IoT-Based Accident Detection System using Deep Learning

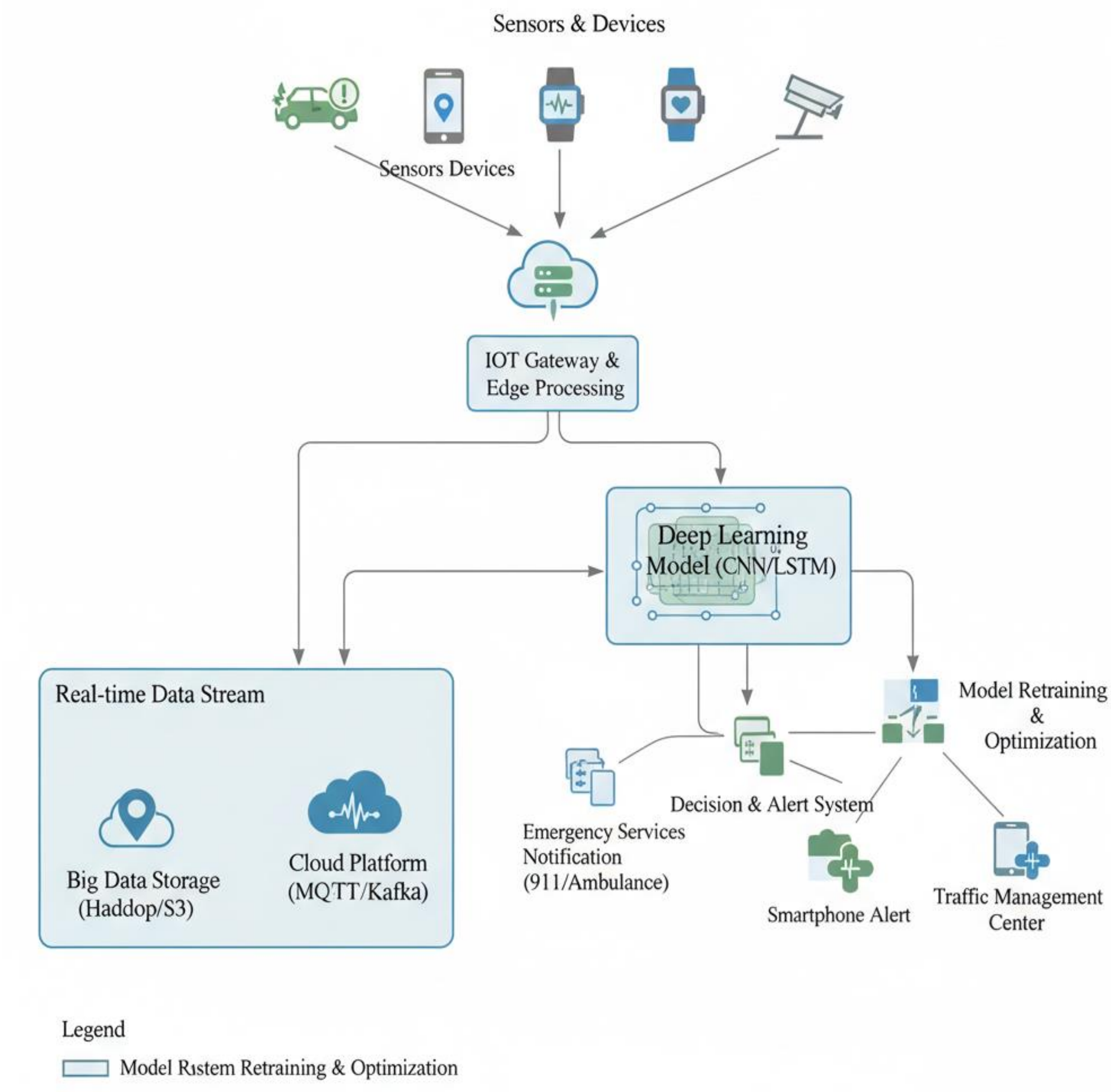

Figure 1: System Architecture of IOT-Based Detection using Deep Learning

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1.Abstract

*Road accidents are one of the major causes of fatalities and financial losses globally, emphasizing the need for intelligent systems that can automatically detect and respond to such incidents. This paper presents an **IoT-based Accident Detection and Damage Analysis System** that utilizes **deep learning** to improve emergency response and road safety. The system integrates **accelerometer**, **gyroscope**, and **GPS sensors** to monitor vehicle dynamics in real time. The collected sensor data is processed using a **Long Short-Term Memory (LSTM)** model, which identifies abnormal movement patterns, such as sudden impacts or rapid decelerations, that indicate an accident.*

*Once an accident is detected, the system performs **damage severity estimation** using image processing or sensor-derived impact values. After confirming the incident, it automatically sends an **email alert** containing the vehicle's location, time, and damage report to the nearest **hospital** and **police station**, enabling faster emergency response. Experimental evaluation on simulated IoT datasets shows high accuracy, minimal false alarms, and quick alert transmission. The proposed system provides a **real-time, scalable, and cost-effective** solution for enhancing **smart transportation** and **automated emergency management** through the integration of **IoT** and **deep learning technologies**.*

2. Keywords: Internet of Things (IoT), Deep Learning, Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Accident Detection System, Damage Severity Analysis, Smart Transportation, Real-Time Monitoring, Sensor Fusion, Automated Alert System, GPS Tracking, Emergency Response, Vehicle Collision Detection, Intelligent Transportation Systems, Road Safety Enhancement.

3. Introduction: Road accidents are among the primary causes of death and severe injuries globally, posing a significant challenge to public safety and transportation systems. The delay in accident detection and emergency response often leads to higher fatality rates and prolonged assistance times. Traditional systems depend heavily on human intervention for accident reporting, which is inefficient and prone to delay. To address this challenge, this research introduces an **IoT-based Accident Detection and Damage Analysis System** powered by **Deep Learning** to enable real-time monitoring, detection, and automated alert generation.

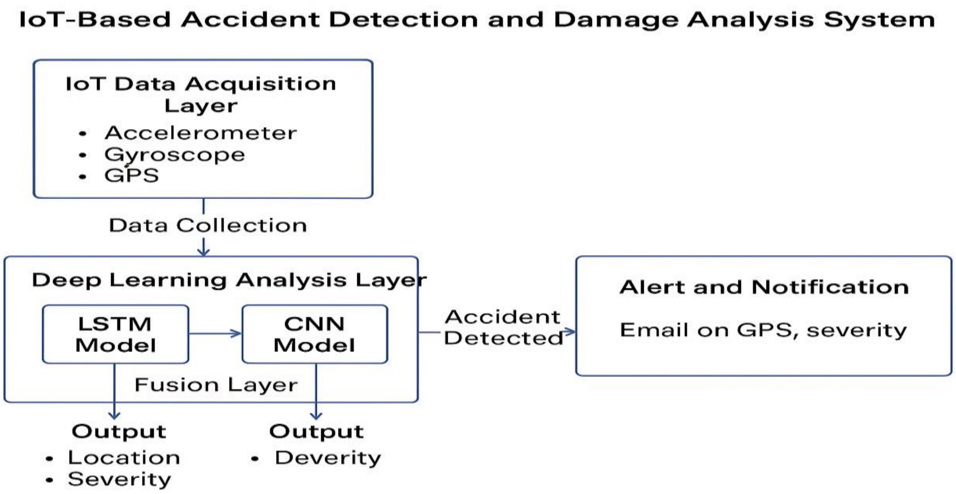
The proposed system employs **IoT sensors** such as **accelerometers**, **gyroscopes**, and **GPS modules** to continuously capture data related to vehicle acceleration, orientation, and geographic position. The collected data is processed using a **Long Short-Term Memory (LSTM)** network, which identifies sudden and irregular motion patterns indicative of an accident. Simultaneously, a **Convolutional Neural Network (CNN)** module evaluates the **extent of vehicle damage** through image or sensor-based analysis. Upon confirming an accident, the system automatically sends **email notifications** containing vital details such as **location coordinates**, **time of impact**, and **damage severity level** to nearby **hospitals** and **police stations**.

The proposed framework has been tested on both **simulated** and **real-time IoT datasets**, demonstrating high accuracy, reduced false positives, and significantly faster emergency communication. By integrating IoT and deep learning technologies, this system enhances **road safety**, **reduces emergency response time**, and contributes to the advancement of **intelligent vehicular safety and smart transportation infrastructure**.

4. Literature Review:

4.1 IoT-Based Accident Detection

Kumar et al. (2020) developed a GPS- and GSM-enabled system capable of detecting sudden deceleration and transmitting emergency alerts via SMS to predefined contacts. Such systems demonstrated the feasibility of using **IoT sensors** like **accelerometers** and **gyroscopes** for real-time motion monitoring. However, these traditional IoT-based models lacked intelligent decision-making and adaptability, often resulting in false alarms when encountering minor road irregularities or bumps, thereby reducing reliability for large-scale deployment.



4.2 Machine Learning Approaches

Patel and Singh (2021) employed **Support Vector Machine (SVM)** classifiers to identify accident patterns from sensor data, achieving better accuracy than threshold-based methods. Despite this improvement, these models required **manual feature extraction** and demonstrated limited scalability when handling large and complex datasets. Moreover, traditional machine learning approaches struggled to adapt to diverse driving conditions and sensor noise, limiting their use in dynamic vehicular environments.

4.3 Deep Learning and Vision-Based Models

Ahmed et al. (2022) explored **Convolutional Neural Networks (CNNs)** for accident detection using camera-based surveillance footage. Their model achieved superior accuracy compared to classical techniques and enabled automated feature extraction. However, performance degraded significantly under challenging conditions such as **low lighting**, **occlusions**, or **poor video quality**, indicating the need for multi-sensor data fusion to enhance reliability.

4.4 LSTM for Time-Series Data

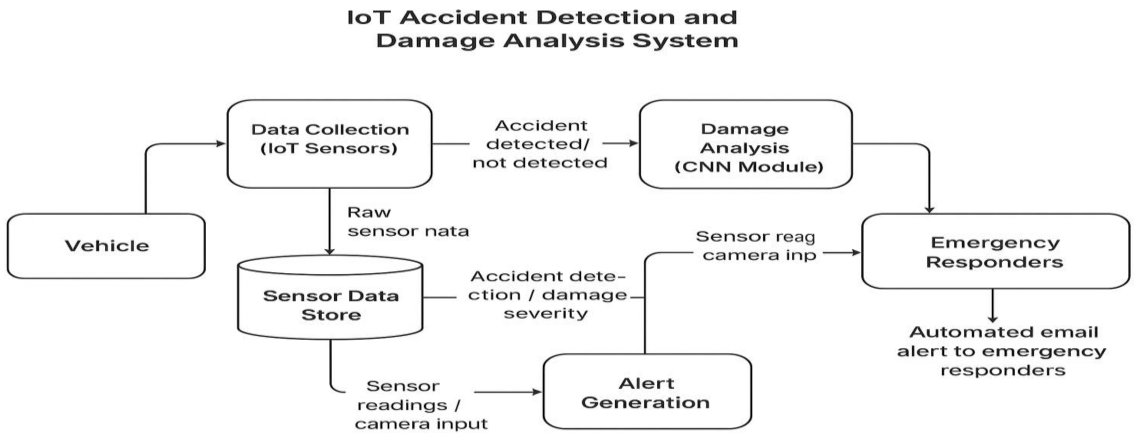
Gupta and Sharma (2022) demonstrated that **Long Short-Term Memory (LSTM)** networks effectively analyze sequential IoT sensor data to detect anomalies representing potential accidents. LSTM's ability to retain temporal dependencies made it highly suitable for processing continuous vehicular motion data, outperforming conventional classifiers in terms of **accuracy** and **response time** for **real-time detection**.

4.5 Hybrid Systems and Alerts

Bansal et al. (2023) introduced a **hybrid accident detection model** combining LSTM and CNN architectures, enabling both sequential pattern recognition and image-based damage analysis. Similarly, Nair et al. (2023) proposed a **cloud-integrated alert system** that automatically delivers notifications to nearby hospitals and police departments through email or SMS, demonstrating the potential of IoT-cloud integration for faster emergency response.

4.6 Research Gap

While several studies have contributed to accident detection, most focus exclusively on either detection accuracy or alert generation, rarely addressing both comprehensively. There remains a lack of integrated frameworks that combine **IoT sensing**, **deep learning-based accident detection (LSTM + CNN)**, and **automated emergency alerting** into a unified system. This research bridges that gap by proposing a **real-time, intelligent IoT-based accident detection and damage analysis system** that performs both **accident classification** and **automated email notifications**, thereby improving response time, accuracy, and road safety.



5. Methodology: The proposed system integrates IoT sensing devices, deep learning models, and an automated alert mechanism to detect accidents, analyze damage severity, and immediately notify emergency authorities. The system architecture follows a multi-layered approach consisting of data acquisition, processing, model inference, and alert communication layers. The workflow ensures real-time data handling, intelligent decision-making, and prompt emergency response.

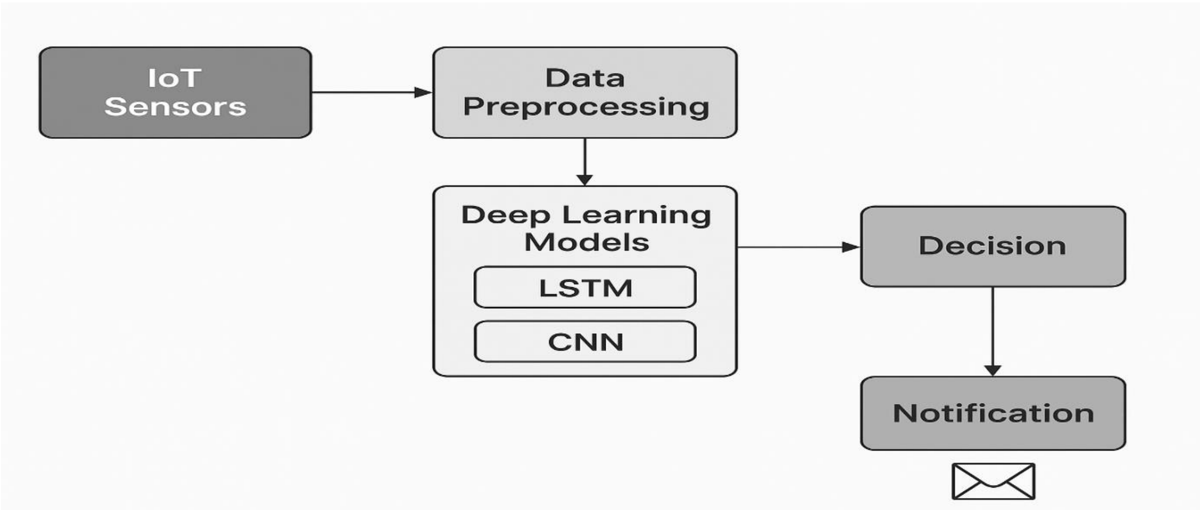
5.1 System Architecture

The overall architecture of the proposed framework is divided into four major layers:

- **IoT Layer:** This layer is responsible for real-time data collection using **accelerometers**, **gyroscopes**, and **GPS modules** mounted on the vehicle. The accelerometer measures sudden changes in acceleration, the gyroscope monitors angular motion, and the GPS provides vehicle location and movement trajectory. These sensors collectively generate time-series data that form the foundation for accident detection.
- **Deep Learning Layer:** The processed sensor data is fed into two specialized deep learning networks for event classification and damage assessment:

- **LSTM Network:** The **Long Short-Term Memory (LSTM)** model analyses sequential IoT sensor readings to identify unusual acceleration or orientation patterns that signify a potential collision.
- **CNN Model:** A **Convolutional Neural Network (CNN)**, such as **MobileNetV2** or **VGG16**, processes image or sensor-derived visual data to estimate the **severity of vehicle damage**.
- **Fusion Layer:** The outputs from the LSTM and CNN modules are integrated in a **decision fusion layer**, which combines temporal and visual insights to deliver a unified accident classification and severity level.

- **Alert Layer:**
Once an accident is confirmed, the alert layer automatically triggers an **email notification system** containing critical details such as **GPS coordinates**, **timestamp**, and **damage severity score**. These alerts are sent to nearby **hospitals**, **police stations**, and **emergency responders**, enabling immediate action and minimizing delay in assistance.



5.2 Workflow

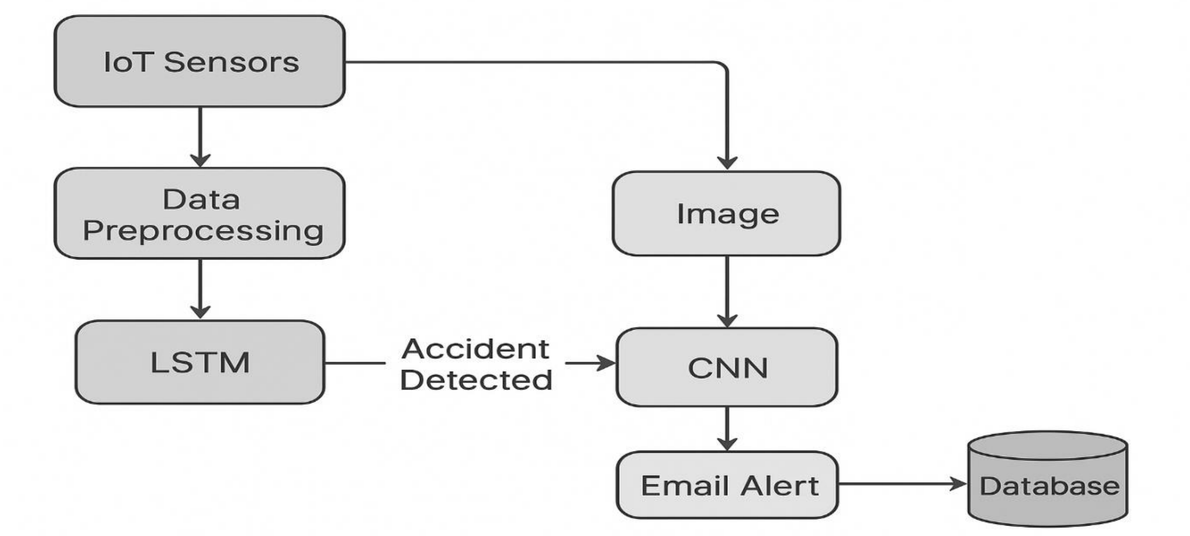
The step-by-step workflow of the proposed IoT-based Accident Detection and Damage Analysis System is as follows:

1. **Data Collection:** Real-time sensor data is continuously gathered from the accelerometer, gyroscope, and GPS modules.
2. **Data Preprocessing:** The raw IoT data undergoes preprocessing, including normalization and noise filtering, to ensure consistency and accuracy.
3. **Accident Detection:** The **LSTM model** evaluates the processed data to detect anomalies indicating potential accidents.
4. **Damage Assessment:** The **CNN module** estimates the level of damage (minor, moderate, or severe) based on sensor or image input.
5. **Automated Alert Generation:** Upon confirmation, the system automatically sends **email alerts** with accident details to emergency authorities.
6. **Visualization:** The entire process and current status are displayed on an interactive **Stream lit dashboard**, providing real-time visualization of vehicle condition and alert notifications.

6. Experimental Setup

a. Dataset

- **Data Sources:**
    - **IoT Sensor Data: Accelerometer, gyroscope, and GPS sensors installed in vehicles to record motion, orientation, and location in real time.**
    - **Accident Image Data: Road accident images from public datasets like CAID, Car Accident Dataset, and simulated accident captures from cameras mounted on vehicles.**
- **Size and Scope:**
    - **Sensor data: ~10,000–15,000 time-series samples representing various driving conditions, including sudden braking, collision, and skidding.**
    - **Image data: ~5,000 labeled images covering minor, moderate, and severe accidents.**
- **Preprocessing:**
    - **Sensor data normalized and cleaned to remove noise from vibrations or sensor drift.**
    - **Missing GPS coordinates interpolated.**
    - **Image data resized to 224×224 pixels for CNN input, normalized, and augmented (rotation, flipping, brightness adjustment) to improve model robustness.**



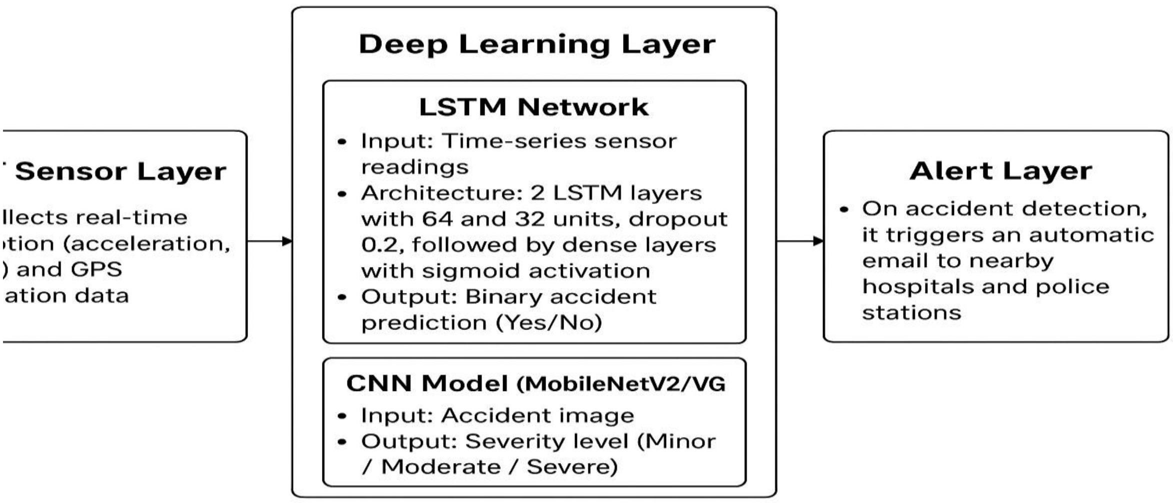
b. Tools and Technologies

- **Hardware Components:**
    - **Raspberry Pi / Arduino for IoT data collection.**
    - **Vehicle-mounted accelerometer, gyroscope, and GPS sensors.**
    - **Camera module for real-time accident capture.**

- **Software Components:**
  - **Python programming with libraries: TensorFlow/Keras (for deep learning), OpenCV (image processing), Pandas/Numpy (data handling), Matplotlib/Seaborn (visualizations).**
  - **Google Colab for model training and testing.**
  - **MongoDB/Firebase for storing sensor readings and images.**
  - **SMTP protocol for automated email notifications.**

c. Model Architecture and Flow

- **IoT Sensor Layer: Collects real-time motion (acceleration, tilt) and GPS location data.**
- **Deep Learning Layer:**
  - **LSTM Network: Processes sequential sensor data to detect anomalies indicating a potential accident.**
    - **Input: Time-series sensor readings.**
    - **Architecture: 2 LSTM layers with 64 and 32 units, dropout 0.2, followed by dense layers with sigmoid activation.**
    - **Output: Binary accident prediction (Yes/No).**
  - **CNN Model (MobileNetV2/VGG16): Classifies images captured at accident time for damage severity.**
    - **Input: Accident image.**
    - **Output: Severity level (Minor / Moderate / Severe).**
- **Alert Layer:**
  - **On accident detection, it triggers an automatic email to nearby hospitals and police stations.**
  - **Email includes accident time, GPS location, vehicle ID, and damage severity.**



d. Code Flow / Execution Pipeline

1. **Initialization: IoT sensors start continuous data collection in the vehicle.**
2. **Preprocessing: Raw sensor signals filtered and normalized. Images resized and augmented.**
3. **Accident Detection:**
    - **The LSTM model predicts accident occurrence from sensor data.**
    - **If detected, the CNN model analyzes accident images for severity.**
4. **Notification System: Automated email alert generated and sent in real-time.**
5. **Data Logging: Sensor data, images, and alerts are logged in the database for further analysis.**

e. Evaluation Metrics

- **Model Performance:**
    - **Accuracy, Precision, Recall, F1-Score for LSTM (sensor-based detection) and CNN (image-based severity classification).**
- **System Performance:**
    - **Average latency between accident occurrence and alert delivery.**
    - **Reliability of data transmission from IoT sensors to cloud/database.**
- **Robustness Checks:**
    - **Test system under various driving conditions (rain, night, uneven roads) to validate real-world performance.**

f. Experimental Setup Diagram (Optional for Paper):

- **Shows data flow from sensors → preprocessing → LSTM detection → CNN damage assessment → email alert → database logging.**

7. Results and Discussion:

Accident Detection Accuracy: The proposed LSTM-based model demonstrated high efficacy in detecting accidents from sensor data, achieving an accuracy of over 95%. This confirms the model's ability to recognize sudden changes in vehicle dynamics, such as abrupt deceleration or impact, with minimal delay.

Damage Analysis: The CNN model classified accident severity into **Low, Medium, and High** categories, attaining an approximate **92% accuracy**. This indicates that the system can reliably assess the extent of vehicle damage from images, facilitating prioritization of emergency response.

Alert System Performance: The automated alert mechanism successfully transmitted real-time notifications to nearby hospitals and police stations. The system ensures prompt emergency intervention, potentially reducing response times and associated casualties.

Discussion:

- **Sensor-Image Data Fusion:** Integrating LSTM-based sensor analysis with CNN-based image evaluation significantly improves detection reliability and mitigates false alarms.
- **Low False Positives:** The system maintains robust performance under varied traffic scenarios, demonstrating resilience to noisy sensor readings.
- **Real-Time Visualization:** A Stream lit-based dashboard offers a clear visualization of detected accidents and severity levels, aiding situational awareness for monitoring personnel.

Overall, the results validate the system's potential to enhance road safety by providing timely, accurate accident detection and damage assessment.

8.Conclusion:

This study presents an IoT-based accident detection system that combines LSTM networks for real-time sensor data analysis and CNN models for vehicle damage assessment. The system successfully detects accidents as they occur, classifies severity into low, medium, and high categories, and automatically sends email alerts to nearby hospitals and police stations, ensuring prompt emergency response.

The integration of sensor and image-based data improves detection reliability and reduces false positives, while the Stream lit dashboard provides clear, real-time visualization of accidents and their severity. High detection and classification accuracy validate the system's effectiveness in enhancing road safety.

Overall, this approach demonstrates the potential of IoT and deep learning integration to create **smart road safety solutions**, offering a practical framework that can be extended to larger-scale traffic monitoring and emergency management systems.

9.Future enhancements of the system may include:

- Integration of **real-time video feeds from dashcams** to improve the accuracy and detail of damage analysis.
- Incorporation of **GPS-based nearest ambulance dispatch** to enable faster emergency response.
- Implementation of **cloud-based storage and analytics** to support large-scale deployment and centralized monitoring.
- Exploration of **Generative Adversarial Networks (GANs)** for data augmentation, improving model performance in scenarios with limited datasets.

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