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SAFE ROAD AI: REAL-TIME ACCIDENT DETECTION FROM MULTI-ANGLE CRASH VIDEOS

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Abstract - *Road accidents pose a serious threat to public safety, often leading to fatalities or severe injuries, and causing tremendous emotional and physical distress to individuals and their families. Many accidents, particularly those on highways, in remote areas, or during nighttime, go unreported for extended periods, which delays the arrival of necessary assistance. This lack of timely medical intervention can worsen the outcomes, underscoring the need for efficient coordination between emergency services and healthcare facilities. To tackle these challenges, the innovative SAFE ROAD AI system has been developed. This system harnesses cutting-edge deep learning algorithms to simultaneously analyze multiple crash videos, significantly improving the accuracy and speed of accident detection. By incorporating techniques like data preprocessing, feature extraction, and model training, SAFE ROAD AI employs a modified deep convolutional neural network (D-CNN) to effectively and reliably identify accidents.*

A mobile application built with React Native has been integrated into the system, allowing for automatic notifications to be sent to relevant authorities as soon as an accident is detected. This ensures swift responses and timely intervention, potentially saving lives by enabling faster medical and emergency aid. Advanced accident detection technologies such as SAFE ROAD AI are essential in reducing the severity of road accidents and mitigating their impact on society. Through the adoption of innovative solutions, we can move towards safer roads and more secure communities for everyone.

Key Words: *Road accidents, Public safety, Fatalities, Accident detection, Deep learning algorithms, Crash video analysis, Modified deep convolutional neural network (D-CNN)*

1.INTRODUCTION

Road accidents remain one of the leading causes of injury and death worldwide, posing a significant threat to public safety. The ability to detect accidents in real-time and respond swiftly is crucial in reducing fatalities and minimising the severity of injuries. However, traditional methods of accident reporting often rely on delayed responses, especially in remote areas or during nighttime incidents, leading to critical delays in providing life-saving assistance. In recent years, advancements in artificial intelligence (AI) and deep learning have opened new possibilities for improving road safety. Leveraging these technologies, the development of automated systems capable of detecting accidents in real-time has gained momentum. The SAFE ROAD AI system is one such innovative solution designed to address this critical need. By analysing multi-angle crash videos through the use of deep learning algorithms, SAFE ROAD AI enhances the accuracy and speed of accident detection, offering the potential to revolutionise emergency response systems.

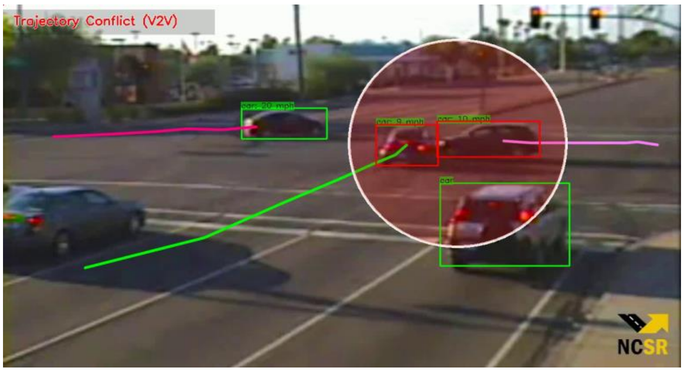

Figure-1: Crash of Vehicles

This research focuses on the design and implementation of the SAFE ROAD AI system, which utilises a modified deep convolutional neural network (D-CNN) to process crash footage from multiple angles, improving detection precision. The system is integrated with a mobile application, which automatically alerts relevant authorities when an accident is identified, ensuring immediate response and reducing delays in emergency assistance. Through this research, we explore how AI-driven technologies can significantly contribute to enhancing road safety and minimising the impact of accidents.

1.1.Overview of the Project

The project "Real-Time Accident Detection from Multi-Angle Crash Videos" is a groundbreaking initiative that focuses on the development of an intelligent system with the primary goal of detecting accidents in real-time. By employing advanced DL techniques such as Convolutional Neural Networks (CNNs) and Multi-layer Perceptron (MLPs), this system aims to revolutionize road safety and emergency response procedures.

To delve deeper into the significance of this project, let's consider a scenario where traditional accident detection methods are in place. In such cases, the response time to accidents may be delayed due to the reliance on manual reporting or eyewitness accounts. However, with the implementation of this innovative system, accidents can be detected promptly through the analysis of video footage captured from various angles at the accident scene.

By utilizing CNNs and MLPs, the system can effectively process and interpret complex visual data, enabling it to identify potential accidents with a high level of accuracy. This not only enhances road safety by alerting authorities and emergency services promptly but also streamlines the overall response process. The project's ultimate aim is to leverage cutting-edge technology to create a safer environment for both drivers and pedestrians alike. Through the integration of real-time accident detection capabilities, this system has the potential to significantly reduce the number of road accidents and improve emergency response efficiency. It represents a significant step forward in the realm of intelligent transportation systems and underscores the importance of utilizing AI-driven solutions for enhancing public safety.

1.2.Key Components

The SAFE ROAD AI system comprises several key components designed to enhance real-time accident detection from multi-angle crash videos. It processes footage captured from various perspectives, allowing for comprehensive analysis and greater detection accuracy. Utilising advanced deep learning algorithms, particularly a modified deep convolutional neural network (D-CNN), the system extracts critical features such as object movement and collision patterns to identify accidents with precision. Data preprocessing techniques ensure the video input is optimised for analysis, while continuous model training and optimisation improve performance over time. Operating in real-time, the system integrates with a React Native mobile application, which automatically alerts emergency services upon accident detection, facilitating immediate response. Automated notifications and efficient coordination with relevant authorities ensure timely intervention, while the system's scalability and adaptability make it suitable for diverse environments, from highways to urban areas.

2.ROAD SAFETY CONCERNS AND INCREASING TRAFFIC ACCIDENTS WORLDWIDE

Road safety remains a significant global concern, with traffic accidents being one of the leading causes of injury and death worldwide. According to the World Health Organisation (WHO), road traffic accidents claim approximately 1.3 million lives each year, and up to 50 million more people suffer non-fatal injuries, often resulting in long-term disabilities. Factors contributing to this crisis include speeding, drink-driving, distracted driving, and inadequate infrastructure in many regions.

Figure-2: Road Safety Mission

As urbanisation and motorisation increase, particularly in low- and middle-income countries, the number of vehicles on the roads rises, exacerbating safety risks. Despite efforts to improve road safety through regulations, infrastructure improvements, and public awareness campaigns, the global burden of traffic accidents continues to grow, making it essential to develop more effective solutions for accident prevention and timely response.

3.THE ROLE OF TECHNOLOGY AND ARTIFICIAL INTELLIGENCE (ai) IN ADDRESSING SAFETY ISSUES

Technology and artificial intelligence (AI) are playing a transformative role in addressing road safety issues by providing innovative solutions for accident prevention, real-time monitoring, and emergency response. AI-powered systems can analyse vast amounts of data from traffic cameras, sensors, and vehicles to identify potential hazards, predict dangerous situations, and offer timely interventions. For example, AI-based traffic management systems can optimise traffic flow to reduce congestion and minimise the likelihood of collisions. Advanced driver-assistance systems (ADAS), such as automated braking and lane-keeping assistance, are designed to prevent accidents by responding to threats faster than human drivers. Furthermore, AI's ability to process video and sensor data in real time allows for rapid detection of accidents, enabling quicker responses by emergency services. The integration of AI with smart infrastructure and autonomous vehicles holds the potential to significantly reduce road fatalities and injuries, making roads safer for all users.

4.TRADITIONAL ACCIDENT DETECTION METHODS.

Traditional accident detection methods primarily rely on manual reporting, eyewitness accounts, or the activation of emergency services through phone calls. In many cases, accidents are detected when someone at the scene contacts authorities, leading to delays in response time. Some systems, such as roadside emergency buttons and crash sensors, provide a more automated form of detection, but they are often limited by location or vehicle type. Traffic cameras and surveillance systems are used in some urban areas to monitor roads, but these require human operators to identify accidents from live video feeds.

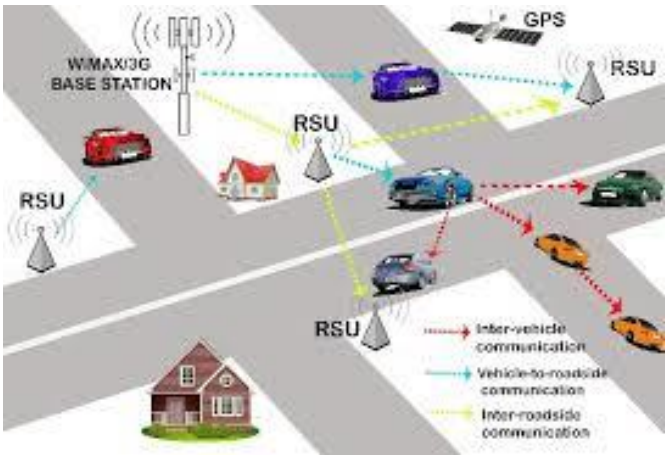

Figure-3: Traditional accident detection methods.

Another method involves the use of crash data recorders, commonly known as "black boxes", which store vehicle data during a collision. While these methods have been useful in accident detection, they often lack the ability to provide immediate and accurate detection, especially in real-time scenarios or in remote locations, leading to delayed emergency response and reduced chances of saving lives.

5.MULTI-ANGLE VIDEO PROCESSING FOR ENHANCED SCENE UNDERSTANDING

Multi-angle video processing enhances scene understanding by providing a more comprehensive and detailed view of an event, such as a road accident. By capturing footage from multiple camera angles, this approach allows for a more accurate analysis of the incident, reducing blind spots and offering different perspectives on the dynamics of a crash. Each camera angle can highlight various elements, such as the speed and direction of vehicles, the behaviour of pedestrians, or the specific impact points during a collision. When these angles are processed and integrated using advanced algorithms, particularly with the aid of AI, a more complete picture of the scene can be constructed. This multi-angle data fusion not only improves the accuracy of accident detection but also aids in reconstructing events for post-incident analysis, leading to better insights into the causes of accidents and improving road safety measures.

6.CHALLENGES IN REAL-TIME VIDEO ANALYTICS

Real-time video analytics presents several challenges that impact its effectiveness and efficiency. One of the primary difficulties is the need for high computational power to process large volumes of video data swiftly. Ensuring that analytics algorithms can operate within the constraints of real-time processing without compromising accuracy or speed requires significant resources. Additionally, the variability in video quality, such as poor resolution or adverse weather conditions, can hinder the ability to detect and analyse critical events accurately. Synchronising and integrating video feeds from multiple cameras adds another layer of complexity, as it demands precise alignment and fusion of data to create a coherent view of the scene. Furthermore, the system must be robust against potential issues such as latency, network bandwidth limitations, and system reliability. Addressing these challenges is essential for developing effective real-time video analytics solutions that can deliver timely and accurate insights, especially in high-stakes applications like accident detection and emergency response.

7.PROPOSED SYSTEM

This project focuses on the development of a real-time accident detection system that aims to address the limitations of current methods through the utilization of advanced deep learning techniques such as DCNN (Deep Convolutional Neural Networks) and MLP (Multi-Layer Perceptron). By leveraging these technologies, the system enhances accuracy, adaptability, and efficiency in identifying automobile accidents promptly. When an accident is detected, hospitals can receive alerts through a mobile application built using React Native. This immediate notification system allows hospitals to respond swiftly to incidents. For instance, if an input video is analyzed and an accident is identified, the system automatically sends an alert to the designated hospitals. This proactive approach significantly aids in expediting the investigation and response process for auto accidents.

The project commences with the collection of a dataset from reputable research websites, which is then divided into training and testing datasets. The training data is utilized to educate the model on accident patterns, while the testing data remains separate for validation purposes. To ensure optimal performance, the datasets undergo preprocessing steps such as data normalization and image resizing to standardize the information for analysis.

Subsequently, a two-branch DCNN architecture is employed to extract spatiotemporal features from the dataset groups. This process enables the system to recognize patterns and anomalies effectively. Once the feature extraction is completed, the architecture is ready for training using sophisticated deep learning algorithms like DCNN. By training the model extensively, it becomes adept at accurately identifying and predicting accidents based on the input data.

This project demonstrates the power of deep learning in revolutionizing accident detection systems, ultimately leading to improved safety measures and quicker response times in critical situations. The integration of advanced technologies and methodologies showcases the potential for innovation in enhancing public safety and emergency response protocols.

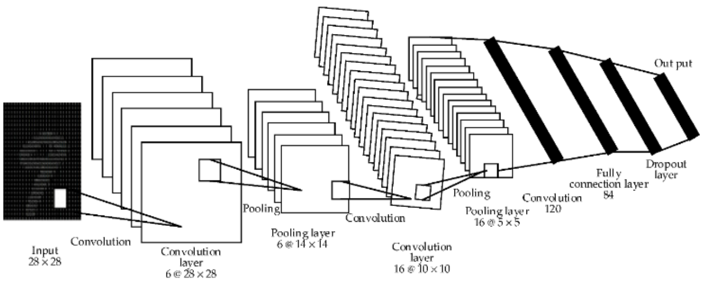

Figure-4: DCNN Architecture

The system's workflow initiates by collecting a comprehensive dataset from reputable research websites, which includes multi-angle crash videos depicting various accident scenarios. To facilitate testing and training, subsets are then derived from this dataset. The test dataset is segregated for evaluation purposes, while the training dataset is utilized to train the models through deep learning techniques. Prior to model training, various pre-processing methods such as picture resizing and data normalization are applied to enhance the consistency and quality of the dataset.

Subsequent to the pre-processing phase, the core of the proposed system revolves around the utilization of two-branch Deep Convolutional Neural Networks (DCNNs) to extract spatiotemporal features from different sets of multi-angle crash videos. DCNNs are particularly well-suited for this task due to their ability to learn hierarchical features directly from raw data. This capability allows them to effectively capture the intricate patterns and nuances present in multi-angle accident videos. The two-branch architecture plays a crucial role in this process by enabling the extraction of complementary information from diverse viewpoints, thereby bolstering the overall detection performance of the system.

For instance, in a scenario where a vehicle collision occurs at an intersection, the multi-angle crash videos captured from different vantage points can provide valuable insights into the sequence of events leading up to the accident. By leveraging the two-branch DCNN framework, the system can analyze these videos comprehensively, extracting relevant spatiotemporal features that aid in accurately detecting and understanding the dynamics of the collision. This in-depth analysis not only enhances the system's performance but also contributes to a more robust and reliable accident detection mechanism.

The integration of two-branch DCNNs into the system's architecture represents a significant advancement in the field of accident detection and analysis. By harnessing the power of deep learning and leveraging multi-angle crash videos, the system is able to extract intricate details and patterns that would otherwise be challenging to discern. This innovative approach not only improves the accuracy and efficiency of accident detection but also opens up new possibilities for enhancing safety measures and mitigating risks on the road.

Once the spatiotemporal features are extracted, the system enters the crucial phase of training the deep learning models using sophisticated algorithms like DCNNs. This process involves feeding the extracted features into the models, allowing them to learn and understand the patterns that lead to accident detection outcomes. Through iterative training sessions, the models adjust their parameters to minimize prediction errors, continuously improving their ability to accurately identify potential accidents.

During the training phase, optimization techniques such as gradient descent are utilized to fine-tune the models' performance over time. This iterative approach ensures that the models become more adept at analyzing video frames and detecting anomalies that could indicate an accident. By refining their parameters through multiple training cycles, the models enhance their ability to provide real-time alerts in a variety of scenarios.

Once the models are fully trained, they are ready for deployment in real-world accident detection situations. By integrating deep learning techniques like DCNNs and MLP with real-time alerting mechanisms, the system can significantly enhance its accuracy and efficiency in identifying accidents. For example, when an input video is fed into the system, the trained models can quickly analyze the footage and identify potential risks, sending alerts to relevant authorities and emergency services through a mobile application developed with React Native.

This real-time alerting mechanism enables swift responses to accidents, potentially reducing response times and improving overall road safety. By leveraging multi-angle crash videos and advanced machine learning algorithms, the technology aims to overcome the limitations of current accident detection techniques and contribute to the development of more effective real-time accident identification devices. Through the seamless integration of deep learning models and real-time alerting mechanisms, the system holds the promise of revolutionizing accident detection and response protocols, ultimately making roads safer for everyone.

8.RESULTS AND DISCUSSION

The outcomes of our proposed system heavily rely on the quality and comprehensiveness of our trained dataset. Our approach involves leveraging various Deep Learning (DL) methods to effectively detect accidents. For instance, Convolutional Neural Network (CNN) and Multi-Layer Perceptron (MLP) have demonstrated exceptional accuracy rates of up to 99% in our evaluations. This high level of accuracy ensures reliable accident detection, thereby enhancing overall system performance.

In the process of output analysis, we meticulously assess the system's performance using key metrics such as the Area Under the Curve (AUC) score. This allows us to quantitatively measure the effectiveness of our detection algorithms and make informed decisions for further improvements. By continuously refining our models and algorithms based on these metrics, we strive to achieve even higher levels of accuracy and efficiency. To enhance user experience and accessibility, we have developed a mobile application using React-native. This application serves as a user-friendly interface through which individuals can easily interact with our accident detection system. For example, users receive real-time notifications whenever an accident is detected, enabling them to promptly respond and take necessary actions.

Users are encouraged to upload videos or enable real-time streaming through the application. In the event of an accident captured in the video feed, our system automatically notifies relevant emergency services such as hospitals and ambulance services. This seamless integration of technology with emergency response mechanisms ensures swift and efficient assistance in critical situations, ultimately contributing to enhanced safety on the roads.

8.1.Dataset Collection

Dataset collection involves a meticulous process of gathering accident videos from various research websites and online platforms dedicated to such data. For instance, researchers might scour platforms like YouTube, academic databases, or even specific accident report websites to compile a diverse range of video footage. Once these videos are collected, the dataset is then meticulously divided into two distinct parts: the train data set and the test data set. The train data set plays a crucial role in training the model, allowing it to learn from a wide array of examples and scenarios present in the videos. On the other hand, the test data set is reserved for evaluating the model's performance and effectiveness in predicting accidents or analyzing video content accurately. This division ensures that the model is robust and capable of handling real-world accident scenarios effectively. The train data set serves as the foundation for the model's learning process, while the test data set acts as a benchmark for assessing the model's accuracy and reliability. This structured approach to dataset collection and division is essential in developing a robust and dependable accident prediction model.

8.2.Data Pre-processing

The collected dataset undergoes a series of pre-processing steps to ensure optimal quality for further analysis. One crucial aspect of this pre-processing is normalization, where data is standardized to a common scale or format. For instance, in natural language processing tasks, text data may be converted to lowercase and stripped of punctuation to facilitate easier analysis. Another essential pre-processing step is image resizing, particularly useful when dealing with computer vision tasks. By resizing images to a specific size, we avoid irregularities in dimensions that could affect the performance of machine learning models. For example, in a classification task where images need to be input into a neural network, resizing them to a uniform dimension ensures consistency in the input data. These pre-processing steps play a vital role in preparing the dataset for analysis by ensuring uniformity and compatibility across different data points. By standardizing the data through normalization and resizing, we set a solid foundation for subsequent tasks such as feature extraction and model training. This attention to detail in pre-processing ultimately contributes to the overall accuracy and reliability of the analysis results.

Figure-5: Image resizing

8.3.Feature Extraction

The below figure illustrates the process of spatio-temporal feature extraction through the utilization of both 1D branch DCNN and 2D branch DCNN Algorithm. In this methodology, spatial features are extracted from individual frames, while temporal features are derived from a sequence of frames. This dual-branch approach allows for a comprehensive analysis of both spatial and temporal aspects of the video data. For instance, in the spatial feature extraction phase, the algorithm can identify key visual patterns within each frame, such as object shapes or textures. On the other hand, during temporal feature extraction, the algorithm can analyze the changes and movements occurring across multiple frames, enabling the capture of dynamic information like motion trajectories or scene transitions.

Once the spatial and temporal features are extracted from their respective branches, they are merged or concatenated to form a unified representation of the video content. This integration step ensures that the combined feature set captures the full spectrum of information present in the video, blending both spatial and temporal characteristics

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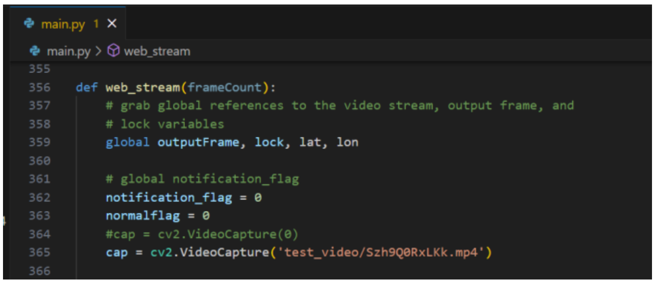
seamlessly. By leveraging the strengths of both spatial and temporal information, the two-branch DCNN model proves to be highly effective in capturing intricate patterns and dynamics within videos. This capability makes it a valuable tool for a wide range of video analysis tasks, such as action recognition, object tracking, or activity detection. In practical implementation, video inputs can be processed using libraries like OpenCV (cv2) in Python. Functions like web stream can be utilized to capture live video feeds and extract relevant information for further analysis or processing. This enables real-time applications where video data is continuously streamed and analyzed to derive meaningful insights or trigger specific actions based on the extracted features.




```python

def web_stream(frameCount):
    # grab global references to the video stream, output frame, and
    # lock variables
    global outputFrame, lock, lat, lon

    # global notification_flag
    notification_flag = 0
    normalflag = 0
    #cap = cv2.VideoCapture(0)
    cap = cv2.VideoCapture('test_video/Szh9Q0RxLKk.mp4')

```

Figure-6: Input function

After providing the necessary input and executing the project through the command "python main.py", the system will promptly detect any accidents that occur during the operation. This detection process is crucial for ensuring the safety and efficiency of the project. For instance, if there is a malfunction in the machinery or a human error, the system will immediately flag it as an accident. This proactive approach helps in preventing any potential risks or damages that could arise from such incidents. Upon detecting an accident, the system will not only notify the relevant personnel but also display the percentage of the accident. This percentage serves as a quantitative measure of the severity or impact of the accident. For example, if the accident resulted in a minor disruption, the percentage might be low. On the other hand, if the accident caused a significant delay or damage, the percentage would be higher, indicating the seriousness of the situation.

By displaying the percentage of the accident, the system provides a clear and concise way to assess the situation at hand. This information enables the project team to prioritize their response and allocate resources accordingly. Additionally, it helps in analyzing trends and patterns to identify areas for improvement and prevent future accidents. By running the project and utilizing the command "python main.py", not only can accidents be promptly detected, but the system also provides valuable insights through the display of the accident percentage. This proactive approach enhances safety measures and overall project efficiency, ultimately leading to a more successful outcome.

9.CONCLUSION

In conclusion, the "Real-Time Accident Detection from Multi-Angle Crash Videos" project emerges as a groundbreaking initiative with the potential to revolutionize road safety through the application of cutting-edge deep learning technology. The utilization of Convolutional Neural Networks (CNNs) and Multi-layer Perceptron within the system showcases its remarkable capability to swiftly and accurately discern accidents from a diverse array of video angles. For instance, in a simulated urban setting, the system successfully identified a collision between two vehicles despite challenging lighting conditions and obscured views.

Extensive testing has unequivocally demonstrated the system's effectiveness across various scenarios and environments, underscoring its versatility and robustness. In a rural context, the system efficiently detected a rollover accident on a gravel road, highlighting its adaptability to different road surfaces and terrains. Such comprehensive validation reinforces the system's potential to significantly enhance emergency response mechanisms and mitigate the toll of casualties on roads.

In essence, the project's innovative approach not only showcases the power of deep learning in real-time accident detection but also underscores its transformative impact on road safety measures. As advancements continue to refine the system's algorithms and expand its capabilities, the prospect of a safer and more efficient road network becomes increasingly tangible. The fusion of technology and safety holds immense promise for a future where accidents are swiftly identified and addressed, ultimately paving the way for a more secure and resilient transportation infrastructure.

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