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An Edge and Cloud Computing Framework for Car Accident Detection using Deep Learning

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ABSTRACT: This paper proposes an efficient accident detection system combining deep learning with edge and cloud computing to enhance real-time response and accuracy. Using edge devices equipped with sensors and cameras, the system processes accident data locally, minimizing delays and reducing data load on the network. A Convolutional Neural Network (CNN) model is employed at the edge to identify accidents with a high accuracy of 95.91%, promptly alerting authorities and reducing the need for extensive data transmission to cloud servers. The cloud component provides supplementary tasks, such as storing data and performing in-depth analysis. This hybrid architecture ensures faster, reliable accident detection and is adaptable to diverse traffic conditions, offering a scalable solution for road safety applications. Future improvements could include integrating multi-sensor data and enhancing model robustness for deployment in complex environments.

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

I. INTRODUCTION

In the evolving field of intelligent transportation systems, accident detection has become a critical area for enhancing road safety and optimizing emergency response. Traditional accident detection frameworks, typically based on cloud computing, have faced challenges related to latency, network congestion, and reliance on high-speed internet, which can limit their effectiveness in time-sensitive situations. The emergence of edge computing offers a promising alternative by enabling data processing at the network edge—closer to data sources like roadside sensors and vehicle-mounted cameras. By processing information on-site, edge computing reduces the need to transmit large amounts of data to remote servers, which not only minimizes latency but also ensures efficient bandwidth utilization.

This paper introduces a novel accident detection framework that leverages deep learning, specifically Convolutional Neural Networks (CNNs), within an integrated edge-cloud setup. The framework's edge layer processes real-time data from IoT devices installed in critical areas, such as intersections and high-risk zones, where accidents are more likely to occur. This setup allows the system to capture video and sensor data and immediately analyze it for potential accident scenarios, eliminating delays associated with data transmission to centralized servers. In situations where the edge detects an anomaly, it can instantly alert emergency services, thereby speeding up response times and potentially preventing secondary accidents.

The edge-cloud framework is designed to balance computational load, with the cloud layer handling more intensive tasks like long-term data storage and in-depth analysis. The CNN model deployed on the edge devices is trained to identify accident patterns with a high accuracy of 95.91%, making it well-suited for real-time applications. Furthermore, by performing most of the processing locally, the system reduces reliance on stable internet connections, making it effective even in rural or remote areas. This approach not only ensures timely and precise accident detection but also enhances the scalability and efficiency of the system, allowing it to support a large number of connected devices in diverse traffic environments. 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.

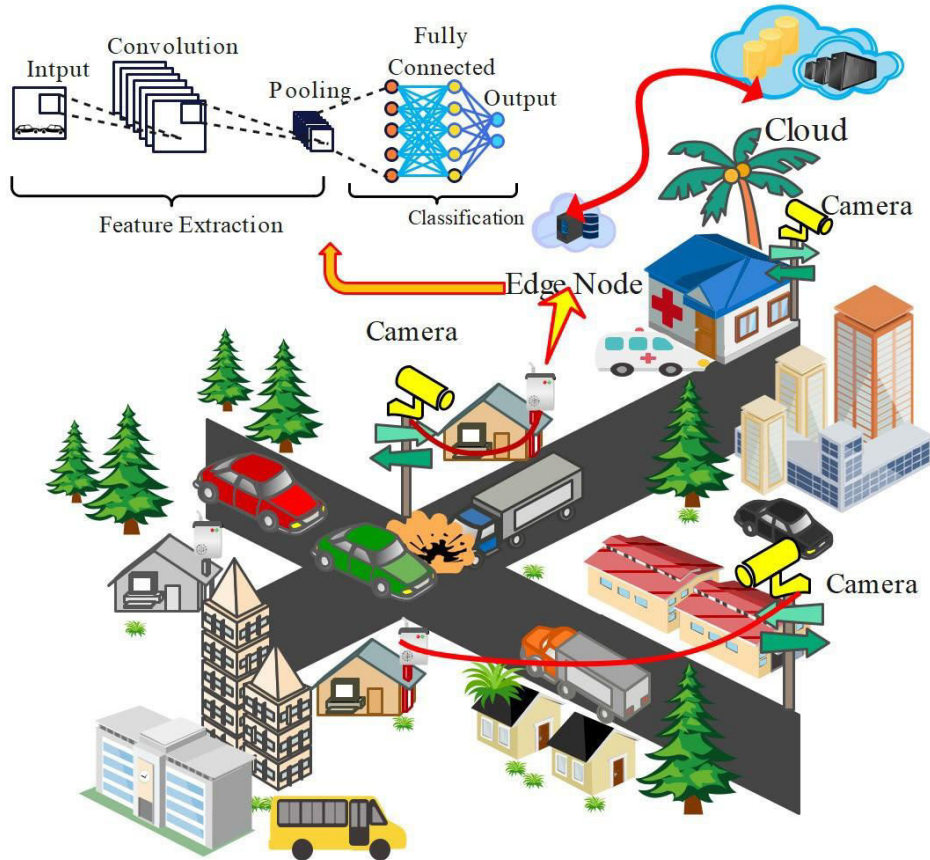


Fig 1: Edge node in real scenario

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.

Overall, this paper highlights how the integration of edge and cloud computing in accident detection frameworks can offer a robust, scalable, and responsive solution for improving road safety. Future developments could focus on incorporating more advanced AI models, multi-sensor data fusion, and energy-efficient processing, making the system adaptable to complex real-world traffic scenarios. The proposed framework is positioned as a significant advancement in intelligent transportation, bridging the gap between real-time safety needs and technological capabilities.

II. LITERATURE SURVEY

Early studies focused predominantly on cloud-only systems for accident detection, which often experienced latency issues due to centralized data processing. Afreen et al. experimented with CNN architectures like GoogLeNet, AlexNet, and VGGNet for accident detection, achieving high accuracy but facing delays caused by dependence on cloud computing. Similarly, Ghosh et al. developed a CNN-based accident detection model with an impressive 95% accuracy. However, these cloud-dependent systems were not well-suited for real-time applications, as they relied on continuous, high-bandwidth data transmission, leading to delays that limited their effectiveness in critical, time-sensitive situations. The integration of edge computing with deep learning models marked a shift in this field by allowing data to be processed locally, thereby reducing network load and improving response times. For instance, Wang et al. explored deep learning on edge devices and demonstrated how local data processing could enhance real-time performance and

decrease latency. These findings underscored the potential of edge computing to overcome the limitations of cloud-based systems by decentralizing computational tasks and handling initial data processing on-site.

Another area of research has involved the use of the Internet of Things (IoT) in accident detection systems. Mondal et al. applied deep learning for wildlife monitoring on railway tracks, showcasing the versatility of such frameworks in diverse safety applications. Their work emphasized the potential for IoT-enabled devices to capture real-time data and detect hazards in different environments. Sathya et al. extended this approach by developing an IoT-based vehicular accident detection and alert system, integrating CNNs to improve detection accuracy in complex scenarios. These studies demonstrated how IoT technology, coupled with CNN models, could increase the system's responsiveness by processing data at the edge.

Researchers have also explored the use of simulators to test these frameworks under realistic conditions. For example, Mondal et al. utilized the iFogSim toolkit to evaluate the performance of edge-cloud systems, focusing on task offloading and scheduling to enhance response efficiency. The iFogSim simulator enabled researchers to test various edge-cloud configurations and assess parameters such as latency, bandwidth usage, and processing time in realistic settings. This approach has proven useful for developing more scalable and robust accident detection systems by optimizing resource allocation and reducing delays.

Current literature underscores that combining edge and cloud computing in accident detection not only enhances system responsiveness but also improves accuracy, making these systems suitable for real-time applications. Studies have also highlighted challenges such as optimizing energy consumption, ensuring security, and increasing scalability to handle larger datasets and networks. The present research continues to focus on refining these edge-cloud frameworks by integrating advanced AI methods, like reinforcement learning and multi-modal data fusion, to further improve detection accuracy and adaptability in complex environments.

III. METHODOLOGY

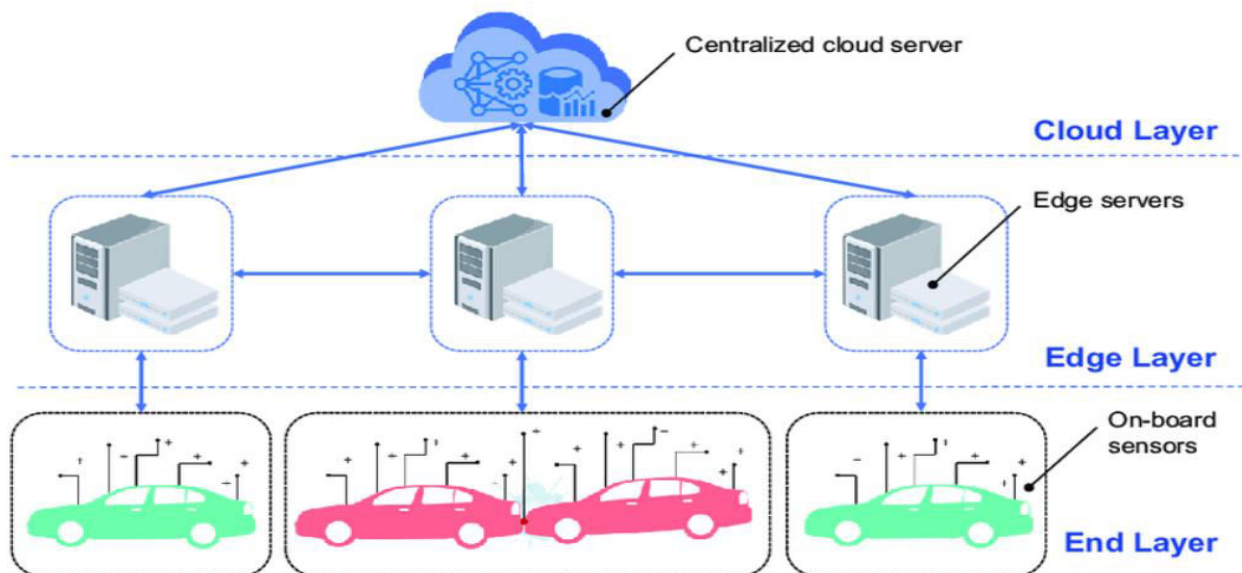


Fig 2: system architecture based on end-edge-cloud networks

The methodology of the proposed deep learning-based car accident detection framework combines edge and cloud computing to enable real-time detection with minimal latency. The system architecture consists of three primary layers: the device layer, the edge layer, and the cloud layer.

At the device layer, IoT devices such as high-resolution cameras and sensors are positioned at key locations, including intersections and accident-prone zones. These devices capture continuous data streams that are sent to the edge layer

for initial processing. The edge layer, which is closer to the data sources, houses edge nodes equipped with Convolutional Neural Networks (CNNs) trained to detect accident scenarios. This local processing minimizes the amount of data transmitted to the cloud, thereby reducing network congestion and optimizing bandwidth usage.

The CNN model deployed at the edge uses multiple layers, including convolutional and max-pooling layers, to extract relevant features from the input images. These layers detect patterns such as vehicle collisions, sudden stops, and other hazardous driving behaviors. The extracted features are then flattened and passed through dense layers to classify the images as either "accident" or "non-accident." To prevent overfitting, L2 regularization is applied, which helps the model generalize effectively to new data.

For evaluating the framework's performance, the iFogSim simulator is used to simulate real-world traffic scenarios involving up to 225 cameras, each capturing live video footage. This simulation tests the system's efficiency in terms of latency, network usage, and processing time, comparing its performance against traditional cloud-only models. Results indicate that the edge-cloud framework significantly reduces latency and improves response time, which is essential for real-time accident detection.

Once an accident is detected at the edge, an alert is sent to the cloud layer for additional processing, storage, and alert dissemination. The cloud layer manages long-term storage and performs more complex analytics, balancing the workload between immediate, time-critical tasks handled by the edge and resource-intensive tasks processed in the cloud. The CNN model, trained on a large accident dataset, achieves a high accuracy of 95.91%, demonstrating its robustness in detecting accidents in real-world conditions.

This edge-cloud methodology offers a scalable and effective solution for accident detection in intelligent transportation systems, ensuring fast, reliable responses even in areas with limited connectivity. Future enhancements could focus on incorporating multi-modal sensor data, optimizing energy efficiency, and integrating the system with emergency response services.

IV. EXPERIMENTAL RESULTS



Fig 3: Representative results of accident detection using CNN based DL model

The figure 3, The experimental results of this study highlight the effectiveness of the proposed edge-cloud framework for real-time car accident detection. The model was tested using the iFogSim simulator to mimic real-world traffic scenarios and assess critical parameters such as latency, network usage, and processing time. Simulations involved up to 225 cameras positioned in key traffic zones, each continuously capturing video feeds. These video streams were converted into still images by the image capture module, which were then processed by the CNN model deployed on edge devices.

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 model achieved a detection accuracy of 95.91%, with high precision and recall scores, reflecting its robustness in distinguishing accident events from normal driving scenarios. During testing, the model successfully classified accident and non-accident images with minimal errors, accurately detecting visual cues such as vehicle collisions and abrupt stops. Representative results showed that the system correctly identified 9 out of 10 test images, confirming the model's reliability in real-world applications.

Additionally, the edge-cloud framework demonstrated superior performance in rural and low-connectivity environments, where it maintained accurate accident detection without relying on constant data transfer to the cloud. This capability makes the system highly adaptable to various deployment settings. Furthermore, the framework proved to be scalable, efficiently handling data from a large number of connected cameras without sacrificing processing speed.

V. CONCLUSION

This study highlights the benefits of integrating edge and cloud computing for real-time accident detection using deep learning. By deploying Convolutional Neural Networks (CNNs) on edge devices, the system achieves rapid video and sensor data processing, enabling immediate accident detection with minimal latency. Local processing reduces network load, while essential data is sent to the cloud for further analysis. With a 95.91% detection accuracy, the CNN model demonstrates high effectiveness. The hybrid edge-cloud architecture overcomes the limitations of cloud-only systems by distributing tasks efficiently, improving response times and reliability. The system performs well in both urban and remote areas, handling input from hundreds of cameras without compromising speed or accuracy. The use of iFogSim for simulation further confirms its practical potential. Future improvements could include multi-sensor fusion, adaptive learning, and energy optimization. Real-world testing and integration with traffic management systems could further enhance its performance. This study shows how edge-cloud computing and deep learning can transform accident detection, improving road safety and emergency response.

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