Accident Detection and Emergency Response System

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***Abstract*— Accidents on roads and in public areas often require prompt emergency response to mitigate potential harm and save lives. In this paper, we propose a real-time Accident Detection and Emergency Response System (ADERS) leveraging computer vision techniques, deep learning, and location-based messaging to detect accidents and notify emergency services promptly. The system integrates OpenCV, a powerful computer vision library, with YOLO (You Only Look Once), an object detection algorithm, to analyze video streams in real-time for signs of accidents. Through machine learning, the model is trained to accurately identify accident-related scenarios, such as collisions, falls, or vehicle crashes. Upon detection of an accident, the system triggers an automated message to the nearest emergency services or hospitals, alerting them to the incident and providing relevant information, such as the location of the accident. Integration with location-based services enables the system to determine the nearest hospital, ensuring a swift response. This paper outlines the key components and workflow of the proposed ADERS, highlighting its potential to enhance emergency response capabilities and improve overall safety in public spaces.**

***Keywords*—** *Computer vision, Deep learning, Object Detection Algorithm, YOLO (You Only Look Once)*

I. Introduction

Accidents, a pervasive threat to human safety and well-being, demand efficient detection and swift emergency response mechanisms. According to the World Health Organization (WHO), road traffic accidents alone claim approximately 1.35 million lives annually, underscoring the urgent need for proactive intervention strategies. In response to this imperative, technological advancements have paved the way for innovative solutions such as the Accident Detection and Emergency Response System (ADERS).

ADERS harnesses the power of emerging technologies, including computer vision and deep learning, to revolutionize accident management paradigms. Leveraging frameworks like OpenCV and YOLO (You Only Look Once), ADERS automates the process of accident detection, enabling real-time analysis of visual data captured by roadside cameras. By swiftly identifying accident scenes, ADERS initiates an expedited emergency response, facilitating timely intervention and medical assistance.

Central to the efficacy of ADERS is the utilization of robust datasets, such as HWAD12 from the Kaggle platform, which provide a diverse range of accident scenarios for algorithm training and validation. These datasets enable machine learning models to learn intricate patterns and characteristics associated with different types of accidents, enhancing their accuracy and reliability in real-world deployments.

This research paper embarks on a comprehensive exploration of ADERS, elucidating its technological foundations, operational methodologies, and impact on accident outcomes. Through a synthesis of existing literature, case studies, and empirical evidence, it aims to demonstrate the transformative potential of ADERS in enhancing emergency response efficiency and saving lives.

By showcasing the integration of cutting-edge technologies like OpenCV and YOLO into ADERS frameworks, this paper underscores the convergence of innovation and safety in modern accident management strategies. Furthermore, it advocates for continued collaboration between academia, industry, and government agencies to harness the full potential of ADERS and address evolving challenges in accident prevention and response.

II. Literature Survey

In [1] the authors propose a novel deep learning approach to predict crash severity, addressing shortcomings of previous models. It utilizes a customized f1-loss function for optimizing precision and recall simultaneously, along with transfer learning and a numeric to image transformation technique. The paper is structured with a literature review, description of the proposed model, results analysis, and conclusions.

In [2], the authors focus on using XGBoost to detect the occurrence of accidents in real-time and analyzing the importance of individual features for accident detection using SHAP (SHapley Additive exPlanation). Authors employed support vector machine and probabilistic neural network for accident detection modeling. The main findings include achieving a high accuracy rate of 99% in accident detection.

In [3], the authors propose a new collision warning system, SCWS, which gathers vehicle data through OBUs and shares it via RSUs. It overcomes cost and penetration rate limitations, exhibiting similar collision risk trends to existing systems. SCWS utilizes edge computing for local data processing and calculates collision risk based on data from the subject vehicle and the road segment.

In [4], the author emphasizes on the need for automated car accident detection to enhance response time and road safety. It proposes a method using Cooperative Vehicle Infrastructure Systems (CVIS) and computer vision, specifically the YOLOCA deep neural network model, to achieve high accuracy and real-time performance. The approach aims to reduce fatalities and injuries resulting from automobile accidents globally.

In [5], the authors use computer vision in detecting accidents and alerting about it. The paper talks about how primitive use of sensors for accident detection is disadvantageous as sensors can be Paper [8] uses computer vision in detecting accidents and alerting about it. The paper talks about how primitive use of sensors for accident detection is disadvantageous as sensors can be damages or sometimes may not work as well. The paper uses YOLOv3 algorithm for accident detection. The project uses 'Selenium' to fetch geolocation of the accident and to send alert.

In [6], the authors dive deep into CNNs. The paper talks about fundamentals of CNNs where it conveys that neural network is class of deep feed-forward neural network. It then tells about the architecture of CNNs and the layers which are present in it. It tell the practical use of CNNs for detecting food such as meat, cereals and cereal products, fruits and vegetables. It then states what are the challenges and problems which one might face while using CNNs. On concluding, it states how CNN is a promising feature extraction tool that has gradually replaced traditional machine learning algorithms. CNN can not only extract the most robust and effective features but also has strong generalization ability, which is infeasible with traditional machine learning methods.

In [7], the authors talk about development and implementation of an accident detection system using video processing technology. The system aims to enhance road monitoring by using cameras mounted at intersections to detect accidents in real-time.

In [8], the authors talk about how serious accidents problems are and how it can affect lives of many people. The paper then proposes a solution to this problem and continues to explain that how an accident detection system can solve this problem. The working of the system is based on deep learning techniques that use convolutional neural networks. By utilizing this system, many people can be saved from death.

III. Proposed Methodology

A. Training the Neural Network

This accident Detection System is designed to detect accidents via video or CCTV footage. This project majorly explores how CCTV can detect these accidents with the help of Deep Learning.

This paper uses technologies like OpenCV, Tensorflow, Keras and Convolution Neural Networks (CNN) to incorporate the required functionality. The CNN is built using Tensorflow library and has a total of 12 layers. The arrangement of the layer can be visualized using the following diagram.

This CNN model is then trained on a subset of the data available. The data is divided into 3 parts which are training, testing and validation. Each subset of the data has 2 different categories which are 'Accident' and 'Non-Accident' to feed the model both positives and negatives. The model is trained using training dataset and the run on the testing and validation dataset.

The summary of the trained model can be visualized using the below table:

TABLE I.

Layer (Type)	**Dimension**	**Parameters**
Batch Normalisation	250x250x3	12
Convolution 2D	248x248x2	896
MaxPooling 2D	124x124x32	0
Convolution 2D	122x122x64	
MaxPooling 2D	61x61x64	0
Convolution 2D	59x59x128	
MaxPooling 2D	29x29x128	0
Convolution 2D	27x27x256	
MaxPooling 2D	13x13x256	0
Flatten	43264	0
Dense	512	2,21,51,680
Dense	2	1,026

B. Vehicle Detection

The task of detecting vehicle is handled easily using python's library OpenCV. OpenCV is a famous python library for computer vision. This library is used here for detecting vehicles and drawing an outline box for each of the vehicle.

C. Collision Detection

Following the object detection stage, we remove every object that was found and keep only the cars that were accurately identified based on their class IDs and scores. The framework's next crucial job is to track every object that is recognized in later time frames of the video once the cars have been identified in a particular frame. This is achieved by applying Centroid Tracking, an object tracking technique that is straightforward but incredibly effective. The foundation of this technique is calculating the Euclidean distance between the centroids of observed cars across a series of frames. We will now use the terms "vehicles" and "objects" interchangeably.

The framework's centroid tracking technique satisfies the aforementioned requirements through a multi-step procedure.

The framework's centroid tracking technique satisfies the aforementioned requirements through a multi-step procedure. The steps are as follows:

1) The intersection of the lines that go through the middle points of the border boxes of the identified cars is used to calculate the centroid of the objects.

2) Determine the Euclidean separation between the centroids of recently discovered items and those that are already in existence.

3) Using the shortest Euclidean distance between the current set of centroid and the centroid that was previously saved, update the coordinates of existing items.

4) Use a dictionary to record the centroid coordinates of newly added objects and provide them a unique ID in order to register them in the field of view.

5) De-register objects which haven't been visible in the current field of view

The fundamental premise of the centroid tracking technique is that, even though the object moves between succeeding frames of the video, the distance between the centroid of the same object and any other object will always be smaller between two successive frames. This clarifies the idea underlying how Step 3 operates.

The following factors are utilized to forecast the likelihood of a collision after each vehicle is given a unique centroid.

1: The overlap of the vehicle bounding boxes

2: Calculating Trajectories and their Intersection Angle

3: Measuring Speed and Acceleration Changes.

There can be several cases in which the bounding box of the cars are overlapping such as cases when there is red traffic light or when there is a lot of congestion on the road, in such cases, false alarms can be ringed which is not beneficial for the model. Therefore to avoid such false cases, two extra factors are being used to detect collision.

IV. Result

A. Running the model

The model after successfully trained is tested on testing data and various performance metrics are visualized in the form of graphs. The graphs obtained are:

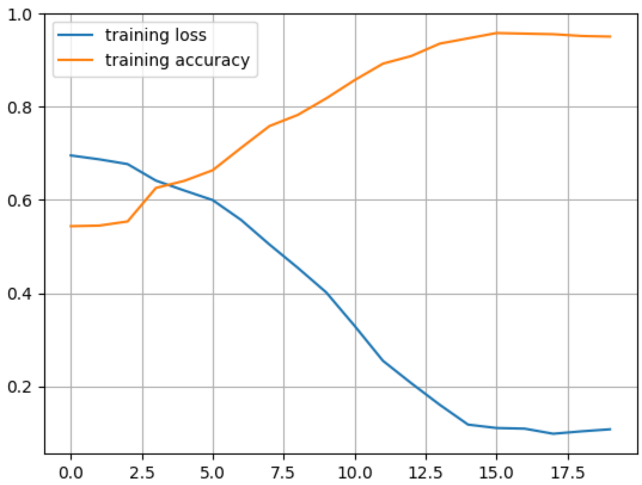

Fig. 1.Graph depicting loss and accuracy on training dataset.

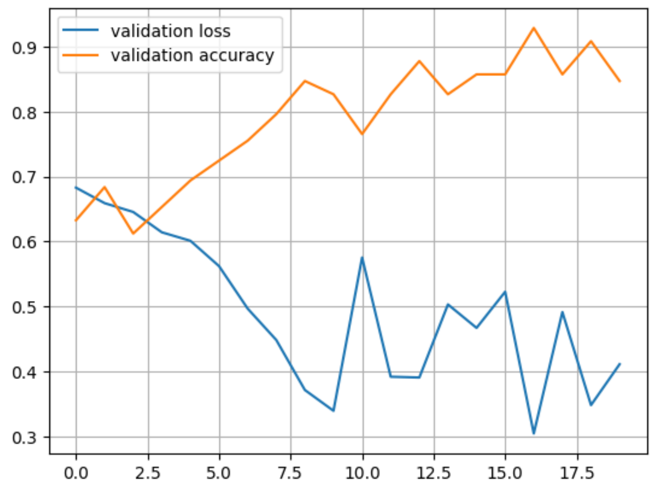

Fig. 2.Graph depicting loss and accuracy on validation data.

The model after running successfully creates a file which contains the weights used for the CNN. After successful training, the model is then run using OpenCV for live video footage capturing and detecting collisions.

The training phase of the CNN is visualized using the following picture:

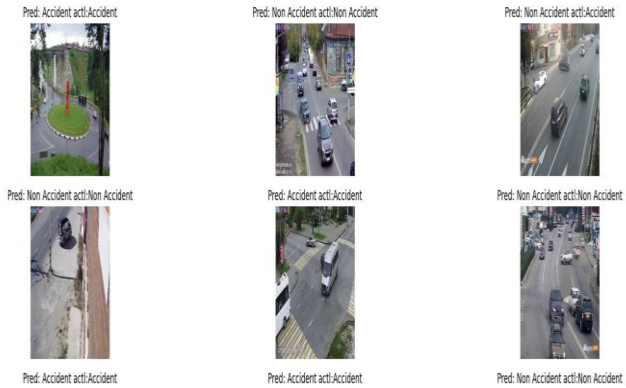

Fig. 3.Showing model's prediction on different images fed into it during training.

The accuracy of the model using proposed CNN was found to be 94.3%.

V. Conclusion

In conclusion, the proposed Accident Detection and Emergency Response System (ADERS) represents a significant advancement in leveraging computer vision, deep learning, and location-based messaging for real-time accident detection and swift emergency response. Through the integration of OpenCV and YOLO algorithms, the system demonstrates the potential to accurately identify various accident scenarios, ranging from collisions to falls, in real-time video streams.

Looking ahead, the horizon for this technology brims with opportunities for further exploration and refinement. Advancements in algorithms, integration of multi-modal data, predictive analytics, and alignment with autonomous vehicle technologies stand out as promising avenues for augmenting the effectiveness and breadth of accident detection systems. Moreover, addressing privacy concerns, optimizing deployment strategies, and assessing long-term societal impacts remain pivotal for the widespread acceptance and implementation of these systems. As we push the boundaries of innovation in accident detection technologies, it is paramount to uphold safety, privacy, and ethical standards. Collaborative endeavors among researchers, industry players, and policymakers will be instrumental in unlocking the full potential of these systems while ensuring their responsible and ethical deployment.

In essence, the development and progression of Accident Detection and Emergency Response Systems signify a pivotal stride towards fostering safer roads and streamlining emergency management processes. Through the judicious utilization of technology, we endeavor to forge a future where accidents are swiftly identified, lives are safeguarded, and road safety is markedly enhanced.

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