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Realtime Accident Detection and Response System

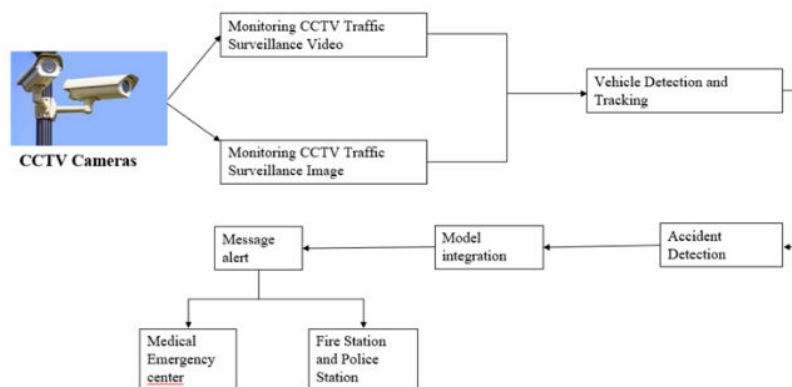
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ABSTRACT: This work outlines a real-time accident detection and response system employing Convolutional Neural Networks (CNN). The system exploits traffic monitoring footage as well as onboard cameras in cars to assess accident incidents with regards to sudden change in motion, vehicle deformities, and crash patterns. A deep learning model based on CNN is trained to identify accidents with high precision and low false positives. After detection, the system initiates an automated response system, alerting emergency services with accurate location information to reduce response time. The model is tested on actual accident datasets and shows remarkable improvement in detection time and accuracy compared to conventional techniques. This study illustrates the capability of AI-based methods in improving road safety and emergency response effectiveness.

KEYWORDS: Real-time accident detection, Convolutional Neural Networks (CNN), Emergency response, Traffic surveillance, Deep learning.



I. INTRODUCTION

Road traffic crashes are a principal killer globally, with delays in detection of an accident and in responding to emergency incidents having considerable impacts on survivor rates. Classical detection techniques that are based on eyewitness accounts and calls to an emergency center always entail slow reaction times, increasing the number of casualties and destruction of property. A need has emerged for the application of effective, automated, and real-time crash detection schemes in contemporary smart transport systems. Recent developments in artificial intelligence (AI) and deep learning, and specifically Convolutional Neural Networks (CNN), provide an encouraging solution for accident detection in real-time. CNNs are known to show exceptional performance in image and video analysis and, hence, are best applied for the detection of traffic accidents from vehicle-mounted cameras and surveillance feeds.

Through observations of abrupt motion changes, deformations of cars, and patterns of collision, a CNN-powered system can efficiently detect accidents and initiate an instant emergency alert.

II. LITERATURE REVIEW

The paper by H. Ghahremannezhad, H. Shi, and C. Liu dives into how deep learning can be used for real-time accident detection in traffic surveillance. It displays some innovative techniques like Convolutional Neural Networks (CNNs) and object tracking methods, such as YOLO, to take a closer look at both spatial and temporal data from traffic videos. By analyzing the paths of moving objects and key factors like speed and distance, this system can determine potential collisions. The authors also discuss the challenges faced in real-time detection, like obstructions in the field of view and changing lighting conditions. Plus, they stress how important it is to weave these systems into existing traffic management frameworks to boost road safety with timely alerts and quick emergency responses.

The research by N. Aldahoul et al. investigates human activity recognition (HAR) from aerial video streams through different human detectors and CNN-based feature extractors. It tests the performance of detectors such as EfficientDetD7, which registered high accuracy (92.9%) under difficult conditions such as blurring, noise, and lighting variations. The study also combines deep pre-trained CNNs such as ResNet and Efficient Net for feature extraction with Long Short-Term Memory (LSTM) networks to capture temporal relationships. The method exhibits remarkable enhancements in HAR accuracy, indicating its applicability to real-world applications in dynamic aerial scenarios.

III. METHODOLOGY

The methodology for the Real-Time Accident Detection and Response System is divided into well-defined steps to ensure seamless design

1. Traffic Monitoring (Input Stage):

- CCTV Cameras are placed according to the plan to provide live video streams and images of road traffic.
- The cameras provide continuous monitoring of traffic activities in real time, serving as the primary input for the system.

2. Video Monitoring and Processing:

- The CCTVs send the live video stream into a vehicle detection and tracking module.
- Advanced algorithms analyze vehicles' movements and behaviours to detect abnormal behaviours (e.g. sudden stops, collisions).

3. Monitoring the Images to Identify an Accident:

- Still images extracted from the video streams are input into a pre-trained machine learning model, a Convolutional Neural Network (CNN).
- The CNN processes images to classify them as: "Accident" If it detects evidence of collision-related patterns, vehicle damage, and debris. "Non-Accident" A normal traffic scene where no indication of an activity occurred.

4. Alert Trigger Mechanism (Output Stage):

- Once the CNN detects an accident, the system activates an automated alert.
- The alert document is then composed and sent to multiple people including:
- Medical Emergency Centres dispatching ambulances in a minimal period of time.
- Fire Stations for rescue operations and hazard management.
- Police stations for traffic control or law enforcement at the accident site.

5. Emergency Communication System:

- The system will employ a system like WhatsApp API or similar messaging service because they provide reliable and fast alerts.
- The alert message will include basic information that includes:
- A timestamp of the accident.
- The location of the accident (using GPS or metadata from the surveillance).

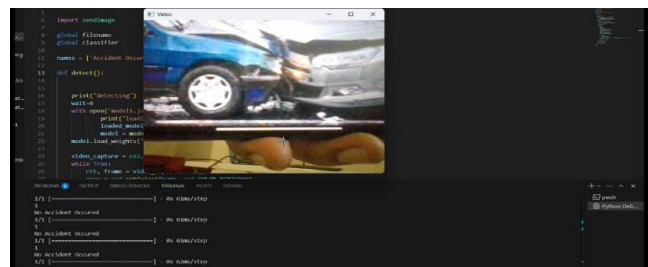


Fig 1: Detection of an accident

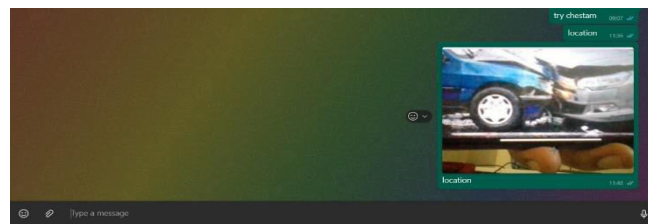


Fig 2: Sending an alert

IV. IMPLEMENTATION

The Real-Time Accident Detection and Response System consists of four components: machine learning; real-time video processing; automated communication technologies. A range of traffic scene datasets that include both accident and non-accident scenes are gathered and pre-processed. This data is then used to train a convolutional neural network (CNN) classifier to identify and classify each frame of a video stream collected from live cameras. After training and cross-validation, the model is deployed and processes live streams of video by analyzing each frame to identify possible accidents. Once an accident is identified, the system captures accident details such as location and timestamp, and sends automated messages through WhatsApp to the police station, hospitals, and fire services. The end-to-end process ensures streamlined accident identification and efficient emergency response, with periodic updates to improve performance under environmental and traffic scene variability.

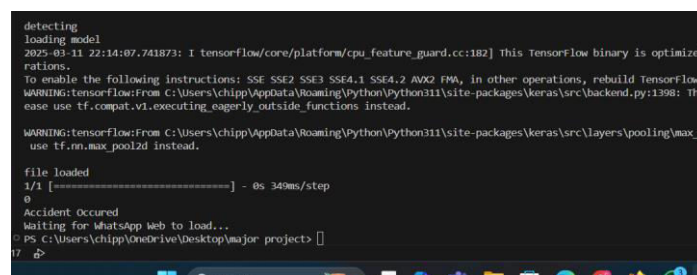


Fig 3: Loading Model

```
17 with open('model1.json', 'r') as json_file:
18     print("loading model")
19     loaded_model_json = json_file.read()
20     model = model_from_json(loaded_model_json)
21     model.load_weights("model/model_weights1.h5")
22
23 video_capture = cv2.VideoCapture(0)
24 while True:
25     ret, frame = video_capture.read()
26     gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
27
28     key=cv2.waitKey(100)
29     wait+=100
30
31     result=""
32     if key==ord('q'):
33         break
34     if wait==500:
35         img = frame
36         img = cv2.resize(img, (120,120))
37         img = img.reshape(1, 120,120, 3)
38         filename="frame"+str(i)+".jpg"
39         cv2.imwrite(filename,frame)
```

Fig 4: Training Model

1. Data Gathering and Preprocessing:

- Collect a dataset of frames or images with and without accidents from the CCTV recordings.
- Preprocess the data by resizing (i.e., adjust image resolution) to 120x 120 pixels, normalizing pixel values between the [0, 1] range, and applying data augmentation methods.

2. Model Development and Training:

- Create a Convolutional Neural Network (CNN) architecture to classify accidents and non-accidents, which included convolutional layers (feature extraction) and dense layers for classification.
- Train the CNN on the pre-processed frames or images, as well as to evaluate the model using accuracy, precision, recall and other metrics.

3. Integration with Live Video Feeds:

- Integrate the system with live video feeds from CCTV cameras.
- Read the video frames, process the videos frames or images, and classify the frames either "Accident" or "No Accident" using the trained model.

4. Accident Detection and Alert Reporting.

- If accident detection occurs, then a location and time of the accident can be noted.
- An alert message will be sent via WhatsApp to emergency services (e.g., hospital, police).

5. Evaluation and Input.

- Continuously monitor the systems logs in order to evaluate performance and retrain the CNN with new and different datasets.
- Try to optimize and train in difficult scenarios such as night time and weather related events.

V. RESULTS AND CONCLUSION

The Real-Time Accident Detection and Response System has proven its capability to accurately detect traffic accidents and relay alerts to emergency services in a timely manner. The Convolutional Neural Network (CNN) that was trained provides impressive accuracy, showing its reliability over multiple traffic scenarios and environmental conditions.

The system's real-time video analysis enables timely detection of accidents, which provides the potential for meaningful reductions in response times, ultimately saving lives. While there are limitations based on false positives and effects from the environment, the system is still more reliable and scalable by utilizing existing CCTV systems.

This project was able to provide a practical and productive contribution into improving road safety while doing it in a way that is automated and adaptable in order to reduce the number of casualties from accidents while simultaneously arranging faster responses from emergency services. Upon further refinement and scheduled updates, the system will be suitable to providing valuable analysis in many regions and traffic conditions.

The effectiveness of the Real-Time Accident Detection and Response System is one of the most significant measures of its reliability and usefulness in the real world. In this project, the CNN model provided training accuracy of 97.70% and validation accuracy of 98.10%, which shows that the model effectively learned the patterns present in the dataset and was able to generalize to the unknown data.

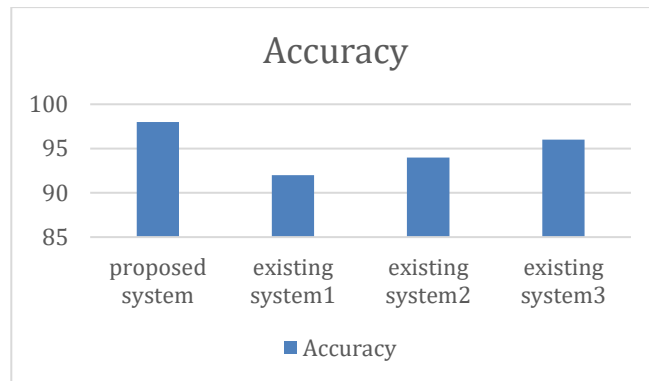


Fig 4: Accuracy Comparison

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This high accuracy supports the claim that the system is quite effective in accurately classifying traffic scenes as "Accident" or "Non-Accident." The model's well-above average performance can be attributed to effective and efficient data preprocessing and augmentation, along with the overall architecture of the CNN properties. However, in practice (real situations), the real-world conditions, including lighting conditions, environmental conditions (weather), and camera angles, would still likely have some impact on the model accuracy, resulting in some false positives or false negatives. These real-world challenges demonstrate the need for continuous improvement of the accuracy through retraining with updated, diverse and current datasets even if the performance is high accuracy conditions or even moderate accuracy conditions.

VI. LIMITATIONS AND FUTURE WORK

The Real-Time Accident Detection and Response System has proven to be very accurate, with a validation accuracy rate of 98.10% in testing, which shows a strong ability to detect accidents from the video feeds. It can analyze a live CCTV feed with a Convolutional Neural Network (CNN), classifying accident situations and non-accident situations. It can automate the process, making the emergency response alert sent to an WhatsApp message much faster than the human element. The system's reliability is lower due to limitations such as the risk of false positives, false negatives, and environmental considerations like darkness or bad weather, which will be addressed in future work.

Future research is planned for the system to provide better reliability using larger and more diverse datasets which include a wider range of traffic scenarios and environmental conditions. The incorporation of internet of things devices such as GPS and accelerometers can enhance metadata reliability, specifically related to emergency responses, and improving the model to be optimized for edge computing will increase processing speed in real-time with minimal latency. Additionally, as communication channels are added and detection algorithm is optimized the system will become scalable and adaptable, thus making the system more effective and useful for any situation in the future. These enhancements can also further improve the potential of it to withstand reliability for improved safety on our roadways.

6.1 Enhanced Data Collection and Augmentation

The increased data collection means obtaining a larger dataset that is more representative of many different types of traffic scenes, such as urban roads, highways, and bad weather conditions. This allows the model to generalize across varying scenarios. Additional data augmentation techniques like rotation, flipping, brightness changes, and zoom are used to create realistic conditions and increase variability of the dataset. All of these changes also provide improved robustness and adaptability of the system to accurately provide accident detection in various testing conditions.

6.2 Model Optimization and Efficiency

Optimizing models is about increasing efficiency and speed, while still retaining accuracy. Methods that can be used to accelerate inference can include reducing the size of the model, using pruning or removing unused layers of the model, and ultimately utilizing quantization which uses reduced precision.

These methods will help achieve more efficient real-time inference. Furthermore, you can deploy the model to the edge or on an edge device, which would also help reduce latency because computation will happen locally (either on the edge or the device). This is extremely useful for analyzing live video streams and detecting accidents in a timely way, especially in resource-constrained environments.

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