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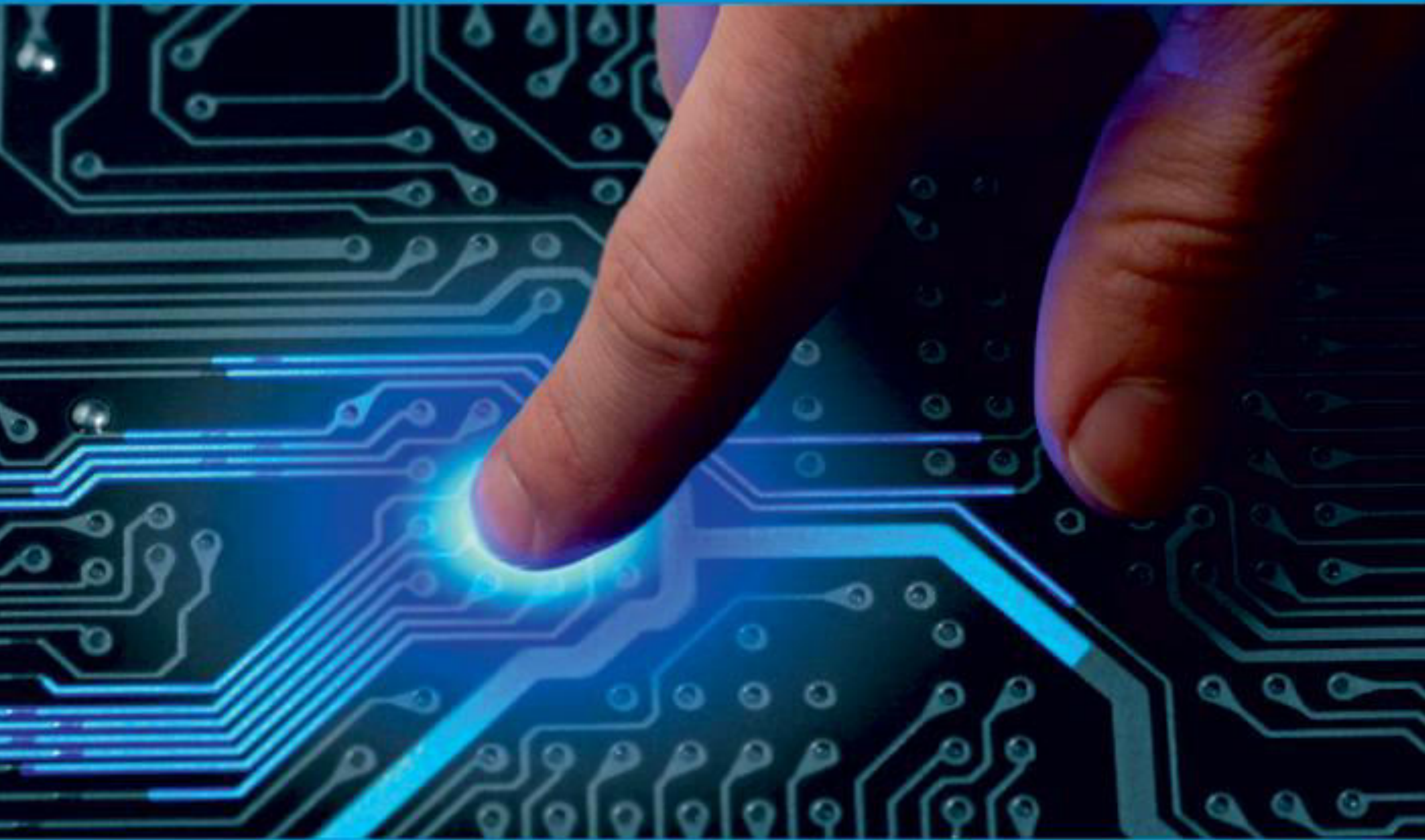

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A Deep Learning-Based Car Accident Detection Framework Using Edge and Cloud Computing

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ABSTRACT: The evolving technological landscape has seen a pivotal shift with the advent of edge computing, transforming various sectors, particularly accident detection. Edge computing enhances road safety by enabling real-time data processing from onboard sensors, cameras, and connected devices, addressing limitations in traditional cloud-based systems. This paper introduces a deep learning-based accident detection framework within an edge-cloud setup. Utilizing a CNN model, accidents are detected at the edge node near the data source, ensuring low latency, reduced network usage, and faster execution times. The model achieves a remarkable 95.91% accuracy,

KEYWORDS: Edge Computing, Cloud Computing, Accident Detection, Convolutional Neural Networks (CNN), Real-Time Processing.

I. INTRODUCTION

In the evolving landscape of intelligent transportation systems, the fusion of edge and cloud computing is revolutionizing accident detection and response frameworks. This integrated approach ensures timely and accurate analysis by leveraging the strengths of both local edge nodes and centralized cloud systems. Edge computing allows for on-site processing of data, collected from sensors and surveillance cameras located in key areas such as intersections and roadways, as depicted in the illustrated framework.

Edge devices, strategically installed in accident-prone zones, represent a significant advancement in road safety technology by utilizing Convolutional Neural Networks (CNNs) to process data locally. These devices are equipped with high-resolution cameras and various sensors that continuously capture real-time visual and sensor data from the roadway and surrounding environment. This setup allows for immediate analysis of driving behaviors and conditions, enabling the early detection of anomalies such as sudden collisions, aggressive maneuvers, and hazardous driving behaviors that could lead to accidents. The initial convolutional layers are responsible for feature extraction, where they apply various filters to the input images to identify essential patterns and characteristics, such as edges, shapes, and movements of vehicles. These filters slide across the images, performing convolutions that help detect and emphasize specific features relevant to driving behaviors. Following this, pooling layers reduce the dimensionality of the feature maps generated by the convolutional layers, simplifying the data while preserving the most important information. This reduction is vital for computational efficiency, as it decreases the amount of data that needs to be processed in subsequent layers and helps the model generalize better to new data. Once the features are extracted and the data has been streamlined through pooling, the fully connected layers come into play. Here, the flattened feature maps are input into dense layers that perform the final classification tasks.

These layers analyze the high-level features and make decisions about the state of the driving environment, determining whether an accident has occurred or if hazardous behaviors are present. Utilizing extensive labeled datasets that contain examples of both normal and abnormal driving scenarios, the models are trained using supervised learning techniques. This training process enables the system to learn to distinguish between typical driving patterns and potential hazards. The entire data processing flow begins with data acquisition, where edge devices capture real-time video and sensor data. As the data is received, the CNN begins analyzing it almost instantaneously. This rapid processing capability significantly reduces latency, allowing for real-time decision-making critical in emergency situations. If an anomaly is detected, such as a sudden stop or collision, the system can immediately alert authorities or activate safety measures, potentially preventing further accidents and saving lives. By processing data locally, these devices minimize the

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amount of data that needs to be transmitted to remote servers for analysis. This is particularly advantageous in remote or rural areas where high-speed internet may not be reliably available. Consequently, edge devices can function effectively even in challenging connectivity scenarios, ensuring that the safety monitoring system remains operational. As the technology continues to evolve, there is significant potential for integrating more sophisticated AI techniques, such as reinforcement learning or multi-modal data analysis, into these systems. Such advancements could further enhance detection accuracy and response capabilities, allowing the system to adaptively learn from new data and improve its performance over time.

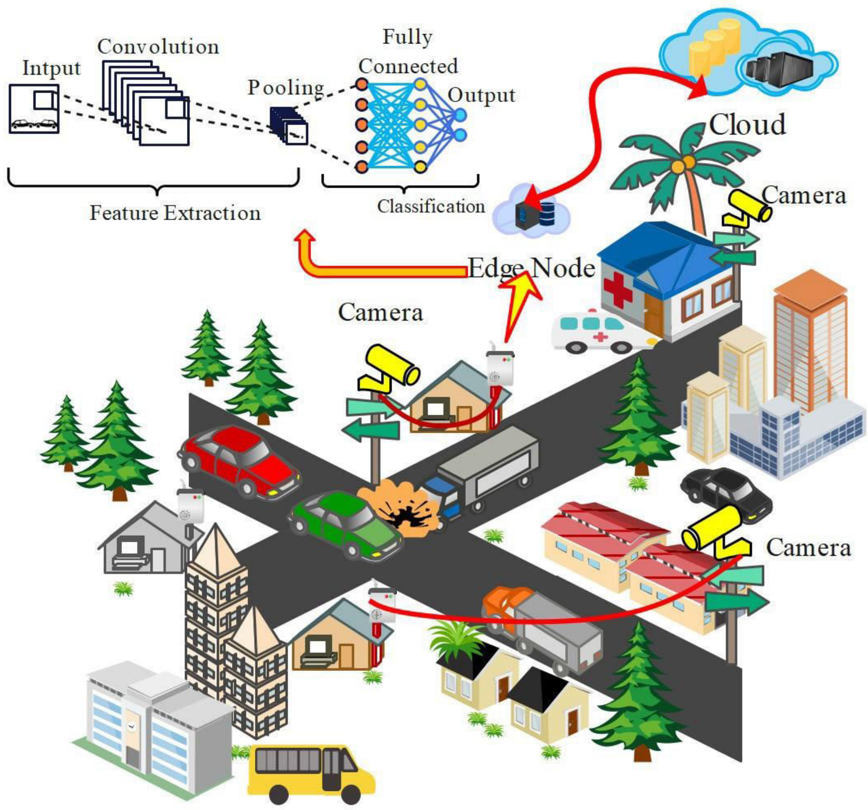

Fig 1: Edge node in real scenario

Once the accident is detected at the edge, the processed information is sent to cloud servers for further analysis, storage, and alert dissemination. This dual processing framework ensures a balanced load, where the cloud handles complex tasks such as long-term data storage and more in-depth analytics, while edge devices minimize latency by handling immediate, time-critical tasks. Additionally, the depicted system architecture highlights the collaboration between edge nodes and cloud platforms, ensuring faster response times, reduced network congestion, and enhanced bandwidth utilization.

This paper proposes an edge-cloud hybrid framework for accident detection, as illustrated, which achieves real-time event identification while maintaining the accuracy of deep learning models, notably CNN. The proposed framework provides an efficient and scalable solution for intelligent transportation systems, demonstrating enhanced detection performance with a 95.91% precision rate and significant reductions in latency compared to traditional cloud-only models. Through this novel architecture, our system ensures rapid accident response, as it strategically places edge devices near critical areas and offloads complex processing to the cloud when needed.

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II. LITERATURE SURVEY

The current body of research on accident detection systems using deep learning (DL) and edge-cloud computing has been evolving rapidly, with several significant contributions focusing on improving efficiency and responsiveness. Early studies concentrated primarily on cloud-based systems, which led to latency issues in real-time detection due to the heavy reliance on centralized processing. For instance, Afreen et al. investigated accident detection using CNN models such as GoogLeNet, AlexNet, and VGGNet, achieving high levels of accuracy. Ghosh et al. also developed a CNN-based accident detection system, reporting an impressive 95% accuracy

In recent years, the shift towards integrating **edge computing** with cloud systems has introduced enhanced capabilities for real-time processing by handling data locally at the edge. This approach mitigates network congestion and reduces response time, which is crucial in time-sensitive applications like accident detection. Wang et al. provided a detailed overview of how deep learning applications can be integrated into edge computing to improve efficiency and reduce latency.

Another branch of research has explored the use of Internet of Things (IoT) technologies in combination with deep learning for traffic and accident detection. Mondal et al. implemented deep learning-based solutions for monitoring wildlife near railway tracks, demonstrating the applicability of such frameworks in diverse safety-critical environments. Similarly, Sathya et al. proposed an IoT-based vehicular accident detection and alert system, integrating CNN models to enhance rescue efforts.

The literature also reflects significant advancements in the use of simulators for testing such frameworks, with iFogSim being widely used to simulate the performance of edge-cloud-based systems under realistic conditions. Mondal et al. further studied the integration of deep learning with edge devices to provide faster responses in edge-cloud environments, underlining the importance of efficient task offloading and scheduling strategies.

This evolving body of work indicates that the collaboration between edge and cloud computing plays a vital role in improving the performance of accident detection systems. Edge computing enhances processing speed and system efficiency, while deep learning algorithms ensure the accuracy of detection models. Future research is expected to focus on further optimizing this integration, with particular attention to minimizing energy consumption, improving security, and expanding the scalability of these systems to accommodate larger networks and more complex datasets.

III. METHODOLOGY

The methodology for the deep learning-based car accident detection framework in this PDF integrates **edge computing** and **cloud computing** to deliver real-time accident detection with minimal latency. The system architecture comprises three layers: **device layer**, **edge layer**, and **cloud layer**. The **device layer** includes IoT devices such as cameras and sensors that capture real-time data. This data is processed at the **edge layer**, which houses edge nodes closer to the source of data generation. The edge nodes perform preliminary analysis using lightweight deep learning models, specifically a **Convolutional Neural Network (CNN)**, to detect accidents instantly. By offloading computational tasks to the edge, the system minimizes the amount of data that needs to be transmitted to the cloud, thereby reducing network congestion and improving efficiency.

The **CNN model** used for accident detection includes multiple layers: three convolutional layers followed by max-pooling layers that extract features from input images (accident vs. non-accident). After this, the flattened output is fed into dense layers to make predictions about accidents. To prevent overfitting, L2 regularization is applied at each convolutional layer, ensuring the model generalizes well to unseen data. The **iFogSim simulator** is used to test the performance of this architecture, simulating various traffic conditions and assessing key parameters such as **latency**, **network usage**, and **execution time**.

During simulations, different scenarios involving up to 225 cameras were tested. Each camera continuously generated video streams, which were converted into still images by the system's image capture module for processing by the CNN model. The results showed that the edge-cloud framework significantly outperformed cloud-only systems in terms of

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lower latency and faster execution. The cloud layer is mainly responsible for long-term storage and more complex processing tasks, but only after the edge nodes have filtered and processed the data locally.

The model was trained on a publicly available **Kaggle dataset**, comprising images categorized as accidents or non-accidents, with hyperparameters fine-tuned empirically over 70 epochs. The CNN model achieved an accuracy of 95.91% with **precision**, **recall**, and **F1 scores** of 0.9574, demonstrating its effectiveness in real-time accident detection. The study concludes that this edge-cloud integration offers a robust and scalable solution for accident detection, improving system responsiveness and reducing bandwidth consumption compared to traditional cloud-only models
.

IV. EXPERIMENTAL RESULTS

The figure 2 serves as a visual validation of the model's performance, showing a high degree of accuracy by correctly labeling the majority of test images as either accidents or non-accidents. The classification results indicate that the proposed framework is effective in real-world scenarios where rapid detection of accidents is crucial. The system maintains precision in identifying accident occurrences with minimal errors

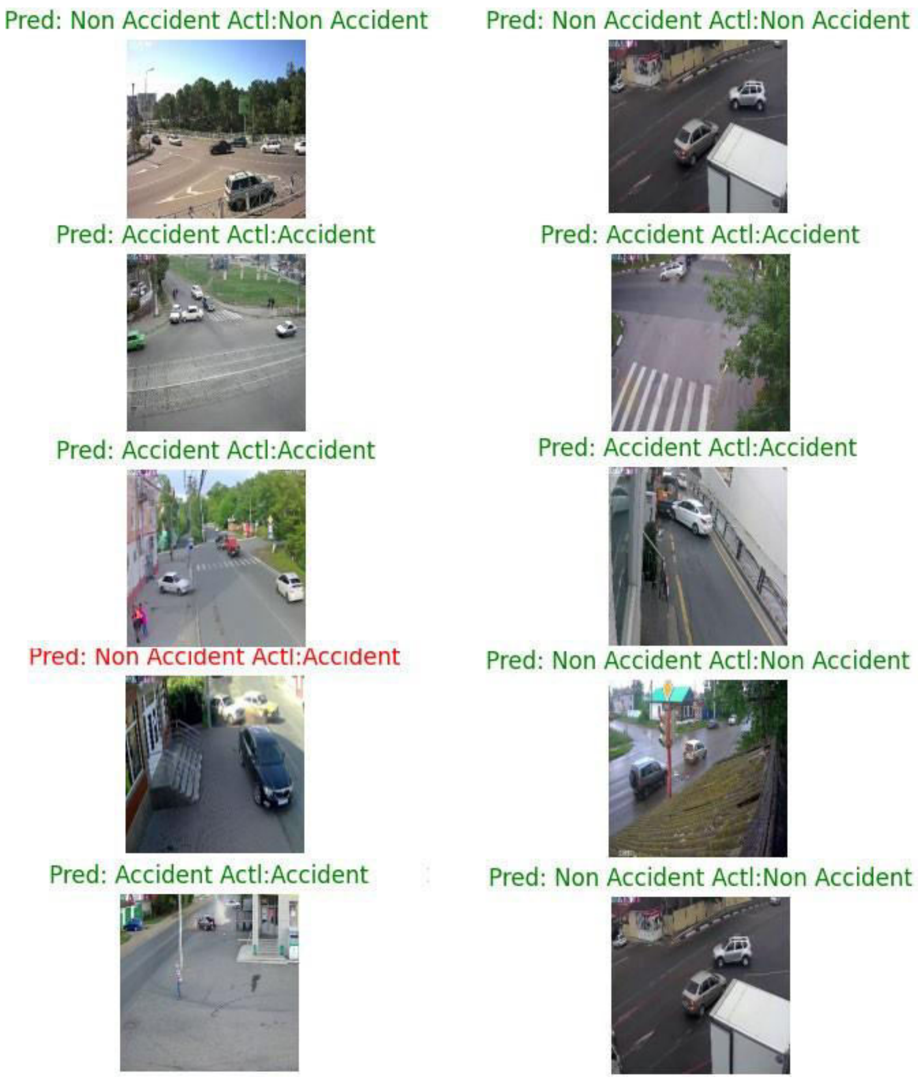

Fig 2: Representative results of accident detection using CNN based DL model

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Accident Detection: The CNN model successfully identifies frames from video footage that represent an accident scenario. The model highlights specific instances where vehicles are involved in crashes or unusual movements indicating an accident. These images are classified as "accidents," and the system flags them accordingly.

Non-Accident Detection: The model also processes images showing normal road conditions or situations that do not involve accidents. These frames are correctly identified as "non-accidents," demonstrating the ability of the CNN to differentiate between ordinary traffic scenes and critical events.

the CNN-based deep learning model for accident detection, showcasing how the model classifies test images as either "accident" or "non-accident." This figure presents a set of representative test images from the dataset, where 9 out of 10 images were correctly classified. The accident detection results highlight the model's capability to accurately identify visual cues from traffic footage, such as vehicle collisions or abnormal movement, indicating an accident. Additionally, the figure demonstrates the model's precision in distinguishing non-accident scenarios, where the images reflect normal road conditions with no crashes or incidents. By effectively separating accident and non-accident cases, Figure provides a visual confirmation of the CNN model's accuracy, which reaches 95.91%, showing its potential for real-time application in detecting accidents through edge computing. The results validate the system's performance in quickly processing and classifying real-world footage, ensuring timely detection and reduced false alarms.

V. CONCLUSION

The proposed deep learning-based accident detection framework using edge and cloud computing demonstrates significant improvements in real-time detection efficiency. By leveraging CNN models at the edge, the system reduces latency, network usage, and execution time compared to cloud-only approaches. With an accuracy of 95.91%, the model effectively identifies accidents while maintaining precision and recall. This study highlights the potential of integrating edge computing for enhanced road safety, providing a scalable and responsive solution for accident detection. Future research could focus on real-world deployments and multi-modal sensor integration to further improve performance.

the deep learning-based car accident detection framework using edge and cloud computing emphasizes the significant advancements achieved through this integration in real-time accident detection systems. The proposed framework, which combines edge computing with cloud-based resources, effectively addresses the limitations of traditional centralized cloud models by reducing latency, network usage, and execution time. The deployment of a Convolutional Neural Network (CNN) at the edge node enables rapid local processing of video footage from connected IoT devices, such as cameras and sensors, minimizing the need to transmit large volumes of data to the cloud for analysis. This leads to faster decision-making, allowing timely detection of accidents and prompt notification to emergency services, which is crucial in reducing response times and potentially saving lives.

The system was tested using the iFogSim simulator, where it demonstrated superior performance in comparison to cloud-only models, particularly in terms of latency and resource utilization. The framework’s CNN-based deep learning model, trained on the Kaggle accident dataset, achieved an impressive accuracy of 95.91%, with precision, recall, and F1 scores of 0.9574. This high level of accuracy in classifying accident and non-accident scenarios highlights the effectiveness of the model in real-world applications. The edge-cloud framework not only improves processing speed but also enhances the scalability and flexibility of the system, allowing it to handle a large number of connected devices and varying traffic conditions.

While the simulation results are promising, the conclusion acknowledges that real-world deployment of such a system would require further validation, particularly with larger datasets and more extensive sensor networks. Additionally, there are considerations for future research, such as enhancing multi-modal sensor fusion, optimizing energy consumption, and integrating the framework with existing traffic management and emergency response systems. Overall, this study demonstrates the potential of edge-cloud computing combined with deep learning to revolutionize accident detection, providing a scalable, efficient, and responsive solution for improving road safety.

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