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Integration of deep learning algorithms for real-time vehicle accident detection from surveillance videos

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ABSTRACT

Major road accidents have increased due to the rapid rise of vehicles on the roads due to affordability and accessibility. While minor accidents can be resolved without the need for escorting to hospitals, significant accidents that involve the deployment of airbags necessitate the immediate attention of authorities. Thus, subsequent action of first aid and proper communication to concerned medical personnel can avoid most fatalities from accidents. The system involves the automatic detection of traffic accidents from videos extracted by closed-circuit television (CCTV) surveillance. In case of an accident, the system will detect and information about the accident will be instantly relayed to the nearest medical center. We have implemented different machine learning models such as Resnet-18, VGG-16, LeNet, and Inception V1 to ensure the accuracy of accident detection. From comparing all these models, the convolutional neural network (CNN) model shows the highest accuracy of 98%. The quick response will be an important step toward a safer and more secure transportation landscape.

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1. INTRODUCTION

In sparsely populated areas or on highways with high- speed traffic, accident victims are at a greater risk of being left unattended for extended periods. The impacts of road accidents are shocking globally, with over 1.3 million deaths recorded annually and tens of millions suffering mild injuries [1]. Reports indicate that in India, 13 people lose their lives every hour due to road accidents. This alarming statistic may place the country at the forefront of global road accident fatalities. Although these figures are disturbing in themselves, a number of accident cases go unreported, further deteriorating the situation. The need to ascertain the occurrence of accidents in real-time through live video streams from closed-circuit televisions (CCTVs) installed across highways has become very important. Several accident detection systems, such as those based on GSM and GPS modules, have been proposed for immediate medical aid [2]. Current GSM/GPS solutions suffer from high latency, costly deployment, and limited scalability. The approach extends these ideas by leveraging CCTV footage for real-time analysis, eliminating the need for additional hardware. The solution proposed would be to use a deep learning convolutional neural network (CNN) model that analyzes every frame of the video feed and classifies it as either depicting an accident or not. CNN have turned out as a strong, powerful, and efficient way of image classification that offers both speed and accuracy. What makes CNN-based image classifiers more suitable for real-time accident detection on highways is the very minimal preprocessing needed, against other algorithms, with reported accuracies of over 95%.

The approach was to pre-train a CNN model from a dataset consisting of frames labeled according to accident and non-accident scenes. This allows the system to efficiently detect an accident in real-time. Moreover, to integrate real-time alerting; this system will trigger an alarm instantaneously and notify the emergency services, including local hospitals, about the location of the accident. In this alert, latitude and longitude details are added as a new feature so that ambulance services may reach the accident spot with more speed, which in turn would result in quicker times for the crash victims with injuries to receive medical treatment. Accident spot with more speed, which in turn would result in quicker times for the crash victims with injuries to receive medical treatment.

This research addresses the major challenge that detection of side-impact collisions poses, which generally occurs in the area of traffic intersections, where accident rates are high and the consequences are serious. Intersections are particularly hazardous due to the meeting of several flows of traffic, with frequent side-impact or T-bone collisions in which the side of a vehicle is impacted by the front or rear of another. This is because most of such collisions have greater injury or death involvement since the sides of the vehicle do not offer much protection. The proposed system goes ahead to check for an accident occurrence to analyze trajectory conflicts at specific points that could lead to an accident. Examples will range from vehicle-to-vehicle collisions, vehicle-to-pedestrian, and vehicle-to-bicycle interactions. By identifying these kinds of conflicts, the system hopes to identify any potential accident in advance, allowing for quicker responses, and wherever possible, reduce the severity of such incidences [3].

Rest of this paper is arranged as follows: section 2 presents a summary of current research on accident detection together with dataset details. It also entails CNN-based accident detection techniques. The experimental results together with performance analysis and accuracy measures are presented in section 3. Section 4 offers a review of the findings together with important notes and restrictions. Section 5 ends the paper with a synopsis of results and recommendations for future research.

2. LITERATURE REVIEW

The study presented in [4] explored how the severity and impact of different types of traffic accidents vary. Consequently, a new approach to traffic accident classification was proposed, expanding from the traditional binary classification (0/1) to multiple, more detailed categories. Balfaqih *et al.* [5] proposed an accident detection and classification system using internet of things (IoT) and machine learning techniques to provide improvement in emergency response in smart cities. The system is composed of a microcontroller, GPS, and sensors that detect vehicle accidents based on speed, crash spot, rotation, altitude, flame, and smoke levels. The authors implemented various machine learning classifiers such as Gaussian mixture model (GMM), decision tree, naive-Bayes tree, and classification and regression trees (CARTs) and the results show that GMM and CART have given the best precision and recall in determining the severity of accidents. Ahmed *et al.* [6] proposed a system enhancing traffic safety by computer vision and AI technologies. The system proposed includes new parallel computing techniques, which will allow the reduction in complexity and inference time to enable the efficient operations of the system in all kinds of traffic. This model employs the YOLOv5 object detection algorithm combined with the DeepSORT tracker to identify and monitor vehicles in real-time.

Dogru and Subasi [7] utilized supervised machine learning algorithms on traffic data, integrating vehicle infrastructure integration and artificial neural networks (ANN) to detect incidents based on vehicle speed and lane changes. Among the tested models, random forest (RF) outperformed others with 91.56% accuracy, compared to support vector machine (SVM) (88.71%) and ANN (90.02%). Balasubramanian *et al.* [8] proposed an IoT-enabled system for real-time traffic data acquisition, using machine learning for traffic prediction and accident detection. An accident alert sound system was also introduced to improve emergency response. According to Adewopo *et al.* [9], a comparison between traditional machine learning and deep learning shows that CNN-based models offer higher accuracy and speed in real-time accident detection, addressing challenges like computational efficiency, latency, and robustness. Pai *et al.* [10] proposed a system that focuses on two major phases of operation: visual feature extraction and temporal pattern detection. In this model, a CNN architecture uses rectified linear unit (ReLU) and Softmax as activation functions to classify video frames into accident and non-accident classes. It goes on analyzing video streams continuously to detect an accident within 2-3 minutes and raises an alert in the nearest hospitals with the location of the accident, which would be identified by the IP address of the CCTV camera. Hooda *et al.* [11] introduced a multiple instance learning (MIL) approach using C3D features and a neural network with a ranking loss to classify video segments for anomaly detection. The method reduces false alarms and can effectively predict anomaly timing without segment-level annotations, making it suitable for real-world use.

Adewopo and Elsayed [12] focused on real-time crash detection systems, addressing the trade-off between computational efficiency and accuracy, and proposing solutions to enhance model performance in real-time applications. Bakheet and Al-Hamadi [13] proposed a framework that predicts traffic accidents in advance with a robust accuracy/speed trade-off, for timely alerts and to take effective action. According to Khalil *et al.* [14] multi-modal systems that combine vision-based technologies (such as CCTV) with sensor-based methods (e.g., ultrasonic and GSM) are used to improve accident detection accuracy. Gour and Kanskar [15] employed a combination of computer vision, neural networks, deep learning, and other methods to detect objects.

3. METHOD

The proposed accident detection system is based on CCTV cameras, wherein advanced algorithms are trained on real accident footage to automatically identify an accident in live video feeds with considerable accuracy. Compared with traditional methods, which require additional sensors to be installed on vehicles, the proposed system leverages only existing infrastructure and is hence very cost-effective and can be widely deployed. This system is real-time, thus it detects the accident immediately and provides important lead time for rescuing the victims. As described in [16], the model divides the accident detection into pre-collision, collision, and post-collision stages and studies vehicle trajectory and motion patterns. Unique among these shall be the automatic alert given to all hospitals in the vicinity about the exact location of the accident, which reduces the response times of medical personnel. Thus, crash victims have a very good probability of survival. The features shall combine to make the proposed system greatly improve road safety. It could reduce traffic fatalities and make the response to emergencies within medically underserved areas much quicker.

3.1. Dataset details

The proposed model uses the highway incidents detection (HWID12) dataset [17], [18], sample image from this dataset are shown in Figure 1. It comprises 2780+ video clips with duration varying between 3 to 8 seconds of events that are caught on camera in accidents compilation. More than 500,000 temporal frames surround these clips. The incidents are considered from different perspectives, i.e., before the incidents take place or immediately after the incidents. The dataset consists of 12 categories: 11 accident categories: each folder corresponds to a distinct type of the highway incident 1 negative sample category: this represents 'normal' traffic scenarios in which nothing has happened. Manual segmentation of video clips was done from the accident compilation videos.

Figure 1. Sample image from HWID12 dataset

3.2. Architecture of proposed system

Figure 2 illustrates the overall architecture of accident detection and alarm system using CCTV footage. The proposed methodology incorporates four stages of processing, namely input data preprocessing, feature extraction, temporal analysis, and accident detection and alert.

3.2.1. Input data preprocessing

The process starts by considering the CCTV footage that captures an accident. It extracts the key frames from the video so that one may pay more attention to those particular instants where an accident could have occurred. The extracted frames are further preprocessed by dataset splitting. The dataset was divided into three sets: training, testing, and validation. It is mainly done for modeling purposes. A 75:15:10 ratio of training-validation-testing splits the dataset. In data augmentation, the application of different transformations on the images improves the model greatly and prevents overfitting. These transformations include the random horizontal flipping and rotations-scaling are used to create a variety of different images to assist in the generalization of the model. The frames are extracted from videos taken during accidents, while some videos are void of accidents.

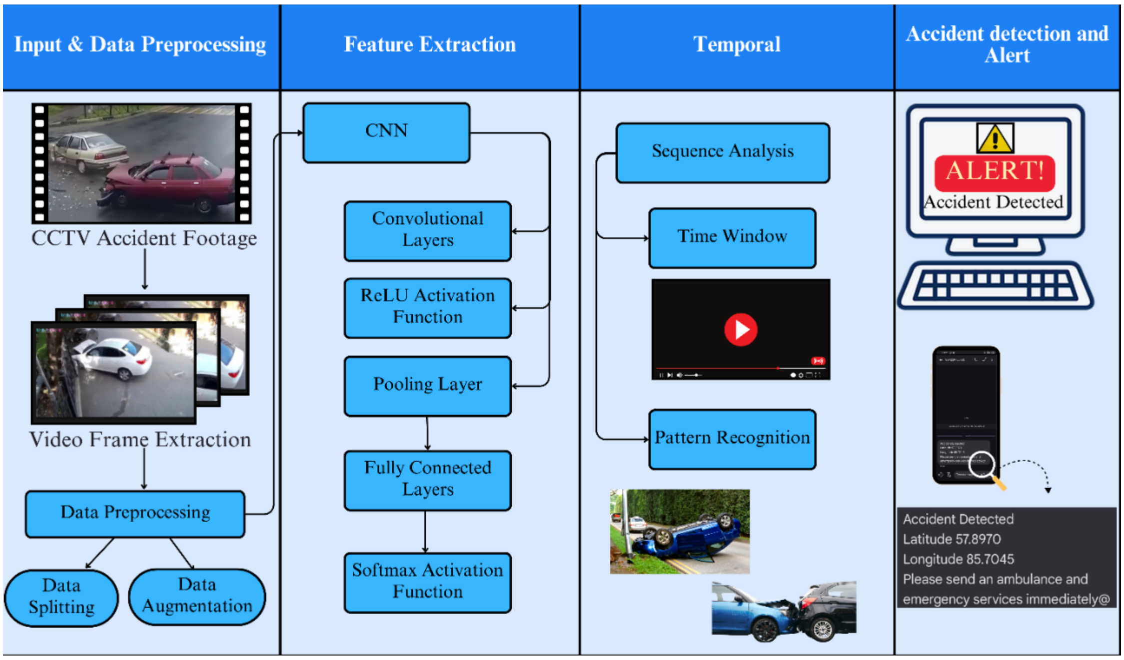

Figure 2. Architecture of proposed system

3.2.2. Feature extraction

The CNN is used to filter the preprocessed data. Edges, patterns, and textures are automatically extracted from the images by the convolutional layers. The ReLU activation function incorporates a degree of non-linearity into the model, which facilitates the acquisition of intricate patterns. The pooling layer reduces the spatial dimensions of the feature maps, thereby making the model more computationally efficient and less susceptible to overfitting. After this the features are passed through fully connected layers, allowing interpretation to the features and decision-making. The SoftMax activation function is used in the last layer for classifying the frames into different categories, whether the accident has happened or not.

3.2.3. Temporal analysis

The output from the CNN is further analyzed on a temporal basis; a time window is considered to study how events evolve in a short time, which may help pinpoint an accident. The pattern recognition works to search for patterns associated with typical accidents, such as sudden stops, collisions, or other abnormalities. Future frame prediction method [19] using spatial and motion constraints, effectively identifying traffic anomalies like accidents.

3.2.4. Accident detection and alert

In case of an accident detection by the system, an alert notification is sent to the computer system or mobile device with information such as the place and time of the accident. The SMS or other emergency notifications are forwarded to the concerned authorities for immediate response. Rapid IoV response mechanism [20], our system similarly focuses on quick detection and alerting to improve accident survival rates.

3.3. Training details and hyperparameters

The model was tuned using the optimal hyperparameters to maximize accident detection performance. With the learning rate of 0.00085, Adam optimizer, and batch size of 4, it was trained for 50 epochs with cross-entropy loss. Generalization was enhanced using dropout (0.10) and pre-trained ImageNet weights enhanced performance. ReduceLROnPlateau scheduler helped in convergence. Training was performed on Google Colab with NVIDIA Tesla T4 GPUs.

3.4. Evaluation methods

To facilitate the reliability and robustness of the results, several evaluation metrics such as accuracy, precision, recall, and F1-score were used in evaluating the performance of the model. We tested the model robustness on day/night videos which showed the impact on performance of the nighttime video feeds. They were hampered by low visibility and high contrast ratios that made object detection a little bit more difficult for the system. The model was tested under various conditions, including nighttime, rainy weather, and different traffic densities, and consistently delivered accurate results.

3.5. Flowchart of proposed system

Figure 3 represents the flowchart for an automated accident detection system. If an accident is confirmed, it further sends an alert to the nearest hospital and to the registered mobile numbers related to the vehicle involved, together with the information of location. Faster regions with convolutional neural network (R-CNN) have demonstrated effectiveness in detecting accidents under suboptimal conditions, such as in tunnels with low visibility, reinforcing the robustness of deep learning for diverse environments [21].

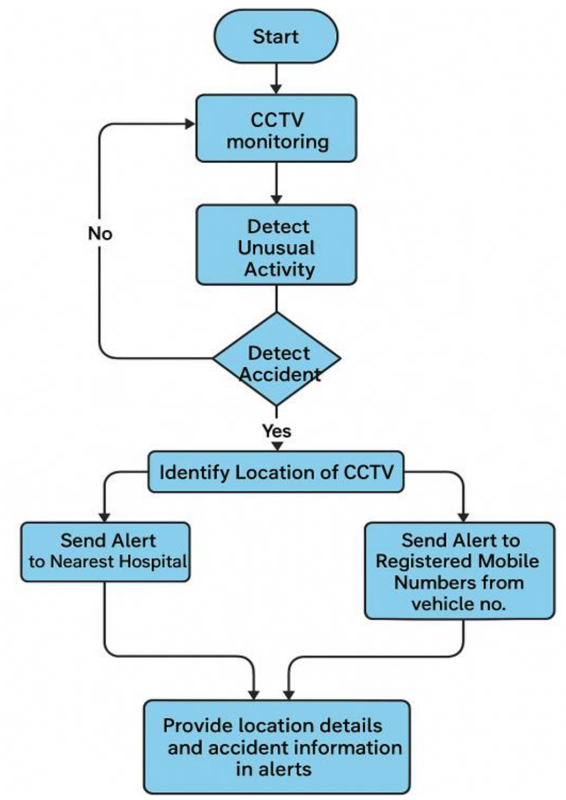

Figure 3. Flowchart of proposed system

CNN model used in the proposed work uses the ReLU activation in the initial layers and SoftMax activation in the final layer for converting probabilities. The method utilizes CNN for real-time accident detection, and just like the research by Naveenkumar [22], which improved accident detection by fusing CNN and YOLO models. The synergy between CNN’s learning capacity of spatial features and YOLO's efficiency in object detection has made the system robust. If the probability of an accident is greater than a threshold, the accident warning is raised. our model is comparable to other advanced deep learning models, such as YOLO-CA [23], which achieved high accuracy in accident detection using CVIS.

4. RESULTS AND DISCUSSION

Comparing four deep learning models: ResNet-18, VGG-16, LeNet, and Inception V1, for accident detection, as can be seen in Table 1, all metrics: precision, recall, F1-score, and accuracy were performed better by ResNet-18.

Table 1. Performance evaluation of algorithms

Algorithm	Accuracy	Precision	Recall	F1-score
Resnet-18	0.95	0.94	0.98	0.96
VGG-16 Net	0.91	0.90	0.95	0.92
LeNet	0.74	0.83	0.85	0.80
Inception V1	0.88	0.91	0.94	0.92

The accident detection accuracy was tested extensively against different input video streams. The model accuracy turned out to be 95%. Other metrics, like training loss, training accuracy, validation loss, and validation accuracy, have been measured. Those have been plotted in the following figures.

The graphs in Figures 4 and 5 illustrate that with more data the model is trained upon, accuracy increases and loss decreases. Training loss is a measure of how good the model is at fitting the training set, whereas validation loss and accuracy are measures of how good it is on unseen data. The model converges extremely early to about 90% validation accuracy and is stable with consistent predictions.

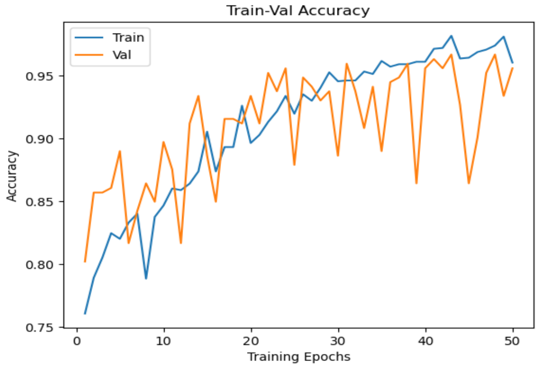

Figure 4. Plot of training accuracy and validation accuracy

Figure 5. Plot of training loss and validation loss

4.1. Statistical analysis

The ResNet-18 model was then validated with 5-fold cross-validation, which demonstrated consistent performance with mean accuracy of 95% and a standard deviation of 0.02. A paired t-test also established its outperformance against VGG-16, LeNet, and Inception V1 with a statistically significant p-value <0.05, and thus it is highly efficient in accident detection from videos.

4.2. ResNet-18 evaluation

ResNet-18 is chosen for car crash detection as it provides a balance between efficiency and accuracy. Its 18-layer CNN with residual learning avoids the issues of deep networks like vanishing gradients. In PyTorch, it extracts the features of video frames from 224×224 pixels via convolutional layers, batch normalization, and max-pooling. Residual connections improve detection accuracy, and fully connected layers predict the probability of a crash.

- Residual block:

$$y = F(x, \{W_i\}) + x \tag{1}$$

- Forward pass in convolutional layers:

$$y_{i,j} = \sum_{m,n} x_{i+m,j+n} \cdot w_{m,n} \tag{2}$$

- Batch normalization:

$$\hat{x} = \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{3}$$

- Cross-entropy loss function:

$$L = -\sum_{i=1}^{N} y_i \log \log (p_i) \tag{4}$$

- Accuracy metric:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

The confusion matrix in Figure 6 emphasizes the model's excellent accident detection capability with zero false positives and false negatives with high accuracy. Employing ReLU and Softmax activation functions, the CNN model ensures high recall and accuracy with real-time accident alerting potential. Figure 7 plots the actual and predicted labels of accidents, emphasizing the model's credibility in accident detection tasks.

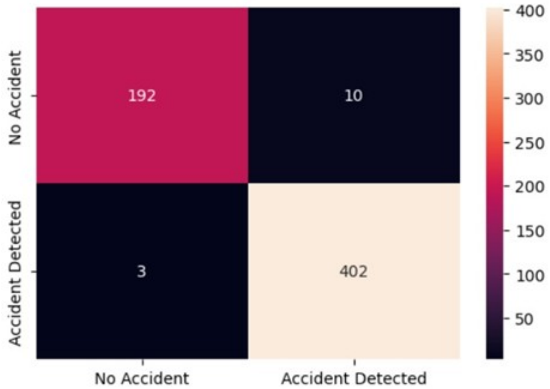

Figure 6. Confusion matrix

	0	1	2	3	4	5	6	7	8	9	...	587	598	599	600	601	602	603	604
Label	1	0	1	1	1	0	0	1	0	0	...	1	1	0	1	1	0	0	1
Prediction	1	1	1	1	1	0	0	1	0	0	...	1	1	0	1	1	0	0	1

Figure 7. Visual representation of true vs. predicted labels

4.3. Real-time performance and computational requirements

The highway incident detection model executes in real-time with 50 ms processing delay per frame for immediate detection and alerting. It is executed on an NVIDIA GTX-1060 GPU consuming 150-200 W of power, executing without major power constraints. Minimum hardware requirements include GTX-1060 (6GB VRAM), quad-core CPU, 8GB RAM (16GB optional), and 20GB disk space. Scalability and response time (2-3 minutes for reporting accidents) are of greatest concern for deployment. Utilizing an ensemble deep learning approach [24], integrating models like I3D and CONVLSTM2D enhances detection accuracy, consistent with current research and enabling a robust real-time traffic monitoring system. The YOLOv8-based model in [25] performs with high accuracy with real-time inference speed and is best suited for deployment enhancements will be developed to strengthen safety and emergency response provisions in the future.

5. CONCLUSION

The conclusion of the study proposes that the OpenCV-based ResNet-18 model detects real-time vehicle accidents efficiently, surpassing VGG-16, LeNet, and Inception V1 in accuracy, precision, recall, and F1-score in all respects. It has 95% accuracy, 94% precision, 98% recall, and a 96% F1-score and can identify highway accidents and enable automated response. Future work will address varying environmental conditions, IoT integration, and edge-computing to reduce response time. Edge-device lightweight implementations and federated learning will introduce scalability, robustness, and flexibility to emerging accident trends.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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