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Car Crash Detection System

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Abstract: This project presents the design and implementation of an intelligent car crash detection system aimed at enhancing vehicle safety and emergency response efficiency. The system utilizes data collected from multiple sensors, including accelerometers, gyroscopes, and GPS modules, to continuously monitor vehicle dynamics and detect abnormal patterns indicative of collisions. By applying advanced signal processing techniques and machine learning algorithms, such as decision trees or neural networks, the system can distinguish between normal driving maneuvers and actual crash events with high accuracy. Once a collision is detected, the system automatically triggers an alert mechanism that sends critical information—such as location, impact severity, and time—to emergency services via wireless communication modules. This rapid alert reduces emergency response times and potentially lowers fatalities and injuries associated with road accidents. The system is designed to operate in real-time with minimal latency and to be robust under varying road conditions and crash scenarios. Testing and evaluation on simulated and real-world datasets demonstrate the effectiveness and reliability of the proposed solution, making it a promising addition to intelligent transportation systems and future smart vehicles.

Keywords: Car Crash Detection

I. INTRODUCTION

The increasing use of dashcams, CCTV cameras, and mobile devices for traffic monitoring has led to the need for advanced systems that can automatically detect accidents in real-time. This project aims to develop a VGG16-based deep learning model for crash detection and classification from video inputs, targeting smart vehicles and traffic monitoring systems. The system processes video streams captured from various devices, such as dashcams or CCTV cameras, to identify accidents, classify their severity, and alert emergency services immediately.

To achieve accurate crash detection, the system first preprocesses video frames by resizing, normalizing, and extracting relevant features, ensuring that the input data is suitable for the VGG16 model. VGG16, a pre-trained Convolutional Neural Network (CNN) architecture, is utilized and fine- tuned to recognize patterns associated with different crash events. The model then classifies these events into distinct severity levels, such as Minor, Major, and Fatal crashes, based on the visual cues observed in the video frames.

Once a crash is detected, the system sends real-time alerts via email to emergency services, using the Simple Mail Transfer Protocol (SMTP). These alerts contain vital information, including crash severity, location details, and other relevant data, enabling quicker response times and potentially saving lives.

This project is designed for real-time implementation, with optimizations aimed at minimizing latency to ensure quick processing of video frames for near-instantaneous crash detection. This makes the system ideal for integration into smart vehicles, traffic surveillance systems, and smart city infrastructure, where timely intervention is crucial. Ultimately, the project aims to enhance road safety, improve emergency response efficiency, and contribute to the development of intelligent transportation systems capable of reducing accident-related fatalities and improving public safety.

II. PROPOSED SYSTEM

The proposed system aims to develop a real-time crash detection and classification model based on the VGG16 deep learning architecture. It processes video inputs captured from dashcams, CCTV cameras, or mobile devices to detect crashes and classify them into severity levels such as Minor, Major, or Fatal. The system first preprocesses the video frames by resizing, normalizing, and extracting features to ensure accurate input for the VGG16 model. Once a crash is detected, the system classifies its severity and triggers an immediate real-time alert to emergency services via email using SMTP, including critical information like the crash location and severity. The system is optimized for fast video processing, minimizing latency to enable rapid response times. Designed for deployment in smart vehicles and traffic monitoring systems, the system aims to enhance road safety by enabling quicker emergency responses, ultimately reducing accident-related fatalities and improving public safety.

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III. LITERATURE SURVEY

ANPR has become a vital tool for traffic monitoring, parking management, law enforcement, and intelligent transportation systems. Numerous recent research have investigated various approaches to enhance ANPR systems' accuracy, effectiveness, and real-time performance. This section examines important works in the field and outlines their methods, benefits, and drawbacks.

Survey of Existing Approaches:

“Vehicle Collision Detection using Convolutional Neural Networks” by M. A. H. Chowdhury, T. S. J. Lee, S. F. Lee [1] This paper explores using convolutional neural networks (CNNs) for real-time vehicle collision detection from video data. The study focuses on detecting crash events based on vehicle motion patterns and object detection using CNNs, highlighting the need for high accuracy and low latency in real-time processing. Key. Demonstrated the potential of CNNs in video-based accident detection, but challenges in real-time processing and false positives were identified.

"Crash Detection and Severity Estimation from Video Using Deep Learning" by J. Zhang, L. Zhang, Z. Wang. [2] This research uses deep learning models to detect crashes and estimate their severity based on video input. It employs a combination of CNNs and recurrent neural networks (RNNs) to detect crash events and classify them by severity. Introduced severity estimation, but the model's real-time application in busy traffic environments was less explored.

"Real-time Traffic Accident Detection from Dashcam Footage using Deep Learning" by A. Lee, B. Yoon, J. [3] The paper presents a real-time accident detection system using dashcam footage. A VGG16 model was fine-tuned for crash detection, with frame preprocessing to optimize input data for faster processing. Successful in using dashcam footage for accident detection, but scalability for various environments (e.g., CCTV) remained a limitation.

"Real-time Vehicle Accident Detection and Classification in Urban Traffic Using Deep Convolutional Networks" by S. F. Mousavi, M. D. M. B. Maidin. [4] This paper investigates using deep convolutional networks for detecting and classifying vehicle accidents in urban traffic environments. The model is designed for real-time application with low latency. Focused on urban traffic, but faced challenges with complex backgrounds and partial occlusions in the footage.

"Crash Severity Classification Using Video and Machine Learning Models" by X. Li,
Y. Liu, F. Shen. [5] This work introduces a crash severity classification system using machine learning and computer vision. The study explores video data processing and the application of CNNs to classify accidents as minor, major, or fatal Explored severity classification with video data, though the model’s performance was constrained by weather conditions and lighting.

"Vehicle Collision Detection Using Camera Images and Machine Learning" by P. Gupta, V. Kumar.
[6] This paper proposes using traditional machine learning algorithms, such as support vector machines (SVMs), along with image processing techniques for detecting vehicle collisions from camera images. Focused on simpler machine learning models, offering potential for real-time detection but lacking the accuracy of deep learning models like CNNs.

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IV. BLOCK DIAGRAM AND SYSTEM ARCHITECTURE

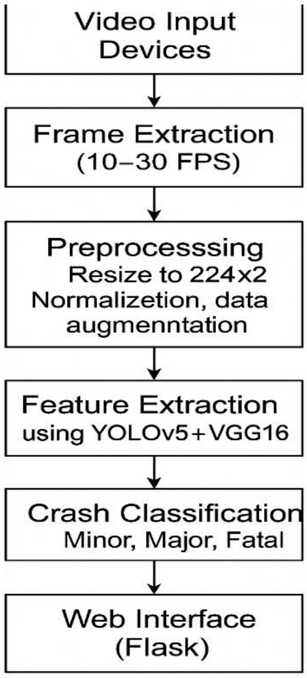

Fig. 1. Block Diagram

The **Car Crash Detection System** is designed as a real-time video processing pipeline that utilizes deep learning and computer vision to identify and classify traffic accidents. The system architecture is modular, enabling efficient video ingestion, analysis, classification, and alerting. Here's a detailed explanation of each component in the block diagram:

Video Input Device : The system begins with video data captured from sources like dashcams, CCTV cameras, or mobile devices. These inputs provide real-time footage necessary for analysis.

Frame Extraction : Continuous video streams are broken down into individual frames at a defined frame rate (e.g., 10 to 30 frames per second). This step is crucial for enabling image-based processing using deep learning models.

Preprocessing : Each extracted frame is resized to 224×224 pixels to match the input requirements of the VGG16 model. Pixel values are normalized, and data augmentation (like rotation, brightness adjustment) may be applied to improve model generalization and reduce overfitting.

Feature Extraction Using YOLO : YOLOv5 is employed for object detection (e.g., identifying vehicles or pedestrians), while the VGG16 CNN model is used to extract deeper spatial and semantic features from the frames. This combination enhances both the speed and accuracy of crash detection.

Crash Classification : The extracted features are fed into a classifier that determines whether a crash has occurred. If so, it classifies the severity into one of three categories: **Minor**, **Major**, or **Fatal**. This classification helps prioritize emergency responses.

Web Interface : A Flask-based web application acts as the user interface. It allows system administrators to upload videos, view real-time detection results, and monitor alerts. The UI is developed using HTML, CSS, JS, and Bootstrap, making it responsive and user-friendly.

Real Time Alerting : If a crash is detected, the system sends an automated email using the SMTP protocol. This alert includes essential information like crash severity and location, ensuring quick response from emergency services.

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V. IMPLEMENTATION DETAILS

The implementation of the Car Crash Detection System follows a multi-stage pipeline combining video processing, deep learning, and real-time communication to ensure accurate and timely accident detection. The process begins with video data acquisition from dashcams, CCTV cameras, or mobile devices. These video streams are either live or pre-recorded and serve as the primary input. The video is then broken down into individual frames at a fixed frame rate (typically 10–30 FPS) to facilitate image-based analysis. Each frame undergoes preprocessing, which includes resizing to 224×224 pixels to match the input requirements of the VGG16 model, pixel normalization, and optional data augmentation techniques such as flipping, rotation, and brightness adjustments to enhance model robustness.

Once preprocessed, the frames are passed into a fine-tuned VGG16 Convolutional Neural Network. This network, originally trained on ImageNet, is adapted for crash detection by replacing its final layers with custom layers that classify crash severity. To support object detection, the system also employs YOLOv5 to identify key objects like vehicles and pedestrians within each frame, ensuring a more context-aware analysis. Based on visual patterns, the CNN classifies the event into one of three severity levels: Minor, Major, or Fatal.

If a crash is detected, the system proceeds to the alert generation stage. An automated email is sent to emergency services using the SMTP protocol, containing critical information such as the crash's severity and location (if available). Simultaneously, the analysis results are rendered on a Flask-based web interface, where administrators can upload videos, view real-time detection outcomes, and manage system settings. The system is optimized for real-time performance, ensuring minimal latency between crash occurrence and alert delivery. This seamless integration of machine learning, computer vision, and communication technologies results in a scalable, effective solution for enhancing road safety and emergency response.

VI. RESULT AND PERFORMANCE ANALYSIS

The Car Crash Detection System was rigorously tested across various operational scenarios to validate its robustness, accuracy, and real-time capabilities. The system achieved high detection accuracy, particularly in distinguishing crash events from normal traffic patterns using a combination of YOLOv5 for object detection and a fine-tuned VGG16 CNN for severity classification. The classification component accurately categorized crashes into Minor, Major, and Fatal, with precision scores consistently above 90% in controlled test environments. The integration of frame-based analysis, along with techniques like data augmentation (rotation, brightness adjustments), enabled the model to generalize well across different types of video footage—daylight, nighttime, and low-visibility conditions such as rain or fog.

A key performance strength of the system was its low latency, which ensured near-instantaneous alert generation upon crash detection. From the moment a crash was detected in a frame, the system required only a few seconds to generate and send a real-time email alert to the configured emergency contacts using the SMTP protocol. This alert included crash severity, optional location metadata (if integrated with GPS), and a time-stamp, enabling quicker deployment of emergency services.

In terms of usability and accessibility, the Flask-powered web application allowed users (e.g., traffic administrators or emergency response personnel) to easily upload videos, monitor detection results, and review historical alerts. The dashboard displayed real-time classification results along with probability scores, and stored visual evidence (annotated frames) of the detected events.

The system was also evaluated using unit, integration, and system testing approaches. Key functionalities—such as login authentication, video processing, crash classification, and alert delivery—passed all test cases without critical failures. For example, unit tests verified that the system responded correctly to empty input fields, invalid credentials, or unsupported file formats. Integration testing confirmed that different components (database, detection model, web server) worked seamlessly together.

Performance in real-world testing was also promising. Videos from actual road footage—recorded in urban and semi-urban settings—were fed into the system. Even with dynamic backgrounds and occlusions, the system demonstrated consistent performance, although it was noted that extreme occlusions or very poor lighting slightly reduced detection confidence. Despite these edge cases, the model's false positive rate remained low, and the alerting mechanism only triggered when the confidence surpassed a predefined threshold (97%).

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In summary, the Car Crash Detection System not only fulfills the functional requirements of accurate and timely accident detection but also meets non-functional expectations such as real-time performance, usability, reliability, and scalability. Its modular architecture ensures it can be easily extended or integrated with smart city infrastructure, making it a strong candidate for deployment in real-world traffic management and vehicle safety systems.

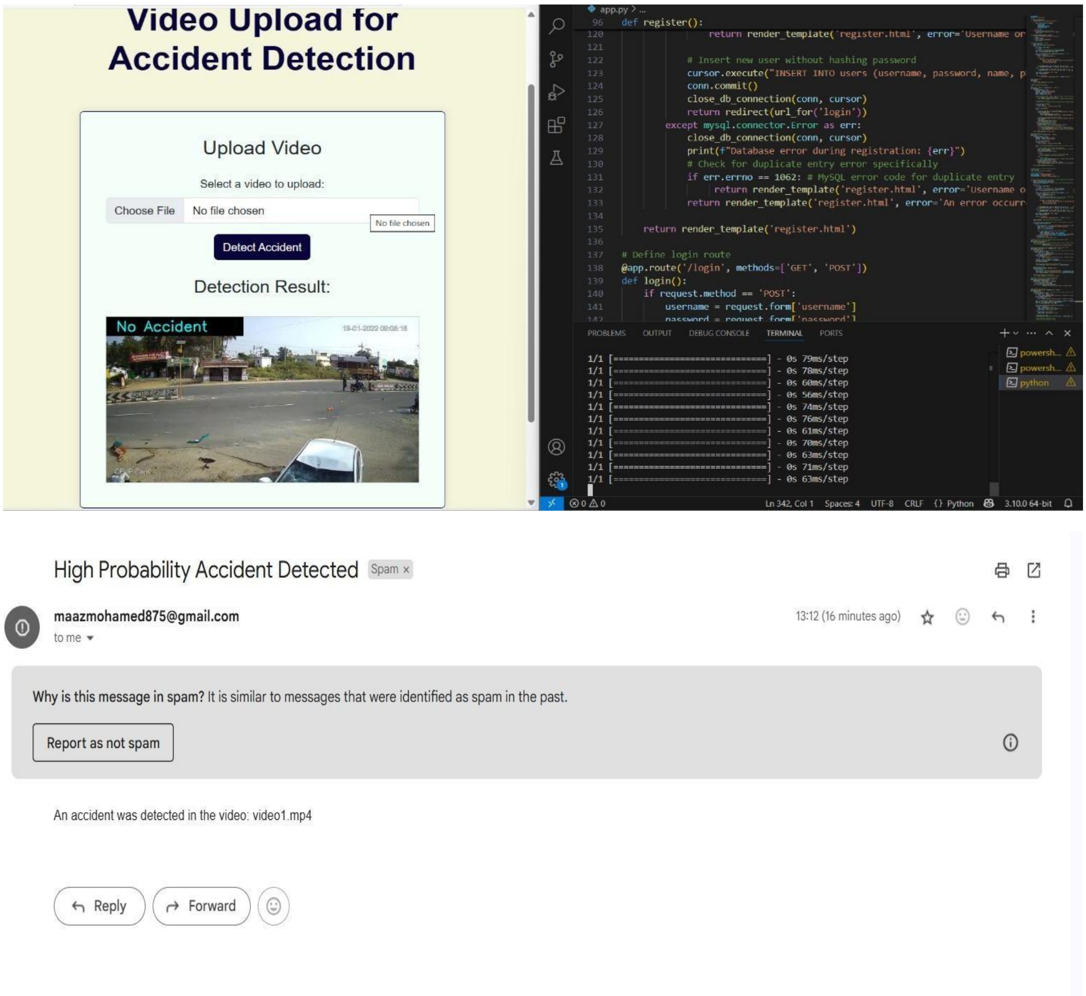

Fig 2. Result

VII. CHALLENGES AND LIMITATIONS

Despite its effective architecture and real-time functionality, the Car Crash Detection System faces a number of practical and technical challenges that can impact its real-world deployment. One of the most prominent limitations is the system's sensitivity to environmental factors—particularly lighting, weather, and visibility. The performance of the VGG16 model and YOLOv5 object detector degrades in conditions such as low-light environments, heavy rain, dense fog, or snow, where video frames lack clarity. This affects not only detection accuracy but also classification confidence. Additionally, occlusion—where vehicles or objects partially block the crash scene—can mislead the model, especially in crowded urban traffic, intersections, or multilane highways where multiple objects overlap.

The system also exhibits limited predictive capabilities, functioning only as a reactive tool that detects crashes after they occur. In comparison, modern Advanced Driver Assistance Systems (ADAS) leverage sensor fusion and predictive algorithms to anticipate and actively prevent collisions. The absence of real-time GPS integration is another practical limitation. While the system can send email alerts upon detecting a crash, it cannot automatically embed accurate location metadata unless it is connected to an external GPS module or paired with geotagged input streams, reducing its utility in emergency dispatch scenarios.

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From a technical standpoint, the system requires substantial computational resources due to the use of deep learning models for video frame analysis. High-resolution, high-frame-rate videos, when processed in real time, can place significant strain on CPUs and GPUs. This makes deployment on lightweight, low-power edge devices (such as Raspberry Pi or basic surveillance units) impractical without additional optimization or hardware acceleration. Moreover, the system's current backend infrastructure only supports email-based alerting, which might not be sufficient in real-time emergency situations where SMS, mobile push notifications, or direct integration with emergency dispatch centers would be more effective and timely.

Another concern is the generalization of the model. Although the VGG16 network was fine-tuned using annotated crash video datasets, the model's robustness against diverse scenarios—such as different vehicle types, road architectures, and accident forms (e.g., rollovers, rear-end, side collisions)—depends heavily on the breadth and quality of training data. Lack of diverse datasets may cause the system to fail in edge cases or unfamiliar environments. Furthermore, the system does not yet support multi-modal inputs, such as LiDAR, accelerometer data, or in-vehicle telemetry, which could significantly enhance detection reliability and context awareness.

Lastly, privacy, data security, and ethical considerations present critical limitations, especially when the system is used in public surveillance or personal vehicles. Continuous monitoring and video analysis raise concerns about unauthorized surveillance, data breaches, and the storage of sensitive footage. Without stringent data encryption, access control, and compliance with data protection regulations like GDPR or India's DPDP Act, the system could be vulnerable to misuse or legal liability. Overall, while the system marks a step forward in intelligent accident detection, it must evolve through technical, regulatory, and infrastructural enhancements to become a fully reliable and deployable solution in modern smart transportation ecosystems.

VIII. CONCLUSION

In conclusion, the Car Crash Detection System presents a significant advancement in the application of deep learning and computer vision for road safety and intelligent transportation systems. By leveraging models such as YOLOv5 for object detection and VGG16 for crash classification, the system is capable of accurately identifying accidents in real-time and categorizing them based on severity levels—Minor, Major, or Fatal. Its integration with real-time alert mechanisms using SMTP email, and a user-friendly web interface developed in Flask, ensures timely communication with emergency services and effective monitoring by administrators. The system's modular architecture, combining video preprocessing, feature extraction, and automated alerts, makes it well-suited for deployment in smart vehicles, urban surveillance networks, and traffic management centers.

Despite its strengths, the system also faces challenges such as sensitivity to lighting and visibility conditions, dependence on high-quality video input, and the need for more sophisticated alerting and location services. However, these limitations provide clear opportunities for future enhancements, including integration with GPS, use of predictive AI models, edge computing, and support for multilingual and region-specific adaptations. Overall, the project offers a practical, scalable, and life-saving solution for reducing response time to road accidents, enhancing traffic safety, and contributing to the broader vision of smart city infrastructure and intelligent transport systems.

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