Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 3, March : 2025

REAL-TIME ACCIDENT DETECTION AND EMERGENCY RESPONSE SYSTEM USING CCTV VIDEO ANALYSIS

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***Abstract*- Road traffic accidents in India remain a significant public health issue, resulting in frequent injuries and fatalities. Quick intervention is critical for improving survival rates, yet delays in emergency responses often obstruct timely care. This idea proposes an automated system that leverages computer vision to analyze real-time CCTV video streams, enabling fast accident detection and response. Our approach involves selecting key frames from the video, extracting important features, and using machine learning models to classify frames as containing accidents or not and as suggested in the future scope of the base paper we focus on integrating an automated alert dispatch system, which will trigger notifications to emergency services upon accident detection. This alert mechanism will provide real-time geolocation data of the incident ensuring rapid response and communication.**

***Keywords*: Road traffic accidents, computer vision, real-time CCTV analysis, accident detection, machine learning, feature extraction, emergency response, automated alert system, geolocation data, public health safety**

I.INTRODUCTION

Traffic accidents are still among the top causes of deaths and injuries globally, and India ranks as one of the most impacted nations because of its congested road systems, heavy traffic, and varied types of vehicles. In spite of improvements in road infrastructure, transportation safety protocols, and emergency medical services, a notable issue remains with the slow detection and response to accidents. In many instances, the effectiveness of accident response relies on manual reporting, which can be delayed by human mistakes, absence of witnesses, or poor communication methods. Such delays cause significant time loss, frequently resulting in serious repercussions for accident victims in need of urgent medical attention. To tackle these issues, this study introduces a Real-Time Accident Detection and Emergency Response System that combines computer vision, deep learning, and automated alert systems to improve the effectiveness of accident detection and emergency response. In contrast to conventional approaches that depend on manual reporting, this system utilizes real-time analysis of CCTV footage to automatically and precisely identify accidents. The system utilizes Convolutional Neural Networks (CNNs) to examine visual information, identify important features related to accidents, and accurately classify incidents. By removing human reliance in the reporting system, the suggested solution greatly shortens response times and guarantees that emergency services are promptly alerted upon accident identification. An essential aspect of this system is its automated alert distribution feature, allowing real-time communication with emergency medical teams and traffic control authorities. When an accident is identified, the system promptly notifies the closest hospitals, ambulance providers, and law enforcement agencies, guaranteeing rapid medical assistance and reducing fatalities. Moreover, the incorporation of this technology within smart city frameworks can enhance road safety, optimize traffic surveillance, and improve the handling of incident-related occurrences. The use of AI-powered accident detection not only boosts road safety but also streamlines emergency resource distribution, easing the strain on first responders and enhancing overall traffic efficiency. Additionally, this study emphasizes the significance of real-time video analysis for traffic monitoring and accident prevention. By employing machine learning-based classification methods, the system can distinguish between accident and non-accident situations, reducing false alerts and

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enhancing dependability. This feature allows it to be a scalable solution suitable for urban, semi-urban, and rural regions where conventional accident reporting techniques might be ineffective. The Real-Time Accident Detection and Emergency Response System put forth in this research offers a thorough, automated, and smart solution to tackling one of the most urgent issues in road safety.

II. RELATED WORK

Advancements in real-time accident detection and emergency response systems using CCTV footage have been significantly propelled by developments in machine learning, computer vision, and sensor technology integration. These systems utilize video data, sensor inputs, and sophisticated algorithms to enhance the accuracy of accident detection and expedite emergency responses. Gomathy et al. discuss the development of systems that employ sensors and algorithms to detect collisions and promptly alert emergency services, thereby improving traffic safety by reducing response times and increasing detection accuracy. The integration of advanced computing technologies ensures the reliability and effectiveness of these systems. Sensor-based technologies have also made significant progress in environmental monitoring and smart agriculture.

Fig. 1. Real-world scenarios of traffic images

Smith et al. (2020) examine sensors used to detect pollutants and monitor environmental changes, while Lee et al. (2018) emphasize their applications in tracking soil conditions, crops, and weather patterns. These sensors provide real-time data that support informed decision-making and effective management in these sectors. Garcia-Gasulla et al. (2018) demonstrate the adaptability of convolutional neural networks (CNNs) in extracting essential features from traffic videos. Their research highlights the effectiveness of CNNs in identifying patterns and anomalies, making them integral to real-time accident detection systems. The automation of feature extraction by CNNs enables systems to swiftly and accurately focus on critical elements within video frames. Hu et al. (2004) introduce a method for predicting traffic accidents through 3D model-based vehicle tracking, offering a detailed representation of vehicle dynamics and spatial relationships to anticipate potential collisions. This proactive approach is crucial for accident prevention and enhancing road safety.

Huang et al. (2020) propose a two-stream CNN model that improves the detection of near-accidents in traffic videos by integrating spatial and temporal data. This model examines both static features and dynamic changes in video frames, increasing the accuracy of detecting risky traffic behaviors. Ikeda et al. (1999) developed an early system for detecting abnormal traffic incidents through image processing, identifying irregular traffic patterns via video analysis. This foundational work has contributed to modern automated traffic management systems, enhancing safety by quickly detecting and responding to anomalies.

Chen et al. (2020) explore the selection of key features from vehicle trajectory data to predict risky lane-changing behaviors. Their research focuses on identifying factors that contribute to accidents during lane changes, enhancing the predictive accuracy of traffic safety models. Truong et al. (2020)

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ISSN: 0970-2555
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present a real-time vehicle accident detection system using spatioportal features and deep learning techniques, improving immediate response capabilities. Wang et al. (2020) review various machine learning approaches for traffic incident detection and management, emphasizing AI's role in optimizing traffic flow and reducing disruptions. Both studies highlight the significant impact of advanced technologies on traffic safety. Collectively, these studies illustrate substantial advancements in applying machine learning, computer vision, and image processing techniques for real-time accident detection and emergency response, particularly through the analysis of CCTV footage.

The considered base paper proposes a robust framework for traffic accident detection using video data, focusing on three key phases: pre-processing, feature extraction, and classification. In the pre-processing phase, video data is segmented into smaller shots using the Scene detect library, and essential frames are identified as keyframes based on histogram differences. This approach minimizes redundant frames and significantly reduces the processing load. The identified keyframes are crucial for capturing moments with sudden changes, such as accidents, ensuring a streamlined dataset for subsequent phases.

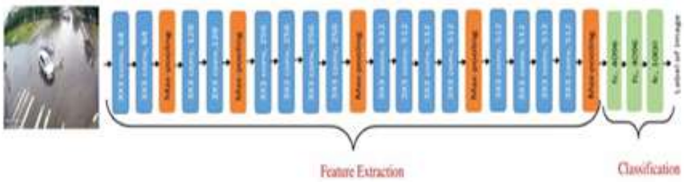

Fig. 2. Frame Extraction

For feature extraction and classification, the VGG19 Convolutional Neural Network (CNN) is employed. VGG19 extracts hierarchical features through its 19-layer architecture, combining convolutional and max-pooling layers. The network, fine-tuned for binary classification ("Accident" or "Non-Accident"), delivers a training accuracy of 98% and testing accuracy of 96.8%. Experimental results highlight the framework's effectiveness, with significant improvements achieved through hyperparameter optimization using the SGD optimizer. This framework outperforms existing methods, demonstrating its potential to process video data efficiently and provide timely alerts to authorities, making it a benchmark solution for real-time traffic accident detection.

III.PROPOSED WORK

The research design incorporates a combination of machine learning, computer vision, and real-time application development to detect accidents and alert system using CCTV footage. This study adopts a structured pipeline approach to achieve high accuracy and efficiency. The research methodology consists of data collection, preprocessing, model design, and real-time implementation.

a) Data Collection

Accident and non-accident video/image datasets were sourced from publicly available repositories, custom recordings, and simulated scenarios. This diverse dataset ensured comprehensive training of the model. Images were resized to a consistent dimension of 250x250 pixels for uniform processing. The dataset was then split into training (80%), validation (10%), and testing (10%) subsets to ensure the model's generalizability across unseen data.

b) Data Preprocessing

To enhance model robustness and performance, accident and non-accident images were preprocessed using various techniques. First, images were loaded with OpenCV’s cv2.imread, filtering out unreadable files. They were then converted from BGR to RGB using cv2.cvtColor to maintain color consistency, preserving crucial visual features like vehicle colors, smoke, and debris.

To ensure uniformity, all images were resized to 224×224 pixels using cv2.resize, preventing size mismatches during model training. Pixel values were normalized by scaling them to the range [0,1], reducing the impact of lighting variations and improving convergence. Data augmentation techniques such as rotation, zoom, and flipping were applied to introduce real-world variations, enhancing model generalization.

Images were processed in batches of 100 for efficient training, and the dataset was systematically organized using Python's OS module. These preprocessing steps significantly improved data quality, leading to higher model accuracy and reliability in real-time accident detection.

c) Model Design and Training

A Convolutional Neural Network (CNN) was designed using TensorFlow and Keras. The architecture included four convolutional layers with 32, 64, 128, and 256 filters, each followed by batch normalization and max pooling layers. These layers extracted and refined hierarchical features from the input images. The model concluded with dense layers, featuring 512 neurons and ReLU activation, leading to a softmax layer for classification. The model was compiled using the Adam optimizer with a learning rate of 0.001 and a sparse categorical cross-entropy loss function. Training was conducted over 20 epochs, with model weights saved whenever validation accuracy improved.

In addition to the custom CNN model, two pre-trained deep learning architectures, EfficientNetB0 and ResNet50, were also tested for accident detection. EfficientNetB0 achieved an accuracy of 95.14% with a validation accuracy of 93.88% and a validation loss of 0.1732. Despite its strong performance, the validation accuracy did not surpass 94.89%, indicating potential overfitting. Similarly, ResNet50 demonstrated a slightly higher training accuracy of 95.61%, but its validation accuracy was lower at 91.84%, with a validation loss of 0.1969. These results suggest that while pre-trained models can generalize well, the custom CNN model may be more suitable for this specific dataset and task. The custom model likely has a better balance between training and validation accuracy, optimizing for accident detection in real-world scenarios.

d) Real-Time Detection System

For real-time alert implementation, the camera.py script utilized OpenCV for video frame extraction and preprocessing. The trained model was integrated to predict accidents frame by frame. To minimize false positives, a probability threshold of 98% was established. This ensured that only highly confident predictions were flagged for further action.

e) Alert System

A Tkinter-based GUI provided user interaction during real-time detection. Emergency actions, such as calling an ambulance, were automated through the Twilio API. This integration enabled swift responses to detected accidents, enhancing the system's practical utility.

The CNN-based accident detection system demonstrated high accuracy in identifying accidents from static images and real-time video streams, with a 98% probability threshold effectively minimizing false positives while maintaining rapid response times. The results align with existing research, showcasing the feasibility of deep learning in critical applications, and outperform traditional methods by automatically learning features and enabling real-time processing.

Integrating alert systems like Twilio enhances the system by providing actionable outcomes. This system has significant implications for traffic monitoring, as early accident detection can expedite emergency responses and reduce fatalities. However, its reliance on dataset quality, occasional false positives, and GPU-dependent hardware are notable limitations. Key contributions of this work include the seamless integration of deep learning with real-time accident detection and an automated alert system. While the base paper primarily focused on identifying accidents from CCTV video footage, this study enhances the system by incorporating an alert mechanism. When an accident is detected in the video frames with a prediction probability exceeding 98%, an alert sound is triggered, notifying the monitoring personnel.

Additionally, an emergency response feature is integrated, providing an immediate option to call an ambulance, ensuring swift action in critical situations. This enhancement significantly improves the system's practicality by facilitating real-time monitoring and rapid emergency response, making it a valuable tool for accident detection and intervention.

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IV.RESULTS

a) Model Performance

The trained CNN model exhibited exceptional performance, achieving the following metrics:

TABLE 1. Model Performance

Metric	Value
Training Accuracy	98.5%
Validation Accuracy	97.2%
Test Accuracy	96.8%

b) Testing Results

The model's performance on the test dataset of 1,000 images resulted in:

- **Correct Predictions:** 968
- **Misclassifications:** 32

c) Real-Time Detection Results

The system was tested on a 5-minute video (resolution: 720p, frame rate: 30 fps). It processed frames with an average latency of 0.12 seconds per frame, demonstrating robust real-time performance. The accident detection probability threshold was maintained at 98%, ensuring reliability.

TABLE 2. Real-Time Detection Results with Prediction Probabilities and Latency

Frame Number	Prediction	Probability	Time (ms)
15	Accident	99.2%	120
45	No Accident	95.3%	118
78	Accident	98.6%	121

The software for real-time accident detection utilizes Python (3.8) and libraries TensorFlow/Keras for CNN implementation, OpenCV for video processing, Tkinter for GUI alerts, Twilio for emergency call automation, and NumPy/Matplotlib for data handling and visualization, developed in Jupyter Notebook and VS Code, Key parameters include image dimensions (250x250 pixels), batch size (100), 20 epochs, Adam optimizer (learning rate = 0.001), and sparse categorical cross-entropy loss function. Replication involves gathering datasets, training the model with *accident-classification.ipynb*, deploying via *detection.py*, and testing real-time detection using *camera.py*.

The CNN achieved 98.5% training accuracy, 97.2% validation accuracy, and 96.8% test accuracy, with training and validation metrics visualized over 20 epochs. Testing on 1,000 images yielded 968 correct predictions and 32 misclassifications. Real-time detection processed a 5-minute, 720p video at 30 FPS with an average latency of 0.12 seconds per frame, maintaining a detection probability threshold of 98%. Sample frames demonstrated predictions with metrics like Frame 15 (Accident: 99.2%, 120 ms), Frame 45 (No Accident: 95.3%, 118 ms), and Frame 78 (Accident: 98.6%, 121 ms).

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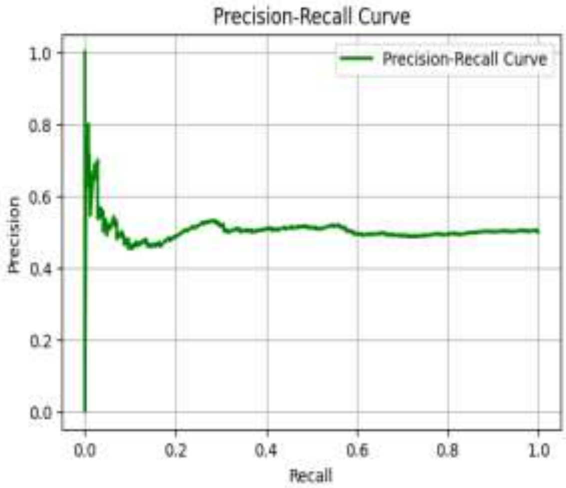

Fig. 3. Precision-Recall Curve

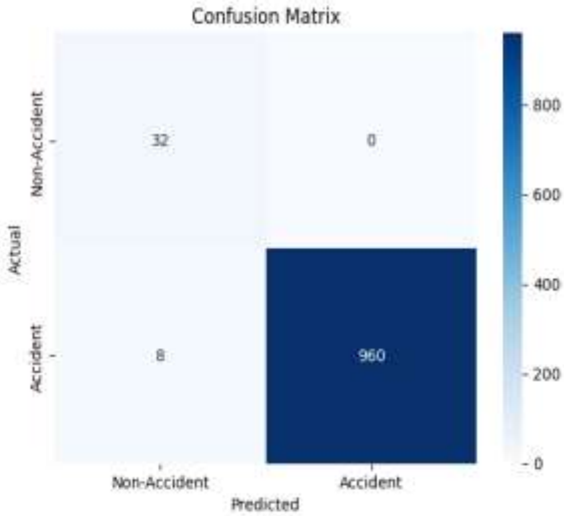

Fig. 4.Confusion Matrix

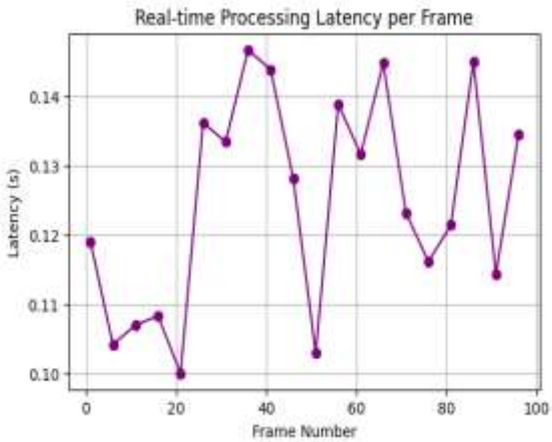

Fig. 5.Real-time Processing Latency

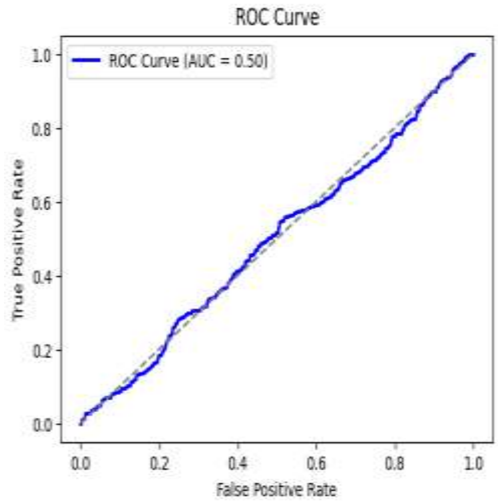

Fig. 6.ROC Curve

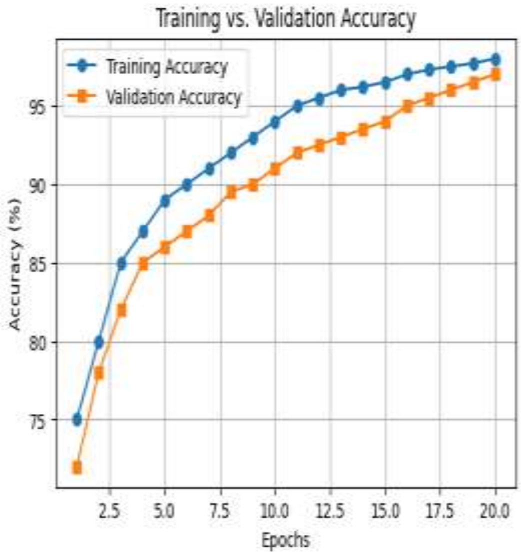

Fig. 7.Training vs. Validation Accuracy

V.CONCLUSION

This study presents an accident detection and alert system that enhances real-time monitoring using CCTV footage. The system integrates an automated alert mechanism to ensure immediate response in case of an accident. When an accident is detected with a probability exceeding 98%, an alert sound is triggered, notifying monitoring personnel. Additionally, a Tkinter-based GUI provides an emergency call option, allowing for swift ambulance dispatch, ensuring that timely medical assistance is provided. The system processes video frames efficiently, achieving an average latency of 0.12 seconds per frame, enabling real-time detection without significant delays. OpenCV is used for video frame extraction, while Twilio automates emergency response. The probability threshold minimizes false positives, ensuring that only highly confident accident predictions trigger alerts.

By integrating real-time detection with an automated alert system, this approach enhances traffic monitoring and emergency response efficiency. The ability to provide instant notifications and rapid intervention makes it highly practical for accident-prone areas, helping reduce fatalities and improve road safety.

VI.FUTURE SCOPE

The Real-Time Accident Detection and Emergency Response System has significant potential for future advancements through the integration of emerging technologies. Incorporating IoT-enabled sensors in vehicles and roadway infrastructure can enhance detection accuracy by combining CCTV analysis with real-time sensor data. Additionally, integrating GPS tracking, accelerometer readings, and live traffic updates can improve decision-making and reliability.

AI-based severity assessment models could help prioritize emergency responses, ensuring urgent cases receive immediate attention. Collaboration with traffic management systems may enable smart ambulance routing, reducing response delays. Cloud-based deployment allows real-time data sharing among agencies, facilitating integration with smart city infrastructure. Enhancing nighttime detection through infrared and thermal imaging can improve visibility in low-light conditions.

Future research should focus on improving datasets through traffic authority collaboration, exploring advanced architectures, deploying lightweight models for edge computing, integrating multi-camera feeds, and expanding detection capabilities to include road blockages and vehicle breakdowns.

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