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Urban incident detection based on hybrid convolutional neural networks and bidirectional long short-term memory

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ABSTRACT

Real-time incident detection is a major challenge in urban roads. This paper proposes an innovative hybrid method for incident detection, combining convolutional neural networks (CNN) and bidirectional-long short-term memory (Bi-LSTM). CNN extracts complex spatial features from raw data, while Bi-LSTMs are used for incident detection by capturing long-term temporal dependencies present in data. The proposed algorithm is evaluated using simulated data from the open-source software simulation of urban mobility (SUMO). This combination improves incident detection's accuracy and robustness by exploiting spatial and temporal information. Experimental results show that our hybrid approach outperforms the support vector machine (SVM), random forest (RF), and Bi-LSTM algorithms, with a substantial decrease in false positives and the speed of detecting urgent situations.

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1. INTRODUCTION

Traffic congestion causes many socio-economic and environmental issues by extended travel time, higher fuel consumption, and more pollution. These problems become even more acute due to ever-increasing traffic and an inadequate roadway system. Conventional ways of managing traffic, such as building more roads, are both expensive and difficult to implement in urban centers with dense populations. Accordingly, increasing the precision and effectiveness in traffic incident detection is an important research topic.

During the last two decades, different methods have been suggested to detect such events [1] from classic sensor-based systems to advanced machine learning techniques [2]. Early techniques were based on loop detectors [3], [4] and statistical algorithms [5], [6] which, even if effective, are characterized by high implementation costs and environmental susceptibility. Higher-level models, such as machine learning algorithms studying traffic-flow patterns, have been studied as well, only to encounter difficulties in feature extraction and to grow problematic in terms of computational requirements. Owing to the progress in deep learning, convolutional neural network (CNN) and long short-term memory (LSTM) models have shown promising performance for the incident detection task. CNNs are also particularly effective in representing the spatial features of traffic data [7]–[9], which are also able to model road-level variations and congestion patterns. LSTMs are well known for modeling temporal dependencies, which allow the system to analyze the sequential traffic fluctuation through time. Our work contributes to the literature by demonstrating that exploiting the complementary nature of CNN and LSTM and fusing their outputs, termed a hybrid model, could significantly improve the accuracy and robustness of traffic incident detection.

This work is a further step in the area of deep learning for traffic analysis. For example, Ahmadzadeh *et al.* [10] used a 1D-CNN to extract high-speed train fault signals and showed the potential for capturing useful spatial features. According to Li *et al*. [11] an hybrid method combining CNN and LSTM is proposed to predict train arrival delays. Our work extends the state-of-the-art findings by integrating CNNs for spatial feature extraction and LSTMs for modeling temporal sequences, providing a comprehensive framework for detecting incidents in real time

The remainder of this paper is structured as follows. Section 2 outlines the data acquisition process and the methodology adopted for detecting incidents on urban road networks. Section 3 provides a detailed description of the proposed algorithm. Section 4 presents the experimental results along with a comprehensive analysis. Finally, section 5 concludes the paper.

2. INCIDENT DETECTION METHODOLOGY

2.1. Automatic incident detection systems

An automatic incident detection (AID) system is essential for the control of traffic flow and optimizing capacity in transportation networks. These systems deploy some state-of-the-art technologies to sense the traffic conditions, such as accidents, congestion, among others, in time and with high accuracy. Through the use of data from multiple sources, including cameras and sensors. There are different types of AID systems available, such as loop finders. These systems use in-road embedded sensors to recognize changes [12]. Such systems are known as camera-based because traffic is recorded on film by mounting the cameras over the road. Algorithms [13]–[15] are used to perform real-time analysis of the video to identify collisions or cars in wrong direction. AID systems use complex algorithms, such as machine learning, to identify anomalies and issue alerts that facilitate a quick response. This fast discovery and response procedure greatly mitigates the effect of such incidents, for a safer, less delayed flow of traffic. With the development of technology, deep learning models, could make the system more precise and dependable, which can be one of the aspects for constructing a smarter and more robust transportation traffic detection provides the system traffic traffic-related information for identifying the occurrence of a traffic event. Other data, such as speed, volume, and occupancy [16], are often provided at a lower rate.

2.2. Data collection

The detection algorithm fundamentally relies on analyzing changes in traffic data. Various metrics, such as velocity, occupancy rate, and traffic flow, are used to depict traffic conditions. In this study, traffic and incident data were generated using simulation of urban mobility (SUMO). Inductive loop detectors captured traffic dynamics at a 30-second resolution, measuring speed, volume, and occupancy. Velocity represents the average speed of vehicles within each 30-second interval, volume indicates the number of vehicles passing through each lane, and occupancy reflects the proportion of time the detector was occupied by vehicles during the detection window.

Traffic incidents can take various forms, including accidents, roadworks, adverse weather conditions, or heavy congestion, all of which disrupt the normal flow of vehicles. To illustrate this phenomenon, we simulated an incident by intentionally stopping a car at a predefined location for a fixed period. This controlled scenario allows us to analyze the impact of such disruptions on traffic flow and evaluate the effectiveness of our detection model. Figure 1 provides a visual representation of this simulated incident. Figure 2 further illustrates how the incident affects traffic metrics as detected by upstream and downstream loop detectors.

In the event of a traffic incident, distinctive patterns emerge in both upstream and downstream loop detectors. Expected changes include a reduction in upstream speed and volume, along with a decrease in downstream volume. Concurrently, there is an increase in upstream occupancy and variations in downstream speed and occupancy. In (1) describes how V is computed.

$$V = \frac{\sum_{i=1}^{N} v_i}{N} \tag{1}$$

Where N is the number of vehicles at a detection location over a given time period, and v_i is the i^{th} velocity. Occupancy rate is computed as outlined in (2).

$$O = \frac{\sum_{i=1}^{N} L_i}{L} \tag{2}$$

Where L is the length of the observed road, and L_i is the length of the i^{th} vehicle. The number of cars that pass through a detection point in a predetermined amount of time is referred to as traffic flow (T). The mathematical formulation of traffic flow is given in (3).

$$T = \frac{\sum_{i=0}^{\tau} N_i}{\tau} \tag{3}$$

Where τ is the time interval and N_i is the number of vehicles seen at a detection location within a 1-second interval.

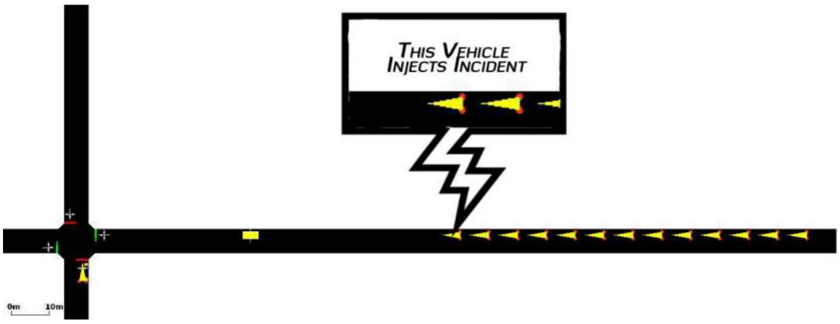

Figure 1. Traffic incident patterns

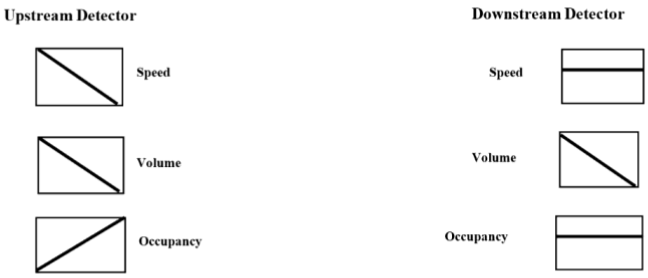

Figure 2. Illustration of a road incident

3. DESIGN OF INCIDENT DETECTION MODEL BASED ON A HYBRID BI-LSTM AND 1D CNN

3.1. Convolutional neural network

CNNs [17]–[19] typically consist of a fully connected layer, pooling layers, related weights, and one or more convolutional layers. To extract features, the convolutional layer makes use of local correlations in the data. Except the convolution procedure being limited to one dimension, the 1D CNN is comparable to two-dimensional CNNs. As a result, it has a shallow architecture that can be trained on embedded development boards or even ordinary CPUs [20]. For classification applications, the convolution method extracts useful hierarchical features from a dataset.

3.2. Bidirectional-long short-term memory

The bidirectional-long short-term memory (Bi-LSTM), which extracts significant characteristics [21], [22], was applied in this research. An input gate, output gate, forget gate, and memory unit (cell) are components of the LSTM structure [23]. The activation of this gate is found using (4) [24].

$$f_t = \sigma(w[x_t, h_{t-1}, C_{t-1}] + b_f) \quad (4)$$

The input sequence is denoted by x_t; h_{t-1} represents the previous block output; C_{t-1} denotes the previous LSTM block memory; b_f denotes the bias vector; W represents the individual weight vectors; and σ denotes the sigmoid function. The input gate utilizes a basic neural network with a tanh activation function and the effect of the previous memory block to create new memory. The operations performed for these calculations by (5) and (6).

$$i_t = \sigma(w[x_t, h_{t-1}, C_{t-1}] + b_i) \quad (5)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tan h\,([x_t, h_{t-1}, C_{t-1}]) + b_c \quad (6)$$

A consciously designing and retrieving long-term information can alleviate the problem of long-term dependency that the LSTM networks are prone to in actual applications.

3.3. Hybrid CNN-Bi-LSTM model for incident detection

For simple operation and faster computation speed, the 1D CNN is employed to extract spatial features from the raw traffic data. This architecture is particularly effective in reducing the computational complexity while retaining essential spatial patterns. In addition, the Bi-LSTM is adopted for incident detection and for capturing long-term temporal dependencies in time series data, making the model more accurate in recognizing complex traffic dynamics. Algorithm 1 illustrates the proposed 1D CNN-Bi-LSTM.

Algorithm 1: Hybrid proposed method 1D CNN-Bi-LSTM
Step 1: initialize training set:
- Consider a training set $N = \{(x_i, t_i) | \, x_i \in \mathbb{R}^n, t_i \in \mathbb{R}^m, i = 1, \dots . N\}$

Step 2: dataset splitting
Step 3: feature extraction with 1 D CNN:
- Apply a 1D CNN layer to extract local features from the input data.

Step 4: temporal feature processing with Bi-LSTM
- Use Bi-LSTM layers to enhance the extracted features by capturing temporal dependencies and patterns.

Step 5: prevent overfitting:
- Incorporate dropout layers to prevent overfitting.

Step 6: Normalization:
- Use a batch normalization layer to stabilize and accelerate the training process.

Step 7: dense layers processing:
- Add fully connected layers to integrate the extracted features and make detection.

Step 8: performance measurement:
- Implement performance measures to assess the classification accuracy and other relevant metric

4. RESULTS AND DISCUSSION

4.1. Performance evaluation criteria

To evaluate the effectiveness of the categorization models, three metrics were used: accuracy, recall, and precision. As demonstrated by (7), accuracy measures a classifier's overall correctness. Recall quantifies the percentage of positive records that the classifier accurately predicts. As a result, recall is calculated using (8). Conversely, precision, as shown in (9), is the percentage of true positive (TP) records among all positively predicted records.

$$Accuracy = \frac{(TN+TP)}{TN+TP+FN+FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{FN+TP} \tag{8}$$

$$Precision = \frac{TP}{FP+TP} \tag{9}$$

4.2. Simulation of urban road mobility

SUMO models and examines several aspects of transportation and mobility in urban settings using computer-based simulation methodologies. To research and forecast how various entities will move and interact within cities, this method involves building virtual models of metropolitan environments, complete with road networks, vehicles, and other relevant elements [25]. Alongside the aforementioned functionalities, SUMO utilizes traffic control interface (TraCI) to enable seamless runtime interaction with external programs [26].

4.3. The scenario used in the simulation

Research by Butt and Shafique [27], upstream and downstream detector stations are separated by traffic lights or crossroads, simulating a traffic environment. This scenario faithfully depicts an urban traffic system with a high frequency of junctions. This setup is particularly relevant for a system managing incidents with two stations. In this arrangement, detectors are placed immediately before traffic intersections. A two-station setup includes an upstream detector station located before the intersection linking two segments, and a downstream detector station situated before the next crossroad at the end of the subsequent segment. Traffic signals in this scenario are expected to significantly impact the captured traffic information from these detectors, which includes characteristics like occupancy, speed, and traffic flow.

4.4. Results analysis

The inputs consist of traffic flow, occupancy rate, and velocity, which are taken from inductive loop detectors located upstream and downstream. The algorithms produce two outputs: one for an incident and zero for a non-incident. Three separate incident locations, 60, 400, and 600 meters from reference points, have data recorded every 30 seconds. The dataset is made up of 5,752 samples that were gathered over a period of 72 hours. Thirty of these incident cases are collected at the precise incident occurrence instances and isolated for testing. A further 1,721 samples are set aside for testing. Table 1 displays the obtained results.

To show the effectiveness of our model, we compared the outcomes of CNN-Bi-LSTM with those obtained from the support vector machine (SVM), random forest (RF), and Bi-LSTM algorithms. The performance comparison was focused on training time, accuracy, and approximation ability using the root mean square error (RMSE) criterion. The RMSE is given by the following equation, where stands for the estimated value, or the estimated concentration, and for the observation, which is based in relation to according to the number n of observations.

Our proposed method was evaluated by comparing the CNN-Bi-LSTM model's performance with that of SVM, RF and Bi-LSTM, as presented in the results section. The evaluation metrics included RMSE, training duration, accuracy level, and estimation size. RMSE served as the primary performance indicator and was computed using the following (10), where y_i is the predicted value, x_i is the observed value, and N represents the total number of observations.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \tag{10}$$

Table 2 show that CNN-Bi-LSTM obtains the lower RMSE than Bi-LSTM, while the training time increase very slightly. It is significantly better than RMSE of SVM and RF, while training speed is very faster. Figure 3 shows that our approach CNN-Bi-LSTM, demonstrated increased accuracy, indicating its superior effectiveness in incident detection, by comparing it with Bi-LSTM, SVM, and RF algorithms.

Table 1. Results obtained for incident detection using CNN, Bi-LSTM, CNN-BI-LSTM, R-extreme learning machine (R-ELM)

Algorithm	Incident duration	Duration rate (DR) (%)	Mean time-to-detect (MTTD) (s)	False alarm rate (FAR) (%)
SVM	Less than 4min	82.81	83.12	2.1
	Less than 6min	90.19	38.41	0.40
RF	Less than 4min	83.78	82.60	2.1
	Less than 6min	91.87	38.32	0.43
Bi-LSTM	Less than 4min	85.82	81.66	2.2
	Less than 6min	90.87	39.95	0.42
CNN-Bi-LSTM	Less than 4min	87.65	80.98	2.2
	Less than 6min	93.78	37.94	0.46

Table 2. Performance measurement based on RMSE and training time

Performance	CNN-Bi-LSTM	Bi-LSTM	SVM	RF
RMSE	0.0911	0.0998	0.7066	0.8129
Training time(s)	1.1433	2.0123	3.0923	4.5032
Accuracy	0.95	0.92	0.90	0.91

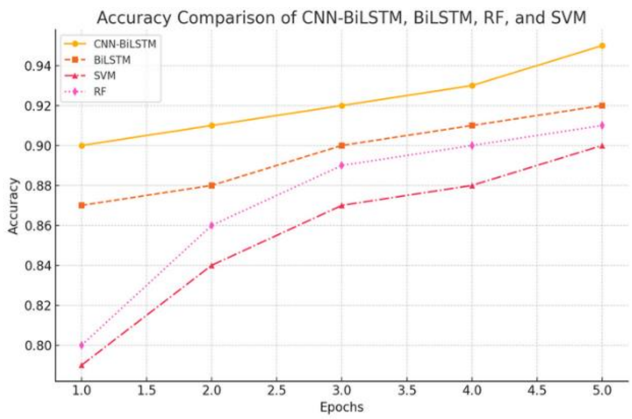

Figure 3. Accuracy comparison of CNN-Bi-LSTM, Bi-LSTM, RF, and SVM

5. CONCLUSION AND FUTURE DIRECTIONS

This study proposes a hybrid model combining 1D CNN and Bi-LSTM networks to enhance AID on urban roads. The 1D CNNs effectively extract spatial features from raw traffic data, allowing for a more refined representation of local structures. In parallel, the Bi-LSTMs capture long-term temporal dependencies, which are essential in traffic fluctuations that may indicate an incident. This hybrid CNN-Bi-LSTM architecture leverages the strengths of both approaches, combining the feature extraction power of CNNs with the temporal sequence processing capabilities of Bi-LSTMs. The performance of the proposed model was compared to that of popular algorithms, including SVM, RF, and Bi-LSTM alone. The results demonstrate a clear advantage of the CNN-Bi-LSTM model, with improved performance and high detection accuracy, highlighting its potential for real-time incident detection in complex urban environments. Although the proposed approach enhances the detection performance and shows promising results, future work could consider several types of uncertainty that can affect the system.

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Jaouad Boumhidi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data used in the paper will be available upon request.

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