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ACCIVUE: REAL TIME ROAD ACCIDENT DETECTION AND ALERT SYSTEM USING DEEP LEARNING NEURAL NETWORKS

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Abstract: Accidents in India have emerged as a leading cause of fatalities, predominantly attributable to delayed assistance reaching victims rather than the accidents themselves. Particularly in areas with sparse and high-speed traffic like highways, victims often endure prolonged unattended periods, amplifying the risk of fatal outcomes due to delayed medical intervention. This paper introduces AcciVue, a proactive system designed to bolster road safety by employing a real-time accident detection mechanism. AcciVue integrates deep learning neural networks, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks[1], to analyze CCTV video feeds for timely accident detection. By promptly alerting nearby hospitals and police stations upon detection, AcciVue optimizes emergency response, mitigating accident repercussions and ultimately enhancing road user safety. This innovative approach showcases the transformative potential of deep learning technology in addressing the multifaceted challenges of road safety.

***Index Terms* – Accidents, Road Safety, Deep Learning, CNN, LSTM.**

I. INTRODUCTION

Road traffic accidents (RTCs) are a major concern for public safety, as emphasized by the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC). These accidents result in millions of fatalities and injuries globally each year, causing profound and lasting physical and psychological trauma for survivors and their families. In addition to the urgent need for effective accident detection and response mechanisms, the application of such systems has shown promise in various domains. One key application lies in the realm of smart cities, where accident detection systems can be integrated into urban infrastructure to enhance overall traffic management and safety. By providing real-time data on accident locations and severity, these systems enable authorities to implement targeted interventions, such as adjusting traffic signals or rerouting vehicles, to minimize congestion and prevent secondary accidents. Furthermore, accident detection systems find utility in fleet management also. In recent years, there has been a growing emphasis on improving accident detection and response mechanisms, driven by advancements in machine learning (ML)[2] and deep learning (DL)[3] technologies. Our proposed system for automobile crash detection leverages convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to accurately identify accident scenarios in real-time. By integrating CNNs[4], our system can efficiently analyze visual data from surveillance cameras or dashcams, enabling rapid identification of potential accident scenes. Additionally, the inclusion of LSTM networks enhances our system's ability to capture temporal patterns within the data, facilitating more informed and timely responses to accidents. Moreover, the application of accident detection systems extends beyond mere detection to proactive response measures. For instance, our system incorporates visual and auditory cues, such as beeping alerts in the user interface, to notify drivers or authorities of potential accident scenarios.This real-time feedback can prompt immediate action, mitigating the severity of accidents and improving overall road safety. In summary, our proposed system represents a significant advancement in accident detection and response technology, with applications ranging from real-time alerts for drivers to enhanced coordination of emergency services. Through these innovations, we aim to minimize the impact of RTCs on public safety and welfare, ultimately saving lives and preventing injuries.

Fig.1: Sample road accidents

II. LITERATURE SURVEY

Traditional approaches to road accident detection, like CNN and LSTM algorithms, face limitations due to fixed features and struggles in varied conditions, such as tunnel environments and vehicle damage identification. Our innovative method combines object detection in CCTV footage with automatic accident detection in tunnels, using CNN and LSTM models.[5]This integration enables real-time alerts to authorities, reducing response times and potentially saving lives. Addressing the increasing traffic volumes, our approach emphasizes AI's role in urban safety infrastructure within smart cities. Unlike prior methods, our solution offers adaptability and comprehensiveness in accident detection, enhancing safety protocols and urban infrastructure efficiency.

III. METHODOLOGY

A. Proposed Method

The proposed methodology for AcciVue's real-time accident detection system integrates three pivotal components to ensure robust and efficient operation. Firstly, continuous video feed ingestion stands as a cornerstone, facilitated by the powerful capabilities of OpenCV.[6] This module orchestrates the seamless capture of real-time video data from strategically positioned cameras distributed along roadways, forming the backbone of AcciVue's surveillance infrastructure[7]. Leveraging sophisticated streaming protocols such as RTSP, the system maintains a consistent and reliable flow of data, crucial for uninterrupted monitoring and swift response to unfolding events. Secondly, the video-to-frame conversion process, also driven by OpenCV's versatile functionality, plays a crucial role in transforming the continuous video stream into discrete frames. This meticulous conversion not only facilitates efficient handling of individual frames for subsequent analysis but also implements frame rate control mechanisms to optimize computational load. By striking a delicate balance between processing speed and system resource utilization, this step ensures that AcciVue can effectively process frames without compromising the accuracy of accident detection. Lastly, the frame input module serves as the conduit through which extracted frames are channeled into a sophisticated deep learning architecture comprising both Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks. Trained on a meticulously curated dataset comprising diverse accident and non-accident scenarios, utilizing leading deep learning frameworks such as TensorFlow this combined CNN+LSTM model[8] is endowed with the capacity to discern subtle spatiotemporal patterns indicative of road accidents. By harnessing the power of deep learning, AcciVue transcends conventional methods, demonstrating unparalleled efficacy in real-time accident detection while laying the foundation for transformative advancements in road safety.

B. Data Acquisition

Our study's dataset was meticulously assembled, drawing from diverse sources to ensure its breadth and representativeness. A significant portion of the dataset was sourced from publicly available repositories on platforms like Kaggle, renowned for their wide-ranging collections of curated data. These repositories provided valuable insights into real-world accident scenarios, offering a rich array of images capturing various accident contexts and environments. Complementing this, we conducted targeted manual downloads from video-sharing platforms like YouTube, focusing on authentic footage depicting actual accident events. This hybrid approach allowed us to compile a robust dataset consisting of 5000 images portraying accident incidents and 10000 images portraying non-accident scenarios. By combining data from multiple sources, we aimed to create a well-rounded dataset that reflects the diverse challenges encountered in real-life road situations.

Fig.2: Accident sample images

Fig.3: Non Accident sample images

C.Data Preprocessing

After obtaining the dataset, consisting of 5000 accident images and 10000 non-accident images sourced from Kaggle and manual downloads from YouTube, we initiated the preprocessing phase. Firstly, we resized all images to a standard resolution of 150x150 pixels to ensure uniformity in size. [9]Following this, we converted the images into grayscale to simplify the computational complexity while retaining essential features for accident detection. Subsequently, we performed pixel normalization to scale the pixel values between 0 and 1, ensuring consistent data representation across all images. These preprocessing steps were essential to prepare the dataset for subsequent training and testing phases of our CNN+LSTM accident detection model.

D. Training

For training DL model utilizing a CUDA-enabled GPU became imperative due to the computationally intensive nature of training machine learning and deep learning models. The specifications of the GPU are detailed in Table 1.

Table 1: Details of the Experimental Platform

Hardware Platform		**Software Platform**	
CPU	Intel(R) Xeon(R) Gold 6242R CPU	OS	Windows 11 64-Bit
GPU	Nvidia RTX A5000	Framework	TensorFlow
RAM	256 GB	Programming	Python 3.10.11

We opted for deep learning techniques for accident detection[10], utilizing a combination of Convolutional Neural Network (CNN) [11]and Long Short-Term Memory (LSTM) architectures. Our model comprised 3 CNN layers, 1 LSTM layer, and 2 dense layers. This choice was driven by the CNN's capability to extract spatial features from video frames and the LSTM's proficiency in capturing temporal dependencies within sequences. The CNN+LSTM[12] model architecture, implemented using Keras, consisted of sequential layers. The CNN component comprised 3 convolutional layers with 32, 64, and 128 filters respectively, each followed by max-pooling layers. This design facilitated the extraction of spatial features from input video frames. Subsequently, the feature maps were flattened and fed into an LSTM layer with 64 units, enabling the model to analyze temporal dependencies within the sequences.[13]Post-LSTM processing involved 2 dense layers,[14]with 128 and 1 units respectively, employing the sigmoid activation function to produce final accident probability estimations. The Fig.4 given below shows the Model flow and Fig.5 below shows the model architecture.

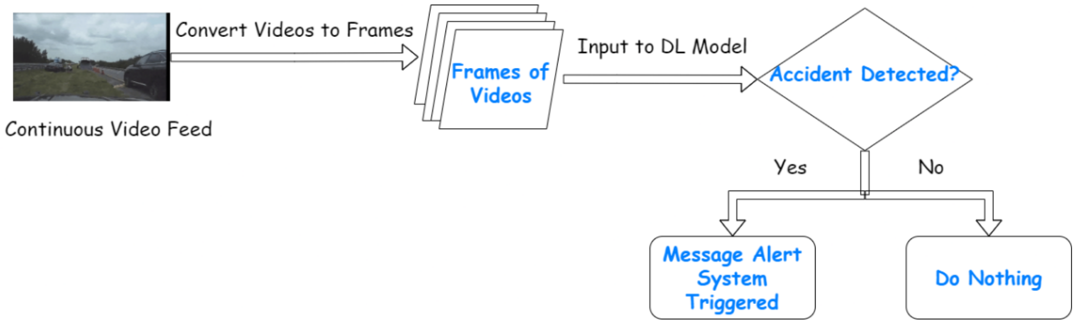

Fig.4: Model flow diagram

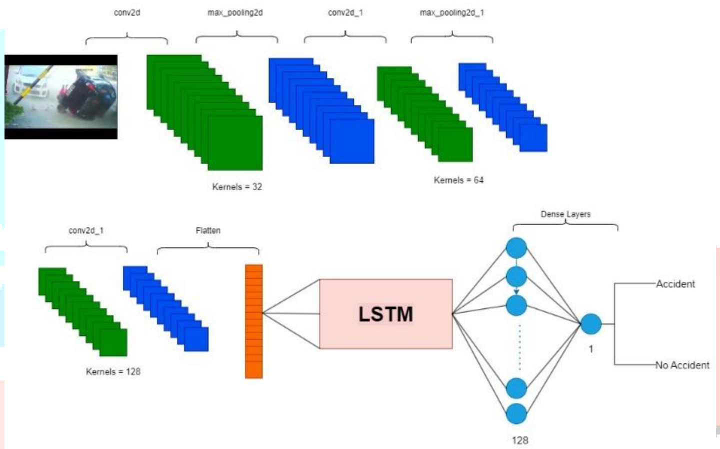

Fig.5 Model Architecture

E. Testing

For generating prediction scores for each class, the model obtained earlier undergoes evaluation using a distinct test dataset. The class with the highest prediction score is then identified as the optimal classification for the test data. It's important to note that we conducted binary classification for our analysis.

IV. EXPERIMENTAL RESULTS

After conducting extensive training and testing on 20% of the overall dataset, we obtained an impressive accuracy score of 85% at 100 epochs. This high accuracy demonstrates the effectiveness of our approach in accurately detecting accidents in real-time scenarios. Moreover, we have included the training accuracy and validation accuracy curves in fig 4 and training loss and validation loss curve in fig 5, providing a visual representation of the model's performance during training. These curves illustrate the convergence of the training and validation accuracies over epochs, highlighting the model's ability to generalize well to unseen data.

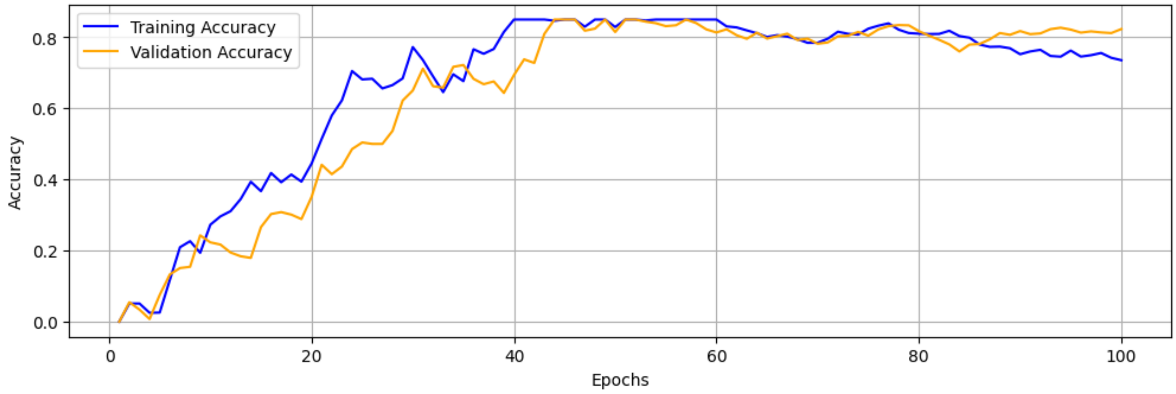

Fig.4: Training and Validation Accuracy curve

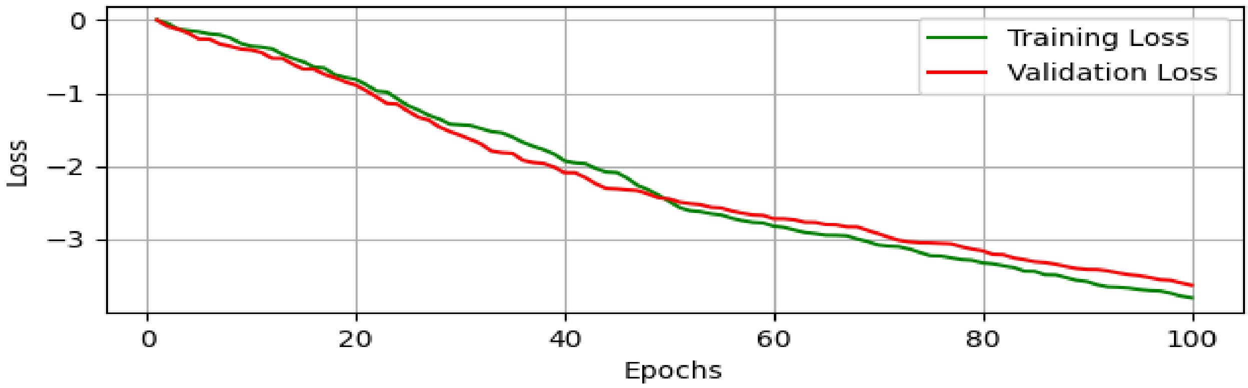

Fig.5: Training and Validation Loss curve

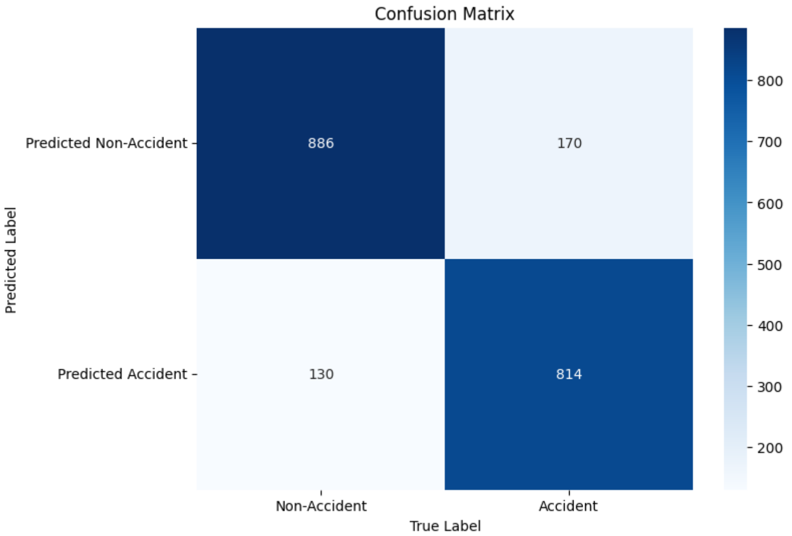

Fig.6: Confusion Matrix

The visualization of the confusion matrix in Fig.6 provides insights into the classification model's performance on the validation set, offering a clear assessment of its effectiveness aimed at improving road accident detection through the application of machine learning techniques. From CNN and LSTM models for severity categorization to object detection systems in CCTV footage, these approaches offer promising avenues for enhancing urban safety infrastructure. By providing real-time alerts to authorities, these systems have the potential to significantly reduce response times, thereby saving lives and minimizing the severity of accidents. Furthermore, the studies emphasize the importance of leveraging advancements in AI to address the pressing challenges posed by increasing traffic volumes and evolving urban environments. Moving forward, continued research and implementation of these innovative technologies are essential for fostering resilience and sustainability within smart cities, ultimately contributing to the creation of safer and more efficient transportation networks.

V. CONCLUSION

It showcases a wide array of methodologies aimed at improving road accident detection through the application of machine learning techniques. From CNN and LSTM models for severity categorization to object detection systems in CCTV footage, these approaches offer promising avenues for enhancing urban safety infrastructure. By providing real-time alerts to authorities, these systems have the potential to significantly reduce response times, thereby saving lives and minimizing the severity of accidents. Furthermore, the studies emphasize the importance of leveraging advancements in AI to address the pressing challenges posed by increasing traffic volumes and evolving urban environments. Moving forward, continued research and implementation of these innovative technologies are essential for fostering resilience and sustainability within smart cities, ultimately contributing to the creation of safer and more efficient transportation networks.

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