Accisure : AI-powered Accident Detection using CCTV and CNN-LSTM Model

A Project Report

Submitted by

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Bachelor of Technology
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Motilal Nehru National Institute of Technology Allahabad
Prayagraj - 211004

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DECLARATION

We certify that the work contained in the project titled **Accisure: AI-powered Accident Detection using CCTV and CNN-LSTM Model** submitted by **Sambhav Jain, Rajat Raj Gautam, and Aman Kumar** in the partial fulfillment of the requirement for the award of Bachelor of Technology in Electronics and Communication Engineering to the Electronics and Communication Engineering Department, Motilal Nehru National Institute of Technology Allahabad is carried out by us and we have not intentionally violated any professional ethics during the work.

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His meticulous guidance, constructive suggestions, elaborate discussions, and clarification of our doubts provided us with a deeper insight into the subject under study. We consider ourselves fortunate to have been associated with him throughout this project work, which has been an invaluable process of learning and growth.

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Lastly, we bow down in reverence to the Almighty and extend our deepest gratitude to our parents for being an eternal source of encouragement, support, and strength throughout this journey.

Sambhav Jain (20215133)
Rajat Raj Gautam (20215149)
Aman Kumar (20215041)

CERTIFICATE

This is to certify that the work contained in the project titled **"Accisure: AI-powered Accident Detection using CCTV and CNN-LSTM Model"**, submitted by **Sambhav Jain, Rajat Raj Gautam and Aman Kumar** in partial fulfillment of the requirements for the award of **Bachelor of Technology in Electronics and Communication Engineering** to the **Electronics and Communication Engineering Department**, Motilal Nehru National Institute of Technology Allahabad, is a bonafide work of the students carried out under my supervision.

Supervisor's Signature
Dr. V. Krishna Rao Kandanvli
Associate Professor
ECE Department
MNNIT Allahabad

Date: May 2025
Place: Prayagraj, India

Abstract

This project presents **Accisure**, an AI-powered accident detection system that leverages existing CCTV infrastructure combined with advanced deep learning techniques to identify vehicular accidents in real time. Utilizing a hybrid **CNN-LSTM** model, Accisure processes continuous video feeds to detect potential collisions with high accuracy and minimal latency. The system integrates a comprehensive video preprocessing pipeline and deploys an edge-cloud architecture to ensure scalability and responsiveness. Upon detecting an incident, it can immediately trigger alerts to relevant authorities, enabling faster emergency response. Developed with the goal of enhancing road safety and urban traffic management, Accisure aims to provide cities with a reliable, automated solution to monitor and respond to road accidents, ultimately reducing response time and potentially saving lives.

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Chapter 1

Introduction

1.0 Understanding AI-Powered Accident Detection

Accident detection using artificial intelligence represents a transformative approach to traffic safety monitoring and emergency response. At its core, this technology leverages computer vision and deep learning techniques to automatically identify vehicular collisions and other road incidents without human intervention. Traditional accident reporting systems rely heavily on human observation and reporting, which introduces significant delays between an incident occurring and emergency services being notified. AI-powered detection fundamentally changes this paradigm by creating an automated system that continuously monitors traffic conditions through video feeds. The process begins with video input from surveillance cameras, which capture the complex visual environment of roadways including vehicles, pedestrians, and static elements. The AI system then applies sophisticated computer vision algorithms to process this visual information frame by frame. Rather than simply looking at individual images, modern accident detection systems analyze sequences of frames to understand the motion patterns and interactions between vehicles. Neural networks—computational systems inspired by the human brain's architecture—form the backbone of these detection systems. These networks learn to recognize the visual patterns associated with normal traffic flow and, critically, the sudden disruptions that characterize accidents. Through exposure to thousands of examples during training, these systems develop an understanding of the visual signatures of various accident types, from minor fender-benders to serious collisions. What makes these systems particularly powerful is their ability to distinguish genuine accidents from normal traffic behaviors that might appear similar to untrained systems—such as abrupt but controlled stops, lane changes, or normal congestion patterns. This discrimination capability develops through deep learning processes where the system progressively refines its understanding based on labeled examples. The application of AI to accident detection offers several fundamental advantages over traditional methods:

- **Continuous Monitoring:** Unlike human observers who may experience fatigue or attention lapses, AI systems maintain constant vigilance across multiple camera feeds simultaneously.

- **Speed of Detection:** When properly implemented, AI systems can identify accidents within seconds of occurrence, dramatically reducing notification delays.
- **Scalability:** A single AI system can monitor numerous camera feeds across large geographic areas, providing comprehensive coverage that would be impossible with human monitoring alone.

Accisure builds upon these foundational principles while introducing innovations in preprocessing methodology and system architecture to create a detection system that balances high accuracy with practical considerations of computational efficiency and hardware accessibility.

1.1 Background

Traffic accidents remain a significant public health concern worldwide, resulting in approximately **1.35 million** deaths annually according to the World Health Organization. Prompt emergency response is crucial for reducing fatalities and minimizing the severity of injuries. However, accident reporting often relies on witnesses or participants, leading to potential delays, especially in less populated areas or during off-peak hours.

1.2 Problem Statement

Current methods of accident detection and reporting face several challenges:

- Reliance on human reporting, which may be delayed or inaccurate
- Limited coverage in certain areas or times of day
- Lack of precise location information
- Delays in emergency response due to reporting lag

1.3 Project Objectives

Accisure aims to address these challenges by:

- Providing continuous, automated monitoring of roadways through existing CCTV networks
- Detecting accidents immediately as they occur using AI-based computer vision
- Minimizing emergency response times through automatic instant notifications

- Implementing efficient image preprocessing techniques to reduce computational requirements
- Designing a cost-efficient hardware solution that can be widely deployed

Chapter 2

System Architecture

2.1 Overview

Accisure operates by processing video feeds from existing CCTV cameras installed throughout the city. The system employs a neural network-based computer vision model to analyze the video frames in real-time, identifying potential accident scenarios. When an accident is detected with high confidence, the system can trigger alerts to relevant emergency services.

2.2 Hardware Components

- **CCTV Cameras:** Existing traffic surveillance cameras deployed across the city
- **Edge Computing Devices:** Deployed near camera clusters for initial preprocessing
- **Central Servers:** For deep learning inference, validation, and alert management
- **Network Infrastructure:** Secure connections between cameras, edge devices, and central servers

2.3 Software Components

The Accisure system comprises three core components that have been developed to date:

- **Video Processing Pipeline:** Extracts frames at 10 fps from CCTV feeds and applies our multi-stage preprocessing routine to reduce data size while preserving critical features. Implements parallel processing to handle multiple camera streams simultaneously and includes adaptive capabilities for bandwidth-limited environments.

- **Neural Network Model:** The core of Accisure's accident detection system is a deep learning model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to capture both spatial and temporal features from CCTV video sequences. The model is trained to perform binary classification: identifying whether a sequence of frames contains an accident or not.

Chapter 3

Methodology

3.1 Data Collection and Preparation

To develop an effective accident detection model, we have collected and prepared a diverse dataset from multiple sources:

- **Primary Data Sources:**
  - **CADP Dataset:** We leveraged the "CADP: A Novel Dataset for CCTV Traffic Camera based Accident Analysis," which provided high-quality, pre-annotated traffic accident footage from actual CCTV cameras. This dataset is particularly valuable as it contains real-world accident scenarios captured from angles similar to those in deployed traffic monitoring systems[1].
  - **YouTube Video Collection:** To enhance the diversity of our training data, we supplemented the CADP dataset with carefully selected YouTube videos showing traffic accidents from various perspectives, lighting conditions, and environmental settings. These videos were manually curated to ensure relevance and quality.
- **Data Annotation:** For the YouTube-sourced videos, we performed manual labeling of accident events, including type, severity, and temporal boundaries. The CADP dataset came with annotations that we standardized to match our labeling scheme.
- **Image Preprocessing Pipeline:**
  - **Resolution Reduction:** Each frame is resized to 128×128 and 64x64 pixels, reducing the original data size by up to 95 percent while retaining sufficient detail for accident detection

(a) Original image

(b) Grayscale image

Figure 3.1: Conversion to grayscale images

- **Grayscale Conversion:** Color information is removed using BGR to grayscale conversion, reducing the data dimensionality by a factor of 3
- **Histogram Equalization:** Applied to enhance contrast and normalize illumination differences between various CCTV sources. The output of the histogram equalized image shown in figure 3.2 [2].
- **Image Sharpening:** A weighted subtraction of Gaussian blur (3×3 kernel) from the original image enhances edges and important features. Shaperened image is shown in figure 3.3
- **Bit-Plane Slicing:** Only the four most significant bits (4-7) are retained, dramatically reducing noise while preserving structural information. The various bits levels of image shown in fig 3.4 and the image generated from planes 4 to 7 is shown in figure 3.5 [3]
- **Normalization:** Pixel values are scaled to the range [0,1] for consistent neural network processing

Figure 3.2: Histogram equalized image

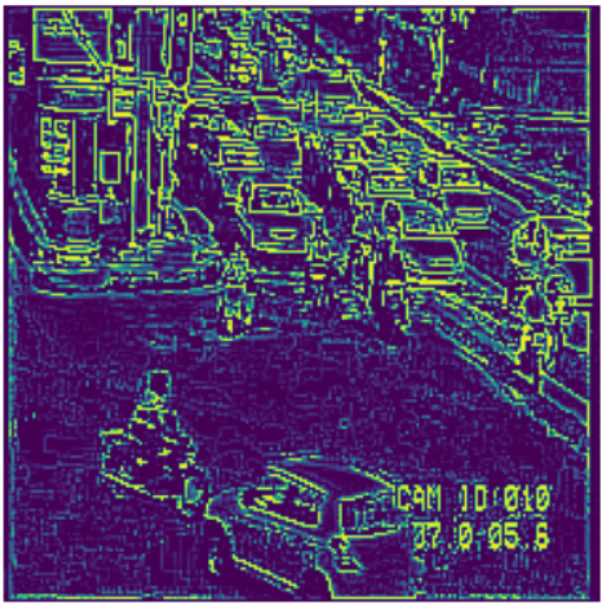

Figure 3.3: Image shaperening (high pass filter)

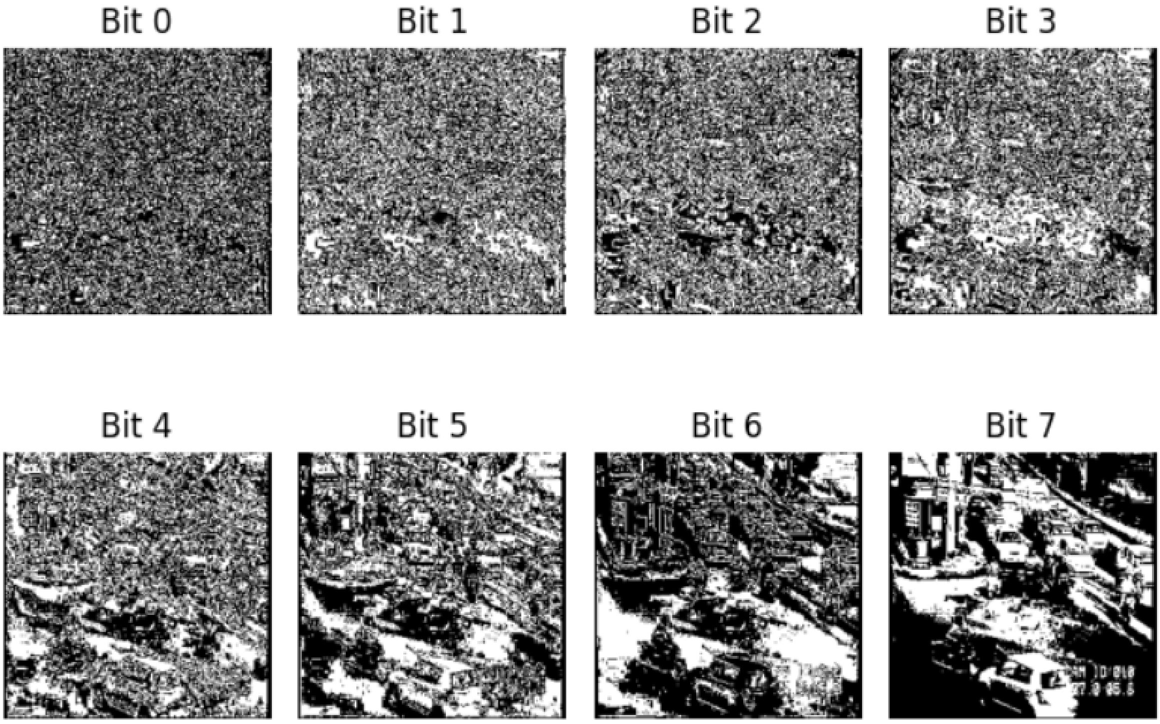

Figure 3.4: Bit slicing from bits 0 to 7 , considering only bits planes 4 to 7 for data reduction

Figure 3.5: Reconstructed image using bits plane 4, 5, 6 and 7

(a) 64x64 image (b) 128x128 image

Figure 3.6: Comparision between 64x64 image and 128x128 image

3.2 Neural Network Architecture

The proposed model for accident detection is a CNN-LSTM hybrid architecture designed to analyze temporal sequences of frames extracted from surveillance videos. Two input resolutions **128×128 and 64×64** were experimented with to evaluate model performance under different computational loads and feature richness[4][5].

- **Input:** The model accepts input sequences of shape (10, H, W, 1) where H × W is either 128×128 or 64×64, representing 10 grayscale video frames per sample.
- **CNN Module (Spatial Feature Extraction):** A TimeDistributed Convolutional Neural Network processes each frame independently to extract spatial features:
  - Conv2D layer with 64 filters of size 3×3, ReLU activation, followed by BatchNormalization and MaxPooling2D[6].
  - Another Conv2D layer with 128 filters of size 3×3, ReLU activation, followed by BatchNormalization and MaxPooling2D.
  - A Flatten layer (wrapped in TimeDistributed) is applied to each processed frame.
- **LSTM Module (Temporal Modeling):** The sequence of feature vectors is passed through an LSTM layer with 64 units to capture temporal dependencies across frames. A Dropout layer (rate 0.5) follows for regularization[7].

- **Output Layer:** A single neuron with sigmoid activation produces a binary output indicating the presence or absence of an accident.
- **Compilation:** The model is compiled using the **Adam optimizer, binary cross-entropy loss function**, and accuracy as the primary evaluation metric.

Chapter 4

Results and Evaluation

4.1 Performance Metrics

The CNN-LSTM model was trained and evaluated on datasets with two different input image resolutions: 64×64 and 128×128. On the training dataset, the model achieved an accuracy of 95.32 percent with 64×64 images and 97.79 percent with 128×128 images. The precision and recall for the 64×64 configuration were 0.94 and 0.98 respectively, while the 128×128 configuration yielded slightly improved values of 0.945 for precision and a perfect recall of 1.0. The training time for the smaller resolution was approximately 39 seconds, with a prediction time of 0.1221 seconds, whereas the larger resolution took about 3 minutes and 2 seconds to train, and had a prediction time of 0.2119 seconds. The final model size for the 128×128 configuration was 395 MB. Importantly, the model was tested on a completely unseen dataset, not used during training, and achieved an accuracy of **77.8 percent**, demonstrating its ability to generalize to new data. The

Table 4.1: Comparison of Model Performance on Different Image Resolutions

Metric	**64 × 64**	**128 × 128**
Accuracy (Training)	95.32%	97.79%
Precision	0.94	0.945
Recall	0.98	1.00
Training Time	39 s	3 min 2 s
Prediction Time	0.1221 s	0.2119 s
Model Size	34MB	395 MB

results shown in table 4.1 indicate that using higher resolution images (128×128) led to improved accuracy and recall, albeit with increased training time and a larger model size. The model demonstrated strong predictive performance with high precision and near-perfect recall, making it well-suited for real-time accident detection scenarios where minimizing false negatives is critical.

4.2 Limitations and Challenges

- **Dataset Quality and Labeling:** Difficulty in finding clean, well-annotated video datasets for accident detection. Required manual labeling of videos, which was time-consuming and prone to human error.

- **Limited Computational Resources:** Training deep learning models, especially with higher-resolution inputs like 128×128, required high compute power. Due to lower GPU/CPU capacity, training took longer and required compromises on model complexity and batch size.

- **Generalization to New Data:** Although the model achieved high accuracy on training data, it performed with 77.8% accuracy on unseen data, indicating overfitting and the need for a more diverse dataset.

- **Model Size and Real-time Suitability:** The final model size (395 MB) and prediction latency (up to 0.21s) may hinder deployment on low-resource or real-time systems without further optimization.

Chapter 5

Implementation in real world

5.1 System Integration

Accisure integrates with existing city infrastructure:

- **Camera Networks:** Direct feeds from traffic management systems
- **Emergency Response Systems:** API integration with emergency dispatch centers
- **Traffic Management Platforms:** Two-way data sharing for coordinated response

5.2 Alert Workflow

When a potential accident is detected:

- The neural network classifies the event with a confidence score
- If the confidence exceeds a threshold, a validation step is triggered
- Validated accidents generate alerts containing location, time, and severity estimate
- Alerts are routed to appropriate emergency services based on location and type
- The incident is logged in the system database for reporting and analysis

5.3 Privacy and Security Measures

The system incorporates several privacy and security features:

- **Data Encryption:** End-to-end encryption for all video feeds and alerts
- **Privacy Preservation:** Automatic blurring of faces and license plates

- **Access Controls:** Role-based access to system features and data
- **Audit Logging:** Comprehensive tracking of system usage and access
- **Compliance:** Adherence to relevant data protection regulations

Chapter 6

Social Impact and Future Work

6.1 Potential Benefits

Accisure offers several societal benefits:

- **Reduced Response Times:** By eliminating the delay between accident occurrence and notification, emergency services can be dispatched significantly faster, potentially saving lives through prompter medical intervention. Studies suggest that reducing response time by even 1-2 minutes can increase survival rates by up to 8% for severe accidents.
- **Improved Resource Allocation:** The system's ability to estimate accident severity allows for more appropriate resource allocation. Minor incidents might require only traffic management, while severe accidents can immediately trigger multiple emergency services.
- **Enhanced Traffic Safety:** Data collected by the system can identify accident-prone locations and conditions, enabling targeted infrastructure improvements and proactive safety measures.
- **Cost Savings:** Reduced post-accident congestion and faster road clearance yield significant economic benefits through decreased traffic delays. The system also minimizes the wasteful dispatch of excessive emergency resources to minor incidents.

6.2 Future Enhancements

As development continues, several key enhancements are planned:

- **Multi-Event Detection:** Expanding the system to identify secondary accidents following initial incidents, which often occur in congested post-accident traffic conditions.

- **Severity Classification:** Implementing more sophisticated classification of accident severity based on visual indicators such as vehicle deformation, number of vehicles involved, and presence of fire or hazardous materials.
- **Predictive Analytics:** Developing predictive capabilities to identify high-risk traffic patterns before accidents occur, potentially enabling preventative measures.
- **Mobile Integration:** Creating mobile applications to extend alerts to nearby drivers, helping them avoid accident areas and reduce secondary congestion.
- **Enhanced Weather Adaptation:** Improving system performance in adverse weather conditions through specialized preprocessing and model adaptations.

Chapter 7

Conclusion

Accisure represents a significant advancement in urban safety infrastructure by leveraging existing CCTV networks with cutting-edge AI technology. The system demonstrates high accuracy in accident detection while maintaining operational efficiency. Early detection of traffic accidents has the potential to significantly reduce emergency response times, potentially saving lives and reducing the severity of injuries. The tests on unseen data confirm the system's effectiveness across various urban environments and traffic conditions. While challenges remain, particularly regarding weather conditions and camera positioning, the results demonstrate the viability of AI-powered accident detection as a valuable component of smart city safety systems. As the system continues to evolve and improve, it promises to become an essential tool for emergency services and traffic management authorities, contributing to safer roadways for all citizens.

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Appendix

.1 Preprocessing Code

Listing 1: Preprocessing code

```
def preprocess_image(img):

    # resized image to 128 x 128
    resized_img = cv2.resize(img, (128, 128))

    # grayscale conversion
    gray = cv2.cvtColor(resized_img, cv2.COLOR_BGR2GRAY)

    # histogram equalization
    equalized = cv2.equalizeHist(gray)

    # image sharpening using subtracting blur from original image
    blurred = cv2.GaussianBlur(equalized, (3, 3), 0)
    sharpened = cv2.addWeighted(equalized, 1.5, blurred, -0.75,
       0)

    # bit slicing
    bit_sliced = np.zeros_like(sharpened)

    for bit in range(4, 8):  # bits 4, 5, 6, 7
        bit_plane = ((sharpened >> bit) & 1) * (2 ** (bit-4))
        bit_sliced += bit_plane

    # normalisation
    normalised_image = bit_sliced / 15.0

    return normalised_image
```

.2 Model Architecture Code

Listing 2: Model building code

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D,
   Flatten
```

```python
from tensorflow.keras.layers import TimeDistributed, LSTM, Dense,
    Dropout, BatchNormalization

def build_model(input_shape=(10, 128, 128, 1)):
    sequence_input = Input(shape=input_shape)

    cnn = TimeDistributed(Conv2D(64, (3, 3), activation='relu',
       padding='same'))(sequence_input)
    cnn = TimeDistributed(BatchNormalization())(cnn)
    cnn = TimeDistributed(MaxPooling2D((2, 2)))(cnn)

    cnn = TimeDistributed(Conv2D(128, (3, 3), activation='relu',
       padding='same'))(cnn)
    cnn = TimeDistributed(BatchNormalization())(cnn)
    cnn = TimeDistributed(MaxPooling2D((2, 2)))(cnn)

    cnn = TimeDistributed(Flatten())(cnn)

    lstm = LSTM(64, return_sequences=False)(cnn)
    lstm = Dropout(0.5)(lstm)

    output = Dense(1, activation='sigmoid')(lstm)

    model = Model(inputs=sequence_input, outputs=output)
    model.compile(optimizer='adam', loss='binary_crossentropy',
       metrics=['accuracy'])

    return model
```

Project Report

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