Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Traffic Incident Detection in Urban Roads Based on Hybrid 1D-CNN and Residual Transformer

Meryem Ayou[1], Jaouad Boumhidi[1]
[1]L3IA Laboratory, Department of Computer Science, Faculty of Sciences Dhar El Mehraz, Sidi Mohammed Ben Abdellah University, Fez, Morocco

ARTICLE INFO

Received: 29 Dec 2024

Revised: 12 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

One of the most essential tasks for guaranteeing safety and operational efficiency in urban road traffic management is incident detection in real-time scenarios. In this paper, we propose a new hybrid framework that focuses on unidimensional convolutional neural networks (1D-CNN) for spatial feature extraction, residual transformers for temporal data modeling, and extreme gradient boosting (XGBoost) for efficient incident classification. This combination of strengths and performances, such as the robustness of 1D-CNN in spatial analysis and residual transformers in the capture of long-range dependencies in the case of temporal data, ensures robust feature extraction for the proposed model. The proposed framework offers significant competitive advantages and high precision, as demonstrated by experimental results.

Keywords: Traffic Incident Detection, One-Dimensional Convolutional Neural Networks, Residual Transformer, Extreme Gradient Boosting.

INTRODUCTION

Accurate and real-time incident detection has become increasingly important in various fields, including traffic management, security surveillance, and industrial monitoring. It is only through rapid detection of anomalies or incidents that Risk can be mitigated and that downtime can be reduced and safety enhanced. but process phantoms are often complex in spatial and temporal dynamics that preclude their identification by traditional methods. It became successful because machine learning models can extract complex rules and patterns from data and they can prune them down. One-dimensional convolutional neural networks (1D-CNN) are a popular approach to spatial data analysis (Y. Liu, C.Li., M. Wang, et al, 2023). On the other hand, transformers are prominent for their self-attention mechanisms, which have set apart sequence modeling by capturing long-term relationships and dependencies in time-series data. Blending these strengths may be a promising avenue towards establishing sound incident detection (A. Khan, M. Islam, Z. Jan, Khan, R.U. Khan., & J. S. Park, (2023). In this article we propose a hybrid model which uses XGBoost for the final classification, residual transformers for temporal modeling (H. Yu, Y. Zhang, X.Li, et al,2022; X. Zheng, J. Li, W. Song, et al,2023). and 1D-CNN for spatial feature extraction. Specifically, the residual transformer captures temporal dependencies effectively through its self-attention mechanism, while the 1D-CNN component focuses on spatially extracting important features from structured data. These temporal and spatial features were combined and fed into XGBoost after extraction; XGBoost is a prediction system that compiles reliable and transparent predictions. The suggested framework outperformed traditional methods in terms of accuracy and resilience after being tested on a dataset of tagged incidents. The outcomes demonstrate how well our method can handle actual incident detection problems in a variety of fields. The rest of the paper is organized as follows: Section 2 presents the related work. The state of the environment is presented in section 3. The proposed approach is presented in Section 4. The findings are reviewed and discussed in Section 5. Finally, a conclusion is presented in Section 6.

RELATED WORK

During the previous 20 years, several machine learning methods, especially with loop detector data, have been presented for traffic incident detection (T. Sivabrahmam, &S. Duvvuri, 2022). Artificial Neural Networks (ANN) have

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

emerged as a robust approach, with several ANN-based models dedicated to incident detection. (Y. Zhang, Liu, Y. Liu, &F. Wang, 2004). leveraged neural networks to classify spatial and temporal traffic patterns, demonstrating their effectiveness in detecting incidents on urban highways. More recently, machine learning models such as Support Vector Machines (SVM) have been employed to enhance traffic incident detection (L. –L. Wang, H. Y. T. Ngan, & N. H. C. Yung, 2015; S. Chen, W. Wang, & H. van Zuylen, 2009; Y. Yao, Y. Zhang, B. Du, & Y. Wang ,2014) An incident detection technique utilizing Support Vector Machines (SVM) was proposed by (L. –L. Wang, H. Y. T. Ngan, & N. H. C. Yung, 2015), where a learning algorithm was employed to establish a decision boundary between different data classes.(S. Chen, W. Wang, & H. van Zuylen, 2009; Y. Yao, Y. Zhang, B. Du, & Y. Wang ,2014) developed an SVM-based freeway incident detection model using the LibSVM toolbox, achieving better results compared to older detection algorithms. (Y. Yao, Y. Zhang, B. Du, & Y. Wang ,2014) applied an SVM classifier for incident detection and evaluated its performance using multiple metrics. More recently, (J. Xiao, 2019) introduced a hybrid method that integrates SVM with K-Nearest Neighbors (KNN), showing its stability on various datasets. It has been studied by previous research on the use of a probe vehicle for incident detection. (C.S. Basnayake, M. Chowdhury, K. Ahmed, & H. Rakha, 2019) are the authors of traffic flow characterization and detection of incidents. Using probing vehicle data collected from GPS devices onboard automobiles. The data collection procedure caused delays, even though this method showed acceptable detection rates. A model for event detection based on probing vehicles was developed by Li and McDonald (Y.Li, & M. McDonald, 2005) using a bivariate analysis of two important variables: the average journey time of the probe cars and the intervals between successive intervals. This method was tested on multiple motorway segments, showing effective incident detection. Other researchers have applied regression-based and hybrid models. These various approaches highlight the evolution of traffic incident detection techniques, ranging from neural networks and SVMs to hybrid models integrating video analysis, regression, and fuzzy logic.

STATE OF THE ENVIRONMENT AND DATASET

Environment Description

Typically, the primary objective of any incident detection mechanism aims to cover incidents quickly with maximum accuracy. In the case of a major incident, one or more lanes may be obstructed, causing traffic congestion, blocking vehicles upstream, and generating a queue that propagates backward, as illustrated in **Figure 1.**

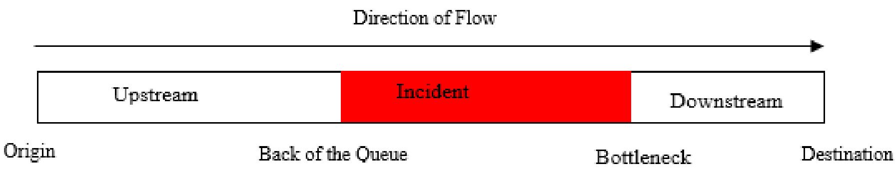

Figure 1. Road sections involved in a road accident.

A traffic incident can have an impact on the dynamics of the flow, which in turn can create disparities between upstream and downstream sections. In the case of the upstream section, a reduction in speed and flow implies an increase in the occupancy rate, as vehicles accumulate due to lane obstructions. While in the downstream section, decreasing velocity and flow mean increasing occupancy since vehicles queue due to lane blockage. Consequently, the occupancy of the downstream detector decreases and the vehicle speed increases. Data collected from both portions exhibits differences in speed, flow, and occupancy, which makes this aberration in the flow of traffic an important event indication. Systems for incident detection monitor these variations in real time, detecting identifiable anomalies in traffic patterns.

Figures 2-4 depict upstream and downstream changes in speed, flow, and occupancy due to the incident, thus indicating the extent of the effects of the incident on traffic parameters. Patterns described by (L. Lin, Y.Li, B. Du, F.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Yang, & B. Ran, 2020) are in agreement with the trends that have been found. The authors are currently creating simulated traffic data under both incident and normal conditions in order to further examine these effects.

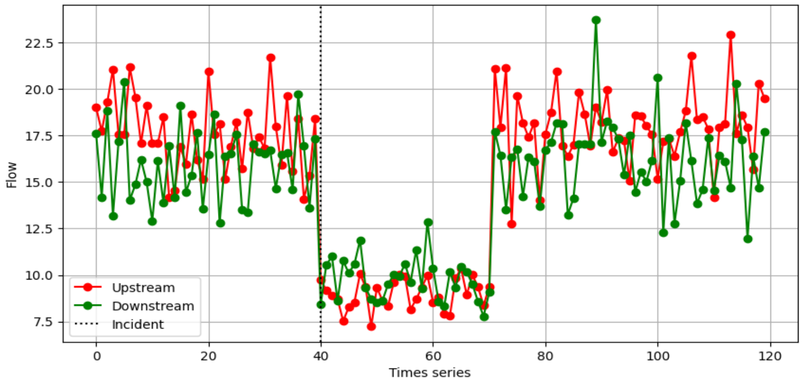

Figure 2. Upstream and Downstream Section Traffic Flow Effects of Incidents.

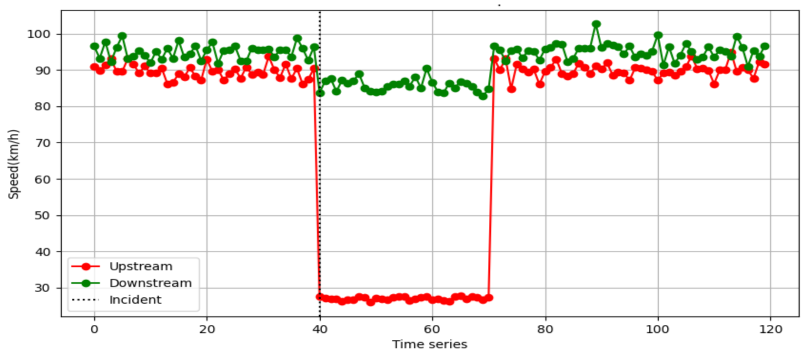

Figure 3. Upstream and downstream influence of incidents on traffic velocity.

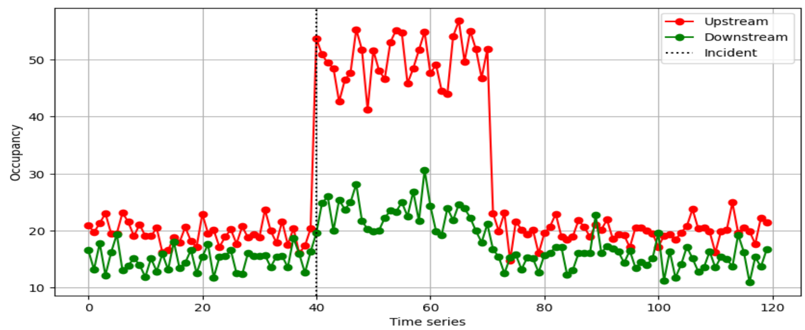

Figure 4. Occupancy effect of incidents with the segments upstream and downstream

State Representation

The input pushes three matrices, one for each agent – the state of the environment is formed by simply stacking the environment state matrices, each corresponding to a key traffic parameter for every incoming road: Speed matrix (Vi) represents the normalized speed of vehicles relative to the maximum allowed speed on the road. The volume matrix (Qi) indicates how many vehicles there are in that segment. The occupancy matrix (Oi) captures the percentage of road segment occupancy based on vehicle presence. At every time interval t, the model receives the state representation (V, Q, O,) ∈ S, where S denotes the complete state space.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Data Collection

The detection algorithm fundamentally relies on analyzing changes in traffic data. Various metrics, including velocity, occupancy rate, and traffic flow, are used to depict traffic conditions. In this study, traffic and incident data were generated using the SUMO simulator. The analysis was performed on both training and validation sets, while incident detection was specifically applied to the test set. Inductive loop detectors captured traffic dynamics at a 30-second resolution, measuring speed, volume, and occupancy. Speed in the 30-second intervals for each lane is the mean speed of vehicles in the specific lane, while volume is the number of vehicles through each lane and occupancy refers to the fraction of the holding period in which cars were present at the detector.
Velocity is the average speed of all vehicles that pass a given detection site in a predetermined amount of time. Equation (1) describes how V is computed.

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

N is the number of vehicles at a detection location over a given time period, and $i^{th}$is the velocity.

Occupancy rate is computed as outlined in equation (2).

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

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 (Q).

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

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

PROPOSED ARCHITECTURE BASED ON THE HYBRIDITY OF 1D-CNN, RESIDUAL TRANSFORMER, AND XGBOOST

In this section, the architecture of the proposed hybrid incident detection model that consists of 1D-CNN, Residual Transformer, and XGBoost, which are combined, is introduced. 1D-CNN extracts local spatial relationships between different feature values in the data. The RT enables the extraction of global temporal features by focusing on crucial sequential data segments. The obtained extracted features are fused and passed to the XGBOOST model for incident detection. The following **Figure 5** illustrates the architecture of the proposed 1D-CNN-RT-XGBOOST model.

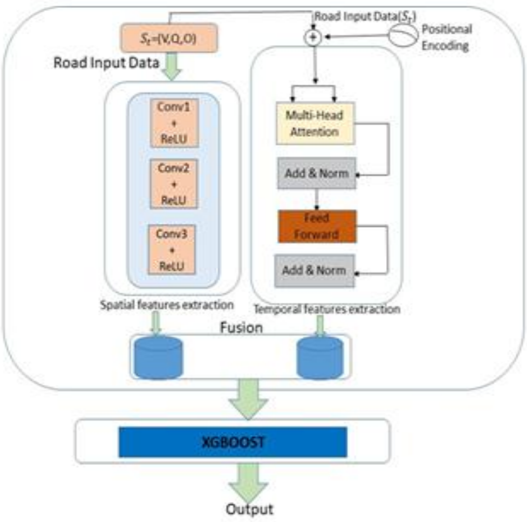

Figure 5. Architecture of 1D-CNN-RT-XGB model

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

1D-CNN-Based Model

A one-dimensional convolutional neural network (1D-CNN) is a feedforward neural network built with a convolutional architecture, where we share internal weights in the system and make use of localized receptive fields. 1D-CNNs are specialized in extracting latent features through convolutional layers, and are useful for various tasks such as incident detection, where spatial relationships of data points are essential to properly distinguish events (Y. Wang, H. Zhang, & X. Liu, 2023; R. Luo, Y. Song, L. Huang, Y. Zhang, & R. Su, 2022). Such architecture maintains a lower model complexity while effectively enabling the extraction of deep local features from the data. The previous convolutional layers apply convolution operations to extract features from the input image and learn local patterns, while the following pooling layers use down sampling techniques to decrease data dimensionality and computation time (G. Tang, Y. Yu, C. Qin, et al, 2021). We use convolution and pooling operations in this study to capture local spatial relationships across the different feature values in the data.

Residual Transformer for Temporal Feature Modeling

The Residual Transformer is an adaptation of the Transformer architecture (M. G. Al-Thani, Z Sheng, Y. Cao, & Y. Yang, 2024) designed to model temporal dependencies in sequential data. Temporal feature modeling is critical in tasks like incident detection, where understanding temporal trends and patterns is essential to identify anomalies or potential events (K. Saleh, A. Grigorev, & A.-S. Mihaita, 2022).
Effective traffic incident detection relies on robust temporal modeling to capture both long-range dependencies (B. M. T. H. Anik, Z. Islam, & M. Abdel-Aty, 2023), such as sustained congestion patterns, and short-term variations, like sudden speed drops, which are critical indicators of incidents. When it comes to modeling long term dependencies, traditional approaches such as RNNs, LSTMs and the GRUs often suffer from gradient issues. Pure Transformers are good at capturing long-range dependencies but are expensive and less stable in deeper settings. Residual Transformers offer a balanced solution by combining the self-attention capabilities of Transformers with residual connections, which enhance gradient flow, stabilize training, and reduce computational demands. This approach enables efficient modeling of temporal variations by focusing on crucial segments of sequential data (H. Kamal, & M. Mashaly, 2024).

XGBoost Model

Robust and efficacy algorithms include XGBoost, widely used for classification tasks due to its robustness, scalability, and high accuracy (L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush., & A. Gulin, 2018).and is particularly valued for its scalability across different scenarios, as highlighted in (C. Bentéjac, A. Csörgö, & G. Martínez-Muñoz,2021) .In the context of our study, XGBoost acts as the final classifier, processing the fused features extracted by the 1D-CNN (spatial features) and the Residual Transformer (temporal features).

Tuning Hyper-parameters with Cross-Validation and Grid Search

The most efficient algorithms include XGBoost, which generally delivers excellent performance. However, it comes with some challenges, particularly the large number of hyperparameters it requires and the fact that varying parameter combinations can lead to different evaluation outcomes. As a result, identifying the optimal hyperparameters is crucial to maximize its potential. to identify optimal hyperparameters by testing all possible combinations, we can use the Grid search method. In our case, we focus on tuning for common parameters: learning rate, number of estimations, subsampling rate, and maximum depth.

SIMULATION AND RESULTS

Parameterization

The experimental parameters for the 1D-CNN-Residual Transformer-XGBoost model generally include several key features: The 1D-CNN layer (convolution kernel size and the activation function), Residual Transformer layer (number of attention head), maximum depth, number of epochs to train, dropout rate, learning rate, number of estimators of the XGBoost classifier. Picking the right values for parameters has a huge influence on how fast the

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

model trains, and how accurate those predictions are. The parameters that were selected for incident detection based on the extensive performance comparison are shown in **Table 1** In addition, the XGBoost model is further tuned with hyperparameter optimization with GridSearch to improve its classification performance and thus to be able to detect more powerful incidents (L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush., & A. Gulin, 2018).

Table 1. Model Parameter Configuration.

Component	Parameter	Value
CNN Layer	Convolutional kernel size	3
	Maximum pooling layer size	2
	Data dimensions	3
	Activation function	Relu
Residual transformer layer	Number of attention heads	12
	Attention Dropout	0,2
	Hidden state dimensions	64
	Activation function	Relu
XGBoost Layer	Number of estimations	100-300
	Maximum depth	3-7
	Learning rate	0.01-0.2
	Subsampling rate	0.7-0.9

Performance Measures

An Automatic Incident Detection (AID) algorithm is generally evaluated in terms of three fundamental parameters, namely the Detection Rate (DR), False Alarm Rate (FAR) and Mean Time to Detect (MTTD) (Y. Zou, G. Shi, H. Shi, & Y. Wang ,2011). Let us define these metrics as follows: DR (Detection Rate): Percent of actual incidents detected by the system (Y. J Stephanedes, A. P Chassiakos, & P. G Michalopoulos1992).

$$DR = \frac{Number\ of\ incidents\ detected}{Total\ number\ of\ incidents\ cases} \times 100\% \quad (4)$$

The FAR or False Alarm Rate is the fraction of alarms that are false. In the literature, two common techniques have been used to compute FAR. There are two ways to hold the FAR, firstly the proportion of falsely detected incidents among all the detected incidents (Y. Sun, T. Mallick, P. Balaprakash., & J. Macfarlane, 2022). Second the ratio of false alarms to the total number of times the algorithm is run is how the second method determines FAR.

$$FAR = \frac{Number\ of\ detection\ intervals\ which\ gave\ false\ alarms}{Number\ of\ detected\ incidents} \times 100\% \quad (5)$$

Mean Time to Detect (MTTD): Measures the time taken by the AID system to correctly identify an incident after it occurs. In a set of (n) events, the TTD (the amount of time it takes to find an incident) is determined by taking the difference in time between the incident's actual occurrence (t_iocc) and the algorithm's identification of it (t_ialg):

$$MTTD = \frac{1}{n}\sum_{i=1}^{n} t_{ialg} - t_{iocc} \quad (6)$$

Together, DR, FAR, and MTTD serve as key indicators of an AID algorithm’s effectiveness, reliability, and efficiency. However, these metrics often involve trade-offs. For instance, raising DR could raise FAR, necessitating

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

striking a balance between reducing false alarms and enhancing detection accuracy) (Y. Zou, G. Shi, H. Shi, & Y. Wang ,2011). Similarly, reducing MTTD could lead to an increase in FAR. A common strategy to reduce false alarms is the persistence test, where an incident is only confirmed if the pattern persists for multiple consecutive intervals. In the case of incident detection, an AID model may achieve high accuracy, primarily due to its strong performance in classifying majority-class instances (non-incident conditions). Since these non-incident instances dominate the dataset, the model may appear effective, even if it struggles to detect actual incidents. These limitations highlight the inadequacy of using accuracy alone as an evaluation metric for incident detection models, as it fails to fully capture the model's effectiveness in detecting incidents. Precision is the percentage of positive events that were indeed positive out of the positive cases predicted by a model (Y. Sun, T. Mallick, P. Balaprakash., & J. Macfarlane, 2022). While precision is an essential evaluation metric, it ignores those positive examples that are predicted with false negatives. Recall is the other important metric, measuring the ratio of correctly identified positive instances compared to the total number of actual positive instances in the dataset (Y. Sun, T. Mallick, P. Balaprakash., & J. Macfarlane, 2022). Having high precision and high recall is not easy because the increase in recall directly decreases precision. The F-score is often used as a balanced evaluation metric to deal with this trade-off. It also provides an overall score that summarizes both sides of your model performance by showing the harmonic mean between those two. And the F-score is calculated using the following formula:

$$\text{F-score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

RESULTS ANALYSIS

Speed, occupancy rate and traffic flow are the input characteristics selected for classification. extraction of these characteristics is carried out using inductive loop detectors at upstream and downstream. The outputs produced are binary: 0 indicates no incidents detected and 1 if there is an incident. Three specific incident locations, located 60, 400, and 600 meters from reference points are used to collect data at 30-second intervals.

There are 5752 samples in the collection, which covers a 72-hour period. Of these, thirty event cases recorded at the precise times of incident occurrence are reserved especially for testing. 1,721 samples are used for testing, while 4,032 samples are used for training from the remaining data. **Table 2** shows a summary of the results.

Table 2. Results obtained for incident detection using 1D-CNN-XGBOOST, LSTM-XGBOOST, RESIDUAL BASED, 1D-CNN-RESIDUAL-XGBOOST.

Algorithm	Incident Resolution Time	Duration Rate DR (%)	Mean time to detect MTTD(s)	False Alarm Rate FAR (%)
1D-CNN-XGBoost	Under four min Under six min	82,81 90,19	83,12 83,41	2,1 0,4
LSTM-XGBoost	Under four min Under six min	83,78 91,87	82,60 38,32	2,1 0,43
TRANSFORMER BASED	Under four min Under six min	85,65 93,87	81,66 38,95	2,2 0,42
MODEL PROPOSED	Under four min Under six min	87,65 93,87	80,98 37,94	2,2 0,46

To assess the performance of the proposed hybrid system, we compared its outcomes with those of the 1D-CNN-XGBoost, LSTM-XGBoost and Transformer-Based Classifier. We compared the performance based upon Accuracy, F1-Score, Precision and Recall. **Table 3** summarizes the performance of our hybrid approach compared to baseline methods.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Table 3. Performance evaluation with accuracy, precision, recall and f1-score.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MODEL PROPOSED	98,1	96,8	97,9	96,4
1D-CNN-XGBoost	89,6	87,2	90,8	89,0
LSTM-XGBoost	92,3	90,4	92,8	91,6
TRANSFORMER BASED	93,8	92,2	94,1	93,1

The superior performance is highlighted by the comparative analysis of the proposed hybrid model, which seamlessly integrates 1D CNNs for spatial feature extraction, Residual Transformers for enhanced temporal modeling, and XGBoost for robust classification. The hybrid model achieved better performance than all baseline methods on all metrics, indicating its strength in capturing spatial-temporal nuances. Residual transformers excelled compared to LSTMs and transfor200000000000000000000000000000000000000000000000000000000000000000000000000000000000 0000000000000000000000000000000000000074mers. XGBoost addressed the curse of high dimensions and the imbalanced problem very well. Moreover, the model showed potential for real-time applications since it reached competitive inference times. In contrast, traditional methods such as Random Forest struggled to capture spatial-temporal complexities, and a baseline method like 1D-CNN-XGBoost and LSTM-XGBoost showed limitations.

CONCLUSION

We introduced in this paper a hybrid model 1D-CNN-RESIDUAL-XGBOOST for early urban traffic incident detection, where the residual Transformers task is the extraction of temporal features, 1D-CNN for extracting special-domain features, and XGBOOST for final incident detection. Experimental results validate the proposed hybrid architecture's potential for effectively addressing the challenges of traffic incident detection. This work identifies strengths and weaknesses of the model, making it a suitable candidate for practical use.

REFRENCES

[1] Liu, Y., Li, C., Wang, M., et al. (2023). A combination network of CNN and Transformer for interference identification. Frontiers in Computational Neuroscience, 17. Retrieved from https://www.frontiersin.org/articles/10.3389/fncom.2023.1309694/full.

[2] Khan, A., Islam, M., Jan, Z., Khan, R. U., & Park, J. S. (2023). Object detection using deep learning, CNNs, and vision transformers: A review. IEEE Access, 11, 378–394. https://doi.org/10.1109/ACCESS.2023.3239355.

[3] Yu, H., Zhang, Y., Li, X., et al. (2022). ConvFormer: Combining CNN and Transformer for medical image segmentation. arXiv Preprint. Retrieved from https://arxiv.org/abs/2211.08564.

[4] Zheng, X., Li, J., Song, W., et al. (2023). A CNN-Transformer network combining CBAM for change detection. Remote Sensing, 15(9), 2406. Retrieved from https://www.mdpi.com/2072-4292/15/9/2406.

[5] Sivabrahmam, T., & Duvvuri, S. (2022). Road traffic accident severity prediction using machine learning. International Journal for Research Trends and Innovation (IJRTI), 7(10), 90–95. Retrieved from https://www.ijrti.org/papers/IJRTI2210015.pdf.

[6] Zhang, Y., Liu, Y., & Wang, F. (2004). A freeway traffic incident detection algorithm based on neural networks. In Computational Science and Its Applications – ICCSA 2004 (Vol. 3044, pp. 930–939). Springer. https://doi.org/10.1007/978-3-540-24767-8_97.

[7] Wang, L.-L., Ngan, H. Y. T., & Yung, N. H. C. (2015). Automatic incident classification for big traffic data by adaptive boosting SVM. arXiv Preprint. Retrieved from https://arxiv.org/abs/1512.04392.

[8] Chen, S., Wang, W., & van Zuylen, H. (2009). Construct support vector machine ensemble to detect traffic incident. Expert Systems with Applications, 36(8), 10976–10986. https://doi.org/10.1016/j.eswa.2009.02.027.
[9] Yao, Y., Zhang, Y., Du, B., & Wang, Y. (2014). A support vector machine with the tabu search algorithm for freeway incident detection. International Journal of Computational Intelligence Systems, 7(6), 1142–1150. https://doi.org/10.1080/18756891.2014.975484.
[10] Xiao, J. (2019). SVM and KNN ensemble learning for traffic incident detection. Physica A: Statistical Mechanics and Its Applications, 517, 29–35. https://doi.org/10.1016/j.physa.2018.10.019.
[11] Basnayake, C. S., Chowdhury, M., Ahmed, K., & Rakha, H. (2019). Automated traffic incident detection with GPS equipped probe vehicles. In Proceedings of the Institute of Navigation International Technical Meeting (pp. 1–10).
[12] Li, Y., & McDonald, M. (2005). Motorway incident detection using probe vehicles. Proceedings of the Institution of Civil Engineers - Transport, 158(1), 11–15. https://doi.org/10.1680/tran.2005.158.1.11.
[13] Lin, L., Li, Y., Du, B., Yang, F., & Ran, B. (2020). Automated traffic incident detection with a smaller dataset based on generative adversarial networks. Accident Analysis & Prevention, 144, 105628. https://doi.org/10.1016/j.aap.2020.105628.
[14] Wang, Y., Zhang, H., & Liu, X. (2023). Spatio-temporal graph attention network for traffic prediction. arXiv Preprint. Retrieved from https://arxiv.org/abs/2312.12345.
[15] Luo, R., Song, Y., Huang, L., Zhang, Y., & Su, R. (2022). STGIN: A spatial temporal graph-informer network for long sequence traffic speed forecasting. arXiv Preprint. Retrieved from https://arxiv.org/abs/2210.01799.
[16] Tang, G., Yu, Y., Qin, C., et al. (2021). Day-ahead interval prediction of bus load based on CNN-LSTM quantile regression. Electric Power Engineering Technology, 40(4), 123–129.
[17] Al-Thani, M. G., Sheng, Z., Cao, Y., & Yang, Y. (2024). Traffic transformer: Transformer-based framework for temporal traffic accident prediction. AIMS Mathematics, 9(5), 12610–12629. https://doi.org/10.3934/math.2024617.
[18] Saleh, K., Grigorev, A., & Mihaita, A.-S. (2022). Traffic accident risk forecasting using contextual vision transformers. arXiv Preprint. Retrieved from https://arxiv.org/abs/2209.11180.
[19] Anik, B. M. T. H., Islam, Z., & Abdel-Aty, M. (2023). inTformer: A time-embedded attention-based transformer for crash likelihood prediction at intersections using connected vehicle data. arXiv Preprint. Retrieved from https://arxiv.org/abs/2307.03854.
[20] Kamal, H., & Mashaly, M. (2024). Advanced hybrid Transformer-CNN deep learning model for effective intrusion detection systems with class imbalance mitigation using resampling techniques. Future Internet, 16(12), 481. https://doi.org/10.3390/fi16120481.
[21] Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: Unbiased
[22] boosting with categorical features. Advances in Neural Information Processing Systems, 31. Retrieved
[23] from https://arxiv.org/abs/1706.09516.
[24] Bentéjac, C., Csörgö, A., & Martínez-Muñoz, G. (2021). A comparative analysis of gradient boosting
[25] algorithms. Artificial Intelligence Review, 54, 1937–1967. https://doi.org/10.1007/s10462-020-09896-5.
[26] Zou, Y., Shi, G., Shi, H., & Wang, Y. (2011). Traffic incident classification at intersections based on image
[27] sequences by HMM/SVM classifiers. Multimedia Tools and Applications, 52, 133–145
[28] https://doi.org/10.1007/s11042-010-0540-6.
[29] Stephanedes, Y. J., Chassiakos, A. P., & Michalopoulos, P. G. (1992). Comparative performance evaluation
[30] of incident detection algorithms. Transportation Research Record, 1360, 50–57.
[31] Sun, Y., Mallick, T., Balaprakash, P., & Macfarlane, J. (2022). A data-centric weak supervised learning for
[32] highway traffic incident detection. Accident Analysis & Prevention, 176, 106779.
[33] https://doi.org/10.1016/j.aap.2022.106779.