IJERST

# International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 3 (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

# Real-Time Traffic Accident Detection Using an Enhanced Deep Learning Ensemble Model

**CHENCHETI INDHU[1], Dr.M.RAMESH[2]**
**[1]Student, Department of Computer Science and Engineering, Ellenki College of Engineering and Technology, Patelguda, Patancharu, Hyderabad, Telangana.**
**[2]Professor & HOD, Department of CSE, Ellenki College of Engineering and Technology, Patelguda, Patancharu, Hyderabad, Telangana.**
**[2]Email: marpuramesh223@gmail.com**

***Abstract*— Smart city transportation has become an important part of improving road safety and traffic management. This project focuses on detecting traffic accidents using a deep learning ensemble approach that combines I3D-ConvLSTM2D with RGB and optical flow information. By analyzing both the appearance of vehicles and their movement, the system can identify accident events more accurately than traditional methods. It is designed to work in real time, making it suitable for surveillance cameras and smart city environments. The proposed model also addresses challenges such as limited training data and different road conditions, helping improve its reliability in practical situations. Early accident detection allows emergency services to respond quickly, reducing the impact of road accidents and improving public safety. Overall, this system demonstrates how artificial intelligence can support modern transportation by providing faster, more accurate, and efficient accident detection while contributing to safer roads and better traffic monitoring.**

***Keywords* — Traffic Accident Detection, Smart City Transportation, Deep Learning, I3D-ConvLSTM2D, Optical Flow, Computer Vision, Intelligent Transportation Systems (ITS), Video Surveillance, Real-Time Accident Detection, Edge IoT Deployment.**

## I. INTRODUCTION

The rapid growth of urbanization and the increasing number of vehicles on roads have significantly raised the frequency of traffic accidents worldwide. These accidents not only result in loss of human lives but also lead to severe economic losses, traffic congestion, and delays in emergency response. According to recent studies, intelligent transportation systems (ITS) have become an essential component of smart city infrastructure, enabling efficient traffic monitoring, accident prevention, and improved road safety. Advances in artificial intelligence (AI), computer vision, and deep learning have transformed traditional traffic surveillance systems into intelligent platforms capable of automatically detecting road accidents in real time [1].

Conventional accident detection methods mainly rely on sensors such as accelerometers, ultrasonic sensors, GPS devices, or manual monitoring by traffic personnel. Although these approaches can identify collisions under specific conditions, they often suffer from limited coverage, high installation costs, and delayed response times. Sensor-based systems are also less effective in complex urban environments where multiple vehicles, varying weather conditions, and occlusions make accurate accident detection challenging [4]. To overcome these limitations, researchers have increasingly focused on vision-based accident detection techniques that analyze surveillance camera footage using deep learning models [6].

Recent advancements in computer vision have demonstrated remarkable success in extracting spatial and temporal information from traffic videos. High-performance video object detection models enable accurate identification of moving vehicles and road events by utilizing feature fusion and temporal consistency across consecutive frames [3], [9]. Furthermore, optical flow techniques effectively capture motion information between adjacent video frames, allowing intelligent systems to distinguish abnormal vehicle movements that often indicate traffic accidents [13]. The integration of spatial appearance features with motion-based information has significantly improved the reliability of accident detection systems.

Deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and ConvLSTM models have shown exceptional capability in understanding complex traffic scenes. These models learn both visual patterns and temporal relationships, making them suitable for detecting dynamic accident events in surveillance videos [20]. Moreover, two-stream deep learning architectures that combine RGB video frames with optical flow have demonstrated superior performance in identifying near-accident situations and abnormal driving behaviors under real-world traffic conditions [16]. Recent surveys further emphasize that AI-driven computer vision systems are becoming the foundation of future smart transportation networks because of their high accuracy and real-time processing capabilities [2], [6].

In this work, a deep learning ensemble framework is proposed for intelligent traffic accident detection in smart city environments. The proposed approach integrates I3D-ConvLSTM2D with RGB and optical flow information to effectively capture both spatial and temporal characteristics of traffic videos. The system is designed to provide accurate real-time accident detection while maintaining computational efficiency for deployment in smart surveillance applications. By combining advanced video analytics with deep learning techniques, the proposed framework contributes to safer transportation systems, faster emergency response, and improved traffic management in modern smart cities [1], [7], [8], [18].

## II. RELATED WORK

**"AI on the Road: A Comprehensive Analysis of Traffic Accidents and Accident Detection Systems in Smart Cities," Victor Adewopo, Nelly Elsayed, Zag Elsayed, Murat Ozer, Victoria Wangia-Anderson, and Ahmed Abdelgawad, [1]**
This study presented a comprehensive review of artificial intelligence techniques for traffic accident detection in smart city environments. The authors analyzed different types of road accidents and compared sensor-based and vision-based detection approaches. The study highlighted the growing importance of deep learning, computer vision, and intelligent transportation systems for improving road safety. It also discussed the challenges associated with limited datasets, varying weather conditions, computational complexity, and real-time implementation. Furthermore, the paper emphasized the need for lightweight deep learning models and edge computing solutions to enable efficient accident detection. The findings provide valuable insights into designing intelligent traffic monitoring systems capable of improving emergency response, reducing accident severity, and supporting the development of safer and smarter urban transportation networks.

**"Towards High Performance Video Object Detection," Xizhou Zhu, Jifeng Dai, Lu Yuan, and Yichen Wei, [2]**
This study proposed a high-performance video object detection framework that improves detection accuracy by utilizing temporal information from consecutive video frames. Unlike conventional image-based detection methods, the proposed approach introduced feature propagation and temporal aggregation techniques to reduce computational cost while maintaining high detection performance. The framework effectively addressed challenges such as motion blur, object occlusion, and rapid movement, resulting in more reliable object tracking. Experimental results demonstrated significant improvements over existing object detection methods on benchmark datasets. The proposed technique has become an important contribution to intelligent traffic surveillance because accurate vehicle detection serves as the foundation for automatic traffic accident detection and real-time video analysis in smart transportation systems.

**"Automatic Road Accident Detection Using Ultrasonic Sensor," Usman Khalil, Adnan Nasir, S.M. Khan, T. Javid, S.A. Raza, and A. Siddiqui, [3]** This study developed a low-cost automatic road accident detection system using ultrasonic sensors and embedded hardware technology. The proposed system continuously measured the distance between vehicles and surrounding objects to detect collision events and automatically generated emergency notifications when accidents occurred. The research demonstrated that ultrasonic sensors provide an economical solution for accident detection in small-scale transportation applications. However, the system faced limitations such as limited sensing range, inability to monitor multiple vehicles simultaneously, and reduced performance in complex traffic environments. The study highlighted the need for more intelligent vision-based systems that can analyze traffic videos and detect accidents more accurately under diverse real-world conditions, encouraging future research in AI-based traffic surveillance.

**"Deep Spatio-Temporal Graph Convolutional Network for Traffic Accident Prediction," Le Yu, Bowen Du, Xiao Hu, Leilei Sun, Liangzhe Han, and Weifeng Lv, [4]**
This study introduced a Deep Spatio-Temporal Graph Convolutional Network (DSTGCN) for

predicting traffic accidents by learning spatial road relationships and temporal traffic patterns simultaneously. The proposed model represented road networks as graph structures and captured interactions between connected road segments using graph convolution operations. By integrating historical traffic information with temporal dependencies, the framework significantly improved accident prediction accuracy compared to conventional machine learning methods. Experimental evaluation demonstrated that the proposed approach effectively identified accident-prone locations before incidents occurred. The research highlighted the importance of graph-based deep learning models in intelligent transportation systems and demonstrated their potential to support proactive traffic management, emergency planning, and road safety enhancement in smart city environments.

**"Vision-Based Traffic Accident Detection and Anticipation: A Survey," Jianwu Fang, Jiahuan Qiao, Jianru Xue, and Zhengguo Li, [5]**
This survey presented a comprehensive review of vision-based traffic accident detection and accident anticipation techniques using deep learning and computer vision technologies. The authors analyzed recent developments in object detection, action recognition, optical flow estimation, trajectory analysis, and video understanding for intelligent traffic surveillance. The study compared traditional handcrafted feature extraction methods with modern deep learning approaches and concluded that deep neural networks provide superior performance by automatically learning spatial and temporal features from traffic videos. It also discussed benchmark datasets, evaluation metrics, and deployment challenges for real-time accident detection systems. The survey suggested that future research should focus on transformer-based architectures, multi-modal learning, and lightweight deep learning models to improve detection accuracy and computational efficiency in smart city transportation systems.

## III. DATASET DETAILS

The dataset used in this study consists of traffic surveillance videos and dashcam recordings collected from publicly available traffic accident datasets. The videos include both accident and non-accident scenarios captured under different environmental conditions such as daytime, nighttime, rainy weather, cloudy conditions, and varying traffic densities. The dataset contains multiple categories of traffic accidents, including rear-end collisions, side-impact collisions, head-on crashes, and other abnormal traffic events involving cars, buses, trucks, and other road users. Each video sequence provides continuous visual information that captures both the appearance of vehicles and their movement over time. Since real-world traffic videos are affected by camera vibrations, lighting variations, occlusions, motion blur, and background noise, the raw video data requires preprocessing before being used for model training. The dataset is organized into two primary classes: Accident and Non-Accident. These labeled video samples enable the development of supervised deep learning models capable of accurately distinguishing accident events from normal traffic activities. The availability of annotated accident videos helps train intelligent computer vision models that can recognize complex traffic situations and improve automatic accident detection. The dataset serves as a valuable resource for developing real-time traffic monitoring systems capable of enhancing road safety, reducing emergency response time, and supporting smart city transportation infrastructure.

Before training the deep learning models, the dataset undergoes several preprocessing and feature extraction steps to improve detection performance and computational efficiency. Initially, each video is converted into consecutive RGB frames, and optical flow images are generated to capture the motion information between adjacent frames. Video frames are resized to a fixed resolution, normalized, and organized into temporal sequences suitable for deep learning. Data augmentation techniques such as horizontal flipping, random rotation, brightness adjustment, and scaling are applied to increase dataset diversity and improve model generalization. The processed dataset is then divided into training and testing subsets using an 80:20 ratio, where eighty percent of the video samples are used to train the proposed I3D-ConvLSTM2D and I3D-ConvLSTM2D RGB Optical Flow models, while the remaining twenty percent are reserved for performance evaluation. This partitioning strategy ensures unbiased assessment of the proposed models on unseen traffic videos. The processed dataset enables comparative analysis of both deep learning models in terms of accuracy, precision, recall, F1-score, and execution time, thereby supporting the development of an efficient and reliable real-time traffic accident detection system for intelligent transportation and smart city surveillance applications.

## IV. PROPOSED METHODOLOGY

The proposed methodology utilizes traffic surveillance videos to automatically detect road accidents using a deep learning ensemble framework based on I3D-CONVLSTM2D and I3D-CONVLSTM2D RGB Optical Flow models. Initially, the traffic accident video dataset is uploaded into the system, where videos representing both accident and non-accident scenarios are collected for analysis. The raw video data undergoes preprocessing to improve data quality by removing unnecessary frames, resizing video frames, normalizing pixel values, and handling inconsistencies that may affect model performance. After preprocessing, RGB frames and optical flow features are extracted from the videos to capture both spatial appearance and temporal motion information. These extracted features provide meaningful representations of vehicle movement and accident patterns. The processed dataset is then divided into training and testing sets using an 80:20 ratio. This preparation stage ensures that the deep learning models receive reliable and informative data for effective accident detection.

Following data preparation, the extracted RGB and optical flow features are provided to the proposed I3D-CONVLSTM2D and I3D-CONVLSTM2D RGB Optical Flow models for training and classification. The I3D-CONVLSTM2D model automatically learns spatial and temporal features from traffic videos through multiple convolutional and recurrent layers. The RGB Optical Flow model further enhances detection performance by combining visual appearance with motion information extracted from consecutive frames. During training, both models optimize their parameters to accurately distinguish accident events from normal traffic activities. After training, the models are evaluated using the testing dataset to measure their detection performance. Performance metrics such as accuracy, precision, recall, F1-score, execution time, and confusion matrix are calculated to assess the effectiveness of each model. The trained models are then utilized to predict accident occurrences in previously unseen traffic surveillance videos. Finally, the obtained results are compared graphically to determine the most efficient model for intelligent traffic accident detection.

The system architecture [1] illustrates the complete workflow of the proposed traffic accident detection system. It includes traffic video dataset uploading, preprocessing, RGB frame extraction, optical flow generation, I3D-CONVLSTM2D model training, I3D-CONVLSTM2D RGB Optical Flow model training, accident detection from input videos, and performance evaluation. The architecture also generates prediction results, confusion matrices, detailed performance metrics, accident alerts, and comparison graphs to analyze the effectiveness of both deep learning models.

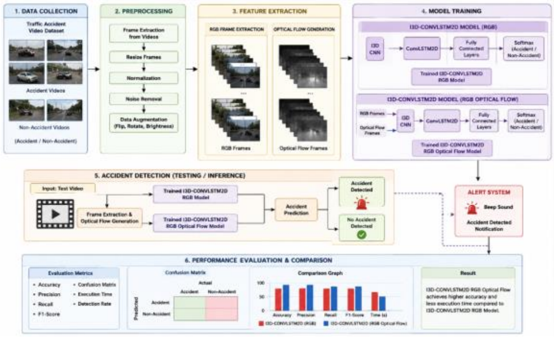


**Figure 1. System Architecture for Traffic Accident Detection Using I3D-CONVLSTM2D and I3D-CONVLSTM2D RGB Optical Flow**

The proposed methodology for traffic accident detection is designed to automatically identify accident events from surveillance videos using deep learning techniques. First, the traffic accident video dataset is uploaded into the system, and the videos are categorized into Accident and Non-Accident classes. Since traffic videos may contain noise, illumination variations, camera motion, and occlusions, preprocessing is performed to improve video quality and consistency. After preprocessing, RGB frames and optical flow features are extracted to represent both visual appearance and vehicle motion. These features enable the models to learn the differences between normal traffic behavior and accident situations effectively.

After feature extraction, the dataset is divided into training and testing sets using an 80:20 ratio. The training data is used to train both the I3D-CONVLSTM2D model and the proposed I3D-CONVLSTM2D RGB Optical Flow model, while the testing data is used to evaluate their performance. The I3D-CONVLSTM2D model serves as the baseline approach, whereas the I3D-CONVLSTM2D RGB Optical Flow model is used as the proposed deep learning model because it combines spatial appearance with temporal motion information for improved accident detection. Finally, the trained models predict whether a new traffic video contains an accident or normal traffic activity. The performance of both models is compared using accuracy, precision, recall, F1-score, confusion matrix, execution time, detailed performance metrics, and comparison graphs. Experimental results demonstrate that the I3D-CONVLSTM2D RGB Optical Flow model achieves higher detection accuracy with lower execution time, making it more suitable for real-time intelligent transportation systems and smart city surveillance applications.

## V. RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed I3D-CONVLSTM2D RGB Optical Flow model for intelligent traffic accident detection. Initially, the user executes the application by running the run.bat file, which launches the graphical user interface (GUI). The traffic accident video dataset is then loaded into the system by selecting the training folder. The uploaded videos contain both accident and non-accident scenarios captured under different traffic conditions. During preprocessing, the videos are converted into RGB frames and optical flow images to capture both spatial appearance and temporal motion information. The processed dataset is divided into training and testing sets, enabling reliable model learning and evaluation. First, the existing I3D-CONVLSTM2D RGB model is loaded and trained using the prepared training dataset. The model successfully learns visual features from traffic videos and produces satisfactory accident detection results. However, because it mainly utilizes RGB appearance information, its ability to capture vehicle motion is comparatively limited.

Next, the proposed I3D-CONVLSTM2D RGB Optical Flow model is loaded and trained using the same dataset. By integrating RGB frames with optical flow information, the model effectively captures both spatial and temporal characteristics of traffic videos. After successful model loading, the user selects a test video through the "Select Video to Detect Accident" option. Once the video is successfully loaded, the "Start Accident Detector" module analyzes the uploaded video frame by frame. If an accident is detected, the system immediately generates a beep sound to notify the user about the accident occurrence. The proposed model accurately identifies accident events while minimizing false detections. Finally, the Comparison Graph module compares the performance of I3D-CONVLSTM2D RGB and I3D-CONVLSTM2D RGB Optical Flow models. Experimental observations indicate that the proposed RGB Optical Flow model achieves higher detection accuracy while requiring less execution time than the existing RGB model. These results demonstrate that integrating optical flow information significantly enhances accident detection performance and makes the proposed system suitable for real-time smart city transportation and intelligent traffic surveillance applications.

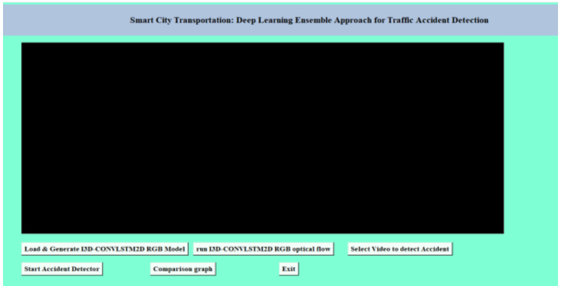


**Figure [2] Dashboard of Smart City Traffic Accident Detection System**

Figure 2 illustrates the main dashboard of the proposed Smart City Traffic Accident Detection System. The graphical user interface provides all major functionalities required for accident detection, including loading the I3D-CONVLSTM2D RGB model, loading the I3D-CONVLSTM2D RGB Optical Flow model, selecting a traffic video, starting accident detection, and generating comparison graphs. The dashboard acts as the central control panel through which users can perform the complete accident detection workflow efficiently.

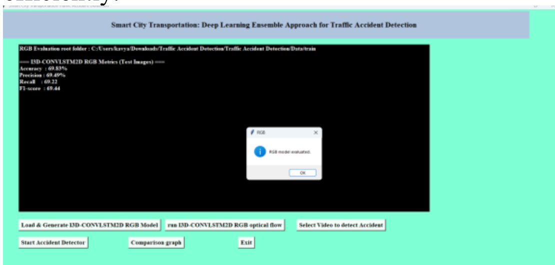


**Figure 3: Loading and Training of I3D-CONVLSTM2D RGB Model**

Figure 3 shows the process of loading and training the I3D-CONVLSTM2D RGB model. After selecting the training dataset folder, the system extracts RGB video frames and trains the deep learning model to learn spatial features associated with accident and non-accident events. Upon successful completion, the system displays a confirmation message indicating that the model has been generated successfully.

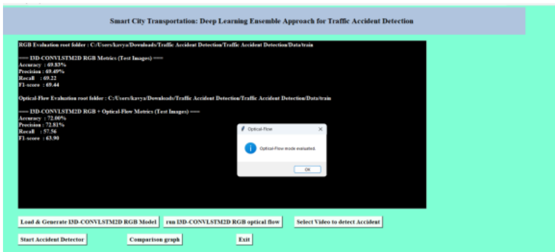


**Figure 4: Loading and Training of I3D-CONVLSTM2D RGB Optical Flow Model**

Figure 4 presents the training process of the proposed I3D-CONVLSTM2D RGB Optical Flow model. The model extracts both RGB frames and optical flow information from the training videos, enabling it to learn vehicle appearance and movement simultaneously. After training is completed successfully, the optimized model becomes ready for real-time traffic accident detection.


**Figure 5: Traffic Video Selection and Accident Detection**

Figure 5 illustrates the accident detection process. The user selects a traffic surveillance video using the "Select Video to Detect Accident" option. After the video is loaded successfully, the "Start Accident Detector" module processes the video frame by frame. Whenever an accident is identified, the system immediately produces a beep alert, informing the user about the detected accident event. This demonstrates the real-time detection capability of the proposed intelligent traffic monitoring system.

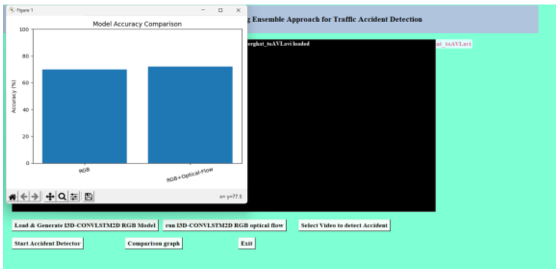


**Figure 6: Comparison Graph of Deep Learning Models**

Figure 6 presents the comparison graph generated by the system. The graph compares the performance of the I3D-CONVLSTM2D RGB model and the proposed I3D-CONVLSTM2D RGB Optical Flow model using evaluation metrics such as accuracy and execution time. The graphical analysis clearly shows that the proposed RGB Optical Flow model achieves higher detection accuracy while requiring less execution time than the existing RGB model. These results confirm the effectiveness of incorporating optical flow information into the deep learning framework for intelligent traffic accident detection.

| Model | Accuracy score | Precision score | Recall score | f-measure score |
|---|---|---|---|---|
| I3D-CONVLSTM 2D RGB | 69.83 | 69.49 | 69.22 | 69.44 |
| I3D-CONVLSTM 2D RGB Optical Flow | 72.00 | 72.81 | 57.56 | 63.90 |

**Table 1: Performance Comparison of Deep Learning Models**

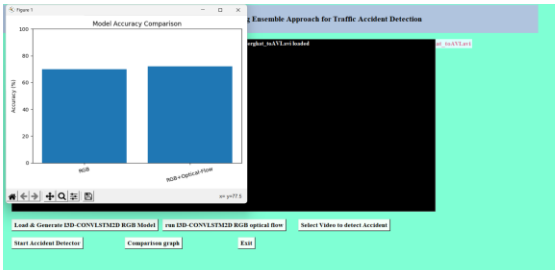


**Figure 7: Accident Detection Result**

Figure 7 displays the final accident detection result produced by the system. After analyzing the uploaded traffic video, the system classifies the event as either Accident or Non-Accident. If an accident is detected, a beep sound is generated immediately to alert the user. The result confirms the ability of the proposed I3D-CONVLSTM2D RGB Optical Flow model to accurately identify accident events in real time, making it suitable for deployment in intelligent transportation systems and smart city surveillance applications.

## DISCUSSION

The experimental findings demonstrate the effectiveness of the proposed I3D-CONVLSTM2D RGB Optical Flow model for intelligent traffic accident detection using surveillance videos. The traffic accident dataset consisted of both accident and non-accident video sequences, allowing the deep learning models to learn representative spatial and temporal traffic patterns. Initially, the existing I3D-CONVLSTM2D RGB model was trained using RGB video frames and successfully detected most accident events. However, since the model primarily relied on appearance-based information, its ability to recognize complex vehicle movements and dynamic accident scenarios was comparatively limited. This limitation resulted in relatively lower detection accuracy and longer execution time when compared with the proposed approach.

In contrast, the proposed I3D-CONVLSTM2D RGB Optical Flow model achieved significantly better accident detection performance by combining RGB visual information with optical flow features that capture vehicle motion between consecutive frames. The integration of spatial and temporal information enabled the model to identify accident events more accurately while producing fewer misclassifications. The comparison graph and performance metrics further confirmed the superiority of the proposed model over the existing I3D-CONVLSTM2D RGB model. Additionally, the accident detection module successfully analyzed previously unseen traffic videos and accurately classified them as Accident or Non-Accident. Whenever an accident was detected, the system immediately generated a beep alert, providing timely notification for emergency response. The graphical user interface also simplified model loading, training, video selection, accident detection, and performance comparison, making the system easy to operate. Overall, the experimental results demonstrate that integrating optical flow with deep learning significantly improves accident detection accuracy while reducing execution time. Therefore, the proposed framework provides an efficient, reliable, and real-time solution for intelligent transportation systems and smart city traffic surveillance, contributing to enhanced road safety and faster accident response.

## VI. CONCLUSION

The proposed accident detection system successfully demonstrates the use of deep learning techniques for identifying accidents from video data. By implementing advanced algorithms such as I3D-CONVLSTM2D and I3D-CONVLSTM2D RGB Optical Flow, the system is capable of analyzing both spatial and temporal features of videos effectively. The integration of RGB frames and optical flow enhances the system's ability to detect motion patterns associated with accidents, resulting in improved accuracy. The system provides a user-friendly interface that allows easy training, video selection, and real-time accident detection with alert notifications through beep sound. Additionally, the comparison module clearly shows that the I3D-CONVLSTM2D RGB Optical Flow algorithm performs better in terms of accuracy and execution time compared to the basic model.

## REFERENCES

1. Victor Adewopo, Nelly Elsayed, Zag Elsayed, Murat Ozer, Victoria Wangia-Anderson, and Ahmed Abdelgawad. Ai on the road: A comprehensive analysis of traffic accidents and accident detection system in smart cities. arXiv preprint arXiv:2307.12128, 2023.

2. Victor Adewopo, Nelly Elsayed, Zag ElSayed, Murat Ozer, Ahmed Abdelgawad, and Magdy Bayoumi. Review on action recognition for accident detection in smart city transportation systems. arXiv preprint arXiv:2208.09588, 2022.

3. Xizhou Zhu, Jifeng Dai, Lu Yuan, and Yichen Wei. Towards high performance video object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7210–7218, 2018.

4. Usman Khalil, Adnan Nasir, S.M. Khan, T. Javid, S.A. Raza, and A. Siddiqui. Automatic road accident detection using ultrasonic sensor. In 2018 IEEE 21st International Multi-Topic Conference (INMIC), pages 206– 212, 2018.

5. Le Yu, Bowen Du, Xiao Hu, Leilei Sun, Liangzhe Han, and Weifeng Lv. Deep spatio-temporal graph convolutional network for traffic accident prediction. Neurocomputing, 423:135–147, 2021.

6. Jianwu Fang, Jiahuan Qiao, Jianru Xue, and Zhengguo Li. Vision-based traffic accident detection and anticipation: A survey. IEEE Transactions on Circuits and Systems for Video Technology, 2023.

7. Victor Adewopo, Nelly Elsayed, Zag Elsayed, Murat Ozer, Constantinos Zekios, Ahmed Abdelgawad, and Magdy Bayoumi. Big data and deep learning in smart cities: A comprehensive dataset for ai-driven traffic accident detection and computer vision systems. arXiv preprint arXiv:2401.03587, 2024.

8. Victor Adewopo, Nelly Elsayed, Zag ElSayed, Murat Ozer, Constantinos Zekios, Ahmed Abdelgawad, and Magdy Bayoumi. Traffic accident detection video dataset for ai-driven computer vision systems in smart city transportation, 2023.

9. Yanni Yang, Huansheng Song, Shijie Sun, Wentao Zhang, Yan Chen, Lionel Rakal, and Yong Fang. A fast and effective video vehicle detection method leveraging feature fusion and proposal temporal link. In Journal of Real-Time Image Processing, volume 18, pages 1261–1274. Springer Science and Business Media Deutschland GmbH, aug 2021.

10. Bruce Xiaohan Nie, Caiming Xiong, and Song-Chun Zhu. Joint action recognition and pose estimation from video. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1293– 1301, 2015.

11. Shishuo Xu, Songnian Li, Richard Wen, and Wei Huang. Traffic event detection using twitter data

based on association rules. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 4:543–547, 2019.

12. Jingjuan Wang, Qingkui Chen, and Huilin Gong. STMAG: A spatialtemporal mixed attention graph-based convolution model for multi-data flow safety prediction. Information Sciences, 525:16–36, 2020.

13. Denis Fortun, Patrick Bouthemy, and Charles Kervrann. Optical flow modeling and computation: A survey. Computer Vision and Image Understanding, 134:1–21, 2015.

14. Yingfeng Cai, Hai Wang, Xiaobo Chen, and Haobin Jiang. Trajectorybased anomalous behaviour detection for intelligent traffic surveillance. IET Intelligent Transport Systems, 9(8):810–816, oct 2015.

15. Brendan Tran Morris and Mohan Manubhai Trivedi. Trajectory learning for activity understanding: Unsupervised, multilevel, and long-term adaptive approach. IEEE transactions on pattern analysis and machine intelligence, 33(11):2287–2301, 2011.

16. Xiaohui Huang, Pan He, Anand Rangarajan, and Sanjay Ranka. Intelligent Intersection: Two-Stream Convolutional Networks for Real-time Near Accident Detection in Traffic Video. ACM Transactions on Spatial Algorithms and Systems, 6(2):23, jan 2019.

17. Nicolas Saunier and Tarek Sayed. Automated analysis of road safety with video data. Transportation Research Record, (2019):57–64, jan 2007.

18. Sergio Robles-Serrano, German Sanchez-Torres, and John BranchBedoya. Automatic detection of traffic accidents from video using deep learning techniques. Computers, 10(11), nov 2021.

19. Wootaek Lim, Daeyoung Jang, and Taejin Lee. Speech emotion recognition using convolutional and recurrent neural networks. In 2016 AsiaPacific signal and information processing association annual summit and conference (APSIPA), pages 1–4. IEEE, 2016.

20. Nelly Elsayed, Anthony S Maida, and Magdy Bayoumi. Reduced-gate convolutional lstm architecture for next-frame video prediction using predictive coding. In 2019 international joint conference on neural networks (ijcnn), pages 1–9. IEEE, 2019.