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Crash Detecting System Using Deep Learning

Yogesh Reddy Muddam

CRASH DETECTING SYSTEM USING DEEP LEARNING

A Project

Presented to the

Faculty of

California State University,

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In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in

Computer Science

by

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ABSTRACT

Accidents pose a significant risk to both individual and property safety, requiring effective detection and response systems. This work introduces an accident detection system using a convolutional neural network (CNN), which provides an impressive accuracy of 86.40%. Trained on diverse data sets of images and videos from various online sources, the model exhibits complex accident detection and classification and is known for its prowess in image classification and visualization.

CNN ensures better accident detection in various scenarios and road conditions. This example shows its adaptability to a real-world accident scenario and enhances its effectiveness in detecting early events. A key contributor to this project was a real-time alert system that quickly notifies authorities when an accident is detected. The CNN algorithm captures high-resolution images, which are then sent to designated email addresses, facilitating coordinated responses and providing visual evidence for post-accident investigations.

Implementing accident detection systems shows a significant improvement in road safety, enabling faster and more accurate accident detection. Using email alerts and their integration into hybrid crash data systems helps improve both response time and road safety efforts and can save lives by reducing serious crashes. Future improvements will focus on improving accuracy, speed, and efficiency to further reduce the frequency and severity of accidents, ultimately saving lives and reducing their social impact.

ACKNOWLEDGEMENTS

I'd like to use this time to offer my heartfelt appreciation to everyone who has been a part of my educational path. Your unshakable faith in my abilities, as well as your encouragement, has been important in my pursuit of education and personal development.

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CHAPTER ONE

INTRODUCTION

Background

In recent times, there has been a growing concern about road safety because of the significant impact of road accidents on both human lives and the economy. According to the World Health Organization (WHO), millions of people are affected by traffic-related injuries each year, making them one of the main causes of mortality and injury. In this context, there is an increasing need for technologically advanced solutions to effectively increase accident detection and response on highways.

By accurately and promptly detecting accidents on the roads, we can significantly reduce response times. Potentially profound injuries or even fatalities Employing algorithms like neural networks (CNN) allows us to develop highly precise detection systems that can operate in real time.

To train and refine the data-learning modality for identifying accident scenarios on highways, they rely on a dataset comprising images and videos of real-world accidents. This collection serves as a valuable resource for this project, allowing us to improve the effectiveness of this method in recognizing incidents in various circumstances.

The key contribution of this project lies in the development of an image-based enabling mechanism. When an attack occurs, the system captures high-quality images. Send them to email addresses. This feature helps emergency services and authorities work together effectively, as well as aid in analyzing incidents and collecting evidence.

This project tackles the need for road safety by utilizing advanced computer vision and machine learning techniques. By detecting accidents and responding quickly, this project aims to lessen the severity of accidents and their consequences, ultimately saving lives and reducing the impact of accidents on highways. With cutting-edge technology and a reliable data set, we have a foundation to develop and implement a real-time alert detection system that has the potential to make highways safer for everyone.

Problem Statement and Challanges

The timely detection of accidents is crucial, in minimizing the severity of road accidents. It is essential for emergency services to respond quickly to accidents, as this can significantly reduce the time it takes to provide assistance to victims and clear the roads, thus preventing accidents caused by traffic congestion or debris. However, traditional accident detection methods have limitations, such as relying on eyewitnesses or manual monitoring of surveillance cameras, which can be slow and unreliable.

A crash detection system that utilizes deep learning algorithms such as CNN and BILSTM. The goal of this system is threefold. Detecting accidents automatically can classify types of accidents in real-time video streams from road surveillance cameras, including collisions, vehicle rollovers, and other incident types. Reduce response times and provide alerts to authorities and emergency services so that they can respond rapidly. Increased road safety is a result of both accident prevention and accident severity reduction. Here are some conclusions and difficulties found in implementing the BILSTM in this crash detection project.

Bidirectional Long Short-Term Memory

Bidirectional Long Short-Term Memory, or BILSTM for short, is a kind of recurrent neural network (RNN) that excels at processing data sequences. One of its key characteristics is its capacity to record dependent variables over extended periods in a bidirectional manner. This makes it appropriate for tasks requiring temporal dependent variables, such as time-series analysis and natural language processing [17]. Within the framework of accident detection systems, BILSTM may be utilized to analyze sequential data from several sources to identify patterns suggestive of incidents.

Decisions and Challenges in Opting Against BILSTMin This Project

After a thorough evaluation of potential models for these crash detection projects, we have decided not to implement Bidirectional Long Short-Term Memory (BILSTM).

Several key factors contributed to this decision:

- Real-Time Processing Constraints: Due to their computational complexity, BILSTM networks provide difficulties in meeting the real-time processing requirements necessary for anomalous detection.The BILSTM computational demands were deemed incompatible with the need for quick response times in detecting and responding to incidents.

- Data Availability and Quality: Acquiring a sufficiently large and diverse dataset for training BILSTM proved to be a significant challenge. The success of BILSTM relies heavily on the availability of labeled data that appropriately responds to various adverse scenarios. The limited data set poses a risk of evolving and may not have captured the complexity of real-world adverse patterns.
- Training Data Requirements: As a deep learning model, list-based learning usually requires large volumes of labeled training data. One constraint may be the quality and accessibility of such data in hypothetical situations.
- Computational Intensity: BILSTM networks need a lot of processing, particularly when handling long-term sequence data. This might result in higher processing times and resource requirements, which makes real-time applications difficult
- Limited Performance with Short Sequences: BILSTM networks may not function at their best when handling brief sequences. This is due to the model's ability to capture long-term dependencies and the possibility that the benefits of bidirectional processing may not be completely realized given the limited historical context.

- Simplicity and Interpretability: BILSTM networks, due to their complexity, can be challenging to interpret. In safety-critical applications like accident detection, having a clear understanding of the decision-making process is essential. Simpler models, such as CNNs, offer greater interpretability.
- Resource Efficiency: Considering the limited computational resources available for deployment, models with lower resource requirements were favored. CNNs, which are more efficient in terms of both computation and memory usage, better aligned with the project's resource constraints.

Alternative Solution Considered

BILSTM offers advantages in capturing temporal dependencies, the specific requirements for accident detection projects, including real-time processing, data availability, interpretability, and resource efficiency, leading to the decision not to implement BILSTM. [15]

The alternative solution, CNN, was chosen for its better alignment with project constraints and demonstrated suitability for accurate detection in specific contexts. This decision ensures that the selected mode not only meets the technical requirements of the project but also aligns with practical considerations, enabling effective and efficient action detection within the defined constraints.

Motivation

The motivation for conducting this research arises from the pressing need to enhance road safety and mitigate the devastating impact of accidents. Accurate accident detection systems hold immense potential in terms of saving lives, minimizing injuries, and reducing economic losses. The following factors underscore the significance of this study.

Preservation of human lives Accidents claim a significant number of lives every year, making any system that aids in life-saving and injury reduction crucial.Recent developments in computer vision and deep learning have opened the way for extremely accurate and efficient accident detection systems.
The concept of smart cities revolves around integrating technology to improve urban living conditions, with accident detection playing a vital role in creating safer and more streamlined urban environments.

Contribution

A crucial contribution to this accident detection system is the incorporation of an email alert system that enables the capture and sending of video images as alerts. This feature enhances the capabilities of this system. Ensures an efficient response to detected accidents. With careful consideration, we created the Email Alert System, enabling the alerts to contain video images. The system does not produce real-time alerts when accidents are detected by the CNN model in video streams. It records pertinent video frames that offer in-depth visual details about the occurrence.

The integration with this accident detection model guarantees that alerts are generated instantly. As soon as it identifies an accident, the system starts the alert process, enabling action and response. The system offers flexibility in configuring email addresses or IP addresses as recipients of these alerts. This adaptability ensures that individuals or organizations, such as emergency services, hospitals, police departments, or road management authorities, can be promptly notified and take action based on each incident.

Aim and Objective

This project's goal is to create and assess an accident detection system by utilizing convolutional neural networks (CNN).

The study's primary objectives are:

- Accurate accident detection: developing a system to detect and categorize various kinds of traffic accidents using real-time video feeds. This covers vehicle rollovers, crashes, and other kinds of incidents.
- Prompt Alert Generation: Making sure that emergency services and pertinent authorities are informed on time about accidents. Cutting down on response times is essential for both maximizing attention and reducing the effects of accidents.
- Algorithm Selection: Choosing CNN based on which algorithm is most appropriate for a certain deployment scenario.

CHAPTER TWO

LITERATURE REVIEW

An in-depth examination of previous research on accident detection systems provides valuable insights into the various methodologies and advancements in the field. Each research endeavor provides unique contributions to the field of accident detection systems. Kodali and Sahu's emphasis on timely data transfer highlights the operational challenges faced by vehicle-based accident detection systems and underscores the importance of efficient alarm mechanisms [1]. Ahmed et al.'s exploration of real-time computer vision techniques into advanced algorithms offers promising avenues for enhancing the precision and efficacy of accident detection systems [2]. Their focus on proactive detection and response frameworks reflects a forward-thinking approach to mitigating the adverse impacts of traffic accidents on road safety.

Similarly, Khot et al.'s development of an Android application addresses the pressing need for innovative solutions in light of the escalating accident rates attributed to the rapid growth in vehicular populations [3]. By leveraging accelerometer sensors, their application aims to automate collision detection and streamline emergency response efforts, potentially saving lives and minimizing the severity of accidents. Raghad and Areej's utilization of IoT-based accident prevention strategies demonstrates the potential of machine learning methodologies in predicting accident severity and refining predictive models to mitigate car crashes [4]. Furthermore, Jethwa's pioneering work in vehicle racking showcases the practical application of GPS and GSM technologies in providing real-time updates on vehicle location and speed, offering enhanced monitoring capabilities for vehicle owners [5]. Lastly, the introduction of TAD as a comprehensive dataset for traffic accident detection using video surveillance marks a significant milestone in advancing intelligent transportation systems and improving traffic safety through empirical experimentation [6]. Another study showed that using LSTM models is promising for irregular travel time prediction models as the error for 1-step-ahead prediction error is relatively small [17].

With the recent advancements in machine learning, many models have shown a promising potential for solving nonlinear problems and handling long-term dependencies. Examples include LSTM and BILSTM models. These models were previously used to forecast future traffic speeds [18], travel times [17].
In other studies, an end-to-end deep learning model has been investigated to predict future traffic flows [20], where one BILSTM layer was added, and the results showed that the model was capable of solving stochastic flow characteristics and overcoming overfitting problems [20].

CHAPTER THREE

SOFTWARE AND HARDWARE REQUIREMENTS

Software Requirements

In this chapter, we discuss the software and hardware components needed to implement and operate the Crash Detection System. This system integrates CNN algorithms to ensure its functionality, efficiency, and scalability.

- TensorFlow: It offers robust capabilities for developing and refining neural networks, encompassing a wide range of applications from academic research to commercial production. Its adaptability makes it a go-to tool in diverse scenarios.
- Keras: Alongside TensorFlow streamlines crafting and honing deep neural networks. It provides an easily graspable interface that caters to both novices and seasoned professionals, positioning it as an invaluable asset for any machine learning endeavor.
- Python: It is favored across the spectrum of machine learning and deep learning projects due to its simplicity, comprehensive library ecosystem, and strong support from an extensive community of developers and data scientists. Its user-friendly nature and versatility have cemented its status as a top choice among practitioners in the domain.
- Numpy: Numpy is a very important library for numerical computations and data manipulation. It provides a set of data structures and mathematical programming functions that are essential for implementing machine learning algorithms.

- OpenCV: OpenCV is a crucial library in the fields of image preprocessing, manipulation, and computer vision. It serves the purposes of image enhancement and object detection, which are essential for an accident detection system.
- Matplotlib: This portable data visualization tool allows users to graph, evaluate, and communicate the performance of a system better than others. Data visualization is important for understanding and interpreting the results.

Hardware Requirements

The hardware requirements depend on the size of the deployment and the workload expected. When implementing the accident detection system, it is recommended to have the following hardware components;

- CPU: It is advisable to use a CPU with processing power to handle real-time video analysis.
- Memory (RAM): To ensure operation during model training, it is recommended to have a minimum of 16 GB of RAM.
- Storage: Sufficient storage capacity is crucial for storing datasets, model weights, and system logs. The requirements include;
    - Storage Capacity: Depending on the dataset size and data acquisition frequency it is advisable to have 500 GB to 1 TB of storage.
    - State Drive (SSD): SSDs provide data access and are preferred for improved system responsiveness.

- Internet Connectivity: Ensure that the cameras are equipped with internet connectivity for streaming video feeds, to the system.

CHAPTER FOUR

SYSTEM MODEL

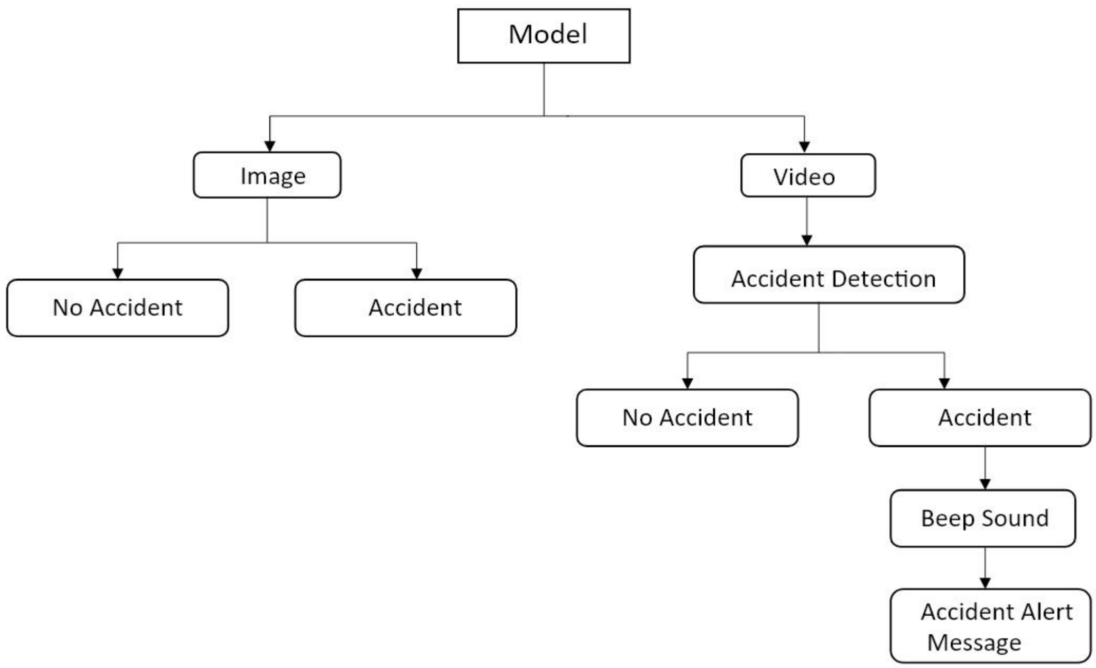

Figure 1 System Model.

In Figure 1, the project flow for accident detection initially starts with a model, where we need to select the CNN model. After selecting the model in the next interface, the input will be loaded in either image format or video format. If the image is loaded, then accident detection happens, and the model gives the result as either an accident or no accident. If the input is loaded in video format, the video starts with a “No Accident” state. When a collision happens between two vehicles or objects, the accident will be detected with a beep sound. The alert will be sent to the email of relevant service teams or emergency services along with the image of the accident.

Data Collection

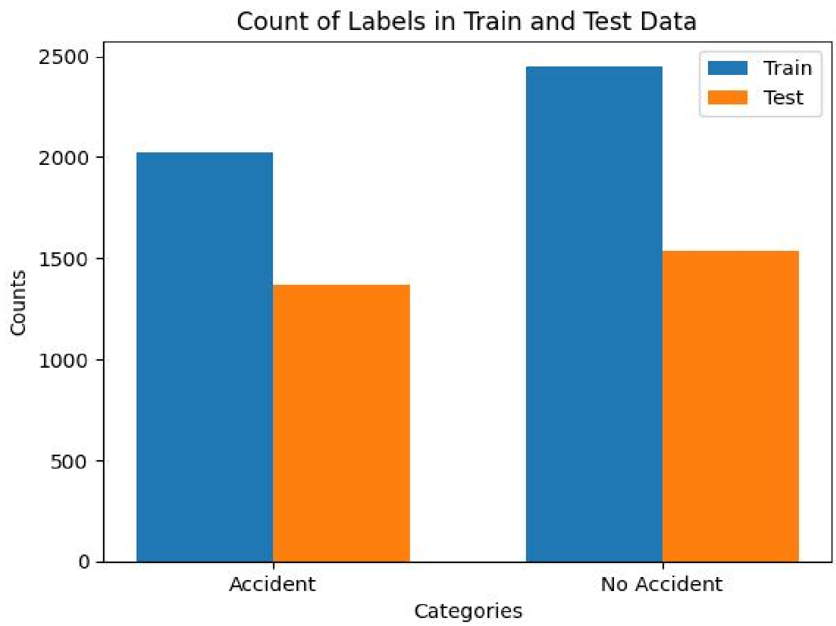

Figure 2 Graphical Representation of Test and Train Data Images.

In Figure 2, illustrates a carefully curated dataset for accident detection, consisting of 7379 images. This dataset contained 4472 images for training the model, with the remaining 2906 images reserved for testing its performance. Specifically, the training set includes 2451 images of non-accident scenarios and 2021 images of accident scenarios. The images were used to train the model to accurately distinguish between accidents and non-accidents.

Subsequently, during the testing phase, the model's accuracy and robustness were evaluated using a separate subset of the dataset. This testing set consists of 1537 non-accident images and 1369 accident images, enabling a thorough assessment of the model's performance on previously unseen data.

The videos and images were sourced from references on YouTube and online resources. The dataset used in this project is composed of pictures depicting accident situations. These pictures were collected from different locations and under various conditions. These images portray real-world situations such as accidents, near misses, and regular traffic scenes.

The intention was to collect data that accurately mimics the challenges faced by accident detection systems. These videos offer perspectives on road accidents and incidents. These are collected from sources, like surveillance cameras and eyewitness recordings. They showcase a range of accidents to enable this system to recognize accidents under certain circumstances.

Data Preprocessing

The images go through a processing stage where their resolution and quality are standardized, making sure that the images are suitable for training models. The data visualization is done to check the label count of accidents and non-accidents by using graphs. In this phase, also resize the images and normalize them to the standard size of 128 x 128.

Deep Learning

Deep learning is to train artificial neural networks to learn from data and make intelligent decisions. By using deep neural networks, or neural networks with several layers, it is termed "deep" learning. These networks can automatically learn features and representations for raw data, thus allowing them to perform tasks that were previously challenging for traditional machine learning techniques. Deep learning is based on artificial neural networks that imitate the human brain's structure and functions. Each artificial neuron is connected to several others, forming layers within the network.

Deep learning models are constructed using artificial neural networks, which are modified after the architecture and operation of the human brain. These networks consist of interconnected layers of artificial neurons, each of which processes incoming data and applies transformations and calculations. It emphasizes the use of deep neural networks, which are networked with several layer's. It is effective at representation learning, which involves learning and refining representations of data as it passes through the network. These learned representations are becoming increasingly abstract and meaningful.

Deep learning models learn by changing the weights (or connections) between neurons. The model undergoes iterative learning when it is exposed to training data. Supervised deep learning is the process of training a model given a labeled dataset that includes both input data and correspondingly correct outputs. For tasks like image classification, speech recognition, and language translation, where the model learns to map inputs to outputs based on the given labels, this method works well.

Non-supervised deep learning also includes unsupervised learning, in which a model examines data without using labeled examples. Using this method, patterns, graphical representations, and underlying structures in data may be found.

Stimulating and semi-supporting Reinforcement learning is a component of deep learning wherein participants learn how to respond in a reinforcement and semi-supervised way. Deep learning includes both semi-supervised learning, which combines supervised and unsupreme learning, and reinforcement learning, which teaches agents how to act in a way that maximizes rewards in a given environment.

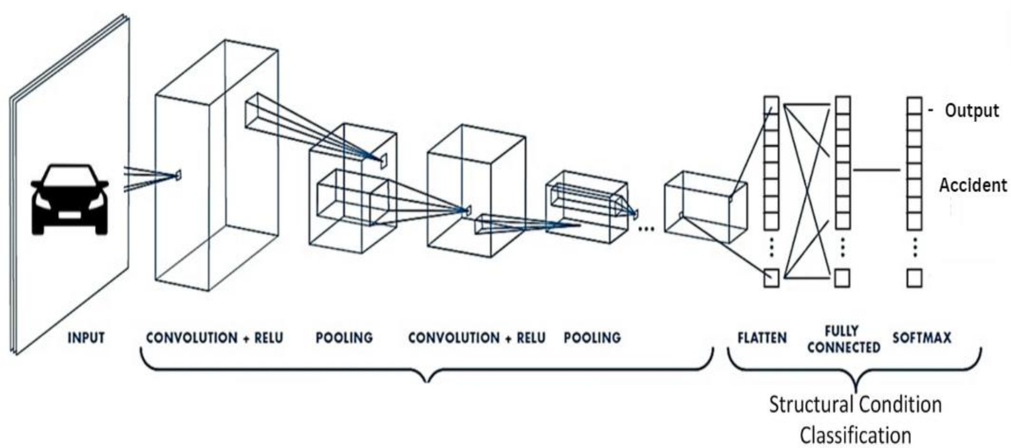

Figure 3 CNN Architecture.

Figure 3 shows how convolutional neural networks (CNNs) can be used in this crash detection system. CNNs are well suited for tasks involving images and have become popular because of their effectiveness in recognizing and classifying objects. This will start by providing an understanding of CNNs. Then delve into the specific architecture defined for the accident detection algorithm. A particular kind of learning model called Convolutional Neural Networks (CNNs) is intended especially for the extraction of significant features from images. They are adept at tasks like classifying pictures because they can identify and learn from patterns, textures, and objects in pictures. Inspired by the human visual system, CNN layers are trained to identify and extract distinct visual characteristics from pictures.

- Input Layer: The input layer of the CNN receives the raw data, with accident detection, could be images or video frames. Every pixel in the image becomes a node in this layer.
- Convolutional layer's: These are the core building blocks of CNNs. These layers consist of filters (also called kernels) that slide over the input data to detect spatial patterns and features. These patterns might include edges, corners, or more complex structures. Convolutional layers are essential for capturing hierarchical features in the input data.
- Activation Function (ReLU) Layer: After each convolutional operation, a rectified linear unit (ReLU) activation function is commonly applied. ReLU introduces non-

linearity to the model, allowing it to learn complex patterns and relationships in the data.

- Max pooling: After each pair of layers is applied to reduce the dimensions of the feature map, this helps maintain efficiency and focuses on the relevant features.
- Flatten Layer: The flattened layer is employed to convert the output from the previous layer into a one-dimensional array. This is necessary to connect the convolutional layers to the fully connected layers.
- Fully connected (dense) layers: This procedure flattens the output from the previous layers. These layers learn global patterns and relationships in the data, helping to decide based on the spatial features identified by the convolutional layers.
- Softmax Activation Layer: If the CNN is used for multi-class classification, a softmax activation function is typically applied to the output layer. This function converts the raw output into probability scores, making it easier to interpret the model's confidence in each class.
- Compilation: To compile the use of the Adam optimizer and specify sparse categorical crossentropy as the loss function, which is well suited for tasks involving class classification. Additionally, we can track the metric of accuracy.

This architecture allows the CNN to automatically learn relevant features from the input data, making it well-suited for tasks like accident detection, where spatial patterns in visual data are crucial for accurate classification.

To accomplish this, we implemented a cutting-edge CNN architecture that was carefully chosen and customized for the detection task. The model underwent training using a ranging dataset of annotated images and video frames. Additionally, we carried out data preprocessing procedures like augmentation, normalization, and resizing to guarantee the caliber and variety of the training data.

CHAPTER FIVE

RESULTS

The use of convolutional neural networks (CNNs) has led to major enhancements in accuracy and efficiency for the Crash Detection System project. These networks have proven to be effective in promptly detecting different types of accidents in live videos from road surveillance cameras. Additionally, CNNs have showcased computational speed, enabling rapid responses that are crucial for real-time scenarios. This project's achievements underscore the effectiveness of CNNs in enhancing road safety and emergency response systems.

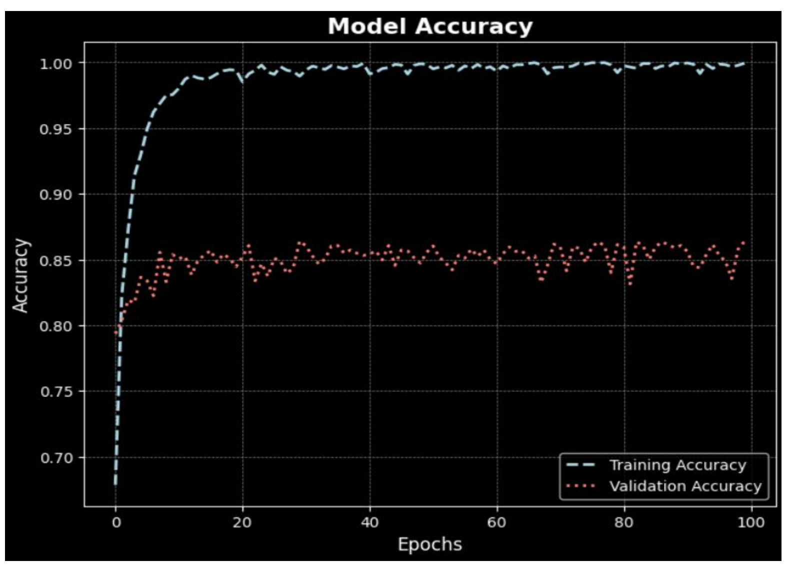

Figure 4 CNN Model Accuracy Result.

In figure 4, the model based on CNNs has achieved an accuracy of 86.40% in detecting accidents. CNNs have demonstrated their effectiveness in dealing with the tasks of analyzing images, particularly when it comes to identifying objects and events related to accidents within both images and videos. This high level of accuracy confirms the ability of CNNs to make differentiations.

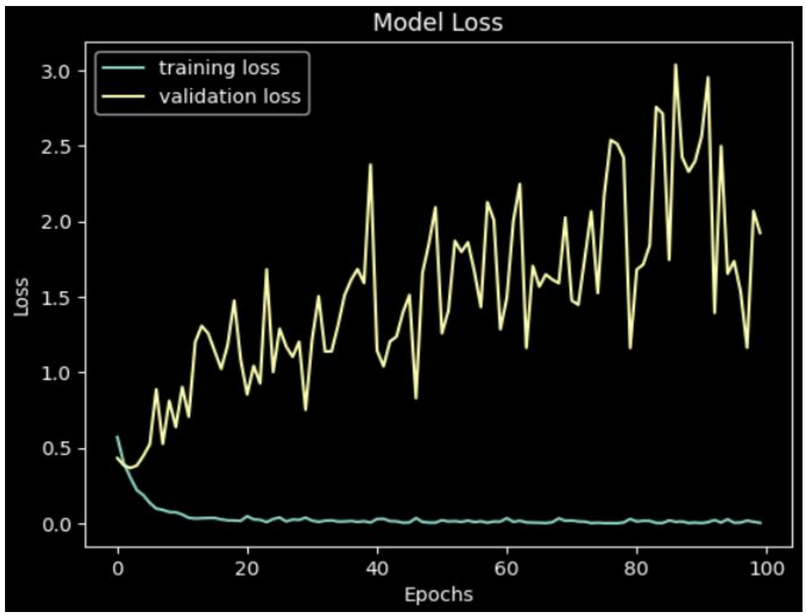

Figure 5 CNN Model Loss

In figure 5, the loss graph visualizes this decrease in loss over time. Typically, it starts at a high value and gradually decreases as the model learns. Ideally,we can see a smooth downward trend in the loss graph, indicating that the CNN is improving its performance with each training iteration.

CCTV Footage Video Based Predicted Outputs From Accident Detection System

Video Based No Accident Predicted Output

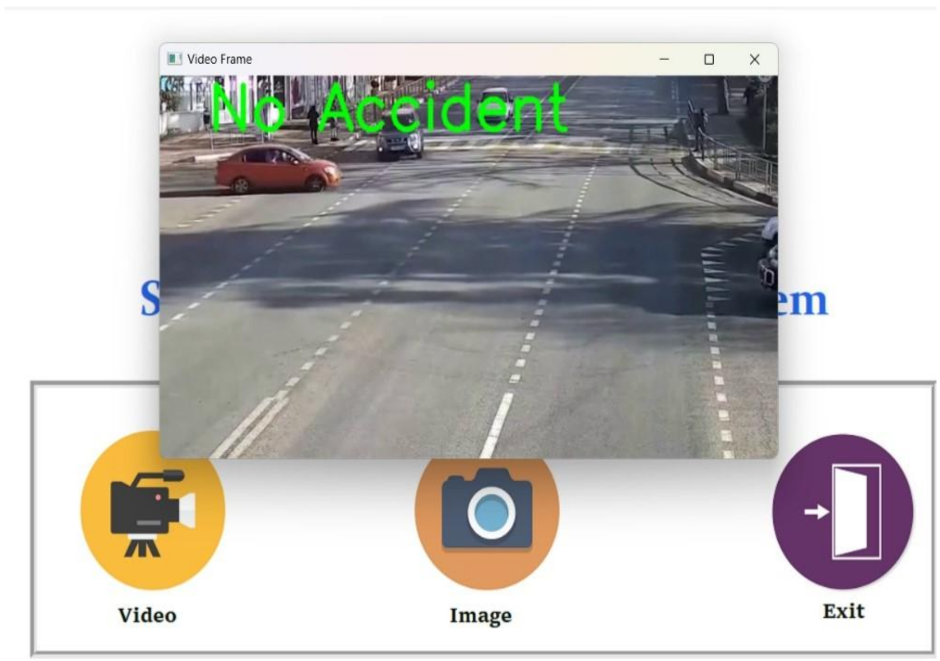

Figure 6 Video Based No Accident Predicted Output.

In figure 6, showing that no accident has been detected implies that, based on the current analysis of the video frames, the system believes the observed scene is free from any accident-related patterns.

Video Based Accident Predicted Output

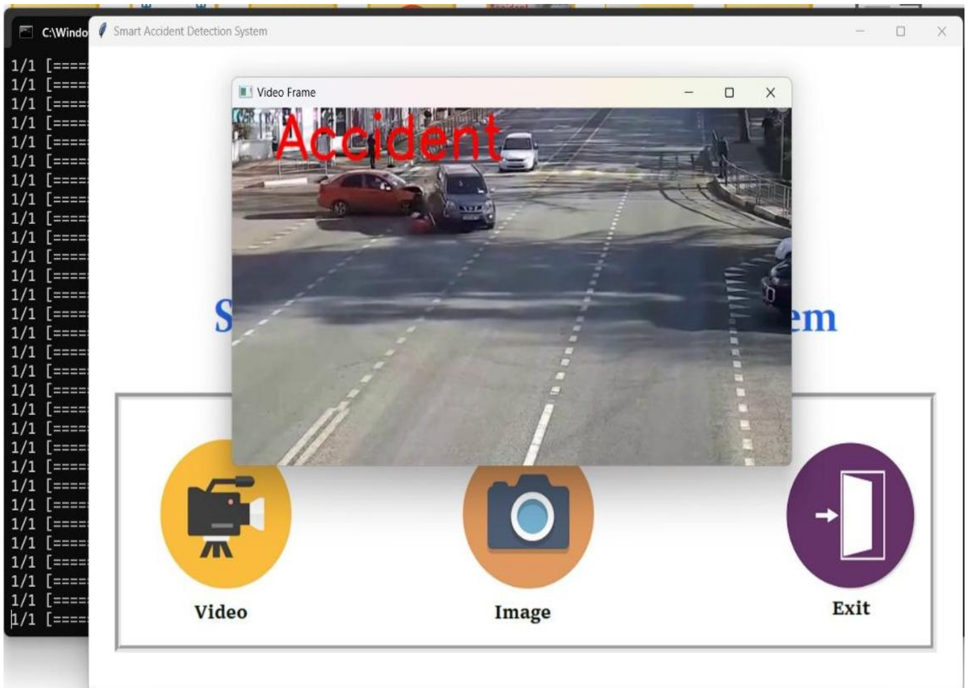

Figure 7 Video Based Accident Predicted Output.

In figure 7, accidents have occurred due to the collision of two cars, indicating the successful recognition of collision-related accidents by the accident detection system.This capability is crucial for prompt responses and interventions in real-world scenarios. The Alert Sound module plays a vital role in the Accident Detection System. Its purpose is to provide alerts when an accident is detected. Whenever the system identifies an accident using its algorithms, this module activates a beep sound. This sound serves as a signal to alert both users and people nearby about the occurrence of an accident. The audible alert plays a role in notifying individuals, allowing them to respond quickly and take the necessary action to minimize further risks and provide timely assistance.

Emergency Alert to Email Address

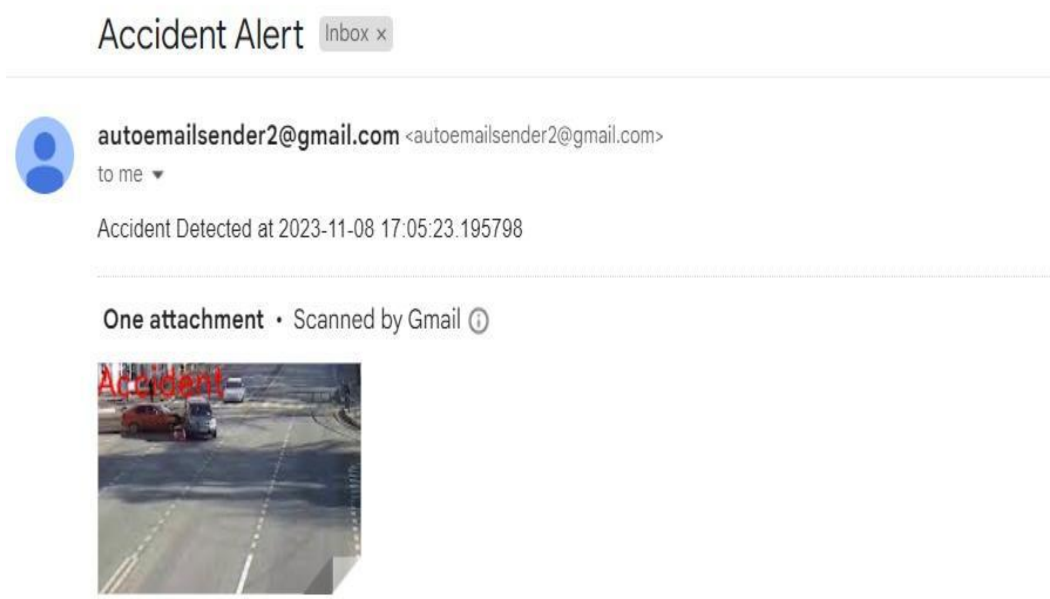

Figure 8 Emergency Alert to Email Address.

Figure 8, shows the alert on the mail module, which is responsible for sending email notifications whenever an accident is detected within the system.

Once an accident is identified, this module automatically sends an email alert to defined recipients. The email contains information about the incident, along with attached images, for reference on the on the date and time. By integrating an emergency email system with an alert detection system, the overall incident response process becomes more efficient, allowing for timely interventions and potentially mitigating the impact of incidents. The steady flow of information through email notifications ensures that relevant parties are informed promptly and can take appropriate actions.

Image Based Predicted Outputs From Accident Detection

<u>Accident for Image-Based Prediction</u>

```
predict_accident("/content/accidents (18).jpg",loaded_model,categories_list)
1/1 [==============================] - 0s 107ms/step
PREDICTION : Accident
```

Figure 9 Image Based Accident Predicted Output.

Figure 9 shows the image-based accident prediction system, with the output labeled "accident detected." This visual representation depicts the system's various components and processes. The labeling of the output indicates the system's ability to analyze input images, most likely obtained from surveillance cameras, in order to predict accidents. When the system detects specific features or patterns in the input images that indicate an accident, it generates an output signal or label to confirm the detection. This visualization effectively conveys the functionality and purpose of the accident prediction system.

<u>No Accident for Image Based Prediction</u>.

```
1/1 [==============================] - 0s 28ms/step
PREDICTION : No Accident
```

Figure 10 Image Based Predicted Output.

Figure 10 shows no accident detected; a car is shown traveling down a road without any indications of an impending collision or dangerous circumstances. The lack of visible damage to the vehicle or surrounding environment indicates that no accidents occurred. This representation effectively communicates the system's ability to recognize scenarios in which vehicles are driving safely and there are no accidents.

CHAPTER SIX

CONCLUSION

Summary

The development of the Crash Detection System made progress in enhancing the ability to recognize incidents in time through images and videos. By combining two deep learning approaches, CNN has achieved results. Accuracy, in accident detection, while CNN has reached 86.40% accuracy. These achievements have implications for improving road safety, security, and emergency response systems.

The integration of an email alert system is an aspect of this project. It ensures that relevant authorities and stakeholders are promptly notified when accidents are detected, enabling informed responses. Additionally, the inclusion of video image capture in these alerts enhances incident management by providing evidence for assessment and decision-making.

This work represents an advancement in enhancing safety and security in real-world situations within traffic management, surveillance, and emergency services domains. These accomplishments highlight the potential of machine learning and deep learning to bring about change and improve the quality of life for individuals and communities.

Future Work

Expanding and diversifying datasets is crucial. This can help to understand the importance of collecting a range of data, including accident scenarios, lighting conditions, and environments. The main focus will be on exploring learning techniques for CNN configurations. These techniques will help us improve accuracy and real-time performance.

It is dedicated to addressing challenges such as weather conditions, occlusions, and night time scenarios to make the system more reliable. To enhance incident response, we are considering incorporating sensor data like GPS coordinates and environmental information to provide context around accidents. Furthermore, we can actively look into providing real-time video streaming to authorized personnel for a coordinated response to accidents. Collaboration with authorities, law enforcement agencies, and emergency services is crucial for integrating this system into existing incident management processes.

In conclusion, this project represents an advancement in utilizing cutting-edge technology for the betterment of society. This can remain committed to pushing the boundaries in accident detection and incident response to create roadways and communities. The future looks promising to continue the journey towards progress and innovation.

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