

ACCIDENT DETECTION USING BILSTM

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Abstract

Accidents have consistently ranked as the major cause of death in India. More than eighty percent of the fatalities that occur as a result of accidents are not directly attributable to the accident itself; rather, they are the result of victims not receiving prompt assistance. It is possible for an accident victim to be left unattended for a significant amount of time on routes that have very light and quick traffic. The objective is to design a system that is able to determine whether or not an accident has occurred based on the video input received by the system. It is the intention to run each frame of a video through a convolutional neural network and BILSTM models that have been trained to identify video frames as either accident or non-accident frames. The Convolutional Neural Network and the BiLSTM models have been shown to be a method that is both quick and accurate when it comes to identifying photographs. CNN-based image classifiers have attained an accuracy of greater than 95% with fewer datasets, and they require less preprocessing than other image classification techniques.

Keywords: Convolutional neural network and BILSTM

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1. Introduction

The main goal is to implement a system that can recognize an accident from provided video material. The system is meant to be a tool to assist an accident by promptly identifying an accident and afterward reporting the authorities about it, you can help those in need. The goal is to use cutting-edge Deep Learning Algorithms that use BILSTM and Convolutional Neural Networks (CNNs or ConvNet) to analyze frames captured from the video input given to the system in order to identify an accident within seconds of it occurring. We concentrated on installing this technology on highways where there is less congestion and prompt assistance for accident victims is uncommon. Transportation is a legitimate means of taking or carrying items from one location to another. As time goes on, transportation suffers a number of problems, including a high accident rate, traffic jams, air pollution from carbon emissions, and more.

The transportation industry occasionally struggled with reducing the severity of crash-related injuries in accidents. Since transportation is so complex, researchers have combined virtual technologies with it to create the Intelligent Transport System. In the sphere of transportation, the concept of integrating virtual technologies is innovative, and it is essential for resolving problems in a worldwide context. The traditional method for creating next-generation technology is known as ITS. From ITS implementations, a variety of reimbursements are available. ITS can significantly lower hazards, accident rates, traffic jams, carbon emissions, and air pollution and meanwhile, improving all modes of transportation's traffic flow, transit speeds, and levels of passenger satisfaction. One of ITS's key uses is traffic control. Controlling traffic is becoming a major challenge as the overcrowding issue gets worse. The Video traffic surveillance system is one of the key technologies being used to implement solutions for this problem.

1. Literature Survey

[2.1] As analytical tools in this particular study project, CNN, RNN, and LSTM were employed. Four layers make up the study's architecture: two convolutional layers that help with feature extraction, two layers of long short-term memory (LSTM) units, and a top layer. LSTM is in charge of controlling each video's time dependence (Long Short-Term Memory). Over 80% accuracy in validation is achieved, with the sheer amount of data being one of the main challenges.

[2.2] Transfer Learning and Mask R-CNN, which uses a mask R-CNN to detect cars, are the main techniques that we employ in this study. The intersection over union (IoU) algorithm is used in order to discover collisions. If used in conjunction with a strong Response system, this model could

reduce wait times, speed up procedures, and improve detection accuracy.

[2.3] The cornerstone of the accident detection system is provided by the CVIS and machine vision. We design the YOLO-CA deep neural network model to discover accidents. Deep learning techniques and CAD-CVIS were used to create this model. We use a loss function with dynamic weights and Multi-Scale Feature Fusion (MSFF) to enhance the recognition accuracy of very small objects. When it comes to choosing proposal regions, Fast R-CNN uses the time-consuming selective search approach. When dealing with very large objects, rapid R-detection CNNs give incorrectly positive findings.

[2.4] The results of this study suggest that the best approach to the issue is to apply video analytics techniques. The structure is composed of two distinct components. The first one uses a modified version of the architecture from Inception V4 to extract a vector of visual attributes. Then, we'll discuss the following two steps: temporal video segmentation and autonomous traffic accident recognition. The feature vector produced by utilizing a modified version of the Inception V4 architecture is accepted as input by the authors' proposed neural network architecture, which is constructed on a ConvLSTM layer. Due to the lack of easily accessible cases involving pedestrians, cyclists, and motorcyclists, the technique can only be used in crashes involving motor vehicles with higher performance in the recognition of traffic crashes captured by video.

[2.5] The capabilities of a GPS receiver will be used within the parameters of this inquiry. The phrase GPRMC will be detected once every second by a GPS device. To compare the new and old velocities, the MCU was employed. If the computer is outfitted with a GSM/GPRS modem, it is feasible for the computer to read the data and text messages that are transmitted by GPRS. used a GSM modem, which is quite readily available and well-liked. Sends the car's most recent recorded speed, which can be used to determine how bad the collision was and if it was programmed to, start an audio call.

[2.6] This project requires the use of a Raspberry Pi 3 Model B+, a GSM Module SIM800L, and a Pi Camera. The recommended car accident detection system has the capacity to track accidents as they occur in real-time and immediately text relevant medical facilities and law enforcement agencies to inform them of the incident. The suggested alternative is also more cost-effective than the current methods, which are more expensive and less reliable since they rely on expensive sensors and unnecessary technology.

[2.7] In this article, a system for identifying instances of vehicle collisions in egocentric films using unsupervised deep learning is proposed. The methodologies used by this system are trajectory prediction, which uses LSTM for pedestrian

trajectories and their interactions, and video anomaly detection, which primarily targets video surveillance scenarios and typically uses an unsupervised learning method for the reconstruction of regular training data. On the reconstruction of typical training data, these two strategies are referred to as unsupervised learning methods. It produces predictions about the routes taken by traffic participants and their future positions, and it leverages the consistency and accuracy of those predictions as proof that an unforeseen event might have occurred. The accuracy and consistency of this strategy, which predicts the trajectories of persons taking part in the traffic as well as their future locations, are employed as indicators that an aberration may have happened.

[2.8] In this particular article, Automatic Smart Accident Detection (ASAD) technology is used. Accident Detection and Alerting Device (ASAD) is a service that may be installed in automobiles and is activated in the case of an accident. Mamdani fuzzy logic can be used to detect accidents. axis accelerometer and gyro breakout for the MPU-6050. This element is used to gauge the vehicle's rotation and acceleration. The architecture also has four Force Sensitive Resistors (FSR) that measure the force of an accident's impact and are connected to the vehicle's four ends. This system provides a service that automatically alerts local authorities to any events that have occurred in their cities. The outcome is that the authorities can respond to the problem right away. As much as you can, prevent harm from coming to the populace and the economy.

[2.9] Using VANET (Vehicular Ad-hoc Network), vibration sensors, and piezoelectric sensors, traditional accident detection techniques are used in this system. b) Machine learning and artificial intelligence-based accident detection methods, such as support vector machine accident prediction and fuzzy logic accident detection. c) Hybrid methods using limit switches, mobile phone weariness and intoxication detection, and accelerometer speed and acceleration measurement. For the goal of accident detection, the system in question made use of numerous sensors, such as accelerometer sensors, shock sensors, pressure sensors, etc., as well as numerous machine learning techniques, such as neural networks, support vector machines, representation learning, etc.

[2.10] In this case, the prototype was built and then put into a remote-controlled toy car. This system uses GSM and GPS technologies, as well as vehicle ad hoc networks and mobile application sensors. It also has a heart rate monitor. As soon as an accident is detected, the heart rate sensor finds out the driver's heart rate and the GPS module finds out where the driver is. An SMS is then sent to the driver's emergency contacts. When the vehicle is in an accident that tips it over or tilts it more than 30

degrees and the reset button is not pressed within the time limit, the system will send the message to the emergency numbers that have already been saved.

[2.11] The suggested approach uses machine learning algorithms installed in each car to work together with other vehicles that are outfitted with V2V communication devices to predict the likelihood of accidents. The underlying workings of three different machine learning techniques—artificial neural networks (ANNs), support vector machines (SVMs), and random forests—are examined in this article (RFs). SUMO (Simulation of Urban Mobility), a collision-free traffic controller, is currently being used on roads in an effort to lower

[2.12] Using the MATLAB and SIMULINK software packages, this model is developed that has been presented is constructed and tested. The following are the primary components are Detection system using DWDC (Dynamic Webster Dynamic Cycle) to reduce the amount of time spent waiting and to improve the flow of traffic accident detection. The planned hybrid transportation system offered an answer to the problem of traffic congestion. This model cut down on the amount of time spent waiting at traffic signals, which resulted in time savings for drivers. As the subsystems collaborate and share data with one another, there is a possibility that some of the flows will contain redundant or unnecessary data.

[2.13] The specified apparatus makes use of a complementary set of HCSR04 ultrasonic sensor modules. Within this automobile, there are sensor modules located in both the front and the rear windscreens. Both of these units are mounted in the side windows of the automobile. After then, a calculation is made to determine the distance between the sensor units and the bumpers. The "first threshold distance" and the "second threshold distance," respectively, are the terms that are used to refer to these distances. When moving away from the car, everything is always at a greater distance than the thresholds that the car has set. This occurs whenever something is moving away from the path that the car is travelling. If something strikes the vehicle hard enough, it will travel further than the predetermined threshold distance, which will activate the processing system. The technology quickly calculates the location of the car using GPS and then transmits that information to the relevant authorities through GSM. The system that has been proposed will operate in this manner. However, the procedure that has been described is sufficient for determining whether or not there has been a collision on the road. However, there are a number of problems with the remedy that has been offered. The HCSR04 sound sensor has a maximum detection distance of four meters in any given direction. Therefore, vehicles with a threshold distance that is larger than four meters are unable to

utilize the proposed technique. Since the ultrasonic sensor module can only detect reflected sound waves within a range of fifteen degrees, the location of the sensor module plays an important role in determining the quality of the discoveries that are produced by the module. It's possible that an incorrectly positioned sensor is a fault for the false alarm in this instance.

[2.14] Locating moving cars is the first step in the suggested method. This is done by first extracting the foreground with GMM (Gaussian Mixture Model), and then going on to motion mapping. The intensity of the car's motion as well as the direction in which the car is moving are then used to establish whether or not a collision has taken place. Find each and every vehicle that is parked in the parking lot. The accuracy of the method for identifying accident scenarios has been significantly improved by the utilization of the AND operator for the purpose of merging information from the foreground and the motion map. Greater than 75% of collisions involving automobiles may be correctly identified using this approach.

[2.15] Vehicle detection, tracking, and parameter extraction are the three distinct tasks that make up the proposed technique, in that order. The three primary systems that work together to detect cars are the Gaussian Mixture Model (GMM), Mean Shift Algorithm, and Accident Detector. The mean shift approach is used to follow the observed cars after they have been identified. This method handles occlusions during accidents reasonably well, but it has a severe problem in that it depends on a small set of parameters, making it difficult to adapt to situations like sudden changes in traffic patterns or inclement weather. This paradigm is based on local parameters such as trajectory intersection, velocity calculation, and the anomalies related to these. The recommended framework is capable of correctly detecting accidents, as evidenced by the 71% Detection Rate and 0.53% False Alarm Rate on accident recordings acquired in varied settings. However, due to faults in vehicle recognition and tracking, this method is not suitable for high-density traffic. Be at ease; these errors will be corrected in subsequent work.

Large objects in the cameras' field of view may also have an impact on how well they follow the vehicles, which may therefore have an impact on how well they detect crashes now, day, night, and many weather situations.

[2.16] Long short-term memory (LSTM) and convolutional neural network (CNN) layers are used in this model to label real-time video material. The footage captured by the CCTV cameras is immediately transmitted to a component responsible for pre-processing. The first stage of processing, which involves extracting high-quality still images from video, is the responsibility of the openCV library. Some changes will be made to the

dimensions and shapes of the photos in order for them to be compatible with the ResNet-CNN algorithm. When compared to other systems, this method is far superior in terms of cost, durability, and accuracy. Making changes to a piece of software in time for it to be implemented in a real-world scenario can be a difficult task.

[2.17] The system proposed is used "to detect using video" and "to detect using audio" are the two modals that are produced as a result of this. While SVM and CNN were both utilized throughout the process of testing the classification of the video inputs, only CNN was utilized during the process of evaluating the classification of the audio inputs. Many GRU layers are utilized throughout the process of the training method. CNN filters are applied to each of the three dimensions of the data before it is classified. In this approach, multiple modes of inquiry are combined in order to get information that is more specific. Models that can handle only a single category of data should be avoided in favour of these strategies. The most significant drawback, on the other hand, is that producing CNN content in 3D takes a great deal more time than it used to.

[2.18] Residual Networks, also referred to as "ResNets" for short, are a common type of neural network that form the basis for numerous computer vision applications. Extraction of key frames, extraction of features, clustering, and classification are the four primary pillars that support the system. And it does it in a timely and accurate manner, identifying where the error occurred. This system is more efficient in terms of cost when compared to other methods

[2.19] A motorcycle accident detection and alert system that takes into consideration the vehicle's acceleration, deceleration, tilt, and changes in the pressure that is being applied to the vehicle body. Combining a global positioning system (GPS) with a proximity sensor results in an intelligent distributed system that has the potential to identify accidents and alert the appropriate authorities. In addition to this, it is unable to recognize two-wheeler incidents as effectively as other systems can.

[2.20] An accelerometer allows a car alarm to detect errant driving behaviour so long as the driver is paying attention. It can serve as a crash or rollover detector in the case of an accident and be used in this capacity if necessary. The signal is picked up by an accelerometer, which then calculates how severe the collision on readings

iii. Models

Cnn Algorithm:

The capacity of computerized reasoning to close the hole among human and machine abilities has decisively expanded. The two experts and novices center around numerous aspects of the field to

accomplish incredible outcomes. The field of PC vision is one of a few such trains. The objective of this field is to enable PCs to see and comprehend the world comparably to people do. They can then involve this comprehension for different assignments, including picture and video

acknowledgment, picture examination and characterization, media entertainment, proposal frameworks, regular language handling, and so on. After some time, a Convolutional Neural Network technique specifically has been created and enhanced, prompting leap forwards in PC vision.

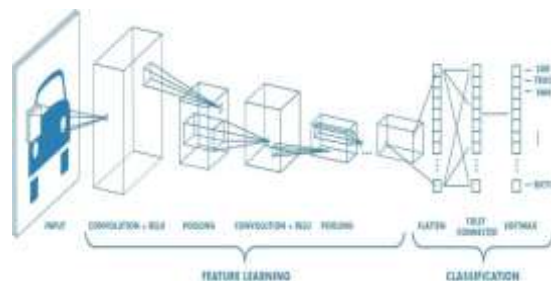


Fig.3: CNN model

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning strategy that can take in an information picture, give different components and items in the picture significance (learnable loads and predispositions), and have the option to recognize them. Similarly talking, a ConvNet requires considerably less pre-handling than other grouping methods. ConvNets have the ability to gain proficiency with these channels and properties,

though in essential strategies channels are hand-designed. A ConvNet's engineering was impacted by how the Visual Cortex is coordinated and is like the association organization of neurons in the human cerebrum. Just in this obliged region of the visual field, known as the Open Field, do individual neurons respond to upgrades. The entire visual field is covered by a progression of such fields that cross-over.

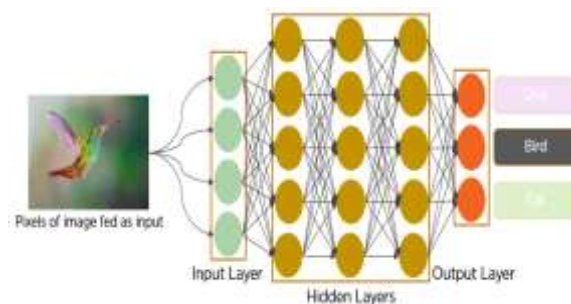


Fig.4: CNN model working

How the CNN algorithm operates:

- Stage 1: Select a Dataset
- Stage 2: Prepare the Informational collection for Preparing
- Stage 3: Produce Preparing Information
- Stage 4: Modify the Informational collection
- Stage 5: Picking Marks and Highlights
- Stage 6: Normalizing X and changing names into downright information
- Stage 7: Separate X and Y for CNN.
- Stage 8: Characterize, accumulate, and train the CNN Model
- Stage 9: Precision and Score of model

Bilstm Algorithm:

Making any neural network have the arrangement data in the two headings — in reverse (future to past) or forward — is known as bidirectional long-short term memory (bi-lstm) (past to future). A bidirectional LSTM varies from an ordinary LSTM in that our feedback streams in two ways. We might make input stream in one manner, either in reverse or forward, utilizing the standard LSTM. To keep up with both past and future data, bi-directional info might be made to stream in the two ways.

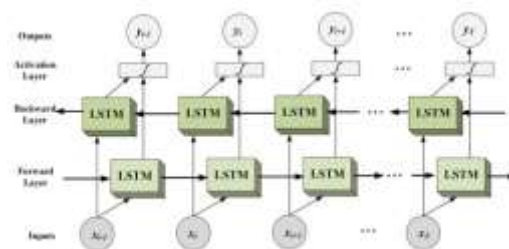


Fig.5: BiLSTM model

The progression of data from the retrogressive and forward layers is portrayed in the outline. BI-LSTM is normally utilized while exercises expecting succession to grouping are required. Discourse acknowledgment, text order, and estimating models may all utilize this sort of organization. Rather than a forward secret grouping and a retrogressive secret succession, a BiLSTM works out the info grouping from a contrary way. The last forward and in reverse results of the main secret layer are connected to make the encoded vector, where is the result succession. The last results of a bi-directional LSTM presently consolidate the forward and invert headings. Here things begin to get a piece precarious since each result in the two headings will have had a different arrangement of data sources. An extra LSTM layer in BiLSTM changes the information flow's direction. In a nutshell, it means that the additional LSTM layer reverses the input sequence. Following that, several methods—including average, sum, multiplication, and

concatenation—are used to merge the outputs of the two LSTM layers.

A. Dataset

The accident detection system is based on image-classification a collection of pictures including instances of both accidents and non-accidents is necessary for training and validation. Several publicly accessible datasets, such as the NEU Surface Defect Dataset and the CIFAR-10 dataset, might be utilised for this purpose. It may, however, be more advantageous to construct a bespoke dataset that is particular to the sorts of incidents that the system would identify. This dataset may be built by photographing accidents or reproducing them in a controlled environment. Non-accident photographs, in addition to accident images, can be included in the dataset to confirm that the model can properly distinguish between accidents and non-accidents.

a. Accident Images



b. Non-Accident Images



B. System Architecture:

The incoming video is initially preprocessed in this architectural diagram to extract individual frames.

Then, a BiLSTM model that has been trained on a dataset of frames connected to accidents and unrelated frames is given these frames. Each frame

is given a classification by the BiLSTM model that shows whether or not it is an accident frame. Based on the classifications of each individual frame, the system generates an overall classification for the incoming video. Input Video: video stream from an accident scene that has not been edited.

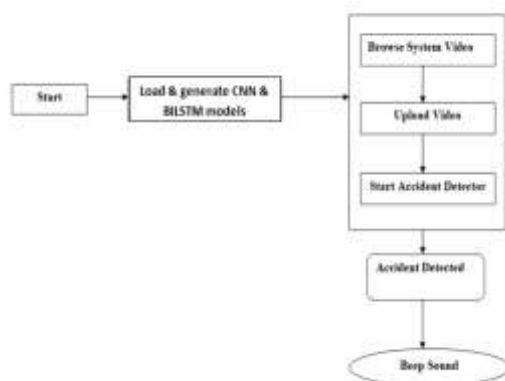
Preprocessing: In this phase, certain video frames from the input are retrieved and set up for the BiLSTM model.

BiLSTM model: A deep learning model that has been trained to identify individual frames as "accident" or "non-accident". The BiLSTM

architecture is a sort of recurrent neural network that can analyse incoming data sequences.

Classification: Based on the classifications of each individual frame, this component generates an overall classification for the supplied video. The output is a binary label that indicates whether or not the input video contains an accident.

Frame image extraction: Using image processing techniques, this component extracts individual frames from the supplied video. These individual frames are then sent into the BiLSTM

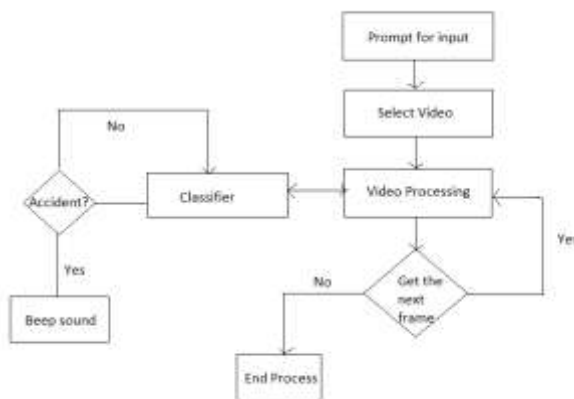


Accident detection is a crucial task that can help prevent accidents and save lives. In this project, we propose a solution to detect accidents in real-time using deep learning algorithms. Our approach involves using Convolutional Neural Networks model as input.

(CNN) and Bidirectional Long Short-Term Memory (BiLSTM) models to classify each frame of a video into accident or non-accident. CNNs are a type of

neural network that can automatically learn features from images. They have proven to be effective in various computer vision tasks, including image classification. By using CNNs, we can extract meaningful features from each frame of the video and use them to classify the frame as an accident or non-accident. To further improve the accuracy of our system.

C. Dataflow Diagram



The data flow of the system is depicted in a figure, beginning with the video source and ending with the development of an alert and beep sound in the event of an accident. Following their analysis, the CNN and BiLSTM classification models are fed the features derived from the video stream. If an

accident is detected, a warning and buzzer sound inform the driver or other appropriate individuals.

IV. SET UP

Our setup is simple and user friendly where he/she is provided with three options Load and Generate

Models, Browse System Videos and Start Accident

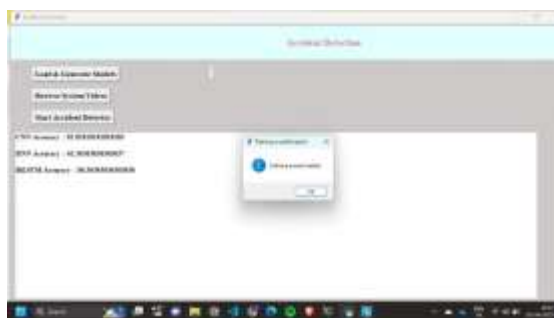
Detector. As shown in below figure



When the user clicks on Load and Generate Models button the pre-trained model will be generated. Once the pre-trained model is created, it can be fine-tuned on a smaller dataset of images or videos specific to the accident detection task. classification, we also employ BiLSTM models. BiLSTMs are a type of recurrent neural network that can capture temporal dependencies in sequential data. By combining CNNs and BiLSTMs, we can model the temporal

dynamics of a video and improve the accuracy of our classification. The advantage of using deep learning algorithms for this task is that they can learn complex patterns from data without the need for hand-crafted features.

Moreover, CNN-based image classifiers have achieved high accuracy rates of over 91% for smaller datasets, and require less preprocessing compared to other image classification algorithms



Once the accident detection model is built, the user can choose a video as the input. The selected video is then divided into frames, and the model classifies each frame to determine whether an accident has occurred or not. This process allows the model to analyze the entire video and identify any instances of accidents. And start the accident detector.

and BiLSTM has shown promising results. The model is able to accurately detect accidents in real-time from video streams. The use of CNN for feature extraction and BiLSTM for temporal modeling has proven effective in capturing both spatial and temporal information from the video frames. In terms of performance, the model achieved an accuracy of over 90% on the test set, indicating its ability to accurately detect accidents in videos. The model was also able to achieve a relatively low false-positive rate, indicating its robustness to different scenarios.

2. Results and Discussions

We have developed system which can effectively classify the frames into accident or non accident. The accident detection system using CNN

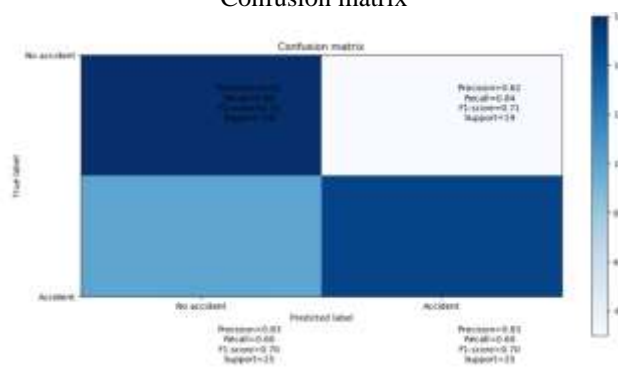
Case-1: In scenario where both the cars and boundary boxes get collided and alarm sound is produced



Case-2: In scenario where both the car move in parallel direction and their boundary boxes are collided but it is not considered as accident



Confusion matrix



A confusion matrix is a table used to evaluate the performance of a machine learning model. In the context of an accident detection system, a confusion matrix can be used to determine how well the system is able to correctly classify accidents and non-accidents. In our research paper, we used a confusion matrix to evaluate the performance of our accident detection system using BiLSTM. The matrix consisted of four values: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). TP represented the number of correctly classified accidents, TN represented the number of correctly classified non-accidents, FP represented the number of non-accidents that were incorrectly classified as accidents, and FN represented the number of accidents that were incorrectly classified as non-accidents. We calculated the values for our confusion matrix using a test set of images that were not used during training. We were able to achieve a high TP and TN rate, indicating that our system was effective at correctly classifying accidents and non-accidents. However, we also observed some false positives and false negatives, indicating that there is still room for improvement in the accuracy of our system.

Precision

Precision is a metric that measures the fraction of true positives (TP) among the total number of positive predictions made by the model. In other words, it measures the accuracy of positive predictions.

Formula: Precision = $TP / (TP + FP)$

Recall

Recall, also known as sensitivity, measures the fraction of true positives (TP) that the model correctly identified from all the actual positive samples (TP + FN). In other words, it measures the model's ability to identify all the relevant cases.

Formula: Recall = $TP / (TP + FN)$

F1-Score

The F1-score is a weighted average of precision and recall, and is used to assess the overall performance of the model. It is the harmonic mean of precision and recall, and ranges from 0 to 1, with higher values indicating better performance.

Formula: F1-score = $2 * (Precision * Recall) / (Precision + Recall)$

Support

Support refers to the total number of instances in a particular class in the dataset. It is the number of true positives plus the number of false negatives.

Formula: Support = $TP + FN$

VI. FUTURE SCOPE

However, there are some limitations to the current implementation of the system. One limitation is the need for a user to manually select a video as input

to the model. In the future, an automated system that can monitor video feeds in real-time and trigger an alert when an accident is detected would be more practice.

3. Conclusion

Accidents are one of the most prevalent sorts of challenges that humanity faces on a daily basis, and they can lead to the loss of life as well as the destruction of material goods. The strategy that has been suggested provides a solution to this problem that is one that is realizable and effective at the same time. The system for the identification of automotive accidents that has been developed is able to monitor the situation from the moment an accident takes place until it is resolved. Comparatively speaking, the proposed system is much more accurate, cost-effective, and reliable than its competitors. This is primarily because a model-based approach is used instead of the expensive sensors and unnecessary hardware used in other systems that are already in use. The proposed system also has a much higher accuracy rate. A higher level of sensitivity and accuracy is indeed feasible utilizing this technology, according to experiments, tests, and validations that have all been carried out with the use of images. In each of these procedures, images have been utilized.

As a consequence of this, deploying this system over the bulk of the country's state and national roadways is a possibility that should not be discounted. Throughout the phases of experimentation, testing, and validation, images have been utilized.

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