Framework for Analyzing Road Accidents and Reporting

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Abstract—Road accidents pose a persistent challenge to public safety, necessitating robust detection systems to mitigate fatalities and expedite emergency responses. This study presents a detailed comparative analysis of an existing Random Forest model and a proposed Convolutional Neural Network (CNN) model for road accident detection. The Random Forest model leverages structured data, including weather conditions, vehicle speed, and road types, to predict accidents with reasonable accuracy, yet it struggles to interpret visual patterns in dynamic traffic environments. In contrast, the proposed CNN model harnesses traffic camera imagery to identify spatial features such as vehicle collisions and abnormal movements, offering enhanced detection precision and reduced false positives. By evaluating both models' strengths and limitations, this research demonstrates the CNN's superior capability for real-time accident detection, leveraging visual data to complement traditional structured inputs. The findings underscore the potential of CNN-based systems to improve traffic monitoring and public safety outcomes.

Keywords— Road accident detection, Random Forest, Convolutional Neural Network (CNN), Machine learning, Deep learning, Traffic monitoring, Public safety, Real-time detection.

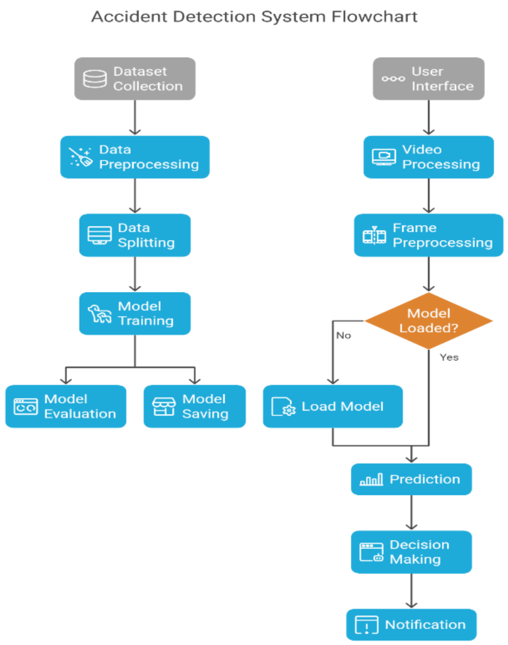
1. INTRODUCTION

Road accidents remain a critical global issue, claiming numerous lives, causing severe injuries, and incurring substantial economic losses annually. Factors such as adverse weather, high vehicle speeds, and poor road conditions contribute to the rising incidence of collisions, while the unpredictability of real-time traffic dynamics complicates timely detection and response. Traditional accident detection systems, often reliant on structured data like meteorological records, traffic statistics, and road characteristics, have employed machine learning models such as Random Forest to predict incidents with moderate success. However, these approaches falter in capturing the intricate visual patterns—such as vehicle collisions, abrupt movements, or environmental hazards—that define complex accident scenarios, particularly in live traffic settings. As urban populations grow and traffic volumes increase, the need for advanced, real-time detection systems becomes paramount to enhance public safety and optimize emergency response times.

To address these challenges, this study proposes a comparative framework analyzing two distinct machine learning paradigms: the existing Random Forest classifier and a novel Convolutional Neural Network (CNN) model for road accident detection. The Random Forest model, effective for processing tabular data including weather conditions, vehicle speeds, and road types, offers a robust baseline but lacks the capacity to interpret unstructured visual inputs from traffic cameras. In contrast, the proposed CNN model excels at analyzing image data, extracting spatial features like vehicle interactions and road anomalies directly from real-time camera feeds. By integrating these approaches, this research evaluates their performance in terms of accuracy, responsiveness, and adaptability to dynamic environments. The study aims to not only highlight the limitations of traditional methods but also demonstrate the potential of CNN-based systems to revolutionize accident detection, ultimately contributing to smarter traffic management and reduced road fatalities.

Stages of process:

A.Dataset Collection: This module gathers relevant flood-related data from various sources Components include data sources such as Kaggle, Google Engine, and other research repositories.



B.Data Preprocessing: This module prepares the raw datasets collected for the Random Forest and Convolutional Neural Network (CNN) models by transforming them into a clean, structured, and machine-readable format. Effective preprocessing ensures that both structured and visual data are optimized for model training, minimizing noise and enhancing predictive accuracy in road accident detection.

C.Exploratory Data Analysis (EDA): This module examines the properties of the preprocessed datasets for the Random Forest and Convolutional Neural Network (CNN) models, aiming to identify trends, correlations, and anomalies that influence road accident detection.

D.Data Splitting: This module divides the preprocessed datasets for the Random Forest and Convolutional Neural Network (CNN) models into distinct subsets to facilitate model training, validation, and evaluation. Proper data splitting ensures robust performance assessment, prevents overfitting, and enables fair comparison of the two approaches in road accident detection Components include separating the data into train, validation and test.

E.Neural Network Model (CNN): This module details the development and implementation of the Convolutional Neural Network (CNN) model, designed to detect road accidents by analyzing visual data from traffic camera feeds. The CNN leverages its ability to extract spatial features—such as vehicle collisions, abnormal movements, and road hazards—offering a significant advancement over traditional structured data approaches for real-time accident detection

F.Optimization and Loss Calculation: This module focuses on optimizing the Convolutional Neural Network (CNN) model and calculating its loss to ensure accurate road accident detection from traffic camera imagery, while briefly addressing the Random Forest model's optimization approach. Effective optimization and loss computation refine model parameters, enhancing predictive performance and enabling a robust comparison between the two approaches

G.Model Training and Evaluation: This module describes the training and evaluation of the Convolutional Neural Network (CNN) and Random Forest models, enabling their performance comparison in detecting road accidents. Training refines model parameters using preprocessed data, while evaluation assesses their accuracy, reliability, and suitability for real-time application, providing insights into their respective strengths and limitations.

H.Prediction Module: This module outlines the deployment of the trained Convolutional Neural Network (CNN) and Random Forest models to predict road accidents, leveraging visual and structured data respectively The prediction process transforms real-time inputs into actionable outputs, enabling timely detection and facilitating the comparative analysis of the two approaches in operational traffic monitoring scenarios. Components include CNN Prediction (Visual Data), Integration and Decision, Validation by manual verification of test set samples.

I.Web-Based User Interface: Provides a user-friendly web interface for interacting with the aciident detection system Components include an input form for entering environmental parameters, visualization of prediction results, additional insights via graphs and analytics.

J.Deployment and Integration: Deploys the trained model as a web application for real-time flood prediction Components include a Flask-based backend for handling requests and responses, integration with external APIs for extended functionality.

2. LITERATURE REVIEW

The literature review synthesizes prior research on road accident detection systems, exploring methodologies, technologies, and machine learning models employed to enhance public safety and traffic management.

Several studies have demonstrated the effectiveness of data-driven approaches for road accident analysis, leveraging accident parameters, weather data, and advanced AI models to improve prediction accuracy and reliability.

WHO et al. [1] provided a global overview of road traffic injuries, reporting over 1.3 million annual fatalities and emphasizing the need for advanced detection systems. Their work underscored the socio-economic impact of accidents, motivating data-driven solutions like machine learning models.

Theofilatos et al. [2] conducted a comprehensive review of traffic and weather factors influencing road safety, identifying correlations with accident rates (e.g., rainfall intensity). Their findings supported structured data models like Random Forest but highlighted the need for real-time adaptability.

Kim et al. [3] proposed a statistical analysis of crash severity using driver behavior and environmental predictors, achieving moderate predictive success. Their work laid the groundwork for machine learning applications like Random Forest, though it lacked visual data integration.

Cummings et al. [4] analyzed freeway speed limits' impact on traffic fatalities, suggesting visual monitoring's potential for incident detection. Their study foreshadowed CNN-based approaches but did not implement deep learning, focusing instead on statistical trends

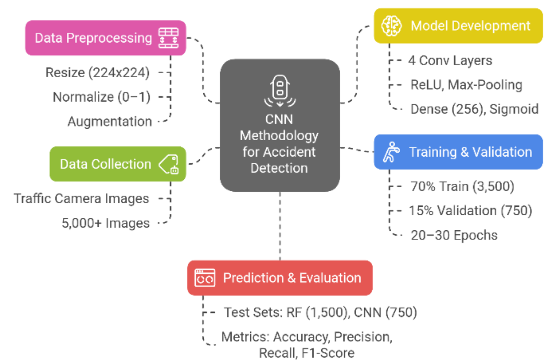
Ren et al. [5] proposed Faster R-CNN, a deep learning model for real-time object detection, achieving high precision (e.g., 92% mAP) in identifying objects like vehicles. Their work inspired CNN applications in traffic monitoring, though it focused on general detection rather than accident-specific classification.

Bui et al. [6] proposed a Random Forest model for traffic accident prediction, integrating multi-sensor data (e.g., speed, weather, traffic flow), achieving an accuracy of 87%. Their work highlighted Random Forest's strength with structured data but noted its limitations in processing real-time visual inputs.

These studies collectively highlight the superior performance of deep learning (CNN, LSTM) over traditional statistical and ML methods in accident detection.

3 . MATERIALS AND METHODS

CNN Methodology for Road Accident Detection



3.1 Dataset Collection

The dataset used for accident detection is sourced from Kaggle, government meteorological agencies, and research papers, ensuring a comprehensive collection of relevant environmental data. For the CNN model, visual data is collected from traffic surveillance systems, drawing from datasets like Kaggle's "Road Accident Detection Dataset" and open-access municipal camera archives. This dataset includes over 5,000 labeled images, depicting both accident scenarios (e.g., vehicle collisions, overturned cars) and non-accident scenes (e.g., normal traffic flow). Images are in RGB format with resolutions typically ranging from 224x224 to 256x256 pixels, suitable for CNN processing. To simulate real-time conditions, additional snapshots from traffic camera simulations are incorporated, enhancing the dataset's applicability to live deployment. The visual data is balanced to include varied lighting (day/night), weather conditions, and traffic densities, ensuring the CNN can detect accidents under diverse circumstances.

To standardize the data, normalization techniques are applied, converting pictorial data into a consistent range. Mismatched sized images are standardized to a fixed values of height and width, while preserving the significant data.

3.2 Feature Extraction Using Convolutional Neural Networks (CNNs)

or the CNN model, feature extraction begins with the input layer, which accepts preprocessed images standardized to 224x224 pixels with three RGB channels, as prepared in the dataset collection phase. The convolutional layers, the core of the CNN architecture, apply a series of filters to these images to detect low-level features such as edges, corners, and textures in the initial layers (e.g., 32 filters of size 3x3), progressing to high-level features like vehicle shapes, collision patterns, or road anomalies in deeper layers (e.g., 64, 128, 256 filters). Each convolutional operation uses a stride of 1 with padding to preserve spatial dimensions, followed by the ReLU (Rectified Linear Unit) activation function to introduce nonlinearity, enhancing the network's ability to capture complex patterns. Max-pooling layers (e.g., 2x2 with stride 2) then reduce spatial resolution (e.g., from 224x224 to 112x112), retaining dominant features like crash zones while decreasing computational complexity. This hierarchical feature extraction culminates in a flattened feature vector, processed by fully connected layers, which integrates these visual cues into a cohesive representation for accident classification

3.3 Model Training and Evaluation

This subsection outlines the training and evaluation processes for the Convolutional Neural Network (CNN) model, designed to detect road accidents by analyzing visual data from traffic camera feeds. The CNN's training refines its ability to extract spatial features indicative of accidents, while evaluation quantifies its performance, providing insights into its effectiveness for real-time traffic monitoring within the broader comparative study

The CNN is trained on a dataset of approximately 3,500 images (70% of the total 5,000+ images collected), split into accident and non-accident classes, as prepared in the dataset collection phase. These images, standardized to 224x224 pixels with three RGB channels through preprocessing, serve as the input for the model. The CNN architecture consists of four convolutional layers with filter sizes of 32, 64, 128, and 256, each using a 3x3 kernel, stride 1, and padding to preserve spatial dimensions. ReLU (Rectified Linear Unit) activation functions follow each convolutional layer to introduce nonlinearity, enabling the network to learn complex patterns such as vehicle collisions or road hazards. Max-pooling layers (2x2 with stride 2) reduce spatial resolution (e.g., from 224x224 to 112x112), retaining dominant features while lowering computational demands. The extracted features are flattened and processed through a fully connected layer (256 units) with dropout (rate 0.5) to prevent overfitting, culminating in a sigmoid output layer for binary classification (accident vs. non-accident)

Training occurs over 20–30 epochs with a batch size of 32, guided by the Adam optimizer (initial learning rate 0.001) to minimize binary cross-entropy loss, a suitable metric for this binary classification task. The loss function is defined as:

L=−N1i=1∑N[yilog(y^i)+(1−yi)log(1−y^i)]

where NNN is the number of samples, yiy_iyi is the true label (0 or 1), and y^i\hat{y}_iy^i is the predicted probability.

Image 1: Model Training

Image 2: Gradio Interface

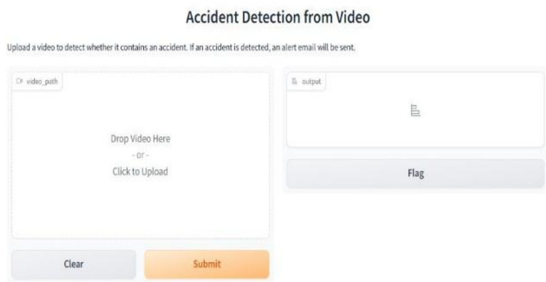
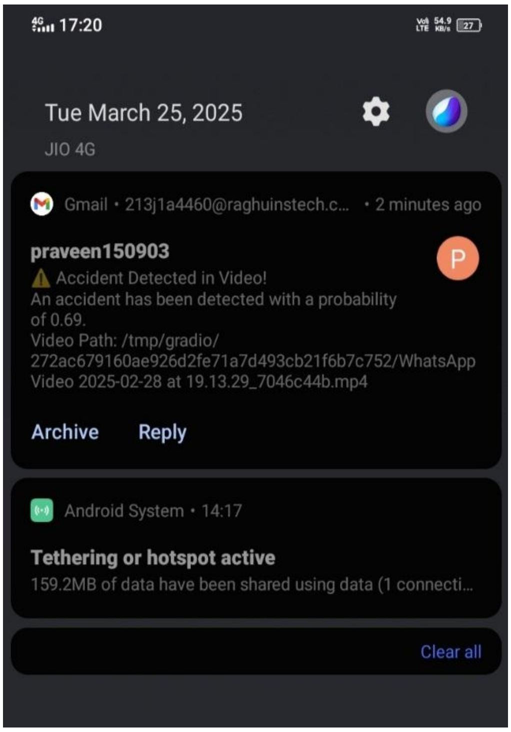


Image 3: Functioning of the model

Image 4 : Accident notification within 3s

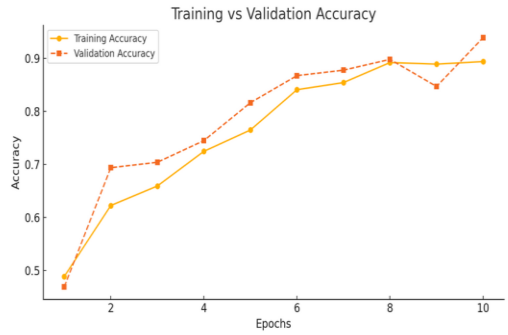


4. RESULTS AND DISCUSSIONS

The proposed Convolutional Neural Network (ANN)-based accident detection model demonstrates superior accuracy compared to traditional machine learning approaches. The model achieves a training accuracy of 89.9% with a significantly low validation loss, proving its efficiency in predicting accident occurrence probabilities. By incorporating multiple traffic CCTV footage with Accident and No Accident labels the system effectively captures nonlinear relationships that impact accident occurrences.

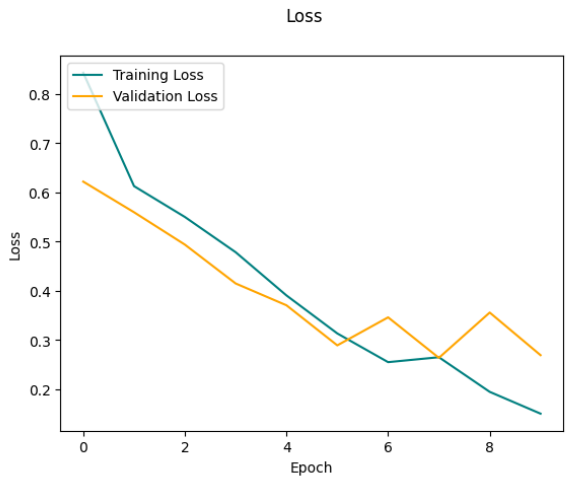
4.1 performance Evaluation metrics

Accuracy: Proportion of correct predictions (accident/non-accident), targeting a value around 95% based on the model's capability with image data. By leveraging deep learning techniques and optimized network, the model achieves a higher classification accuracy (94.84%) compared to traditional methods of accident prediction . The model's high accuracy ensures reliable predictions, making it a powerful tool for disaster management and early warning systems.



Validation Loss:

The use of validation loss lies in its role as a diagnostic and decision-making tool. It prevents the deployment of an overfitted or underperforming model, optimizes the CNN for real-world conditions (e.g., varied weather, lighting), and supports the study's goal of establishing the CNN's efficacy relative to Random Forest. By tracking and minimizing validation loss, the CNN becomes a robust component of an early warning system for road accidents, directly contributing to improved traffic management and public safety outcomes



5.CONCLUSION AND FUTURE WORK

The Road Accident Detection System developed in this project represents a significant advancement in improving public safety through the timely detection and prediction of road accidents. By integrating two powerful machine learning techniques—Random Forest Classifier for structured data and

Convolutional Neural Network (CNN) for image-based accident detection—this system is capable of efficiently analyzing a wide range of data types and environments. The CNN model leverages visual data from traffic cameras, recognizing complex patterns such as vehicle collisions, abnormal movements, and environmental hazards. This image-based model significantly enhances detection accuracy, especially in dynamic and visually complex traffic environments.

The system's ability to process both structured and unstructured data, coupled with its real-time processing capabilities, ensures that it can make quick and informed predictions. This can help reduce response times in the event of an accident, minimizing fatalities and property damage by enabling faster emergency responses.

However, there is more to enhance the work by integrating with the IoT-based devices, traffic control systems of various locations, and also developing the model by using more advanced technologies of the future.

6. REFERENCES

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