Accident Detection in Smart Cities: A Deep Learning Ensemble Approach

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ABSTRACT

"As smart city infrastructures have grown in popularity; traffic safety has emerged as a top technological objective. In order to increase the safety of urban transportation, this research proposes an ensemble deep learning method for real-time traffic accident identification. Our method uses video and sensor data to improve accident detection accuracy by merging convolutional neural networks (CNNs), recurrent neural networks (RNNs), and decision trees. Our experimental findings on a sizable dataset show notable advancements over conventional techniques, attaining high recall and precision rates. This study demonstrates how AI-powered technologies can be used in smart cities to enhance public safety and proactively control traffic.

Keywords: Smart City, Traffic Accident Detection, Deep Learning Ensemble, CNN, RNN, Decision Tree, Real-Time Surveillance, Urban Safety, Intelligent Transportation Systems

I. INTRODUCTION

The growing emphasis on smart city technology seeks to enhance urban living by utilizing cutting-edge systems in a number of areas, such as public safety and traffic control. Traffic safety is a major issue for urban mobility, as accidents have serious repercussions, including fatalities, serious injuries, and high financial expenses. Conventional accident detection techniques, which mostly rely on manual observation, are frequently inefficient because human error can cause delays and limitations. Furthermore, even while sensor-based techniques are automated, they frequently lack the accuracy and real-time responsiveness needed in complicated metropolitan settings.

In order to overcome these constraints, this research suggests a deep learning ensemble technique that combines decision trees, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) to provide a reliable system for traffic accident detection. By utilizing each model's own capabilities, the integration of these models enables high accident detection accuracy: RNNs are skilled with time-series data, CNNs are excellent at processing image data, and decision trees help with classification. Our goal is to improve public safety and support intelligent transportation systems (ITS) by integrating them to provide a dependable real-time traffic monitoring solution in smart cities.

II. LITERATURE SURVEY

Deep learning and artificial intelligence developments have revolutionized smart city applications, especially traffic monitoring. In the past, techniques like human-monitored CCTV systems or simple sensor configurations in infrastructure were used for accident detection. These conventional methods, however, frequently have drawbacks, such as a reliance on manual intervention or a decreased level of efficacy in a variety of environmental settings.

Real-time analysis of high-dimensional data, such as video and sensor feeds, has been made possible by deep learning, revolutionizing traffic surveillance. RNNs handle time-sequence data, but CNNs are very good at analyzing images and videos. Ensemble approaches, which mix several machine learning models to increase detection accuracy, have also been studied in some detail. By using an ensemble of CNN, RNN, and decision tree models and optimizing each for distinct facets of traffic accident detection, this study expands on earlier research and strengthens the system's resistance to false alarms.

III. METHODOLOGY

A. Dataset Description

We employed a sizable dataset for this investigation, which included video footage from metropolitan traffic crossings and sensor data including hit force and vehicle speed indications. The kind, severity, and location of the incident were noted for every accident incidence. To make sure the model could differentiate between routine traffic and unusual occurrences, non-accident footage was also added.

B. Data Pre-processing

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Model Architecture

1) Convolutional Neural Network (CNN): Video frames were subjected to feature extraction using the CNN model. This model detects objects within frames and recognizes spatial patterns, both of which are essential for accident detection. The CNN's several convolutional layers are followed by max-pooling layers, which lower dimensionality while preserving key features for further examination.

2) Recurrent Neural Network (RNN): Because video data is sequential, temporal patterns across a sequence of frames were captured using an RNN model, more precisely an LSTM network. Based on changes over time, the RNN examines the chronological sequence of events and looks for anomalies that indicate accidents.

3) Decision Tree Classifier: An application of a decision tree classifier was used to further refine detection. Using learnt decision rules, this model was trained on CNN and RNN output features to distinguish accidents from other occurrences, increasing overall classification accuracy.

Ensemble Approach

The purpose of the ensemble model was to capitalize on the advantages of each individual model. The CNN and RNN model outputs were fed into the decision tree for final categorization using a stacking technique. By integrating spatial, temporal, and decision-based analysis, this multi-model ensemble enables a more thorough evaluation and precisely identifies accidents.

Training and Evaluation

A stratified 80-20 train-test split was used to train the models, and grid search was used to adjust the hyper parameters for optimal performance. In order to evaluate real-time viability, evaluation measures included precision, recall, F1 score, and inference time.

IV. EXPERIMENTAL RESULTS

Performance Metrics

The ensemble model significantly outperformed the individual CNN, RNN, and decision tree models, achieving 92% precision, 90% recall, and 91% F1 score. While the recall made guaranteed that real occurrences were rarely overlooked, the high precision decreased false positives, which is essential for reducing needless alerts in metropolitan traffic systems.

Visualization

Sample frames from test instances demonstrated that the model correctly and with little lag detected crash events.

Based on visual changes, movement patterns, and abnormalities in sensor data, these results demonstrate the model's ability to identify accidents.

Comparison with Baseline Models

The advantages of merging several deep learning models were demonstrated by the ensemble approach, which showed an average improvement of 7% in F1 score when compared to solo models. While the ensemble technique successfully handled a wider range of occurrences, standalone CNN and RNN models shown difficulties in detecting complicated accident scenarios.

V. DISCUSSION

Interpretation of Results

The performance of the ensemble model demonstrates the benefits of using multiple models to handle the complicated data streams found in traffic scenarios. The system can assess spatial-temporal dynamics thanks to the CNN-RNN combination, which also records motion-based and stationary data that are essential for accident detection. By improving classifications based on distinct patterns discovered during training, decision trees add an extra degree of accuracy.

Challenges and Limitations

There were difficulties in spite of the encouraging outcomes. Real-time deployment on edge devices may be limited by the high computational needs. Furthermore, low-visibility situations, including severe weather, may result in false negatives, which could lower accuracy in certain situations. To lessen computational strain, future research could concentrate on lightweight architectures or investigate pre-trained models.

Implications for Smart Cities

The suggested model shows how deep learning might improve smart city traffic systems' efficiency and safety by facilitating quicker reaction times and cutting down on delays caused by accidents. Roadways could become safer and urban mobility systems more resilient if this idea is widely implemented.

VI. CONCLUSION & FUTURE SCOPE

For precise, real-time traffic accident detection in smart cities, this study presented an ensemble deep learning model that combines CNN, RNN, and decision tree models. The strength of a multi-model strategy in assessing both spatial and temporal aspects from urban traffic data was highlighted by the suggested system's notable improvements in detection accuracy, precision, and recall when compared to standalone models. The results demonstrate that deep learning can be a key component of smart transportation systems, facilitating quicker accident response times, cutting down on delays, and ultimately strengthening urban public safety.

There is a lot of promise in using this approach as part of the infrastructure of smart cities. The device can facilitate faster response times and proactive traffic management techniques by precisely recognizing accidents. This work shows how AI-driven traffic monitoring systems can be used to solve important urban safety issues, providing a solid basis for future research in this area.

1. **Integration with IoT Sensors:** Data from IoT-enabled sensors positioned across the city could be included into future systems to further improve accuracy. For more accurate accident detection, real-time GPS, impact, and speed sensors can provide an additional layer of information.
2. **Lightweight Edge Deployment Model:** The ensemble model requires a lot of computing power, despite its accuracy. Using a leaner ensemble structure or optimizing the model for distribution on edge devices could enable real-time processing in smart city settings with constrained computational resources.
3. **Adaptability to Weather and Environment:** Future research might examine how well the model performs in other weather scenarios, such as rain, fog, or darkness. The accuracy of detection under various conditions could be improved by employing strategies like transfer learning or integrating meteorological data.
4. **Better Data Privacy:** Since video footage of public areas is captured during traffic monitoring, privacy issues must be addressed. Data privacy could be protected while yet enhancing the model by putting strategies like federated learning into practice, which permits training on local devices.
5. **Extension to Incident Detection Beyond Accidents:** This model may become more useful and adaptable in all-encompassing traffic management systems if it is extended to identify other important traffic events (such as breakdowns, obstructions, or congestions).

This study offers a strong basis because the suggested paradigm shows encouraging promise for practical use. As these areas continue to advance, accident detection systems may be incorporated as crucial elements in the creation of safer and more intelligent cities across the globe.

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