Smart Road Safety System: Detecting Potholes, Sharp Turns, Speed Bumps, and Signboards for Driver Safety

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ABSTRACT
The increasing demand for intelligent transportation systems has spurred research into computer vision applications, particularly traffic sign detection, to enhance road safety and navigation. This project presents a robust deep learning-based approach for automatic traffic sign detection along with speed bumps, sharp turns and potholes using YOLO V8. A pothole detection using deep learning typically focuses on addressing the challenges associated with identifying and mapping potholes on roads. The growing emphasis on road safety has prompted the drivers for identifying and alerting drivers to the presence of speed bumps. Traffic sign detection contributes to advanced driver assistance systems by providing real-time information to drivers. This assistance is especially valuable in situations where visibility may be compromised or when navigating unfamiliar roads. Along with it the detection of potholes, speed bumps, and sharp turns using deep learning is multifaceted, encompassing aspects of road safety, infrastructure maintenance, driver comfort, and the broader goals of creating intelligent and responsive transportation systems.

Keywords
Traffic sign boards, Potholes, Speed Bumps, Sharp turns detection, YOLO V8, Tensorflow, Deep learning, Object detection, PyTorch, Ultralytics, Roboflow.

1. INTRODUCTION
In today's tech world, introducing a smart solution called the "Road Safety Monitoring System for Drivers" to tackle the growing problem of road accidents. This project uses advanced technology like artificial intelligence and computer vision to spot and understand traffic signs, speed bumps, potholes, and sharp turns in real-time. Why? Well, because human drivers often face challenges like getting tired or distracted, leading to delayed reactions to important road signs. So, creating a smart system that doesn't rely heavily on humans, aiming to significantly reduce the chance of accidents caused by human mistakes. Main goal is to build a smart system that seamlessly fits into vehicles, providing real-time detection and understanding of road features. sing a powerful tool called YOLOv8, a type of computer program that's really good at quickly and accurately spotting things in images. The system goes through a detailed process, including gathering and labeling a bunch of pictures, training the computer to recognize signs and road features, and then making sure it works well in different situations. By adding special techniques, it can also spot potholes, sharp turns, and speed bumps effectively, making roads safer.

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 in-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. In essence, this initiative goes beyond technicalities, recognizing the multidimensional challenges and opportunities in creating a sophisticated, globally applicable, and continually evolving road safety.

2. LITERATURE SURVEY
According to Huibing Zhang, Longfei Qin, Jung li, Yunchuan Guo, Ya Zhou, Jingwei Zhang and Xua new, 2022[1], they have developed a detection scheme called MSA_YOLOv3 for detecting small traffic signs in real-time using the YOLOv3 model. The proposed scheme improves detection efficiency by applying image mix-up technology for data augmentation and training on random convex combinations of pairs of examples. The MSA_YOLOv3 scheme reduces false and missed detection rates in a complex background. The technologies/algorithm used here is image mix-up, Multiscale spatial pyramid pooling, Fine-grained features, YOLOv3 detection pipeline, datasets are collected from Cityscapes dataset combined with VGG16 model. The performance was improved accuracy and efficiency in complex backgrounds.

Dr. A. Sivasangari, Dr. P. Ajitha, S. Nivetha, Dr. R. M. Gomathi, Pavithra, 2020[2]. In this paper the algorithm/technology used is image mix-up, Multiscale spatial pyramid pooling, Fine-grained features, YOLOv3 detection pipeline. Datasets used in this paper is cityscapes dataset combined with VGG16 model. The overall performance was improved the accuracy and efficiency in complex backgrounds. Looking towards the future Scope the authors are making it more accessible on low/medium-end graphics cards.

Jinghao Cao, (Member, Ieee), Junju Zhang, And Xin Jin, 2021 [3]. This paper proposes a novel Transformer-based traffic sign detection algorithm that uses a backbone enhanced with attention mechanisms to improve the multi-scale representation ability of the model. Technology/Algorithm used here is transformer-based detection, Attention mechanisms. TT100K datasets are used for small traffic sign detection. Future Scope Enhancing accuracy and robustness, extending detection to roadside object.

According to Dharneeshkar J, Soban Dhakshana V, Aniruthan S, Karthika, Lath Parameswaran, 2020[4]. In this paper, a new 1500 image dataset has been created on Indian roads. The dataset is annotated and trained using YOLO (You Only Look Once). The new dataset is trained on YOLOv3, YOLOv2, YOLOv3-tiny, and the results are compared. The results are evaluated based on the mAP, precision and recall. The model is tested on different pothole images and it detects with a reasonable accuracy. Future Scope is real-time implementation with Raspberry Pi and GPS integration. Weaknesses are complex models, time-consuming training, potential overfitting, limited generalization.

As per Ping Ping1, Xiaohui Yang1, Zeyu Gao, 2020[5]. In this paper four modern deep learning models are trained to see which model or ensemble of models produces the best results, including Yolo V3(You Only Look Once) Algorithm, SSD (Single Shot Detector) Algorithm, HOG (Histogram of Oriented Gradients) with Support Vector Machine and Faster R-CNN. For Dataset images are collected from a car dashboard. The overall Performance of YOLOv3 achieved 82% accuracy, specific evaluation metrics not mentioned. Weaknesses includes noise in grayscale conversion, unwanted edges, limitations in size calculation. Future Scope of this paper is expanding detection to other objects, using images from moving vehicles.

Abhishek Kumar, Chakrapani, Dhruba Jyoti Kalita, Vibhav Prakash Singh, 2020[6]. This paper proposed a deep learning-based model that can detect potholes early using images and videos which can reduce the chances of an accident. This model is basically based on Transfer Learning, Faster Region-based Convolutional Neural Network(F-RCNN) and Inception-V2. Technology is based on the pothole detection using the transfer learning technique. Some common techniques are FRCNN, inception V2 model. Weaknesses are lack of specific performance metrics (e.g., accuracy, precision, recall). Future Scope involves exploring newer CNN architectures like Inception-V3 and Inception ResNet. Dataset details are not provided, raising questions about data quality and diversity. Performance Computational resource requirements for real-time processing are not discussed.

Muhammad Jefri Muril, Nor Azlina Ab Aziz, Nor Hidayati Abdul Aziz, Hadhrami Ab. Ghani, 2020[7]. This research paper is about making cars safer by using technology to detect lanes on the road. It talks about different methods, like using cameras and smart algorithms, to help cars know where the lanes are. This is important because it can prevent accidents. The paper also mentions that current systems still have some challenges, especially in bad weather or when the road markings are not clear. Researchers are working to improve these systems for better and safer driving. Technology/Algorithm used here is Android smartphones, GPS, accelerometers, Firebase, Z-THRESH algorithm. Weaknesses are reliability, user-dependent data, limited scope, speed requirement, data accuracy. Future Scope could be enhanced algorithms, real-time data sharing, collaboration with authorities, broader safety issues, data validation. Datasets are user-generated through smartphones.

According to Dan Qiao; Xiaoyu Wu; Tiantian Wang, 2020[8]. In this paper the technology/algorithm used is line-CNN, LaneNet, VGG16, ResNext Weaknesses are limitations in extreme situations, no specific performance metrics provided. Future Scope is testing in diverse conditions, comparison with existing methods, parameter adjustments, and more Dataset TuSimple benchmark dataset, Caltech Lane Dataset Competitive performance mentioned, but specific metrics not provided.

P. Maya, C. Tharini, 2020[9]. The paper discusses the challenges associated with the full 360-degree Hough transform, leading to increased data processing. Technology/Algorithms are Hough Transform, Partial Hough Transform, Image Processing Techniques, Edge Detection. Weaknesses are extreme conditions limitations are not discussed, no specific performance metrics provided. Future Scope is testing in diverse conditions, comparison with existing tests, optimization, and more Dataset Not specified. Overall performance was improved speed and accuracy highlighted, but specific metrics not provided.

Deepak Kumar Dewangan, Satya Prakash Sahu, 2020[10]. The research paper focuses on the development of a real-time embedded system prototype for speed bump detection in an autonomous driving scenario. It proposes a two-module approach: the first module deals with dataset preparation, training, and speed bump detection using Convolutional Neural Networks (CNN), while the second module governs the operational performance, altering the vehicle's speed based on the detected objects. The system uses a vision camera, Raspberry Pi, and Arduino microcontroller to implement intelligent vehicle behavior.

Technology/Algorithm used here is Deep Learning, CNN, Raspberry Pi, Arduino. Overall weaknesses are lack of specific CNN architecture, limited dataset discussion, absence of some metrics, hardware details lacking. Future Scope is CNN architecture exploration, additional sensors integration, real-world testing, dataset expansion, hardware planning Dataset Mention of capturing 575 speed bump images, but limited dataset details.

Sandeep Shah, Chandrakant Deshmukh, 2019[11]. This paper addresses the problem of road safety by focusing on the detection of potholes and speed bumps in India. Potholes and speed bumps are known to cause accidents and discomfort for motorists. The authors propose a machine learning approach that uses convolutional neural networks (CNNs) to classify road surfaces into three categories: pothole, speed bump, and normal road. They achieve a true positive rate of 88.9%. In the second phase, they use the YOLO (You Only Look Once) algorithm for object detection to pinpoint the exact location of speed bumps. The research aims to improve road safety and enhance driving comfort based on road condition analysis using a camera. Technology/Algorithm are Deep Learning, CNN, Raspberry Pi, Arduino. Overall weaknesses are Lack of specific CNN architecture, limited dataset discussion, absence of some metrics, hardware details lacking. Future Scope is CNN architecture exploration, additional sensors integration, real-world testing, dataset expansion, hardware planning.

Mention of capturing 575 speed bump images, but limited dataset details.

According to Ezzaldeen Edwan, Nader Sarsour, Manar Alatrash, 2019[12]. This research paper introduces a mobile application designed to detect speed bumps and potholes using smartphone sensors, with a focus on enhancing road safety. The app uses built-in smartphone sensors such as GPS and accelerometers to collect data on a vehicle's position, speed, and acceleration. This data is then analyzed to identify bumps in the road.

3. PROPOSED WORK

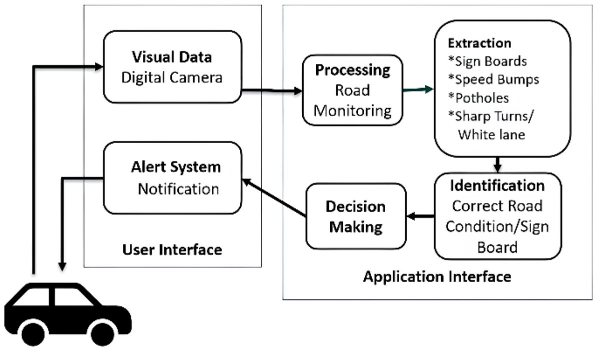

Figure 1. Schematic diagram of Road Safety Monitoring System for drivers

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.

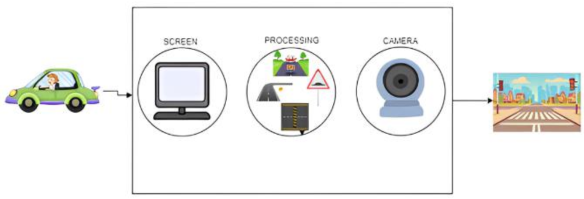

Figure 2. Road Hazard Detection and Alert System Workflow Module

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.

4. SOFTWARES AND FRAMEWORKS

Roboflow – It is a platform that provides tools and services for building and deploying computer vision models. Computer vision is a field of artificial intelligence that focuses on enabling machines to interpret and understand visual information from the world, similar to how humans do. Roboflow offers a range of features to help developers and data scientists with various aspects of computer vision model development. Some of the key features include: Data Annotation, Data Augmentation, Model Training, Integration and Model Deployment.
Ultralytics - YOLOv8, the latest version of the acclaimed real-time object detection and image segmentation model. YOLOv8 is built on cutting-edge advancements in deep learning and computer vision, offering unparalleled performance in terms of speed and accuracy. Its streamlined design makes it suitable for various applications and easily adaptable to different hardware platforms, from edge devices to cloud APIs.
Deep learning - It is like the brain of the AI world. It's a subset of machine learning that uses neural networks with multiple layers (deep neural networks) to analyze and learn from data. These networks attempt to simulate the way the human brain works, allowing the AI to automatically learn and make intelligent decisions without explicit programming for each task.
Deep Learning Framework – PyTorch - PyTorch is a fully featured framework for building deep learning models, which is a type of machine learning that's commonly used in applications like image recognition and language processing. PyTorch is widely used in object detection tasks because of its powerful capabilities in building and training neural networks. In object detection, the goal is to teach a computer to recognize and locate different objects within an image or a video. PyTorch provides a user-friendly environment to create and train complex object detection models.
YOLO V8 - The YOLO (You Only Look Once) version 8 is the latest iteration of a groundbreaking object detection algorithm in computer vision. Known for its speed and accuracy, YOLO v8 employs a single neural network to predict bounding boxes and class probabilities directly from input images in one pass. This efficiency distinguishes YOLO from other object detection methods, making it a popular choice for real-time applications. With each version, the YOLO algorithm undergoes improvements in terms of accuracy, speed, and the

ability to detect a wider range of objects. YOLO v8 is specifically designed for object detection tasks.

Tensorflow - It provides a comprehensive ecosystem of tools, libraries, and community resources for building and deploying machine learning models. TensorFlow is designed to be flexible, allowing developers to create a wide range of machine learning models, from simple linear regressions to complex deep learning architectures.

Computer Vision Libraries- The specific computer vision libraries are not explicitly mentioned, but common libraries include OpenCV for image processing and manipulation, and scikit-image for various image-related tasks.

Custom Dataset - A custom dataset of 15,025 annotated road images was created, featuring traffic signs, potholes, speed bumps, and sharp turns under varying lighting and weather conditions. The dataset includes 6,125 traffic sign images, 3,300 speed bumps, 3,100 potholes, and 2,500 sharp turns. These distinct categories were combined into a single deep learning model, designed for comprehensive road condition analysis.

5. SOFTWARE IMPLEMENTATION

Python widely used for its simplicity and versatility, it is the primary programming language for developing the backend logic of the project, including the implementation of the deep learning model. HTML, CSS, JS: These web development technologies are likely used for creating the frontend of the user interface. HTML structures the content, CSS styles it, and JS adds interactivity.

Figure 3. Visual representation of user interface

Figure 4. Visual representation of backend processing

6. RESULT ANALYSIS

The provided road conditions model utilizes the YOLOv8s architecture, a state-of-the-art object detection model known for its efficiency and accuracy in real-time applications. The model has been trained and evaluated on four distinct categories of road conditions: Sign Boards, Potholes, Speed Bumps, and Lane/Sharp Turns. Where Sign Boards are of 45%, Potholes are of 20%, 20% are Speed Bumps and only 17% Lane configuration is included.

For Sign Boards, the model achieves a mean Average Precision (mAP) of 82.2%, indicating a moderate level of accuracy in localizing and classifying sign boards within the given dataset. The Precision of 91.2% suggests that the model correctly identifies sign boards. while the Recall of 82.0%. This indicates room for improvement in both precision and recall for Sign Boards detection.

In the case of Potholes, the YOLOv8s model demonstrates a significantly higher performance with a mAP of 96%. The Precision of 94.9% indicates a relatively high accuracy in correctly identify in potholes, potholes, while the Recall of 93.5% suggests that there is some room for improvement in capturing all instances of potholes within the dataset.

Speed Bump detection showcases the model's strength, achieving an impressive mAP of 91.9%. The high Precision of 93.1% indicates a robust ability to accurately identify speed bumps, and the Recall of 88.5% signifies a strong capability in capturing the majority of speed bumps present in the dataset. This category demonstrated the model's proficiency in precise and comprehensive detection

The performance of the YOLOv8s model in detecting critical road elements has been evaluated using the following metrics: Mean Average Precision (mAP)- This metric provides an overall assessment of the model's accuracy in object detection across all classes. Precision- It measures the ratio of true positive detections to the total number of detections made by the model, indicating its ability to avoid false alarms. Recall- This metric measures the ratio of true positive detections to the total number of ground truth objects, reflecting the model's capability to identify all relevant objects within the input data.

Table 1. mAp, Precision and Recall

Road Conditions	Model Type: yolov8s		
	mAp	Precision	Recall
Sign Boards	88.2%	91.2%	82.0%
Pothole	96%	94.9%	93.5%
Speed Bump	91.9%	93.1%	88.5%
Lane/SharpTurns	90.5%	99.1%	86.5%
Combine	94.0%	90.0%	84.4%

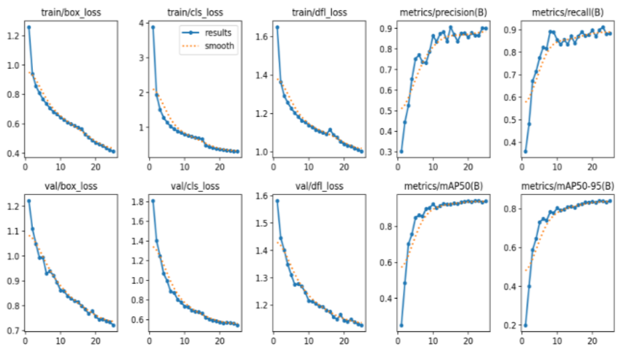

Figure 5. Training Results /Predications

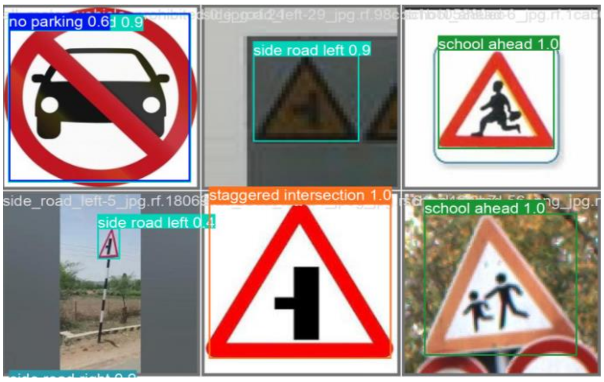

Figure 6. Traffic signs detection with custom dataset

Figure 7. Potholes detection with custom dataset

Figure 8. Speed bumps detection with custom dataset

Figure 9. Sharp turns detection with custom dataset

7. CONCLUSION AND SUGGESTIONS FOR FUTURE WORK

The Road Safety Monitoring System, leveraging the YOLOv8s model, showcases robust performance across various road conditions. With an impressive mean Average Precision (mAP) of 93.6%, signboard detection demonstrates high accuracy, supported by precision and recall scores of 90.3% and 85.4% respectively. Pothole detection exhibits even greater precision and recall, boasting an mAP of 96.0% alongside precision and recall scores of 94.9% and 93.5% respectively. Speed bump detection stands out with an mAP of 91.9% and precision and recall scores of 93.1% and 88.5%, indicating accurate identification of speed bumps. Lane and sharp turn detection display exceptional precision at 99.1%, contributing to safer driving environments. The combined performance of the model, encompassing signboard, pothole, speed bump, and lane/sharp turn detection, achieves an mAP of 94.0% with precision and recall scores of 90.0% and 88.4%. Despite these successes, opportunities for improvement exist, particularly in signboard detection. Overall, the Road Safety Monitoring System represents a significant advancement in enhancing road safety and optimizing traffic management, with the potential to minimize accidents and improve transportation efficiency. Dynamic Object Detection and Tracking: Extend the system's capabilities to dynamically detect and track moving objects, including vehicles, pedestrians, and cyclists. Adaptive Learning from User Behavior: Introduce adaptive learning mechanisms that analyze driver behavior over time. Implement reinforcement learning techniques to customize the system based on individual driving patterns, improving the accuracy of alerts and warnings. Large-Scale Datasets for Training: Continuously update and expand the training datasets to include diverse scenarios and variations in road conditions and Multi-Sensor Fusion: Investigate the integration of additional sensors, such as radar and lidar, to complement the existing camera-based system.

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