Accident Detection System Using Video Data

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Abstract. In this research, we suggested an accident detection system that enables the camera while driving and detects accidents and alerts the nearest area emergency contacts. The accident detection is handled by using CNN (convolution neural networks) and the location details are handled by Google geocoding and reverse coding. The details of the location and occurrence of the accident details are stored in the app database. The video is also a collection of frames and hence we can also detect multiple accidents in different frames and can also predict the likeliness of the accident occurrence by probability. The live featuring of videos also help to detect different accidental zones around the state or country. The system certainly gives a lot of chances to balance the human loss ratio in accidents and gain safe roads among the different places. The data analysis can also be done to ensure the accidental warning signs can be posted among the most important spots after the analysis in different locations.

Keywords: CNN · Accidental zones · Geotagging · Reverse coding

1 Introduction

Majorly, the loss of human life is due to accidents. Each year, the World Health Organization reports that road traffic accidents result in the loss of more than 1.3 million lives globally. Alongside this devastating loss of life, an estimated 50 million individuals also suffer non-fatal injuries as a consequence of these accidents. These statistics underscore the urgent need for effective measures to prevent road accidents and mitigate their impact on individuals and communities worldwide. According to statistics, road transportation is considered the most dangerous means of transportation when compared to others such as air and sea. Hence to eradicate this problem, the proposed system takes into account the number of accidents, and without using any IoT the model takes in the video as input and splits into frames as well as finds the location so that human life is not wasted, and the necessary assistance is also provided to those in need after the accident. Accidents can be categorized into three phases based on the timing and severity of the outcomes they produce. The first phase involves immediate fatalities, where approximately 10% of accident-related deaths occur within a few minutes or seconds of the incident. The second phase, which occurs within an hour after the accident, has the highest mortality rate, accounting for 75% of all deaths. Timely assistance and intervention during this

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critical period can significantly reduce fatalities. The third phase occurs days or weeks after the accident and carries a death rate of around 15%. To prevent deaths during this phase, it is crucial to provide adequate medical care and allocate necessary resources. The primary objective is to assist accident victims during their most critical hour of need, enabling prompt and effective intervention to save lives.

2 Related Work

2.1 Smart Car: An IoT Based Accident Detection System

This system employs an automated response mechanism to detect and address accidents promptly. It utilizes sensors and microprocessors to detect collision events and transmit the location data to a centralized Cloud platform. From there, notifications are promptly sent to hospitals, ambulances, and emergency contacts. The core of this system revolves around the Raspberry Pi single-board computer, coupled with GPS technology that leverages positional data.

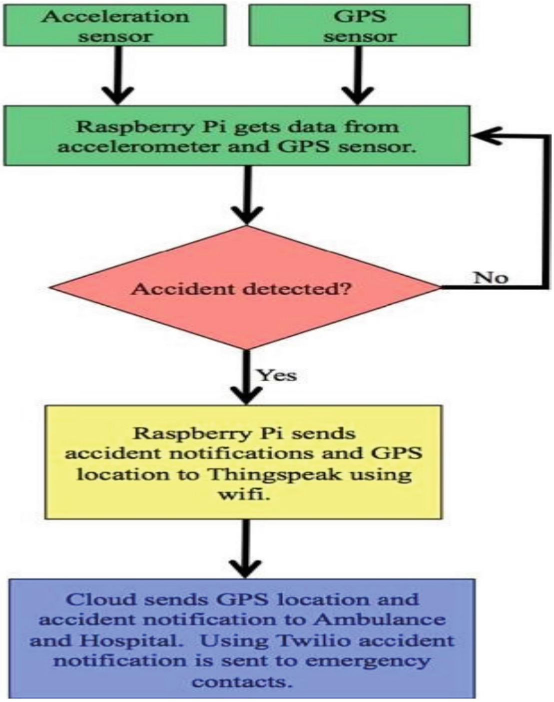


Fig. 1. Smart Car Process

The device is designed to swiftly identify collisions involving the vehicle it is installed in. To achieve this, it utilizes the ADXL345 accelerometer, which has proven compatibility with Raspberry Pi 3B+ and has been successfully employed in various projects.

The accelerometer offers a triple-axis feature, enabling detection of acceleration along different directions. The x-axis captures forward or backward acceleration, facilitating the identification of front or rear-end collisions. The y-axis measurement detects impacts from the sides of the vehicle, while the z-axis reading detects collisions from above or below. To illustrate the system's operational flow, a comprehensive flow chart is provided in the accompanying figure Fig. 1 [1].

2.2 Vehicle to Vehicle Communication

This research paper focuses on wireless technologies employed in vehicle-to-vehicle (V2V) communication. It provides a comparative analysis of system reliability, throughput, and latency. Furthermore, the paper discusses the significant challenges faced by V2V, including scalability and topological variations. It examines three recent schemes that aim to address these challenges. The key contributions of this paper include: [2]

1. Offering an overview of the wireless access technologies utilized in V2V communication.
2. Identifying and discussing the technical challenges encountered by V2V.
3. Introducing the Loss Differentiation RA (LORA) scheme, which enables V2V safety communications to rapidly and appropriately adapt data rates based on environmental dynamics.
4. Proposing an adaptive modulation and coding technique that dynamically adjusts coding and modulation methods in response to current channel conditions.
5. Presenting a selection scheme for adaptive data rates that considers changes in the physical network topology.

These contributions enhance our understanding of wireless technologies in V2V communication and provide potential solutions to tackle the associated challenges.

2.3 Smart Automatic Accident Detection

1. The proposed model employs GPS for accurate accident location and GSM for quick information relay. It can also detect alcoholic drivers and vehicle fires, generating alerts. A buzzer enhances detection accuracy, and a user-controlled switch prevents unnecessary messages. Automatic notifications are sent to police and responsible parties upon accidents. Alcohol detection and flame sensors further enhance safety by notifying responsible parties and rescue teams in case of alcohol consumption or vehicle fires, minimizing potential loss [14].

2.4 Wireless Access Technologies in V2V

A. Cellular V2x

V2X communication is a highly efficient and reliable technology that plays a crucial role in facilitating real-time information exchange for safe, efficient, and environmentally conscious transportation services. Specifically developed within the

3rd Generation Partnership Project (3GPP), C-V2X operates in two distinct modes: Device-to-Device (D2D) and Device-to-Network (D2N). The D2D mode of operation allows for direct communication between vehicles or devices without the need for network involvement, enabling efficient and instant data exchange. On the other hand, the D2N mode utilizes traditional cellular links to establish communication between devices and network infrastructure, thereby enabling the integration of cloud services as part of the overall end-to-end solution. By leveraging these two modes, V2X communication technology enables a comprehensive and versatile approach to transmit critical information, contributing to safer and more efficient transportation systems.

B. DSRC

To address the communication challenges posed by the demanding vehicular environment, IEEE introduced a modified version of the Wireless Local Area Network (WLAN) protocol called IEEE802.11p DSRC. This standard utilizes the same physical (PHY) layer as the IEEE 802.11a standard, which was originally designed for indoor stationary environments. However, the high-speed and unstable nature of vehicular environments can lead to reliability issues in the performance of 802.11p packets.

One significant drawback of DSRC is its limited scalability. This hinders its ability to meet the required time-probabilistic characteristics, particularly in densely trafficked areas. The scalability issue poses a challenge in providing consistent and reliable communication in such scenarios.

In summary, while IEEE802.11p DSRC addresses the vehicular communication challenges by utilizing WLAN technology, its reliance on the IEEE 802.11a PHY layer and low scalability pose limitations on its performance and ability to meet the demands of dense traffic situations.

C. 4G-LTE

LTE technology is capable of meeting the reliability, mobility, and scalability requirements for V2V communication. It can be redesigned to provide simultaneous low latencies and higher throughput. Operating on the 1.88–1.9 GHz frequency range with TDLTE protocol, it offers potential benefits. However, challenges arise with LTE network overload and meeting stringent delay requirements during high cellular traffic. Optimization is crucial for successful implementation.

D. WLAN/WI-FI

To facilitate wireless access for V2V communication, we integrate a wireless local area network (WLAN) utilizing IEEE 802.11 standards. Specifically, IEEE 802.11a operates at a frequency of 5 GHz and offers a communication range of approximately 140 m outdoors and a minimum of 38 m indoors, delivering a data rate of 54 Mbps. However, a significant drawback of IEEE 802.11a is its primary design for stable indoor environments, resulting in poor reliability and continuity in outdoor or highway scenarios. This limitation hampers its performance and suitability for seamless V2V communication in such settings.

E. UWB (IEEE 802.15.3a), or Ultra-Wide Band

Ultra-wideband (UWB) technology utilizes short-pulse and low-powered radio signals to transmit data across a wide range of frequency spectrums, making it highly resilient to various types of disturbances. However, when it comes to V2V communication, UWB faces challenges related to latency, throughput, and scalability, which limit its suitability for this application.

F. ZigBee (IEEE 802.15.4)

A new low-cost and low-power wireless personal area network (PAN) standard was developed to meet the needs of control devices and sensors. However, considering factors like range limitations and other challenges, it is not deemed suitable for V2V communication in demanding vehicular environments.

G. BLUETOOTH (IEEE 802.15.1)

Blue tooth is the least preferred communication systėm for V2V communication because of its small range data rate and many other issues.

In a related work survey, research introduces a novel blind-spot [12] vehicle detection method for commercial vehicles, combining multi-convolutional neural networks (CNNs) and faster R-CNN. Two distinct approaches are presented:

1. The first method employs two custom CNNs to extract features, which are then concatenated and processed by a third custom CNN. Faster R-CNN utilizes these high-level features for vehicle detection [13].
2. The second method combines two ResNet CNN networks (ResNet-50 and ResNet-101) with the custom CNN to extract features, subsequently used by Faster R-CNN for blind-spot vehicle detection.

3 Technical Challenges

The V2V wireless channel presents a challenging signal propagation environment due to two key factors. Firstly, the motion of both the receiver and transmitter, along with the presence of stationary and mobile scatterers, results in a limited channel coherence time. Secondly, the presence of distant scatterers introduces long multipath components, leading to a narrow coherence bandwidth in the V2V environment (Fig. 2).

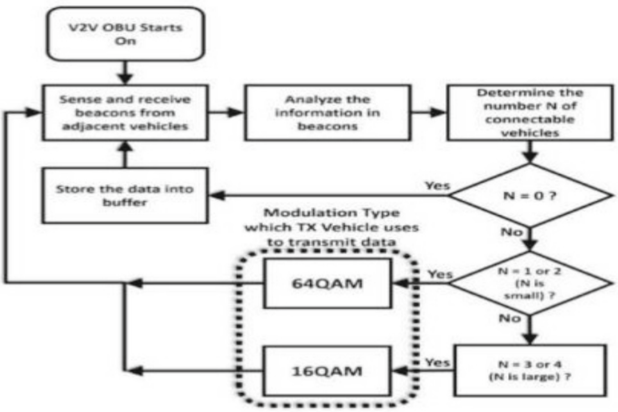


Fig. 2. V2V Environment

These factors contribute to a harsh wireless communication environment character ized by interference, attenuation, and fading. The dynamic nature of V2V communication further exacerbates the challenge of achieving reliable and stable communication. This is particularly evident in highway scenarios, where data transmissions often suffer from fading and shadowing, resulting in unreliable and intermittent communication.

4 Methodology

The proposed system as mentioned in the summary is the accident detection system using CNN or convolutional neural networks. Convolution is a fundamental mathematical operation that merges or combines two functions together to create a third function that shows how one function affects the other. In signal processing, this process involves multiplying two signals, shifting one of them, and then integrating the product of the signals. This results in a new signal that represents the interaction between the original signals. Convolution is used in many applications, including image and audio processing, data analysis, and deep learning, where it is applied to multi-dimensional arrays that represent various types of data. As we do not have any free geotagging datasets available we have used software like movie Avi to edit and add text overlays and add location coordinates in the video frames and this process is forward geocoding. The process of converting the non-human readable format into GPS coordinates is called as reverse coding. The CNN architecture and flowchart of the whole process model are demonstrated below in Fig. 3 and Fig. 4.

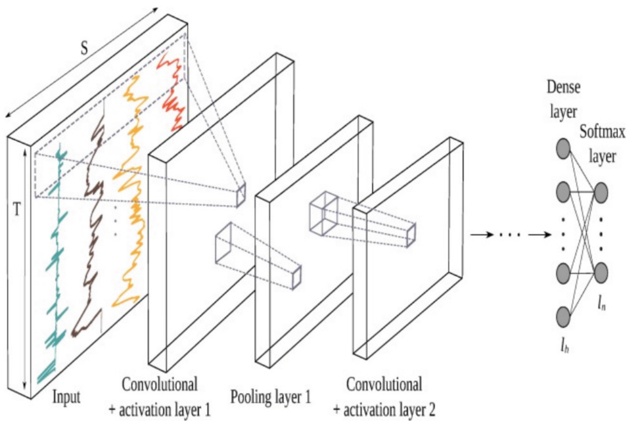


Fig. 3. The architecture of CNN

5 Implementation and Results

The result of the CNN Model is divided into two classes they are accident and non-accident, the frames from the CNN Model are divided into classes based on the SoftMax function used in flattening layer in CNN Model, SoftMax function will gives the output

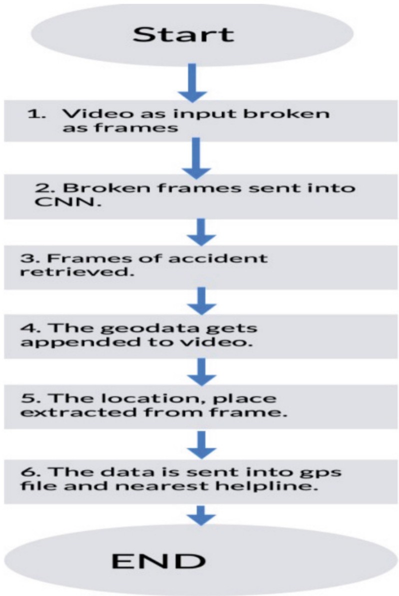
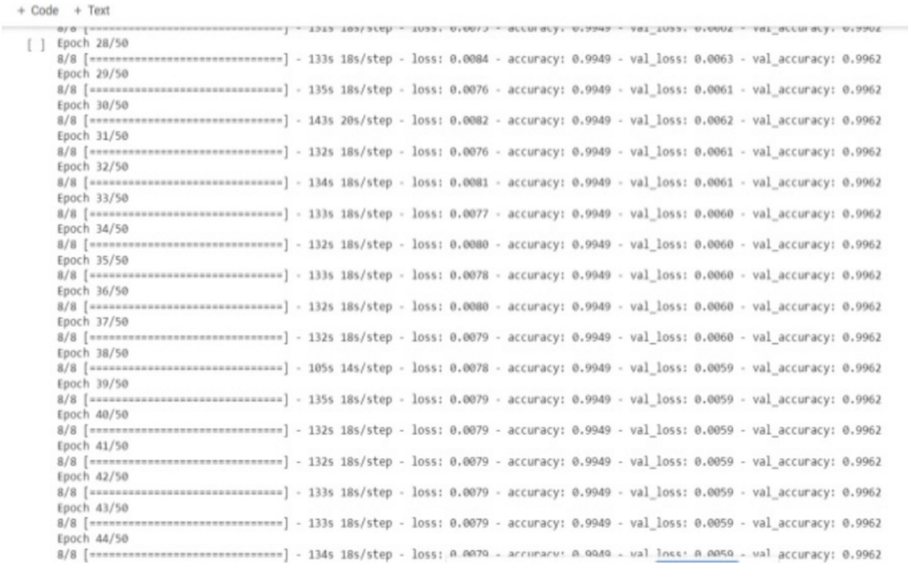


Fig. 4. The flowchart of the proposed model

as the probability distribution, based on the probability from the SoftMax function the frame is divided into two classes as shown below (Figs. 5 and 6)

Fig. 5. Division of Frames into two classes

The Training losses and accuracy of the model are represented in a graph shown in the below figure (Fig. 7).



```
+ Code  + Text
[ ] Epoch 28/50
8/8 [==============================] - 133s 18s/step - loss: 0.0084 - accuracy: 0.9949 - val_loss: 0.0063 - val_accuracy: 0.9962
Epoch 29/50
8/8 [==============================] - 135s 18s/step - loss: 0.0076 - accuracy: 0.9949 - val_loss: 0.0061 - val_accuracy: 0.9962
Epoch 30/50
8/8 [==============================] - 143s 20s/step - loss: 0.0082 - accuracy: 0.9949 - val_loss: 0.0062 - val_accuracy: 0.9962
Epoch 31/50
8/8 [==============================] - 132s 18s/step - loss: 0.0076 - accuracy: 0.9949 - val_loss: 0.0061 - val_accuracy: 0.9962
Epoch 32/50
8/8 [==============================] - 134s 18s/step - loss: 0.0081 - accuracy: 0.9949 - val_loss: 0.0061 - val_accuracy: 0.9962
Epoch 33/50
8/8 [==============================] - 133s 18s/step - loss: 0.0077 - accuracy: 0.9949 - val_loss: 0.0060 - val_accuracy: 0.9962
Epoch 34/50
8/8 [==============================] - 132s 18s/step - loss: 0.0080 - accuracy: 0.9949 - val_loss: 0.0060 - val_accuracy: 0.9962
Epoch 35/50
8/8 [==============================] - 133s 18s/step - loss: 0.0078 - accuracy: 0.9949 - val_loss: 0.0060 - val_accuracy: 0.9962
Epoch 36/50
8/8 [==============================] - 132s 18s/step - loss: 0.0080 - accuracy: 0.9949 - val_loss: 0.0060 - val_accuracy: 0.9962
Epoch 37/50
8/8 [==============================] - 132s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0060 - val_accuracy: 0.9962
Epoch 38/50
8/8 [==============================] - 105s 14s/step - loss: 0.0078 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
Epoch 39/50
8/8 [==============================] - 135s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
Epoch 40/50
8/8 [==============================] - 132s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
Epoch 41/50
8/8 [==============================] - 132s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
Epoch 42/50
8/8 [==============================] - 133s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
Epoch 43/50
8/8 [==============================] - 133s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
Epoch 44/50
8/8 [==============================] - 134s 18s/step - loss: 0.0079 - accuracy: 0.9949 - val_loss: 0.0059 - val_accuracy: 0.9962
```

Fig. 6. Epochs of Model

```
plt.plot(history.history['loss'], label = 'training loss')
plt.plot(history.history['accuracy'], label = 'training accuracy')
plt.grid(True)
plt.legend()
```

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<matplotlib.legend.Legend at 0x7fdc7cea0d00>
```

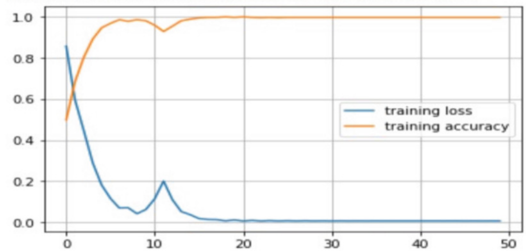

Fig. 7. Training Loss and Accuracy

The model layers are as shown in below figure (Fig. 8).

The output of reverse geocoding is stored in a csv file, the reverse geocoding will extract the details of latitude and longitude and find the location based on the coordinates (latitude and longitude) (Fig. 9).

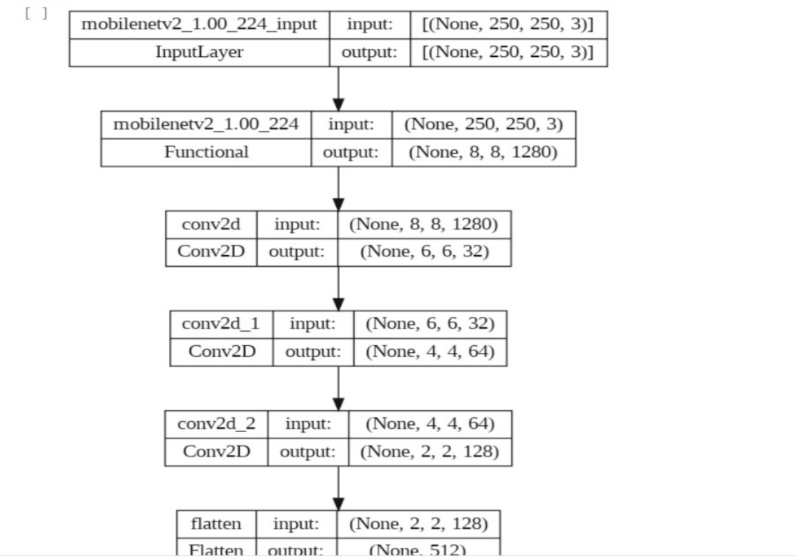

Fig. 8. Model architecture

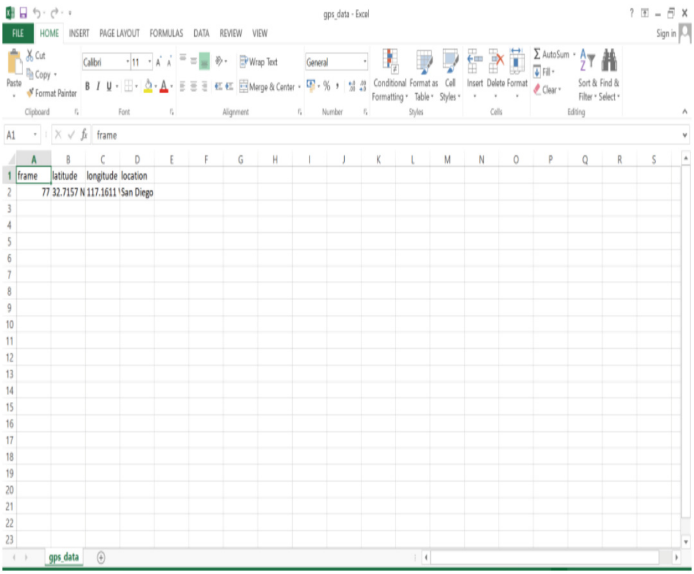

Fig. 9. Location latitude and longitude

6 Conclusion

An accident detection system is a critical technology designed to enhance road safety and potentially save lives. By promptly detecting accidents, this system can swiftly notify emergency services, leading to reduced response times and improved chances of survival for individuals involved in the accident. The proposed system follows a sequential process: it detects the accident, extracts the location information using geocoding, stores the collected details in a CSV file, notifies the designated emergency contacts about the accident, and shares the location details (CSV file) with emergency centers for further assistance.

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