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Towards Safer Roads: AI-Powered Accident Prevention for Real Time Driver Monitoring and Pothole Detection

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Abstract - Road accidents and dangerous driving conditions, such as potholes, are major cause to accidents and injuries worldwide. This Paper presents an AI-driven road safety system that combines an approach to reduce accidents with real-time pothole detection aims to enhance road safety and improve driving experiences. This system collects data from different sources, which includes cameras, road sensors, and weather updates. Using deep learning models, like Long Short-Term Memory (LSTM) networks, it identifies potential risks such as sudden braking, dangerous driving, or hazardous road conditions. These help to enable real-time, such as issuing driver alerts, notifying emergency response teams. Additionally, the system uses computer vision and sensor-based analytics to detect potholes and other road anomalies, creating a comprehensive safety framework. The system maintains a monitoring distance of 30 meters, continuously capturing real-time scenes using cameras and AI algorithms. Alerts are sent to users to slow down when hazards are detected, ensuring safety. The system also informs local authorities to facilitate timely road maintenance. This dual functionality helps to reduce accidents, enhance traffic flow, and maintain road quality. This intelligent and proactive approach to road safety aims to minimize human errors, reduce accident rates, and enhance overall traffic management. Scalable and adaptable to urban and rural settings, the proposed solution represents a significant step toward building safer, smarter, and more sustainable transportation ecosystems.

***Key Words*:** Artificial Intelligence, Deep Learning, Long Short-Term Memory (LSTM) network, IOT, Recurrent Neural Networks, Computer Vision, Road Safety, Accident prevention.

1.INTRODUCTION

Technology has turned to the cornerstone in the art of addressing challenges with novel solutions that avail the use of Artificial Intelligence. Among the many techniques in AI, Long Short-Term Memory models have become strong tools in handling sequential data and also appropriate for accident prevention and road safety systems. LSTMs are a special kind of RNN (Recurrent Neural Network) designed to analyze and predict outcomes from time-series data. They can process sequential data on the vehicle's speed, acceleration, and braking patterns to offer deep insight into road safety. LSTMs will analyze driving behavior in detecting anomalies, predicting probable collisions, assessing real-time road conditions, and even finding potholes. The architecture diagram for the AI-Driven Road Safety System for Accident Prevention includes:

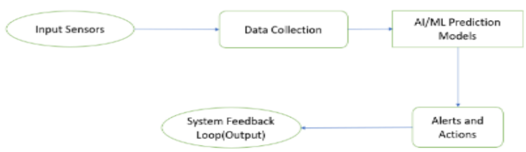

Fig.1: Architecture for AI-Driven Road Safety System for Accident Prevention

AI-powered accident prevention in road safety using LSTM, with real-time processing, marks a new approach in transport safety. The poor infrastructure and human error together are blamed as the major causative factors for accidents in traffic worldwide, taking millions of fatalities and injuries across the world every year. This is not a loss to an individual but economic destruction, disruption of societies, and emotional distraught for several. This paper offers enhanced driver assistance, monitoring of road conditions, and the prediction of possible hazards, including potholes. This paper discusses an AI-based system that is designed to enhance road safety through: Predicting potential risks with AI models.

- Providing timely warnings to drivers and authorities in real time.
- Using IoT sensors for monitoring roads and vehicles.

The philosophy behind this paper involves the use of computer vision and LSTM models in proactive safety to reduce road accidents. In this system, the road surface and weather analysis, in conjunction with driver behavior, predict hazards within a set range of 30 meters. It integrates real-time alerts using IOT sensors in support of drivers for safer decision-making.

PROBLEM STATEMENT

Road accidents are a leading cause of fatalities worldwide. It also poses a significant global threat, resulting in millions of fatalities and injuries each year. The traditional systems like manual monitoring, basic driver monitoring and speed detection cameras lack in real time monitoring of the driver behavior, weather conditions and potholes. The existing systems have limited functionality and prone to human error.AI driven road safety systems aim to minimize the accidents by utilizing AI, Machine learning and IOT models.

2. LITERATURE SUREVY

ABHIRAM KARUKAYIL et.al. (2024) In this article, the authors were presented about the methodology that integrates LiDAR (Light Detection and Ranging) with RGB camera data to enhance depth information for accurate pothole characterization. The data Generated from this methodology are trained using different versions of YOLO models.

MALIK HASNAIN AHMED et.al. (2024) In this article, the authors were presented about the leverage transfer learning, employing the VGG-16 model, for depression detection in drivers. The proposed model could be integrated with other technologies such as GPS, telemetry, and driver monitoring system.

POOYAN KHOSRAVINIA, et.al (2023) In this Paper, the author presented DBD system deployed on Raspberry Pi at the network edge to analyze the driver's driving behavior locally. The proposed system consists of monitoring dashboard to display sensor data, prediction results, and daily reports on driving behavior conditions.

K. RAVEENDRA REDDY, ANDA.MURALIDHAR (2023): In this paper, the authors were presented Federated learning which is a ML technique that allows multiple edge devices to collaboratively train a shared model while keeping the data locally. With the use of ML algorithms has gained significant attention in recent years especially in road traffic and vehicle safety in the context of the Internet of Vehicles (IV).

ASANKA G. PERERA, et.al. (2022) In this article, the authors were presented about the Deep learning and image processing which can build an automatic roadside severity detection system and combine camera configuration data with a neural network detector to develop a distance vs pixel model for reliable road severity distance calculation.

UMA MAHESWARI, et.al. (2022) In this article, the authors were presented about methods such as EAR, MAR, and the proposed novel FAR were used for feature extraction and adopting ensemble classification algorithms and CNN. The proposed work tested on datasets such as NTHU-DDD, Yaw DD, and a proposed dataset EMOCDS (Eye and Mouth Open Close Data Set).

Khan Muhammad, et.al (2021) In this article, the authors were presented about the advanced artificial intelligence (AI) techniques and deep learning (DL) approaches which includes measurement, analysis, and execution, with a focus on road, lane, vehicle, pedestrian, drowsiness detection, collision avoidance, and traffic sign detection through sensing and vision-based DL methods for Safe Autonomous Driving.

ALEXEY KASHEVNIK, et.al (2021) In this article, the authors were presented about the road accidents reduction, to detect driver inattention and distraction that visualizes the whole detection information chain from used sensors, behavior and inferred distraction type for detecting the three main distraction detection approaches: manual distraction, visual distraction, and cognitive distraction

QIWEI XU, et.al (2020) In this article, the authors were presented about Yolo network. The underlying core algorithm of this system adopts the YOLO v3 network with the best comprehensive detection performance in the end to-end network. Besides, the YOLO v3 network, mAP (mean Average Precision) is also used to improve by setting the scale that meets the target to be detected.

Kyle Sama, et.al. (2020) In this article, the authors were presented about extracting Human-Like driving behaviors from expert driver data using Deep Learning to extract latent features from the collected data. Results in a simulator implemented in ROS show that the autonomous agent built with the driving behaviors was capable of driving similarly to expert human.

RESEARCH GAPS

- The common research gaps include limited integration with technologies like in-vehicle sensors, IoT systems, or traffic management networks restricts holistic solutions.
- sensor fusion techniques, like LiDAR and deep learning techniques like CNN, RNN(LSTM) are underexplored for consistent performance across varied conditions.
- A lack of diverse, representative datasets reflecting various demographics and environmental conditions affects model generalization.
- Insufficient focus on real-time detection, adaptive capabilities for dynamic conditions, and also giving alerts to the drivers incase of drowsiness.
- Robustness under diverse conditions, such as varying weather, lighting, and road scenarios, as well as sensor failures while detecting the potholes.
- Challenges in scalability, with many solutions not optimized for large-scale urban environments or complex scenarios.

OBJECTIVES

- To Reduce road accidents and injuries by detecting and addressing hazardous driving conditions in real-time.
- To Implement advanced deep learning models, such as LSTM networks, CNN, for risk identification and driver alerts.
- For achieving the goal we use computer vision (YOLO, Mask R-CNN) using ai frameworks (Open CV, Tensor flow) and sensor(proximity)-based analytics for pothole detection and road anomaly monitoring.
- Provide continuous monitoring of road conditions within a 30-meter distance and issue alerts to improve driver safety.
- Enable timely road maintenance by notifying local authorities and improving overall traffic management.
- Offer a scalable and adaptable solution for enhancing road safety in both urban and rural environments.

3. METHODOLOGY

The Methodology focuses on developing a AI-Driven Road Safety System for Accident Prevention Using LSTML Models. Basically, The Road accident is a global issue, contributing to a significant number of fatalities and injuries annually. The primary causes often include driver drowsiness, poor road conditions such as potholes, adverse weather, and unforeseen obstacles. These accidents not only result in the tragic loss of human lives but also have far-reaching consequences that ripple through societies. To Reduce road accidents, This paper introduces a AI based System for road safety. Leveraging advancements in Artificial Intelligence, Long Short-Term Memory models, a type of recurrent neural network (RNN), provide a robust framework for analyzing time-series data to predict and prevent accidents. By continuously monitoring and processing sequential data from sensors, cameras, and other inputs, LSTM models enable the detection of hazardous patterns and real-time alerts, ensuring proactive measures to enhance road safety.

- Predicting potential risks using AI models.
- Providing real-time alerts to drivers and authorities.
- Using IoT sensors for road and vehicle monitoring.
- Additional feature: Incorporating blockchain for secure data logging and sharing.
- The basic method concentrates on reducing road accidents by leveraging **computer vision** to provide a proactive safety solution. The system analyzes road surfaces, weather conditions, and driver behavior to predict hazards within a set range of **30 meters**. It combines real-time alerts and data analytics to assist drivers in making safer decisions.

Proposed architecture

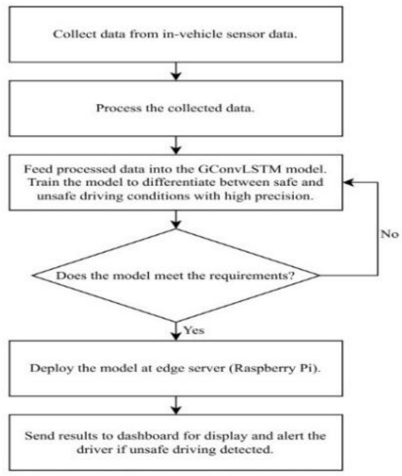

Fig.2. Architecture of Road Safety System

Algorithm:

Algorithm to Develop AI-Driven Road Safety System Using LSTM Models:

1. Step-1: Focus on detecting potholes, driver drowsiness, and objects.
2. Step-2: Use sensors, cameras, and APIs for road, driver, and environment data.
3. Step-3: Clean, normalize, and organize data into sequences.
4. Step-4: Design an LSTM-based model to analyze time-series data.
5. Step-5: Train using labelled data and validate its performance.
6. Step-6: Install the model on edge devices for real-time use.
7. Step-7: Issue warnings or take actions like braking when risks are detected.
8. Step-8: Use new data to refine the model over time.

The proposed AI-driven road safety system employs a combination of Deep Learning, IoT sensors, and Computer Vision to enhance road safety and minimize accidents. Real-time data is collected from cameras, road sensors, and weather updates to monitor road and vehicle conditions. Using Long Short-Term Memory (LSTM) networks, the system analyzes sequential data such as speed, acceleration, and braking

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patterns to predict potential hazards, including sudden braking or collisions. Simultaneously, Computer Vision algorithms detect road anomalies like potholes and surface irregularities. The system provides real-time alerts to drivers and notifies authorities for timely road maintenance. This proactive methodology ensures a safer driving environment, improves traffic management, and supports sustainable road infrastructure development.

4. RESULTS AND DISCUSSIONS

This paper demonstrates significant advancements in road safety, autonomous driving, and infrastructure management using AI and deep learning. The optimized Our-YOLO model improved road detection accuracy by 5.43%, while a CNN-based system accurately detected drowsiness using features like EAR, MAR, and FAR, validated on datasets like EMOCDS and NHTU-DDD. A holistic distraction detection framework successfully identified manual, visual, and cognitive distractions, integrating modern vision techniques. In autonomous driving, deep learning methods enhanced safety tasks such as pedestrian detection and collision avoidance, though challenges like explainability, robustness, and energy efficiency persist. Pothole detection combined YOLOv5 with LiDAR for precise 3D analysis, while the GConvLSTM-based Driving Behavior Detection system achieved 98.1% accuracy with real-time edge deployment. Despite these successes, issues like computational efficiency, adaptability to dynamic scenarios, and scalability for diverse environments remain key areas for future research and development.

Road Information Detection using Our-YOLO Model: The Our-YOLO network, an enhanced version of YOLOv3, demonstrated a notable improvement in road detection accuracy, achieving a 5.43% increase compared to the original model. This improvement was primarily due to the integration of a dual feature extraction network structure and an attention mechanism that fused auxiliary and backbone network features effectively. While the detection accuracy was significantly enhanced, the computational cost increased due to the addition of auxiliary networks, resulting in slower detection speeds. However, the model still performed satisfactorily under practical conditions, proving its usability. Future optimization is essential to strike a balance between speed and accuracy, making it suitable for embedded devices via edge computing.

Driver Drowsiness Detection System: The proposed drowsiness detection system effectively identified key gestures such as eye closure, mouth opening, yawning, and nodding using feature extraction methods like EAR, MAR, and the novel FAR. The CNN-based classification approach achieved high accuracy on the EMOCDS, NHTU-DDD, and YawDD datasets, outperforming state-of-the-art methods. However, variability in individual gestures remains a limitation, affecting system consistency. This challenge underscores the need for further enhancement through ensemble classification techniques and advanced feature extraction methods to improve robustness and adaptability to diverse user behaviours.

Driver Distraction Detection Framework: The comprehensive distraction detection framework successfully categorized manual, visual, and cognitive distractions by integrating sensor data acquisition, behavior inference, and distraction type classification. Modern computer vision techniques strengthened the framework's detection capabilities, making it a valuable tool for researchers and practitioners. While the framework effectively addressed distraction, distinguishing subtle cues and overlapping features with drowsiness indicators remain challenging. Future efforts should focus on refining behavior inference models and incorporating multimodal real-time sensor data for a more holistic analysis.

Automatic Pothole Detection: The combination of YOLOv5 with LiDAR data successfully detected potholes, estimating their area, volume, and depth using a 3D Convex Hull model. The integration of 2D and 3D data, along with geo-positioning information, provided comprehensive insights into road health. This system offers a scalable, real-time solution for monitoring road networks with minimal human intervention. Future work should explore scaling this approach to larger road networks and integrating predictive maintenance capabilities to enhance road infrastructure management.

Unsafe Driving Behavior Detection System: The GConv LSTM-based Driving Behavior Detection (DBD) system achieved impressive accuracy rates of 97.5% using public sensor data and 98.1% when incorporating non-public data. Deployed on a lightweight Raspberry Pi, the system demonstrated its practicality for real-time edge-based applications. The monitoring dashboard provided intuitive visualizations and voice alerts, enhancing driver awareness. Future enhancements include creating dynamic graph-based sensor networks to improve accuracy and robustness and expanding dashboard functionalities to provide more actionable insights for drivers.

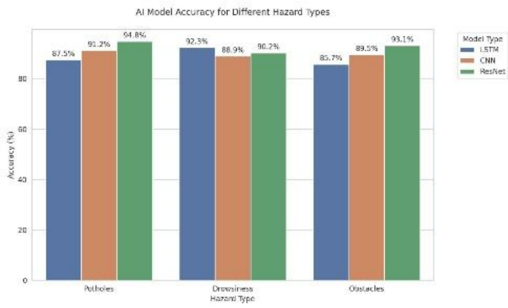

Fig.3: Hazard Detection Accuracy Graph

Fig.4: System Performance Comparison Graph

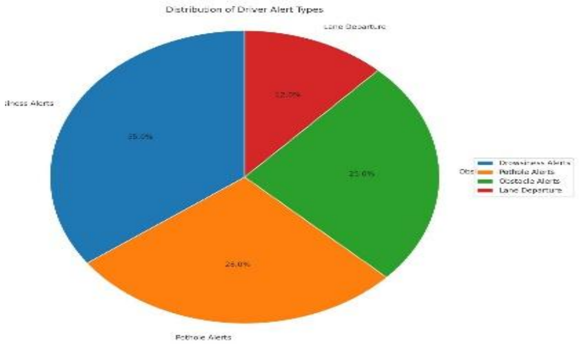

Fig.5: Alert Distribution Pie Chart

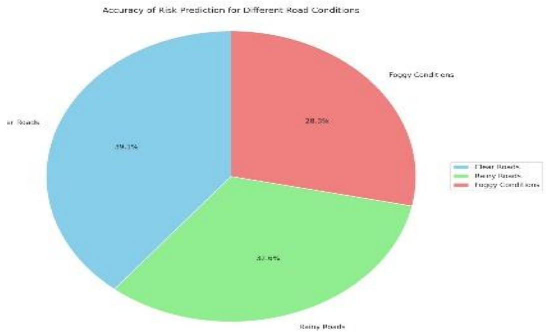

Fig.6: Risk Prediction Accuracy Pie Chart

Fig.4: To compare AI model accuracies across hazard types, create a pandas DataFrame with hazard types, model names, and accuracies. Use matplotlib and seaborn to define plot size and style, with Hazard_Type on the X-axis and Accuracy on the Y-axis. Visualize data using a grouped bar plot (sns.barplot), add value labels for precision, and adjust the layout and legend for clarity before displaying with plt.show().

Fig.5: To create a line graph comparing processing times for different data types, first, define a list of data types (e.g., Sensor Data, Camera Feed, GPS Data) and their corresponding processing times in seconds. Use the plt.plot function to plot the data types on the X-axis and processing times on the Y-axis, incorporating markers and a solid line for clear visualization. Customize the graph by adding a title, axis labels, a grid for better readability, and a legend to identify the line. Finally, display the graph using plt.show() and ensure proper layout with plt.tight_layout. This process highlights the variation in processing times across different data types in a clear and concise manner.

Fig.6: To generate a pie chart showing the distribution of different alert types, first, define a dictionary with alert types as keys and their counts as values. Use the plt.pie function to create the chart, setting the values, labels, and percentages. Customize the chart by adding a title and placing a legend outside the chart for clarity. Finally, display the chart using plt.show() and ensure proper layout using plt.tight_layout. This process visually represents the proportion of each alert type, providing an easy-to-understand summary.

CONCLUSION

This study proposed an AI-driven road safety system to reduce accidents and enhance driving experiences through real-time pothole detection and hazard identification. Leveraging data from cameras, sensors, and weather updates, the system employs LSTM models for accurate risk prediction and proactive alerts. With a monitoring range of 30 meters, it notifies drivers and authorities, ensuring timely responses and gives alerts for pothole. Integrating technologies like IoT and AL/ML, it provides a scalable and adaptable framework to improve traffic flow and road quality. This approach highlights the transformative potential of AI in road safety, emphasizing innovation for safer and sustainable transportation systems globally. Future enhancements could focus on expanding the system's functionality and integrating additional technologies for a more comprehensive approach to road safety and traffic management.

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