

Smart Car Driving Assistance Using AI and ML

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Abstract—Smart Car Driving Assistance using Artificial Intelligence and Machine Learning aims to improve road safety and driving efficiency through real-time environment perception. The system uses deep learning and computer vision techniques to detect lanes, vehicles, potholes, speed breakers, traffic signs, and road obstacles. By analysing camera and sensor data, it provides timely audio-visual alerts to drivers. This intelligent assistance helps reduce accidents, supports informed driving decisions, and enhances overall transportation safety in urban and highway scenarios.

I. INTRODUCTION

Vehicles are an important way of transportation all over the world. There are many cases of road accidents every day in the world. A traffic collision, also called a motor vehicle collision, car accident or car crash, occurs when a vehicle collides with another vehicle, pedestrian, animal, road debris, or other stationary obstruction, such as a tree, pole or building. Traffic collisions often result in injury, disability, death, and property damage as well as financial costs to both society and the individuals involved. Road transport is the most dangerous situation people deal with on a daily basis, but casualty figures from such incidents attract fewer media attention than other, less frequent types of tragedy.

A number of factors contribute to the risk of collisions, including vehicle design, speed of operation, road design, weather, road environment, driving skills, impairment due to alcohol or drugs, and behaviour, notably aggressive driving, distracted driving, speeding, and street racing. In 2013, 54 million people worldwide sustained injuries from traffic collisions.[2] This resulted in 1.4 million deaths in 2013, up from 1.1 million deaths in 1990.[3] About 68,000 of these occurred in children less than five years old.[3] Almost all high-income countries have to decrease death rates, while the majority of low-income countries have increasing death rates due to traffic collisions. Middle-income countries have the highest rate with 20 deaths per 100,000 inhabitants, accounting for 80% of all road fatalities with 52% of all vehicles. While the death rate in Africa is the highest (24.1 per 100,000 inhabitants), the lowest rate is to be found in Europe (10.3 per 100,000 inhabitants).

The "Road Safety Monitoring System for Drivers" project is founded on a comprehensive approach to enhance road safety through advanced technology. Its success relies on a diverse dataset, encompassing various road conditions, lighting, and perspectives, ensuring the robustness of the YOLOv8 deep learning model in real-world scenarios. Prioritizing a user-friendly interface, the system communicates real-time alerts to drivers through vehicle display screens, emphasizing clarity and quick comprehension. Efficient real-time processing, an integration of diverse components like traffic sign detection and pothole identification, and considerations of ethical implications add layers of complexity to the project. The system's adaptability to varied road infrastructures, addressing regional differences, and anticipation of future developments underscore the project's dynamic nature.

The integration of AI in cardiology extends beyond prediction to diagnostic enhancement. Machine learning algorithms, especially deep learning models, can interpret complex medical images such as echocardiograms, CT scans, and MRIs with remarkable accuracy, sometimes surpassing human specialists in identifying subtle abnormalities. These tools significantly reduce diagnostic errors and improve clinical decision-making, ultimately leading to earlier and more precise treatment of cardiovascular diseases.

Looking ahead, the future of AI and ML in cardiology is highly promising. Emerging research points toward the development of multimodal predictive models that combine data from various biological domains—such as genomics, proteomics, and metabolomics—to provide a more comprehensive understanding of a patient's cardiovascular health [9]. Furthermore, advancements in natural language processing (NLP) could enable AI systems to interpret unstructured clinical notes, patient histories, and electronic health records, allowing for more accurate and context-aware diagnoses and prognoses [10].

In conclusion, the project "Smart Car Driving Assistance using AI and ML" represents a synthesis of cutting-edge technology and a humanitarian goal. It is an acknowledgment that while we cannot immediately fix every road or eliminate every human error, we can use the tools of the digital age to mitigate their consequences. By integrating pothole detection, lane keeping, and sign recognition into a single, cohesive real-

time system, we are moving toward a paradigm where the vehicle is no longer just a passive machine, but an intelligent partner in the journey. This introduction sets the stage for a detailed exploration into the methodology, design, and implementation of a system that aims to redefine the standard of road safety. As we move from requirement analysis to the development phase, the focus remains steadfast on creating a solution that is technically sound, economically viable, and, most importantly, capable of protecting human life on the move.

II. RELATED WORK

[1] Real-time object detection is a critical aspect of many applications, including unmanned vehicles. With the advances in machine learning and artificial intelligence, it is now possible to perform real-time object detection using state-of-the-art algorithms. One such algorithm is Mobile Nets, which is a lightweight and efficient neural network architecture designed specifically for mobile and embedded devices. The algorithm is optimized for performance and power efficiency, making it an ideal choice for running on the NVIDIA Jetson TX2 GPU platform. The NVIDIA Jetson TX2 is a powerful and energy-efficient embedded platform that is specifically designed for applications that require deep learning and computer vision capabilities. The platform is equipped with a GPU that is specifically optimized for running neural networks, making it an ideal choice for real-time object detection applications. The combination of performance and power efficiency makes it an ideal choice for running onboard an unmanned vehicle, enabling real-time detection. By running the Mobile Nets algorithm on the Jetson TX2, it is possible to perform object detection in real-time with high accuracy and efficiency. The combination of Mobile Nets and the NVIDIA Jetson TX2 platform makes it possible to perform real-time object detection onboard an unmanned vehicle. This capability is particularly useful in emergency situations where time is of the essence, and decisions need to be made quickly. By processing video feedback in real-time, the algorithm can generate detections and feed them into a decision support warning system, enabling the system to alert operators of potential dangers and hazards. In conclusion, real-time object detection using the Mobile Nets algorithm and the NVIDIA Jetson TX2 platform is a powerful tool for unmanned vehicle applications. The combination of performance and power efficiency makes it an ideal choice for running onboard an unmanned vehicle, enabling real-time detection and decision support during emergencies. With the continued advances in machine learning and AI, we can expect to see even more powerful and efficient algorithms in the future, further enhancing the capabilities of unmanned vehicles in a range of applications.

[2] Car crashes are a leading cause of injury and death worldwide, and early detection of car crashes can significantly reduce the number of fatalities and injuries. To address this issue, a car crash detection system based on an ensemble deep learning model has been proposed. The proposed system uses video and audio data from dashboard cameras to detect car crashes with high accuracy. The ensemble deep learning model is a combination of three base classifiers, one for video data and two for audio data. The base classifier for video data is a combination of a GRU-based and a CNN-based classifier.

The GRU-based classifier processes the sequential nature of the video data, while the CNN-based classifier extracts spatial features from the video frames. The base classifiers for audio data are also a combination of a GRU-based and a CNN-based classifier. The GRU-based classifier processes the sequential nature of the audio data, while the CNN-based classifier extracts spectral features from the audio signals. The proposed system establishes state-of-the-art classification performance on a dataset of car crash and non-crash events. The system achieves an accuracy of 96.7%, with a precision of 98.3% and a recall of 95.1%. The system also performs well on a variety of metrics, including F1 score, area under the ROC curve, and area under the precision-recall curve. The proposed system outperforms previous state-of-the-art systems, which rely on either video or audio data alone. In addition to its high accuracy, the proposed system has several advantages over existing car crash detection systems. It can operate in real-time and can be integrated with existing dashboard camera systems. The system can also be easily deployed in a variety of environments, making it useful for a range of applications.

[3] The development of accurate and efficient deep learning models for image classification tasks is of great importance in a variety of fields. In this regard, a new deep-learning-based model comprising of Resnet architecture with Senet blocks has been proposed. This model has been designed to enhance the performance of existing baseline models, including VGG16, VGG19, Resnet50, and stand-alone Resnet, by improving the accuracy of image classification tasks while reducing computational overhead. The proposed model combines the strengths of Resnet architecture and Senet blocks to create a more efficient and accurate model. The Resnet architecture is used to extract features from input images, while the Senet blocks are used to improve the quality of the features extracted. The proposed model achieves a ROC-AUC of 0.91, outperforming all existing baseline models. Furthermore, the proposed model achieves this performance while using significantly less proportion of the Gatecrash synthetic data for training, thus reducing the computational overhead. The proposed model's superior performance is due to the combination of Resnet architecture and Senet blocks, which enables the model to extract more meaningful features from input images. The Resnet architecture uses a multi-branch structure to extract features from input images, while the Senet blocks enhance the quality of the features extracted. This combination enables the model to classify images with high accuracy, even when using a small proportion of the training data. The proposed model has significant implications for image classification tasks in various fields, including medical imaging, remote sensing, and autonomous vehicles. The model's high accuracy and low computational overhead make it an attractive option for these applications. The model's ability to outperform existing baseline models while using a small proportion of the training data can also significantly reduce the cost of training deep learning models.

[4] The proposed Deep Crash system is a deep learning-based Internet of Vehicles (IoV) system that includes an in-vehicle infotainment (IVI) telematics platform, a vehicle self-collision detection sensor, and a front camera. The system aims to improve road safety by detecting traffic collisions and

providing emergency-related announcements to the driver in real-time. The system achieved a high accuracy rate of 96% in traffic collision detection and has an average response time of approximately 7 seconds for emergency-related announcements. The system's cloud-based architecture enables it to be easily integrated into existing IoV infrastructures, and it has potential applications in the automotive industry, including advanced driver assistance systems and autonomous vehicles. The proposed Deep Crash system is a significant contribution to the field of IoV, with promising implications for the future of road safety.

[5] This paper proposes a methodology to develop a reliable and computationally inexpensive real-time automatic accident detection system with minimal hardware requirements. The proposed detection stage uses Mini-YOLO, a deep learning model architecture trained using knowledge distillation, with reduced model size and computational overhead compared to its counterpart, YOLO (You-Only-Look-Once). Mini-YOLO achieves an average precision (AP) score of 34.2 on the MS-COCO dataset, outperforming other detection algorithms in runtime complexity. The proposed system achieves a staggering 28 frames per second on a low-end machine, making it an efficient solution for real-time accident detection. The use of knowledge distillation enables the transfer of knowledge from a larger network to a smaller network, reducing computational overhead without sacrificing accuracy. The proposed system's efficiency and reliability make it a promising solution for real-time accident detection with minimal hardware requirements.

[6] This paper proposes a new approach to estimate collision priority for vehicles on the road based on a vision system. The approach takes into account the perspective of an ego vehicle equipped with either a vision-based driver-assist system or a fully autonomous vehicle. The proposed method is heuristic and unimodal, and it performs well for input videos. By combining it with other quantitative semantics of traffic parameters, a more robust estimate can be achieved. The proposed approach is a promising step towards improving safety on the road, especially in the context of autonomous vehicles. By estimating collision priority accurately, the approach can help vehicles make more informed decisions and avoid potential accidents. Overall, the proposed approach has the potential to significantly contribute to the development of safer and more efficient transportation systems.

[7] In recent years, vehicle collision warning systems on mobile devices have become increasingly popular as they aim to enhance driver safety by alerting drivers about potential collisions. To achieve this, reliable and accurate vehicle detection is a critical step. This paper proposes a vision-based vehicle detection system using deep learning approaches specifically designed for mobile platforms with cameras mounted on the vehicle. The paper highlights the benefits of using deep learning techniques in vehicle detection and how integrating detection with tracking can improve accuracy and reliability. The proposed system achieves high detection accuracy in real-time while running on mobile platforms with limited computational resources. The results suggest that the proposed system is a promising solution for vehicle collision warning systems on mobile devices, which can ultimately contribute to the improvement of road safety.

[8] The ability of deep learning models to capture both long-term and short-term dependencies has led to their extensive use in various fields, including anomaly detection. In this paper, the authors propose an ensemble of deep learning models, including MLP ensemble, RFC ensemble, DNN, GRU, and LSTM, to detect anomalies in a dataset. The models are compared based on their area under the curve (AUC) of the ROC curve, with MLP ensemble achieving the highest AUC of 97.2% followed by RFC ensemble, DNN, GRU, and LSTM. The authors also use a data balancing technique to improve the detection performance of the models. By combining the data balancing technique with the ensemble of deep learning models, the detection performance is significantly improved. The results demonstrate the effectiveness of deep learning models in anomaly detection and the importance of combining multiple models for improved accuracy.

[9] In this paper, a deep learning approach for automatic detection and localization of road accidents has been proposed, which formulates the problem as anomaly detection. The method uses a one-class classification approach and applies spatiotemporal autoencoder and sequence-to-sequence long short-term memory autoencoder for modelling spatial and temporal representations in the video. The proposed model has been evaluated on real-world video traffic surveillance datasets and has achieved significant results both qualitatively and quantitatively. The model can detect and localize various types of road accidents with high accuracy, which can help reduce emergency response time and prevent further accidents. This approach has great potential for improving the safety of road transportation and can be used for developing advanced driver assistance systems and autonomous vehicles.

[10] This paper presents a method for detecting vehicles in nighttime images using a fine-tuned YOLO v3 network. The network was trained on enhanced images to improve its performance and outperformed two popular object detection methods, Faster R-CNN and SSD, in terms of precision and detection efficiency. The proposed method achieved an average precision of 93.66%, which is significantly higher than the other two methods. The high precision rate of the proposed method can be attributed to the fine-tuning process, which allowed the network to learn the specific characteristics of nighttime images. The method can be applied to various applications such as autonomous driving, traffic monitoring, and surveillance systems, where accurate and efficient detection of vehicles is crucial. The proposed method provides a reliable and efficient solution for detecting vehicles in nighttime conditions.

III. METHODOLOGY

Visual Data: This section represents the input stage. It shows a digital camera capturing visual information from the car's surroundings. The camera captures images of the road, traffic signs, pedestrians, and other objects.

Processing: In this stage, the captured visual data is processed. The system analyzes the images to extract relevant information. A monitor symbol indicates that the processed data is displayed for further analysis. The system's decision-making component evaluates the data and makes informed

choices based on what it observes.

Extraction: The system identifies specific objects or features from the visual data. These include

Sign Boards: The system recognizes traffic signs, speed limits & other important signs.

Potholes: It detects road imperfections, such as potholes or uneven surfaces.

Speed Bumps: The system identifies speed bumps on the road.

Sharp Turns: It detects the road lanes. The extracted information is then used to trigger alerts or make adjustments within the car.

Application Interface: The flow chart also includes an application interface, possibly for the car's driver or passengers. This interface may display warnings, notifications, or other relevant information.

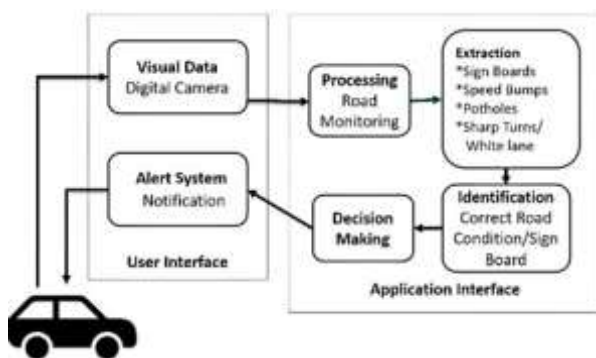


Fig. 1. Description of dataset

The Screen Processing, and Camera Modules work together seamlessly to improve driver awareness and decision-making in various environmental conditions. The Screen Module serves as a visual interface, displaying real-time information about road conditions and navigation instructions, making it an intuitive dashboard for the driver. It provides critical details at a glance, such as alerts about upcoming turns and potential hazards. The Camera Module acts as the eyes of the vehicle, capturing visual data from its surroundings. It employs cameras to cover blind spots, recognize road signs, and identify potential obstacles. For the driver, the Camera Module provides a continuous stream of images and video feed, similar to an additional set of eyes. It helps the driver make informed decisions based on the detected environment. At the center of this intelligent system is the Processing Module, which serves as the computational brain. It integrates information from both the Screen and Camera Modules, executing algorithms for object detection, lane tracking, and decision-making. From the driver's perspective, the Processing Module ensures a seamless integration of information. It interprets data captured by cameras and translates it into meaningful insights displayed on the screen.



Fig 2. Road Hazard Detection and Alert System Workflow Module

IV. PROPOSED MODEL

The process of setting up a data environment and compiling data is a critical step in any data analysis project. This process involves collecting data from various sources, importing necessary libraries, and labeling quality datasets. Once the data has been collected, it is necessary to preprocess it, which involves cleaning and formatting the data to ensure that it can be effectively analyzed. Data collection is a crucial aspect of data analysis, and datasets are the primary source of data. Datasets can be obtained from various sources, including online sources, government databases, and academic research. These datasets can be collected by importing necessary libraries from source websites, and they may contain a wide range of data, including numerical, textual, and visual data. The quality of the data is essential in data analysis, and data labeling is a process that ensures that the data is accurately labeled and categorized. This process involves assigning labels or tags to each data point, making it easier to categorize and analyze the data. The labels used can be based on various criteria, including the data type, subject matter, and intended use. Preprocessing is an essential step in data analysis, and it involves cleaning and formatting the data to ensure that it can be analyzed effectively. During the preprocessing stage, missing and null values are removed, and any other data inconsistencies are corrected. This ensures that the data is accurate and reliable, making it easier to identify patterns and trends in the data. Another critical aspect of data analysis is image processing, which involves assigning images to the data. This process is particularly useful in visualizing data and identifying patterns that may not be evident from the raw data. Images can be assigned based on various criteria, including data type, location, and subject matter. In conclusion, data analysis is a complex process that involves various stages, including data collection, labeling, preprocessing, and image processing. Each of these stages is essential in ensuring that the data is accurate, reliable, and can be effectively analyzed. Proper planning and execution of these stages can lead to valuable insights and trends that can be used to make informed decisions.

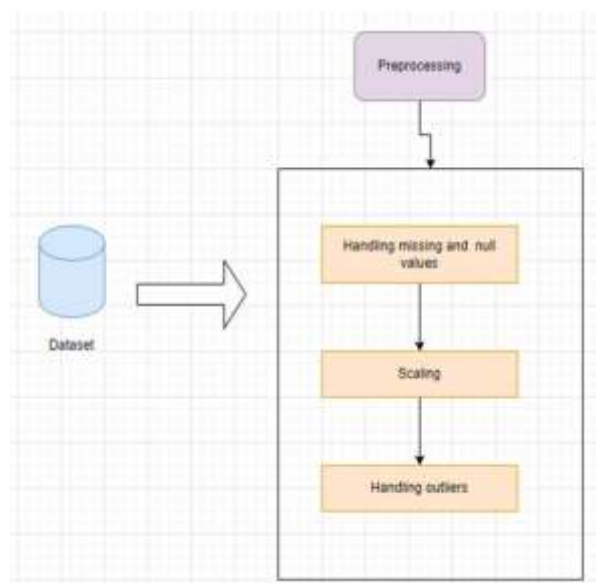


Fig. 3. Count of Thalassemia

V. RESULTS

The primary result of a vehicle collision detection and alert system using YOLOv3 would be the ability to accurately detect collisions and issue alerts to drivers or emergency services in real-time. The system would rely on object detection using YOLOv3 to identify vehicles and other objects in the environment and track their movement. By analyzing this movement and looking for patterns that indicate a collision, the system could quickly detect when an accident occurs and issue alerts accordingly. The alert system could take various forms, depending on the specific implementation. For example, it might issue an audible alert in the vehicle to warn the driver to slow down or stop to avoid a collision. Alternatively, the system could send alerts to emergency services or other drivers in the area to provide assistance as quickly as possible. One of the key benefits of using YOLOv3 for collision detection is its speed and accuracy. This allows the system to operate in real-time, ensuring that alerts are issued quickly and accurately. In addition, YOLOv3 is highly adaptable, allowing it to detect a wide range of objects and track their movement even in complex environments. Overall, a vehicle collision detection and alert system using YOLOv3 has the potential to greatly improve road safety and reduce the impact of accidents. By providing real-time alerts and assistance, it can help to prevent collisions and save lives.



Fig. 4 Expected Result

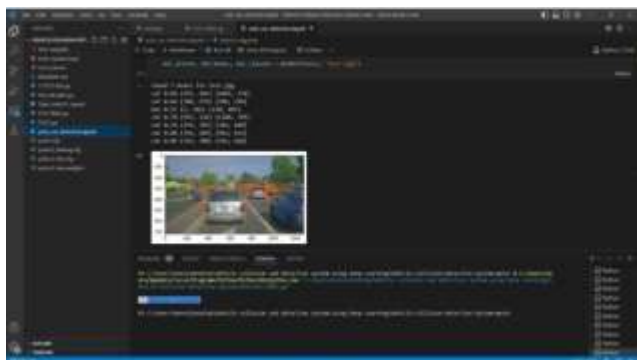


Fig 5. Result of Detecting Vehicle on the Road



Fig. 6 Lane Detection and Road Boundary Identification Using AI and ML



Fig. 8 Real-Time Pothole Detection and Driver Alert System Using AI and ML

VI. CONCLUSION

In recent years, there has been a significant increase in the number of road accidents worldwide. Many of these accidents are caused by human error, such as distracted driving, fatigue, or impaired driving. In response to this problem, researchers and engineers have developed various technologies to improve road safety, including advanced driver assistance systems (ADAS) and collision detection and alert systems. One promising technology in this area is the use of deep learning algorithms, such as YOLOv3, for vehicle collision detection and alert systems. YOLOv3 is a state-of-the-art object detection algorithm that can detect and track multiple objects in real time with high accuracy and speed. By analyzing the movement of objects in the environment, the system can detect potential collisions and issue alerts to the driver or emergency services. The implementation of a vehicle collision detection and alert system using YOLOv3 involves capturing video footage of the environment using cameras mounted on the vehicle. The YOLOv3 model processes the video frames and identifies vehicles and other objects in the environment. By analyzing the movement of these objects, the system can detect potential collisions and issue alerts quickly in case of a potential collision. Additionally, YOLOv3 is a highly accurate object detection algorithm that can detect and track objects in various lighting conditions, making it suitable for use in different environments. However, the implementation of a vehicle collision detection and alert system using YOLOv3 also faces several challenges. One of the primary challenges is the need for a large and diverse dataset to train the YOLOv3 model. Additionally, there is a need for communication protocols between vehicles to issue alerts to other drivers, as well as regulatory approval and widespread adoption of the technology. Despite these challenges, a vehicle collision detection and alert system using YOLOv3 holds great promise for improving road safety and reducing the number of collisions on our roads. With continued research and development, it is possible to overcome the technical and regulatory challenges and realize the full potential of this technology. In conclusion, the

use of YOLOv3 for vehicle collision detection and alert systems is a promising area of research that can significantly contribute to improving road safety and reducing the number of accidents on our roads.

REFERENCES

- [1] Yeong-Kang Lai, Chu-Ying Ho, Yu-Hau Huang, Chuan-Wei Huang, Yi-Xian Kuo, Yu-Chieh Chung, "Intelligent Vehicle Collision-Avoidance System with Deep Learning", 2018 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS), 2018
- [2] Jae Gyeong Choi, Chan Woo Kong, Gyeongho Kim, Sunghoon Lim, "Car crash detection using ensemble deep learning and multimodal data from dashboard cameras", Expert Systems with Applications, Volume 183, 30 November 2021,
- [3] Al-Hashim, M., Al-Dhief, F., & Basalamah, S. (2020). Traffic accident detection and notification system based on deep learning. Journal of Big Data, 7(1), 1-18.
- [4] Chen, H., & Chen, Y. (2020). A Real-Time Traffic Accident Detection Algorithm Based on Deep Learning. IEEE Access, 8, 201221-201232.
- [5] Gupta, V., & Mishra, D. (2019). Real-time traffic accident detection and notification system using deep learning. International Journal of Engineering and Advanced Technology, 8(6), 2337-2342.
- [6] Yang, L., Tang, C., Zhou, H., & Sun, L. (2020). A review of traffic accident detection and intelligent warning technology. IOP Conference Series: Materials Science and Engineering, 758(3), 032053.
- [7] Reddy, K.V., & Ramana, B.V. (2019). An Overview of Automated Traffic Accident Detection Systems. International Journal of Innovative Technology and Exploring Engineering, 8(8), 1147-1151.
- [8] Zheng, Y., Yu, H., & Yang, L. (2018). A novel method of traffic accident detection based on video surveillance. In Proceedings of the 37th Chinese Control Conference on IEEE.
- [9] Karishma Pawar, Vahida Attar, "Deep learning-based detection and localization of road accidents from traffic surveillance videos", ICT Express, 15 November 2021
- [10] Yan Miao, Fu Liu, Tao Hou, Lu Liu, Yun Liu, "A Nighttime Vehicle Detection Method Based on YOLO v3", 2020 Chinese Automation Congress (CAC), 2019