r}{p + r} \tag{8}$$

The following Table 2 displays the CNN-RNN's effectiveness metrics for the three parameters of recall, F1score, and precision. The outcomes demonstrated that the suggested method performs satisfactorily and has superior recognizing capability.

Table 2: Performance Measure of Deep learning

Techniques	Precision (%)	Recall (%)	F1 Score (%)
CNN	93	80	86
SVM	78	86	91
KNN	82	65	90
Proposed (CNN)	34	54	42

The graphic depiction of the traffic accident prediction is presented in figure 3. The outcomes demonstrate the suggested approach's superior performance.
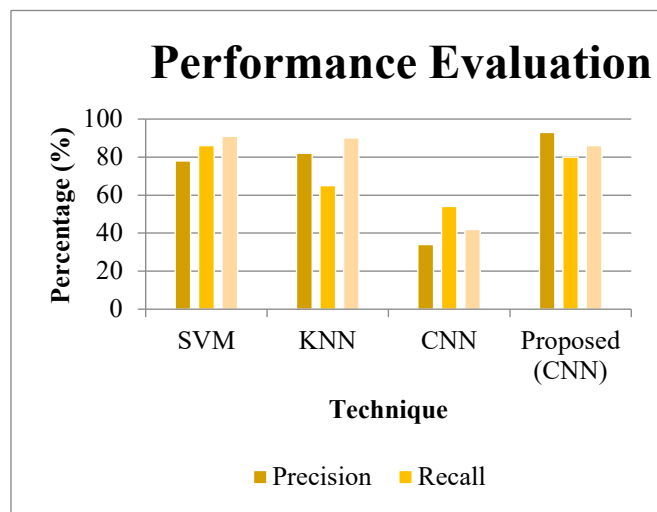

Figure 3. Performance evaluation of Traffic accident Prediction

5.2. Performance Comparison

The following table 3 shows the accuracy obtained in based on three different methods. From the table it shows that the suggested (CNN) has the superior accuracy than other three methods and the graphical representation of the comparison is shown in Figure 4.

Table 3: Accuracy Comparison

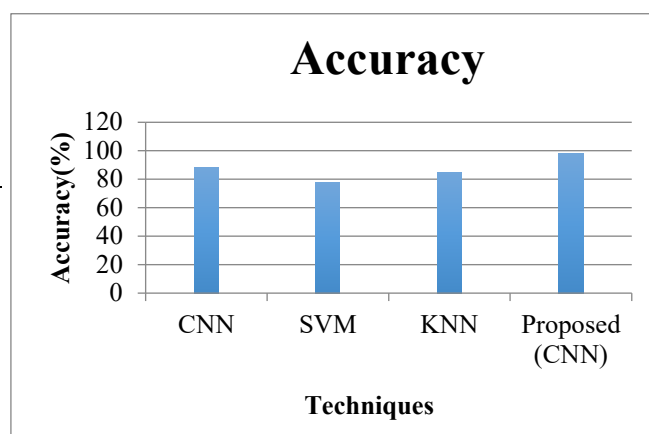| Technique	Accuracy (%)
CNN	88
SVM	78
KNN	85
Proposed CNN	98

Figure 4. Effectiveness Assessment of the proposed system

6. Conclusion and Future Works

The suggested architecture for traffic accident prediction includes crucial elements such feature extraction using Recurrent Neural Networks (RNN) and CNN, tracking and monitoring with deep sort, and data processing through normalisation. Accurate analysis and model training is made possible by the data processing step, which guarantees uniform scaling across features. Employing tracking and monitoring techniques in combination with deep sorting makes it easier to identify and keep track of pertinent entities in real-time, providing useful information for the feature extraction process that follows. While CNNs extract spatial data, such as road characteristics and visual cues linked with accidents, extract temporal patterns and dependencies.

The framework offers a thorough method for predicting traffic accidents by combining various methodologies, improving traffic safety measures. The suggested approach has a great deal of potential for increasing the accuracy of accident prediction, enabling proactive interventions, and ultimately lowering the frequency and severity of traffic accidents, enhancing overall road safety and transportation infrastructure. The effectiveness of the suggested approach in contrast to the existing methods is demonstrated by the outcome of the study.

The collected Traffic Accident Prediction data exhibits superior accuracy when contrasted with the existing method. There are several intriguing areas for further research in our study of deep learning-based traffic accident prediction. In order to enhance the precision and timeliness of predictions, we need first investigate the integration of real-time data streams, such as traffic and weather data.

Furthermore, the performance of predictions can be improved by creating more complex spatial and temporal models and by devising methods for dealing with data imbalances. To gain further insight into accident patterns, efforts should be made to develop interpretable models that incorporate geographic analyses. Effective road safety improvement also requires cooperation with transportation authorities and ongoing model upgrading.

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