ACCIDENT DETECTION USING VIDEO SURVEILLANCE

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***Abstract*—Computer vision-based accident detection through video surveillance has become a beneficial task. There are many existing technologies to detect accidents in traffic but the speed and accuracy of the system does not meet the requirements. Thus the author formulates the idea of accident detection using video surveillance. The system consists of three phases: Vehicle detection, Vehicle tracking and Accident detection. The proposed framework capitalizes on Mask R-CNN for accurate object detection and uses an efficient centroid-based object tracking algorithm for surveillance footage. The accident detection phase includes Acceleration Anomaly, Trajectory Anomaly, and Change in Angle Anomaly. The probability of an accident is determined by speed and trajectory anomalies in a vehicle after an overlap with other vehicles. If the value is greater than the threshold value, then we can confirm that there is an accident. The proposed framework provides a robust method to achieve a high Detection Rate and a Low False Alarm Rate on general road-traffic CCTV Surveillance footage.**

Keywords- Accident Detection, Mask R-CNN, Vehicular Collision, Centroid based Object Tracking

I. INTRODUCTION

Accident detection using video surveillance is a technology that uses computer vision and machine learning techniques to detect accidents in real time from video feeds obtained from surveillance cameras. This technology is becoming increasingly important in today's world, as it can help to improve road safety and reduce the number of accidents on our roads.The system works by analyzing video feeds from cameras placed in strategic locations along the road network, such as intersections, highways, and busy city streets.

The system can detect accidents by analyzing the movement patterns of vehicles, pedestrians, and other objects in the video feeds, and using algorithms to detect abnormal or unexpected behavior. Once an accident is detected, the system can alert emergency services, such as police and ambulance services, in real time. This can help to reduce response times and improve the chances of saving lives and minimizing injuries. Overall, the use of video surveillance for accident detection is an important technology that can help to improve road safety and save lives. As this technology continues to evolve, we can expect to see even more advanced systems that are capable of detecting a wider range of accidents and responding even more quickly and effectively.

The combination of accurate object detection, efficient tracking, and multi-anomaly detection in the proposed framework may contribute to improving the speed and accuracy of accident detection systems, addressing the limitations of existing technologies in this field.The main objective of the system is that it automatically detects accidents. The system proposes how human life on road can be simplified by using extraction techniques on the surveillance video.

By using Artificial Intelligence all the surveillance videos that are being recorded and can revert back directly to emergency services without any intervention. This could save the time wasted by the manual communication as every second is important to save lives during an accident. The accident detection algorithm to the surveillance cameras would provide a great safety feature for the detection and to alert the emergency services without any waste of time made due to manual work.

This paper administers broader benefits for transportation authorities to take practical steps to effectively reduce the incidence and severity of accidents along with the costs associated with such accidents. In addition, the research results identify important environmental factors that affect the occurrence of traffic accidents. Although road accidents are rare events and might not be an everyday activity, anytime one takes place, it could be a life-and-death situation. This video rendering and filtering and detecting anomalies from that video plays an important part in road safety. The proposed framework has the potential to be applied to general road-traffic CCTV surveillance footage, which is a widely available and commonly used source of video surveillance in traffic monitoring systems.

II. Related Works

The researchers have several proposed techniques to develop a system to detect accidents on road.The main issue of the transportation sector are:

- Transportation sector faces many issues with the increase in population, such as traffic congestion, traffic jams, and traffic accidents.
- It becomes very difficult to predict an accident and to locate the position where it has happened.

As a result, numerous approaches have been proposed and developed to solve this problem.

One of the solutions, proposed by Singh et al.[21] discusses a method that utilizes stacked autoencoders, which are a type of deep neural network architecture, to represent spatiotemporal data for the purpose of detecting road accidents. The paper likely uses a deep learning technique called a stacked autoencoder. Autoencoders are a type of neural network that is used for unsupervised learning, and they consist of an encoder network that maps input data to a lower-dimensional representation, and a decoder network that reconstructs the original data from the lower-dimensional representation. Stacked autoencoders are multiple layers of autoencoders stacked on top of each other, and they can learn hierarchical representations of the input data. They also propose a method to represent spatiotemporal data, which refers to data that has both spatial (geographical) and temporal (time-based) components, using the stacked autoencoder [21].This could involve encoding and decoding spatiotemporal data using the stacked autoencoder to capture meaningful representations of the data. However, it suffers a major drawback inaccurate predictions when determining accidents in low-visibility conditions, significant occlusions in car accidents, and large variations in traffic patterns.

Similarly,Ki et al.[22] have demonstrated an approach that has been divided into two parts. The first part takes the input and uses a form of gray-scale image subtraction to detect and track vehicles. The second part applies feature extraction to determine the tracked vehicles acceleration, position, area, and direction. The approach determines the anomalies in each of these parameters and based on the combined result, determines whether or not an accident has occurred based on pre-defined thresholds. Even though their second part is a robust way of ensuring correct accident detections, their the first part of the method faces severe challenges in accurate vehicular detections such as, in the case of environmental objects obstructing parts of the screen of the camera, or similar objects overlapping their shadows and so on.[22]

The system proposed by C. Wu et al. combine computer vision, machine learning, and data mining techniques for traffic accident detection and prediction. The system uses video feeds from traffic cameras and analyzes various features, such as vehicle speed, lane departure, and collision risks, to detect accidents and predict their severity.[23]

T. N. Truong et al. propose a real-time vehicle accident detection system that uses spatiotemporal features and deep learning techniques. The system analyzes video feeds from surveillance cameras to detect accidents based on motion patterns, vehicle trajectories, and other visual cues.[24]

III. PROPOSED METHODOLOGY

A. System Overview

An accident Detection System is designed to detect accidents via video or CCTV footage. Road accidents are a significant problem for the whole world. Many people lose their lives in road accidents. We can minimize this issue by using CCTV accident detection. The system components interact with each other to provide a complete solution for accident detection in video surveillance. The system should be designed to operate in real-time, providing prompt detection and response to accidents, while also ensuring privacy and security compliance.

B. Functionality

A video surveillance accident detection system is a type of security system that uses video cameras and computer algorithms to automatically detect and alert security personnel or relevant authorities of accidents or other incidents that occur within the monitored area. The system typically analyzes video streams in real-time and uses image processing techniques to detect changes in the environment, such as changes in motion, presence of objects, or sudden impact. The system can also be programmed to recognize specific events, such as car accidents or falls, and send alerts when these events occur. The goal of a video surveillance accident detection system is to enhance the safety of the monitored area, reduce response times in the event of an accident or emergency, and provide evidence for investigation purposes.

C. Mask R-CNN

Mask R-CNN is a deep learning-based architecture for object detection and instance segmentation. It extends Faster R-CNN, which is a popular object detection frame- work, by adding a branch for predicting an object mask in parallel with the existingbranch for bounding box recognition. The model can identify objects within an image and draw a bounding box around each object while also generating a binary mask for each individual object, indicating the pixels that belong to the object and the pixels that do not.[2]

IV. Methodology

1) **Problem definition:** The first step is to define the problem, identifying the type of accidents to be detected and the requirements of the deployment site.
   The problem of accident detection in video surveillance is the task of automatically identifying and alerting about accidents in real-time, based on video data captured from cameras. Accidents can include various types of incidents such as car crashes, pedestrian accidents, falls, or any other unexpected events on the road or in public spaces.
   The problem definition can include the following aspects:
   - Real-time detection:
     Accidents must be detected as they occur, within a short time frame, to ensure prompt response and minimize harm.[6]
   - False positive/negative reduction:
     The system must have a low rate of false positive (false alarm) and false negative (missed detection) events to ensure accurate and reliable results.
   - Privacy and security:
     The system must comply with privacy and security regulations, such as protecting personal information and ensuring secure storage of data.
   - Scalability:
     The system must be scalable to accommodate large amounts of video data from multiple cameras and locations.
   - Robustness to environmental conditions:
     The system must be able to function under varying lighting, weather, and other environmental conditions.
     The goal of accident detection in video surveillance is to improve public safety, inform emergency response systems, and provide valuable data for improving transportation infrastructure and reducing accidents.
2) **Data collection:** The video data is collected using cameras installed at the deployment site and stored for later analysis.
   Data collection in video surveillance for accident detection typically involves capturing and analyzing video footage from cameras installed at various locations. This data is then processed using computer vision algorithms to detect accidents, such as collisions, falls, or other unexpected events. The information gathered can be used to improve road safety,

monitor traffic patterns, and inform emergency response systems. Some systems may also incorporate additional sensors, such as radar or lidar, to provide additional data for accident detection. The data collected must comply with privacy regulations and be securely stored to ensure the protection of individuals' rights.

3) **Data preprocessing:** The video data is pre-processed to prepare it for analysis, which may involve cropping the images, resizing, and removing unwanted background information. Data preprocessing in video surveillance for accident detection involves cleaning and transforming the raw video data into a format that can be analyzed by computer vision algorithms. This can include tasks such as:
   - Image/video rectification:
     This involves correcting the distortion caused by cameras' lenses to ensure a uniform image quality.[8]
   - Background subtraction:
     This involves separating the foreground objects from the background to focus on the relevant objects in the scene.[2]
   - Object detection:
     This involves detecting and isolating the objects of interest in the scene, such as vehicles, pedestrians, and other road users.[3]
   - Motion analysis:
     This involves tracking the movement of objects in the scene to detect abnormal behavior, such as sudden stops or rapid acceleration.[6]
   - Data augmentation:
     This involves creating additional training data by applying transformations to existing data, such as flipping, rotating, or resizing images, to increase the diversity of the training set.

   The goal of data preprocessing is to make the data more suitable for analysis by reducing noise and increasing the accuracy and efficiency of the computer vision algorithms. The preprocessed data is then used as input for accident detection algorithms.[10]

4) **Feature extraction:** The next step is to extract features from the preprocessed video data that are relevant for accident detection. This may involve extracting spatial, temporal, or color-based features from the video data.
   Feature extraction in video surveillance for accident detection involves identifying and extracting meaningful information or characteristics from the preprocessed video data. This information is then used to train machine learning algorithms or to make decisions about the presence of an accident. The extracted features can be based on various characteristics of the objects in the scene, such as shape, color, size, motion, or texture. Some common feature extraction methods include:
   - Histograms of Oriented Gradients (HOG): This method uses gradient information to describe the shape of objects.
   - Scale-Invariant Feature Transform (SIFT): This method uses a scale-invariant approach to detect and describe local features in an image.
   - Speeded Up Robust Features (SURF): This method is similar to SIFT but is faster and more robust to changes in illumination and viewpoint.
   - Deep learning-based feature extraction: This involves using Convolutional Neural Networks (CNNs) to automatically learn features from the data.The extracted features are then used to train machine learning algorithms for accident detection.[20]

5) **Model selection:** A machine learning model is selected based on the requirements of the deployment site and the type of accidents to be detected. Model selection in video surveillance for accident detection involves choosing the most appropriate machine learning algorithm for the task. The choice of model depends on various factors, including the type and amount of data available, the complexity of the task, and the desired performance characteristics. Some commonly used models for accident detection include:
   - Traditional computer vision-based models: These models are based on hand-crafted features and include techniques such as object detection, motion analysis, and event

recognition.

- Convolutional Neural Networks (CNNs): These models are deep learning-based and can automatically learn features from the data. They have been widely used for various computer vision tasks, including accident detection.[5]
- Recurrent Neural Networks (RNNs): These models are particularly well-suited for processing sequential data, such as video. They can be used to analyze the temporal evolution of objects in a scene to detect accidents.
- Hybrid models: These models combine the strengths of multiple models, such as traditional computer vision techniques and deep learning, to achieve better performance.
  The model selection process should be informed by empirical evaluation, such as cross-validation, to determine the best-performing model for a given task.

6) **Model training:** The machine learning model is trained on the preprocessed video data, learning to recognize the features associated with accidents.
7) **Model evaluation:** The trained model is evaluated on a separate dataset to determine its accuracy and reliability in detecting accidents. Model evaluation in video surveillance for accident detection involves measuring the performance of the machine learning model in detecting accidents. The following metrics are commonly used for this task:
   - Accuracy: This metric measures the proportion of correct predictions made by the model, out of all the predictions it made.
   - Precision: Precision measures the proportion of true positive predictions (accidents correctly identified as accidents) among all positive predictions made by the model.
   - Recall: Recall measures the proportion of true positive predictions among all the actual accidents that occurred.
   - F1 Score: F1 Score is the harmonic mean of precision and recall, and provides a balance between the two metrics.
   - Receiver Operating Characteristic (ROC) Curve: This curve is a graphical representation of the model's performance in terms of its ability to detect accidents, as the threshold for classifying a scene as an accident is varied.
   - Confusion Matrix: A confusion matrix is a table that shows the number of true positive, true negative, false positive, and false negative predictions made by the model.
     These metrics should be used in combination to provide a comprehensive view of the model's performance, and to identify areas for improvement. It is also important to perform cross-validation, where the model is trained and evaluated on multiple subsets of the data, to ensure that it generalizes well to new data and is not overfitting.
8) **Deployment:** The trained model is deployed in the video surveillance system and integrated with the data collection and storage systems. Deployment in video surveillance for accident detection involves integrating the chosen machine learning model into a complete system that can operate in real-world conditions. The deployment process includes the following steps:

   - Hardware selection: The system needs to be deployed on suitable hardware, such as servers or edge devices, that can handle the processing requirements of the model and the volume of video data.
   - Integration with cameras and storage systems: The system needs to be connected to the cameras and storage systems that provide the video data for analysis.
   - Data pipeline implementation: The data pipeline, which includes preprocessing, feature extraction, and accident

detection, needs to be implemented and optimized for real-time performance.

- Alarm and alert systems:
  The system needs to be integrated with alarm and alert systems that notify relevant parties, such as emergency services, when an accident is detected.

- Monitoring and maintenance:
  The system needs to be monitored to ensure it is functioning correctly and to perform routine maintenance, such as updating software or tuning parameters, as necessary.
  The deployment process should ensure that the system operates reliably and efficiently in real-world conditions and that it complies with privacy and security regulations. The deployment should also include performance evaluation to ensure that the system meets the desired accuracy, speed, and reliability requirements.

9) **Monitoring and maintenance:** The video surveillance system is monitored and maintained to ensure it continues to operate effectively and efficiently.

This methodology provides a general outline for developing a video surveillance system for accident detection. The specific steps and techniques used may vary depending on the requirements of the deployment site, the type of accidents to be detected, and the available resources. However, the overall process of problem definition, data collection, feature extraction, model selection, training, evaluation, deployment, and monitoring and maintenance is common to most video surveillance systems for accident detection.

A. Vehicle Detection

The object detection framework used here is Mask RCNN (Region-based Convolutional Neural Networks).Mask R-CNN is an instance segmentation algorithm that enables the automatic segmentation and construction of pixel-wise masks for each object in a video. This method improves upon Faster R-CNN by utilizing a new technique referred to as RoI Align, rather than the conventional RoI Pooling approach. The use of RoI Align has proven to result in a significant increase in mask accuracy, ranging from 10 perc to 50 perc, as it effectively resolves the issue of location misalignment that is encountered with RoI Pooling. The RoI Align algorithm not only provides the benefits of instance segmentation, but it also enhances the overall accuracy of the system.

The result of this process is a comprehensive output dictionary that contains the class IDs, detection scores, bounding boxes, and generated masks for each frame of the video. This information can be used for a wide range of applications, including object recognition, object tracking, and video analysis. With Mask R-CNN, video analysis becomes more efficient and precise, providing valuable insights into the objects within a video.

B. Vehicle Tracking and Feature Extraction

After the object detection phase, we filter out all the detected objects and only retain correctly detected vehicles on the basis of their class IDs and scores. Once the vehicles have been detected in a given frame, the next imperative task of the framework is to keep track of each of the detected objects in subsequent time frames of the footage. This is accomplished by utilizing a simple yet highly efficient object tracking algorithm known as Centroid Tracking. This algorithm relies on taking the Euclidean distance between centroids of detected vehicles over consecutive frames. The Centroid Tracking process involves the following steps:

1) The centroids of the objects are determined by calculating the intersection of the lines passing through the mid-points of the boundary boxes of the detected vehicles.
2) The Euclidean distance is calculated between the centroids of newly detected objects and existing objects.
3) The coordinates of existing objects are updated based on the shortest Euclidean distance from the current set of centroids and the previously stored centroid.
4) New objects are registered in the field of view by assigning a unique ID and storing their centroid coordinates in a dictionary.
5) Objects that have not been visible in the current field of view for a predetermined number of consecutive frames are de-registered.

The Centroid Tracking algorithm to be used in this project is based on the assumption that while the objects in the video footage will move between frames, the distance between the centroids of the same object in two successive frames will be smaller than the distance to the centroids of any other object. After the assignment of individual centroids to each vehicle, the following criteria are employed to predict the occurrence of collisions:

- C1: The overlap of bounding boxes of vehicles
- C2: Determining Trajectory and their angle of intersection
- C3: Determining Speed and their change in acceleration

In the current framework, the overlap of the bounding boxes of two vehicular objects plays a critical role in the prediction of a potential collision. It is widely accepted that prior to the occurrence of a collision, the bounding boxes of the involved objects will overlap. However, it must be acknowledged that there are scenarios in which the bounding boxes may overlap, but a collision may not necessarily occur. For instance, two vehicles may be temporarily stopped at a traffic light, or two automobiles may simply be passing by each other on a highway. These situations may trigger false alarms, hence it is important to use other criteria in conjunction with assigning nominal weights to the individual criteria in order to mitigate such occurrences.[4][7]

C. Accident Detection

In the proposed system,we will incorporate three parameters, namely, Acceleration Anomaly,Trajectory Anomaly, and Change in Angle Anomaly to effectively monitor for anomalies that could result in accidents.

To determine the Acceleration Anomaly , we first find the acceleration of the overlapping vehicles using the speeds captured in our dictionary. The average acceleration of the vehicles in the 15 frames prior to the overlapping condition (C1) and the maximum acceleration of the vehicles in the 15 frames after C1 are calculated. The change in acceleration of each vehicle is then obtained by subtracting the average acceleration during the overlapping condition from the maximum acceleration. This change is used to define the Acceleration Anomaly , which detects a collision based on this difference against a predefined set of conditions. This parameter is critical in capturing the significant changes in speed during a collision, thereby enabling the detection of accidents.

The Trajectory Anomaly is determined from the angle of intersection of the trajectories of the overlapping vehicles at the overlapping condition (C1). If it is within the range of θL and θH, (β) is determined based on the value of (θ) against a predefined set of conditions. If θ falls outside this range, (β) is determined based on θ and the distance of the point of intersection of the trajectories against a predefined set of conditions. Next, we use the Change in Angle Anomaly (γ) to account for abnormalities in the orientation of a vehicle during an accident scenario. This parameter will be used in conjunction with the other two parameters to effectively monitor for accidents. The procedure for determining a specific parameter involves calculating the angle (θ) of a vehicle relative to its own trajectory over a series of five frames. In the event of an accident, a vehicle experiences a degree of rotation with respect to an axis. As a result, the trajectories act as tangential vector relative to the axis. By evaluating the change in angles of the vehicle's trajectories, we are able to determine the degree of rotation and thus comprehend the extent to which the vehicle's orientation has changed. Based on the calculated angles for each of the vehicles in question, we then calculate the Change in Angle Anomaly (γ) based on a pre-established set of conditions. Finally, the individual anomalies are combined through the use of a function to determine whether or not an accident has taken place. This function, f(α, β, γ), considers the weighting of each individual threshold based on their values and generates a score between 0 and 1. A score greater than 0.5 is considered to be a vehicular accident, while a score lower than 0.5 is disregarded. This is the fundamental principle utilized for detecting accidents.[14][16]

V. Conclusion

There are many technologies for monitoring anomalies in accidents,but they have many limitations and thereby affects the system performance.Using the modern techniques and references we are able to find a system that resolves the limitations of the existing technologies. The proposed framework capitalizes on Mask R-CNN for accurate object detection and uses an efficient centroid based object tracking algorithm for surveillance footage.The probability of an accident is determined by speed and trajectory anomalies in a vehicle after an overlap with other vehicles.If the value is greater than the threshold value,then we can confirm that there occurs an accident. Future work will seek to develop a high-risk accident prediction and analysis platform based on the environmental factors of intersections. Based on the location of traffic accidents, data collection and analysis will be carried out to achieve the following goals:

- This system platform can integrate and analyze traffic accident data and GIS layer information, thus understanding the overall accident location.By analyzing the accident cause,we can formulate relevant improvement strategies as a reference for future intersection design.
- Use predictive models to estimate the likely locations of high-risk accidents to allow traffic management authorities to better prevent high-risk road accidents or serious casualties.

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