AI-Based Road Accident Detection and Emergency Response Systems: A Systematic Survey of Vision-Driven and Intelligent Transportation Approaches

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***Abstract*—Road traffic accidents continue to be a critical global safety challenge, causing millions of fatalities and severe injuries annually due to delayed detection and inefficient emergency response mechanisms. Existing traffic monitoring and dispatch systems often fail to provide timely intervention, particularly in densely populated urban environments and high-speed road networks.**

The objective of this survey is to systematically review Artificial Intelligence (AI) and Machine Learning (ML) based approaches for automatic road accident detection and emergency response. The study focuses on analysing vision-based detection systems, traffic data analytics platforms, and intelligent emergency management frameworks reported in the literature.

Research papers published between 2015 and 2025 were collected from IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar using keywords related to accident detection, computer vision, intelligent transportation systems, and emergency response. Relevant studies were selected based on methodological rigor and applicability to real-world scenarios.

The survey findings indicate that CNN-based vision systems, real-time traffic analytics, and AI-assisted emergency dispatch platforms significantly improve detection accuracy and reduce response time. However, challenges such as lack of real-time deployment, limited datasets, poor model explainability, and weak system integration remain unresolved.

Future research should emphasize unified, explainable, and real-time AI-driven frameworks that seamlessly integrate accident detection with intelligent emergency response to enhance road safety and save lives.

***Index Terms*—Road Accident Detection, Artificial Intelligence, Deep Learning, Emergency Response, Intelligent Transportation Systems**

I. INTRODUCTION

Road traffic accidents are among the leading causes of mortality worldwide, with approximately 1.19 million deaths reported annually. In addition to fatalities, millions of individuals suffer long-term disabilities, placing a significant burden on healthcare systems and national economies. Developing countries experience disproportionately higher accident rates due to rapid urbanization, inadequate infrastructure, and limited access to timely emergency care.

A major factor contributing to high fatality rates is delayed accident detection and slow coordination among emergency responders. Conventional accident reporting mechanisms rely

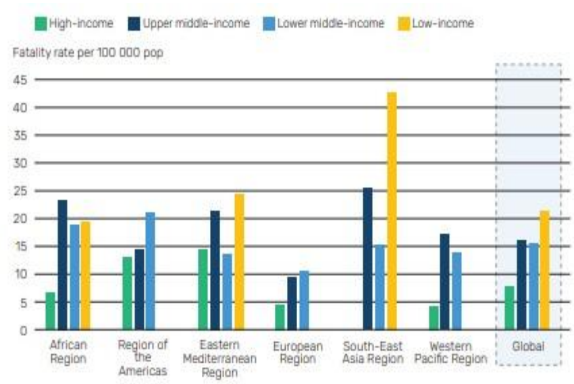


Fig. 1. Global road traffic fatality rate per 100,000 population by WHO region and income level (reproduced from [1]).

heavily on manual intervention through eyewitness reports or police notifications, leading to critical delays during the "golden hour" following an accident.

Advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled automated accident detection systems using surveillance cameras, traffic data, and intelligent transportation infrastructure. These systems aim to reduce detection time, assess accident severity, and initiate rapid emergency response.

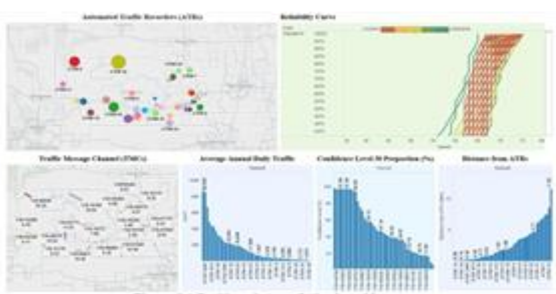
II. LITERATURE SURVEY

A. Vision-Based Accident Detection Systems

Vision-based accident detection systems utilize roadside or traffic surveillance cameras combined with deep learning models to automatically identify accident scenarios. Convolutional Neural Networks (CNNs) are the dominant architecture used due to their ability to extract spatial and structural features from images.

Gupta et al. evaluated CNN architectures such as EfficientNet, DenseNet, and MobileNet for classifying accident and non-accident images [2]. These models analyse visual cues including vehicle deformation, abnormal orientation, collision angles, and road obstructions.

Fig. 2. General architecture of CNN-based vision-driven road acci detection systems (adapted from [2]).



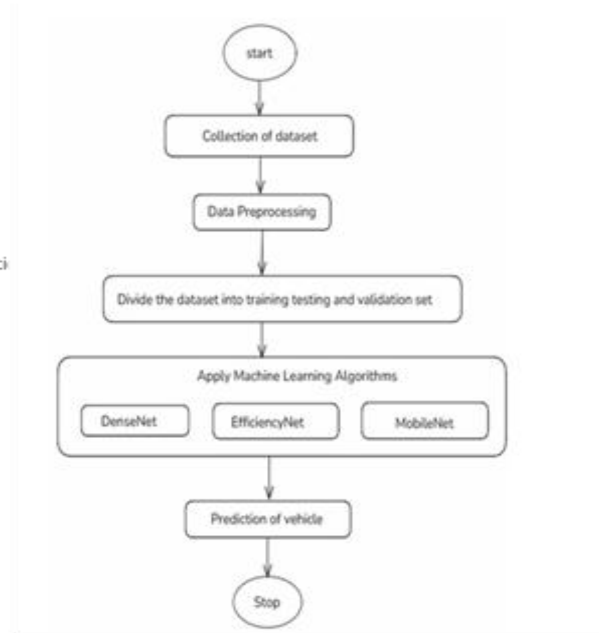


Fig. 3. INRIX real-time and historical traffic data monitoring framework (adapted from [6]).

The effectiveness of CNN-based architectures in accident detection is consistent with their performance in other safety critical applications. Gupta et al. demonstrated that optimized CNN embedders and activation functions significantly improve classification accuracy in medical imaging tasks [8], supporting their adoption in vision-based road safety systems.

While vision-based approaches demonstrate high detection accuracy, their performance is sensitive to environmental factors such as lighting conditions, weather variations, occlusions, and camera placement.

B. Traffic Data–Driven Incident Detection

Traffic data-driven approaches infer accidents by analysing real-time and historical traffic patterns. Platforms such as INRIX collect data from connected vehicles, GPS-enabled mobile devices, and roadside sensors to monitor traffic speed, density, and congestion. Sharma et al. demonstrated that abnormal speed drops and congestion anomalies can indicate potential accidents [6]. These systems offer wide-area coverage and scalability.

Machine learning challenges such as data imbalance and large-scale processing are also relevant in this domain. Gupta et al. highlighted that probabilistic models such as Na¨ıve Bayes require careful handling of imbalanced datasets to avoid biased predictions [9]. Further studies emphasize scalable bigdata learning frameworks for real-time analytics [10].

C. Emergency Response and Dispatch Systems

Emergency response systems such as Computer-Aided Dispatch (CAD) platforms improve coordination between police,

Fig. 4. LLM-driven emergency communication and crisis response framework (adapted from [11]).

ambulance, and fire services. Cullison et al. showed that intelligent CAD systems enhance dispatch efficiency but remain dependent on human operators [3].

WebEOC enables centralized emergency information sharing but lacks automated accident detection [5]. Public Alert and Warning Systems (PAWS) further support emergency communication. Sadiq et al. reviewed PAWS frameworks and identified gaps in alert dissemination, timeliness, and public trust during emergencies [4].

D. AI-Powered Crisis Management Systems

Recent research explores the use of Large Language Models (LLMs) for emergency management. Otal and Canbaz proposed an AI-powered crisis response framework using LLaMA2 to analyse emergency messages and social media content. LLM-based systems complement traditional emergency response mechanisms by enabling rapid analysis of unstructured textual data. During large-scale incidents, emergency centers receive massive volumes of reports through social media, emergency calls, and messaging platforms. Otal and Canbaz demonstrated that LLMs can summarize, classify, and prioritize such information in real time [11].

Despite these advantages, LLM-based frameworks operate primarily in the digital information space. Without integration with physical sensing systems such as cameras and traffic sensors, their situational awareness remains incomplete. Hybrid architectures combining vision-based detection, traffic analytics, and LLM-driven decision support represent a promising direction for intelligent emergency response systems.

TABLE I COMPARATIVE ANALYSIS

Author	Year	Method	Dataset Used	Accuracy	Limitation
Kushawah et al. [2]	2024	CNN-based vision system with automated alert generation	Traffic surveillance video frames	92–95%	Limited real-time deployment and dependency on camera quality
Sharma et al. [6]	2019	Traffic speed and congestion anomaly detection	INRIX real-time and historical traffic data	Not explicitly reported	Cannot visually confirm accidents; false positives possible
Sadiq et al. [4]	2020	Public Alert and Warning System (PAWS) analysis	Emergencyalert and warning records	Not applicable	Alerts are manually triggered; no automatic detection
Jour [5]	2012	WebEOC emergency coordination platform	Emergency event logs	Not applicable	Lacks AI-based or automated accident detection
Otal and Canbaz [11]	2024	LLM-based crisis response and communication system	Social media posts and emergency messages	Not explicitly reported	Not integrated with physical accident sensing systems

III. RESEARCH GAP

Despite substantial progress in AI-based road accident detection and emergency response systems, several critical research gaps remain evident from the existing literature.

Firstly, most current solutions focus on isolated components such as accident detection or emergency communication, resulting in the lack of unified end-to-end frameworks that seamlessly integrate accident detection, severity assessment, emergency dispatch, and public alert mechanisms [2], [3], [5]. This fragmentation limits the overall effectiveness of intelligent transportation safety systems.

Secondly, the availability of large-scale, diverse, and real-world accident datasets remains limited. Many vision-based approaches rely on curated or synthetic datasets captured under controlled conditions, which restricts model generalization when deployed in complex real-world environments involving varied lighting, weather, and traffic conditions [2].

Thirdly, deep learning models used for accident detection often function as black-box systems, offering limited explainability. The lack of interpretable decision-making poses significant challenges in safety-critical applications, where transparency, accountability, and trust are essential for adoption by emergency authorities and policymakers.

Additionally, there is insufficient emphasis on real-time and edge-based deployment of accident detection systems. Most studies validate models in offline environments without addressing computational constraints, latency, and scalability issues associated with continuous real-time monitoring on edge devices or roadside infrastructure [6], [10].

Finally, institutional and organizational factors influencing system deployment are largely overlooked. Weak institutional risk maturity, inadequate coordination among emergency stakeholders, and lack of standardized operational protocols significantly hinder the effective implementation of intelligent emergency response systems [7]. Addressing these organizational challenges is crucial for translating AI-based research solutions into real-world impact

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IV. FUTURE RESEARCH DIRECTIONS

Based on the identified research gaps, the following future research directions are recommended:

- Unified End-to-End Frameworks: Future systems should focus on developing integrated architectures that combine accident detection, severity estimation, emergency dispatch, and public alert mechanisms into a single end-to-end intelligent framework.
- Large-Scale Real-World Datasets: There is a strong need for publicly available, large-scale accident datasets captured under diverse real-world conditions, including different weather, lighting, traffic density, and camera perspectives, to improve model robustness and generalization.
- Explainable AI for Safety-Critical Systems: Future research should incorporate Explainable AI (XAI) techniques to improve transparency and interpretability of deep learning models, enabling better trust, accountability, and adoption by emergency authorities.
- Real-Time and Edge-Based Deployment: Lightweight deep learning models and edge-computing solutions should be explored to support low-latency, real-time accident detection on roadside cameras and embedded devices.
- Multi-Modal Data Fusion: Integrating vision-based data with traffic sensor information, GPS data, and textual inputs from emergency communications and social media can enhance detection accuracy and situational awareness.
- Integration with Intelligent Emergency Response Systems: Future solutions should enable seamless interoperability between AI-based detection systems and existing emergency response platforms such as CAD and public alert systems to reduce response time.
- Organizational and Institutional Readiness: Research should address institutional risk maturity, standard operating procedures, and inter-agency coordination frameworks to ensure effective real-world deployment and sustainability of intelligent emergency systems.

V. CONCLUSION

This survey presented a comprehensive review of Artificial Intelligence (AI)-based road accident detection and emergency response systems, with a focus on vision-driven approaches, traffic data analytics, and intelligent emergency management frameworks. Vision-based accident detection systems utilizing deep learning and convolutional neural networks demonstrate strong potential for automatic and timely identification of road accidents, significantly reducing detection delays. Traffic data–driven incident detection methods offer scalable monitoring capabilities across large transportation networks but lack visual verification, highlighting the importance of integrating multiple data sources for improved reliability.

The review further indicates that existing emergency response platforms such as Computer-Aided Dispatch (CAD), WebEOC, and Public Alert and Warning Systems enhance coordination among emergency agencies but remain largely dependent on manual incident initiation and are not fully integrated with automated detection technologies. Recent advances in AI-powered crisis management systems based on Large Language Models improve situational awareness by processing unstructured data; however, their limited connection with physical accident sensing infrastructure restricts their standalone effectiveness.

Overall, the comparative analysis reveals that current research predominantly addresses individual system components rather than holistic end-to-end solutions. Critical challenges persist, including the scarcity of real-world accident datasets, limited model explainability, insufficient real-time deployment studies, and weak institutional readiness. Addressing these limitations through unified, explainable, and real-time AIdriven frameworks has the potential to significantly enhance road safety outcomes and the effectiveness of emergency response systems.

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