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Original Article

SafeRoute Scanner: A Comprehensive System for Pothole Detection, Traffic Sign Recognition, Mapping, and Automated Reporting to Local Authorities

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Abstract - *The frequency of road accidents is on the rise with each passing day, with one of the leading causes being drivers' unawareness of traffic signs and damaged roads due to the presence of potholes. This paper introduces a web application that helps drivers make better driving decisions by warning them of potholes and traffic signs. The application maps detected potholes on Google Maps, providing alerts to other users travelling on the same road. Additionally, it reports the detected pothole locations to local authorities for repair. This approach utilizes the YOLOv8 algorithm for traffic sign and pothole detection. The proposed system aims to enhance driver safety while also engaging users in assisting local authorities with road repairs, which is cost-effective and less time-consuming.*

Keywords - *Mapping, Potholes, Traffic Signs, Voice alerts, Yolov8.*

1. Introduction

Traffic accidents are one of the leading causes of injuries and fatalities worldwide. In the year 2022, a total 4,61,312 number of accidents were recorded, out of which 33.8% were fatal accidents and 60.4% were injury-causing accidents. Road accidents can happen due to various reasons which include human error, damaged road conditions, or due to lack of vehicle maintenance.

One of the major causes of accidents is traffic rule violations like driving on the wrong side, speeding as well as not following traffic light signals, stop sign signals by the driver due to unawareness. Damaged road conditions due to the presence of potholes can also lead to fatal accidents [22]. Potholes not only contribute to accidents but also result in vehicle damages, reduced travel comfort, and increased cost of maintenance of the vehicle.

The potholes in the road surface resemble bowls in shape. Potholes filled with rainwater weaken the road surface, and the constant weight of passing vehicles can gradually damage the road. Traditionally, manual inspection is done in order to find damaged roads, but it is expensive and takes too much time [6]. It is imperative to address these issues to enhance road safety and overall transportation efficiency.

Several systems exist for pothole detection that use different sensors like ultrasonic sensors, an accelerometer for detecting the road anomalies and generating the dataset for model training, and uses Global Positioning System (GPS) for mapping the potholes on Google Map [2]. This is a costly process as sensors are expensive, and collecting datasets manually is a time-consuming task. Some systems use deep learning algorithms like Convolutional Neural Networks (CNN), Region-based Convolutional Neural Networks (R-CNN), and Faster R-CNN [3].

All the algorithms performed well for object detection but lacked real-time object detection. Currently, various standalone systems exist for pothole detection, traffic sign recognition, and mapping potholes, but a unified system that seamlessly integrates these functionalities is lacking. Moreover, existing systems often exhibit limitations in terms of precision and the ability to detect objects in real-time. To solve the issue, a comprehensive system that can detect potholes on roads, map the potholes on Google Maps, and report the potholes to the authorities for repair, as well as give voice alerts to the driver about the presence of potholes and traffic signs is needed.

This paper introduces a system that is developed using the You Only Look Once (YOLOv8) model which is the latest model in the YOLO family. The You Only Look Once (YOLOv8) algorithm uses the Non-Maximum Suppression (NMS) technique for post-processing, which helps by discarding duplicate detections and making best predictions with bounding boxes for the pothole and traffic sign in real time [21]. The novelty of this system is its ability to provide a comprehensive service to the public via a web application that can identify the presence of potholes and traffic signs on the road from real-time video and the mapping of detected potholes on Google Maps, which helps the users in planning their route to reach the destination and preventing vehicle damage.

This application will provide the overview of the road conditions in advance to the user with the help of the mapping done by previous users on Google Maps. Simultaneously, the system reports the detected potholes to the road authority, equipping them with the necessary data to take prompt and informed action in response to identified potholes. After repairing the road damages, the authority can mark the complaint as resolved, and the mapping of the potholes from Google Maps will be removed automatically.

This system will also provide voice alerts to drivers about potholes, traffic lights, speed-breakers, speed limits, stop signs, no parking signs, and crosswalks which help prevent road accidents. This means users can rely on a single, user-friendly web app to not only identify potholes but also recognize traffic signs and visualize pothole locations on the widely-used Google Maps platform. By doing so, this method improves road safety as well as streamlines the process of addressing road maintenance issues, fostering a more efficient and responsive approach to road infrastructure management. The following are the main contributions of the project:

- Web application for traffic sign and pothole detection in real-time.
- The YOLOV8 model for real-time pothole detection and traffic sign recognition gives better results as compared to existing systems that use CNN and, the RCNN algorithm.
- Voice alerts for notifying users about detected potholes and traffic signs offer an advantage over text alerts, as they capture the immediate attention of the driver. None of the existing systems has the capability of voice alert, which makes this system unique and highlights its potential as a significant enhancement for improving road safety and user experience.
- Automatic reporting of potholes to road authorities for repair, along with location information, helps in cost-effective and time-saving road maintenance, a feature lacking in existing systems.

This paper is composed as follows: Section 2 contains the literature review, section 3 outlines the proposed architecture, section 4 has the results, and section 5 gives the conclusion.

2. Literature Survey

Satish Kumar Satti et al. (2021) [1] proposed a driver alerting system consisting of two modules: pothole and traffic sign detection. The proposed solution makes use of hybrid Features from the Accelerated Segment Test (FAST) and Random Sample Consensus (RANSAC) algorithm for traffic sign detection and extracted features from an Enhanced Canny Edge Detector (ICED) and Bio-Inspired Counter Detection (BCD) technique for pothole detection.

In addition, the bounding box regression model was used to determine the sizes of the identified potholes, and the Support Vector Machine (SVM) classifier was used to distinguish between potholes and traffic signs. The suggested method surpassed the current technologies, according to the experiment's data, with good accuracy for pothole detection and traffic sign detection.

Vijay Kumar et al. (2021) [2] proposed a real-time system to monitor driver and road conditions. The system alerts drivers about the road conditions and identifies signs of drowsiness. The data was collected using sensors like the Global Positioning System (GPS), accelerometer, and ultrasonic sensors. The k-means algorithm was used to find spots with a high probability of danger, and face recognition techniques and body posture tracking was used to track the driver's behaviour. The system accurately predicted drowsiness alerts, while danger spots were predicted with a slight deviation. This system can be an excellent tool for improving road safety.

Vivek Srivastava et al. (2023) [3] introduced a framework to reduce road accidents and assist drivers by traffic sign recognition. The author used the YOLOv4 model which was trained on an annotated dataset having 43 different traffic sign classes. Additionally, a comparison of various objection detection algorithms like Fast Regions with Convolutional Neural Networks (Fast RCNN), Faster Regions with Convolutional Neural Networks (Faster RCNN), YOLOv3 as well, as YOLOv4 identified that the proposed approach performed 90.7% more accurately than the other alternatives under various environmental conditions.

Hanxiao Rong et al. (2020) [4] suggested an approach to identify the Region of Interest (ROI) in a given RGB-D picture: the suggested approach comprised object extraction, K-means depth image segmentation, and image semantic object detection. YOLOv3 was used for image semantic object detection by calculating bounding box and centre coordinates for detecting objects of interest. K-means segmentation separated objects more quickly and accurately with depth information. The difference in size and related domain analysis of objects were performed for object extraction. The size score and diagonal score were utilized to find the area where the detected object is most likely to be. Experimental results showed that the improved K-means algorithm was more accurate with a shorter processing time compared to the conventional K-means algorithm for segmentation.

Prabhat Singh et al. (2023) [6] proposed a pothole-finding system using the Improved Long Short-Term Memory model (ILSTM). This detection system focused on classifying whether the route is dangerous or safe by categorizing the roads based on the size of the pothole. This classification process occurred in two stages: initial ILSTM analysis and subsequent feature extraction, aided by a 1D LBP layer and several LSTM layers. A sensor in the mobile phone collected pothole images present on the roads and then, using the ILSTM system, predicted whether the road was safe or not by classifying the potholes. The evaluation showed a 96.26% accuracy rate and a 98% recall rate, indicating improvements in classification performance.

Ronghua Du et al. (2020) [7] proposed methods for cost-efficient identification of abnormal road surface conditions to enhance road safety using smartphone-based systems. The identification of abnormal roads based on vehicle speed involved the use of the Gaussian background model with the K-Nearest Neighbours algorithm (KNN) for classifying abnormal roads and normal roads. Furthermore, to monitor the condition of the road surface in real time, the collection of abnormal road surface data was accomplished using cellular network technology. The smartphone uploaded the exact location and kind of surface to the cloud whenever a car travelled over a cracked road surface. The results demonstrated a 96.03% accuracy in recognizing road surface potholes, with limitations on the amount and type of unusual damage to the road surface.

Mohan Prakash B. and Sriharipriya K.C (2022) [8] developed a method for identifying potholes by using the YOLOX algorithm and studied different types of YOLOX algorithms. A model was capable of identifying potholes, but the challenge lay in identifying them when obscured by vehicles and pedestrians. The study also compared different YOLO models for improved accuracy and precision. However, the challenge was that potholes had irregular sizes and shapes, and the YOLOx algorithm was employed to highlight these irregularly shaped potholes. The proposed system offered promising applications in real-time road maintenance and safety enhancement and also incorporated a GPS module to mark pothole coordinates.

Ji-Won Baek and Kyungyong Chung (2020) [9] proposed a method that involved converting images to grayscale to reduce computational load and used the YOLO algorithm to detect and remove objects other than potholes by setting their background to white (RGB value 255) during pre-processing. This made it easy to identify the only potholes with better accuracy. The focus was on image-based detection because it was a cost-effective solution for detecting large areas of potholes compared to sensor-based approaches. In future research, directions were explored for extracting the details and features of potholes and predicting their actual size from image data.

Kashish Bansal et al. (2020) [10] presented an innovative machine learning-based model called Deepbus, which was primarily designed for pothole detection using Internet of Things (IoT) sensors. The proposed model focused on pinpointing the location of potholes and immediately informing government authorities to take immediate action. It also notified the driver regarding the pothole and the road surface condition. It displayed a real-time map with updated information related to road surfaces and potholes, providing drivers with up-to-date data for route planning.

Susmita Patra et al. (2021) [11] proposed an approach for pothole detection on road surfaces that differs from existing works through the implementation of a complete system for pothole mapping and real-time monitoring. This approach utilizes a custom CNN model with an accuracy of approximately 97.6% and an Area Under the Curve (AUC) of 0.97, providing a real-time pothole monitoring system for the entire city based on participatory sensing. Additionally, the authors used the Google Maps API to create real-time pothole-marked maps, facilitating visual identification and avoidance of potholes throughout the city. It is important to note that this proposed system is currently a small-scale research prototype, and challenges related to reliability, scalability, and performance may arise when implementing a large-scale solution.

Zahid Hasan et al. (2020) [12] developed a system to identify road-related issues such as potholes, deep ridges, and speed bumps using techniques from machine learning and computer vision. They used the Tensorflow pre-trained model, specifically the Faster R-CNN (Regional Convolutional Neural Network), for identifying speed breakers, deep hills, and potholes. The Faster R-CNN algorithm is known for its good performance in object detection and its ability to detect speed. In this, proposal extraction and integrated feature extraction are included. The researchers developed a customized dataset known as 'Bumpy' in order to train their machine learning methods, which was manually collected using smartphone cameras. The experimental results of the study demonstrated a high level of accuracy, ranging between 87% to 96% in detecting these road hazards.

Abhishek Kumar et al. (2020) [13] introduced an innovative approach for detecting potholes up to approximately 100 meters ahead and alerting the driver about road conditions. They used deep learning techniques, including Transfer Learning, F-RCNN, and Inception-V2. Transfer Learning allowed them to use a pre-trained model as a foundation for training the pothole detection model. The F-RCNN accurately localized and detected potholes in images and videos, while the Inception-V2 model enhanced detection accuracy. They tested the model's performance and found that it worked exceptionally well. The reason for this superior performance is the use of Transfer Learning, F-RCNN, and Inception-V2 in the model.

David Mijic et al. (2020) [14] presented an approach for detecting a specific set of 11 traffic signs using the YOLOv3 algorithm. The algorithm was trained on a custom dataset derived from video signals captured in the city of Osijek, Croatia, under different atmospheric conditions. The dataset consists of 28 video sequences captured using a GoPro Hero5 camera with a resolution of 720x480 pixels. The proposed solution uses the default YOLOv3 architecture, and the YOLOv3 loss function is employed for model training. The final weights for the model are selected from the 13,000th iteration. They analyzed the performance of the model, which demonstrated high accuracy in detecting the specific set of traffic signs, with a Mean Average Precision (mAP) value of 89, as well as good precision and recall values at different threshold settings. The model is capable of processing approximately 20 Frames Per Second (FPS) and shows potential for accurately calculating the gap between the car and the traffic sign.

Kavitha R. and Nivetha S. (2021) [15] contributed to the sector of object detection for autonomous vehicles by implementing the YOLO algorithm and utilizing deep learning techniques, such as CNNs and max-pooling layers, to enhance the accuracy of object detection in real-world scenarios. The first part of this system focuses on object detection using the YOLO algorithm, which provides accurate classification and position of objects in the environment. The second part explores the use of the Raspberry Pi4 for running object detection algorithms, specifically for detecting potholes and wetlands, which helps improve the performance of self-driving vehicles and solves road-related issues.

Ping Ping et al. (2020) [16] developed a way to detect potholes using deep learning algorithms capable of automatically identifying potholes on roads, thereby enhancing road safety and efficiency. They used modern deep learning models such as SSD, HOG with SVM, YOLOv3, and Faster R-CNN to ensure accurate and reliable detection results, potentially reducing the risk of traffic accidents caused by potholes. Through comparative analysis, they determined YOLOv3 to offer faster as well as more accurate detection solutions compared to other models. The system they developed, needing simply an internet connection and a camera mounted on a car's dashboard, simplifies implementation and enhances the accessibility of such technology for road maintenance and safety purposes.

Mallikarjun Anandhalli et al. (2022) [17] proposed deep learning techniques like convolutional neural networks and YOLOv3 in order to evaluate the models' resource and detection performance. The proposed solution uses a vision-based approach to detect potholes by gathering data on their presence in a variety of Indian traffic situations. In this paper, a comparison between sequential CNN and YOLO is provided. CNN is shown to require shorter training time than YOLO (anchor-based) without compromising pothole identification performance. The trials were conducted on both models, and a conclusion was reached to highlight the advantages of the model with 83% precision on the YOLOv3 and 98% accuracy on the CNN.

Braian Varona et al. (2019) [18] suggested a technique to detect potholes by developing deep-learning models that are capable of identifying various road surfaces. Data is collected from mobile accelerometers and GPS sensors and used by different models like CNN and LSTM, for training the data. They highlight the significance of strategies for data augmentation and segmentation while highlighting the need for these techniques to facilitate the application's deployment across multiple cities with minimal effort. Furthermore, their future work aims to expand the analysis to include additional road surface types and explore how this data can be leveraged to adjust stability to event detection automatically.

Savita Chougule and Alka Barhatte (2023) [19], a deep learning system, is used to identify the video pictures taken by the camera as normal roads and potholes. Additionally, the device camera will show the front of the car, emphasizing the pothole. The model is trained using deep learning YOLOv3 and YOLOv5 algorithms, and its detection accuracy is evaluated using Kaggle pothole detection datasets. The suggested method will assist in keeping an eye on the state of the road, counting how many potholes there are, and producing a warning signal; also system's primary goals are to find potholes, count them, and show the vehicle's front from above. The results show that the YOLOv5 has precision, recall, and Average Precision (AP) values of 0.763, 0.548, and 0.635, respectively.

Yanzhao Zhu and Wei Qi Yan (2022) [20] evaluate the performance of YOLOv5 and SSD for Traffic Sign Recognition (TSR) using their dataset, with YOLOv5 achieving higher mean average precision and recognition speed compared to SSD. The traditional visual object recognition methods have limitations, and the paper demonstrates how deep learning-based models like YOLOv5 can overcome these limitations and provide accurate and efficient traffic sign detection and recognition.

Ganesh Babu R et al. (2020) [24] proposed a new system to monitor road surfaces, using Convolutional Neural Network-based Deep Learning to recognize speed bumps and potholes accurately. Their system incorporates GPS to locate and report hazards to control rooms. When compared to traditional methods like Kirchoff's theory and the KNN algorithm, their system, called CNN-DL, demonstrated superior performance in detecting potholes. Their experiments validated CNN-DL's effectiveness in reducing road hazards.

Rahul Dhingra et al. (2024) [25] built a two-step approach that separates the data collection and pothole identification processes. The focus of their paper is on visual-based techniques, particularly comparing popular machine learning models and algorithms for pothole detection. They explored transfer learning techniques like YOLO and SSD, as well as proposed techniques using CNNs and classification algorithms like SVM. Additionally, the use of morphological techniques to determine the actual dimensions of potholes is covered in this work. The conclusion highlights the selection of YOLO, SSD, HOG, and CNNs as the most reliable detection algorithms, with YOLO achieving the highest accuracy of 82%.

Rohan Borgalli (2020) [26] proposed a pothole detection and road maintenance system that highlights the economic and safety impacts of potholes. Advances in sensor technologies like ultrasonic sensors and cameras, along with deep learning algorithms, show promise in automating pothole detection. Crowd-sourced data and smartphone apps contribute to real-time mapping and citizen engagement, streamlining maintenance efforts and improving accountability. Integrating these technologies offers efficient and accurate ways to identify and prioritize pothole repairs, enhancing overall transportation infrastructure management and public service delivery.

Etukala Jaswanth Reddy et al. (2020) [27] proposed a system that recognizes that poor road conditions, particularly potholes, contribute significantly to traffic congestion and accidents. Many methods for pothole detection rely on complex equipment and algorithms, which can be slow and power-intensive due to extensive data processing. This paper proposes a straightforward approach using depth-based analysis with an ultrasonic sensor. By comparing depth measurements to vehicle ground clearance, potholes can be identified and their severity assessed. The system then notifies maintenance authorities via email using GPS and IFTTT server integration. This cost-effective method offers a continuous and proactive approach to road maintenance, enhancing overall road safety and efficiency.

Oche Alexander Egaji et al. (2021) [28] proposed a system that shows concern due to its adverse effects on vehicle damage and road safety. Studies show a significant increase in filled potholes in regions like England and Wales, resulting in substantial financial burdens for motorists and businesses. The high costs associated with repairing pothole-related damages emphasize the urgent need for efficient pothole detection and reporting systems. Traditional methods often rely on costly hardware, whereas recent advancements in mobile sensor technologies offer a more accessible and cost-effective approach. Utilizing machine learning models based on mobile sensor data has shown promising results, with techniques like Random Forest Tree and KNN demonstrating effective pothole detection capabilities. Further developments in this area can lead to improved road maintenance strategies and safer travel experiences for all road users.

Yik YK et al. (2021) [29] proposed a system to keep roads safe by using deep learning to find potholes. This helps make sure roads are safe for drivers and prevent accidents caused by road damage like potholes and landslides. The system is important because many accidents happen due to deep potholes and bad roads, especially when it is raining heavily, and drivers cannot see well. The system uses a special algorithm called YOLOv3 in order to locate potholes in real time using a webcam. When a system detects a pothole, its location is recorded and shown on a map using Google Maps. The system was tested with 330 sets of data and showed good results, with a 65.05% accuracy rate in detecting potholes. Their system could be a helpful way to quickly find and fix potholes, making roads safer for everyone.

Chitale PA et al. (2020) [30] introduced a method for detecting and determining the size of potholes on roadways that uses deep learning and image processing. With the rise of autonomous systems, ensuring road safety is crucial, especially as potholes pose a significant threat. The proposed system uses the YOLO algorithm, trained on a custom dataset of various potholes, to detect potholes accurately. Additionally, the exact dimensions of the identified potholes are provided via a dimension estimator based on image processing. The objective of this technology is to reduce the dependency on workers for road maintenance, especially in consideration of the COVID-19 pandemic. According to the study, the YOLOv4 model surpasses YOLOv3 in terms of pothole detection accuracy and estimating their dimensions. Future work includes integrating the system into surveillance vehicles for automatic and precise monitoring of road conditions, aiding in efficient road maintenance planning.

3. Proposed Architecture

3.1. Methodology for Pothole and Traffic Sign Detection

Figure 1 shows the methodology of the proposed system, which includes data collection, data prepossessing, and annotation, training the model using the YOLOv8 algorithm, and integrating the trained model with a web application with having user-friendly interface. The web app will give voice alerts to drivers about the pothole and different traffic and report the road authority for repairing the pothole detected.

3.1.1. Data Collection of Pothole and Traffic Sign

The research primarily aims to detect potholes and traffic signs using publicly available datasets from sources like Kaggle and Roboflow. Table 1 shows that the dataset consists of a diverse 4604 images distributed in 9 classes, which include classes like pothole, no parking, speed limit, speed breaker, crosswalk, speed-breaker sign, stop, traffic light, turn left and turn right. Figure 4 shows the distribution of images in different classes. Figure 2. Represents pothole images from the dataset filled with water, without water and potholes of various shapes and sizes.

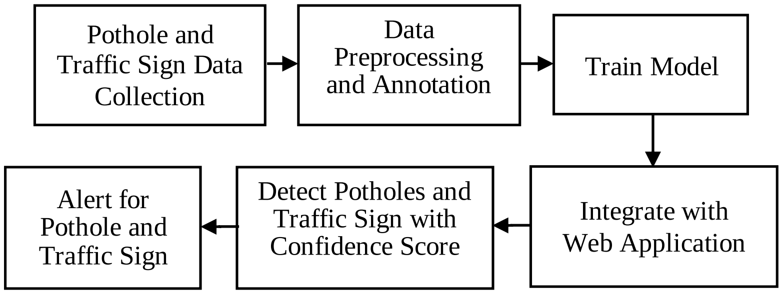

Fig. 1 Methodology for the proposed system

Fig. 2 Images of different potholes from the dataset

Fig. 3 Sample images of traffic signs from the dataset

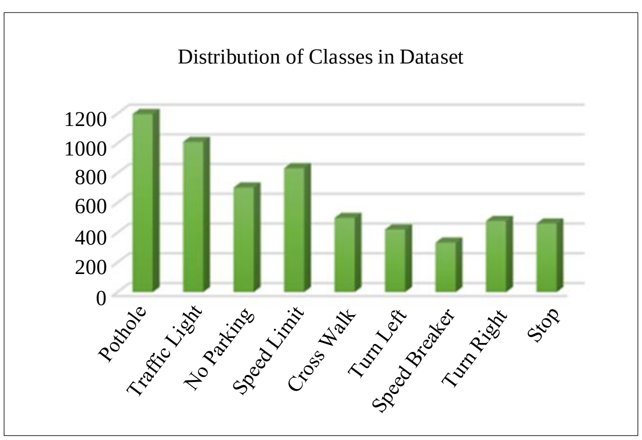

Fig. 4 Distribution of different classes in the dataset

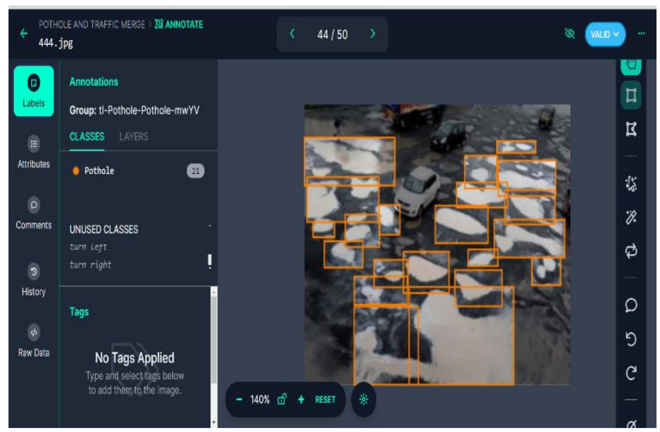

Fig. 5 Annotating image using roboflow tool where the bounding box in orange colour shows the potholes in the image

Table 1. Details statistical description of the dataset

Index Name	Description
Total Classes in Dataset	9
Total Number of Images	4604
Total Images after Data Preprocessing and Augmentation	7862
Training Dataset	6516
Validation Dataset	992
Testing Dataset	554

The dataset consists of various traffic sign images which are shown in Figure 3. Different traffic signs in the dataset include speed limit symbols, traffic lights, stop symbols, no parking symbols, and speed breaker symbols.

3.1.2. Image Annotation

Annotation of the image is the most important task for the training model for detection of objects. Roboflow is a web-based tool used for annotation of the gathered dataset. It is easy to use and publicly available. The raw images from the dataset need to be annotated before training the model for object detection. All the raw images are labelled by using a Roboflow to make the raw data understandable for the YOLOV8 algorithm.

Labels are added manually to potholes and traffic signs present in the dataset. Figure 2 shows the annotation of the sample image consisting of potholes. After drawing the bounding box around the pothole, the class name pothole was given to it. This same process is applied to all the images present in the collected dataset for labelling. Labels are given according to the item present in the bounding box; it can be potholes or traffic signs.

3.1.3. Data Preprocessing and Augmentation

The next step after image annotation is data preprocessing, which improves the quality of the dataset. In this stage, images are resized and stretched to achieve an image of size 640 X 640 pixels. Data augmentation addresses issues such as overfitting by rotating the images between -15° to +15°, flipping the images horizontally, scaling, cropping images, and adding noise near to 0.1 percent of pixels. After this step, the size of the dataset increases to 7862, as shown in Table 1.

This dataset then becomes ready for training purposes. The step-by-step process of the data collection and data preprocessing is mentioned in Algorithm 1.

Algorithm 1 - Data collection and data preprocessing.

1. Start
2. Collect pothole and traffic sign image data from sources like Kaggle, videos, and images.
3. Create an account on Roboflow and create a new project.
4. Upload the collected dataset on Roboflow.
5. Annotate the data on Roboflow by labelling it with appropriate classes.
6. Resize the images and auto-orient the images.
7. Augment the images by rotating, blurring, and cropping.
8. Split the dataset for training, testing, and validating.
9. Generate the dataset.
10. End.

3.1.4. Training Model

In order to train the YOLOv8 model, the dataset is split for training, testing and validation. The training dataset consists of 83% images, while 10% of the dataset is used for validation, and the rest 7% of the dataset is used for testing, as described in Table 1.

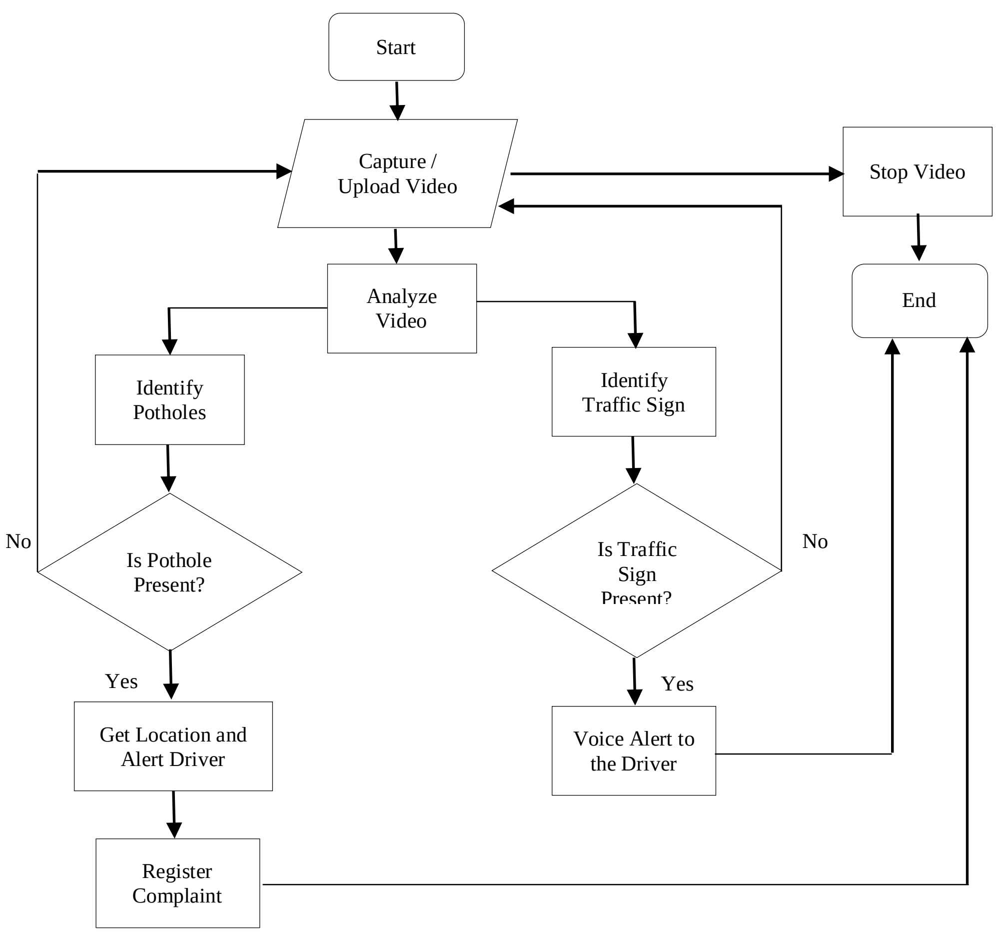

Fig. 6 Proposed flowchart of pothole and traffic sign detection

3.2. Proposed Flowchart of Pothole and Traffic Sign Detection

Figure 6 shows the flowchart of Pothole and Traffic Sign Detection. A web application is developed for pothole and traffic sign detection. A laptop's camera is used by the application to start recording live video or the user can upload the recorded videos. The trained model analyses the captured real-time video or uploaded video to detect the presence of potholes and traffic signs within the frame. Once potholes are confirmed, the GPS location is retrieved by the application using the latitude and longitude of these potholes. It alerts the appropriate local authorities in charge of road maintenance as well as the driver of the hazard.

Alert traffic signs to drivers if detected by the model. Concurrently, complaints are registered on a centralized dashboard, creating an official record of the potholes. The dashboard allows the authorities to view the complaints that have been filed. As potholes are repaired, the status of every complaint is to be updated and indicated as "repaired" on the dashboard when potholes are fixed. In this way, the resolution of reported problems can be tracked.

Algorithm 2 - Working of proposed system,

1. Start
2. Input real-time video or recorded video to the application.
3. Divide input frames into S X S grid cells by the YOLO model.
4. Predicts bounding boxes for objects within grid cells.
5. Predict the vector for each grid cell having the box's width, height, centre, probability of the object, and class probabilities.
6. If no bounding box is present in a grid cell, then the probability of the object is zero.
7. If multiple bounding boxes are detected for the Potholes, then Non-Maximum Suppression (NMS) is applied.
8. Then the detected Potholes with their associated bounding boxes, labels of the class, and confidence scores, along with the GPS location, are sent to the Database.
9. This information will be displayed on the Dashboard of Authority.
10. If the pothole is repaired, then the complaint can be marked as resolved.

3.3. YOLOv8 for Pothole and Traffic Sign Detection

YOLOv8 was released by Ultralytics in January 2023 [21], which belongs to the You Only Look Once (YOLO) family. The YOLOv8 uses a single neural network to predict bounding boxes and class labels for the identified object [5]. Since YOLOv8 is an anchor-free model, there are a number of benefits, such as lesser box predictions and a more effective Non-Maximum Suppression (NMS), sometimes referred to as intersection over union [21]. YOLOv8 model can process and make object detection predictions for 280 frames in a video in one second. The accuracy of the model for identifying objects at a particular Intersection over the Union (IoU) threshold is quite strong, as seen by its average precision at IoU 0.5 (AP50) of 53.9% [21]. High Frames Per Second (FPS) values are very important for real-time applications where quick and accurate object detection is essential. In the proposed system, the mobile phone is mounted on the dashboard of the car while driving to capture real-time video for the detection of potholes and traffic signs. Due to the feature of YOLOv8 having a high FPS value with good accuracy, the YOLOv8 model is used in the proposed stop system.

The YOLO algorithms fall in the category of regression problems. The YOLO algorithm works by predicting the presence of a particular object in the image with the help of a vector having class probability, centre, height, width, and class prediction for that object. If an object is present in the frame, then the probability will be 0; otherwise, 1. Additionally, classes are predicted using 0 or 1 to determine which object is present [22].

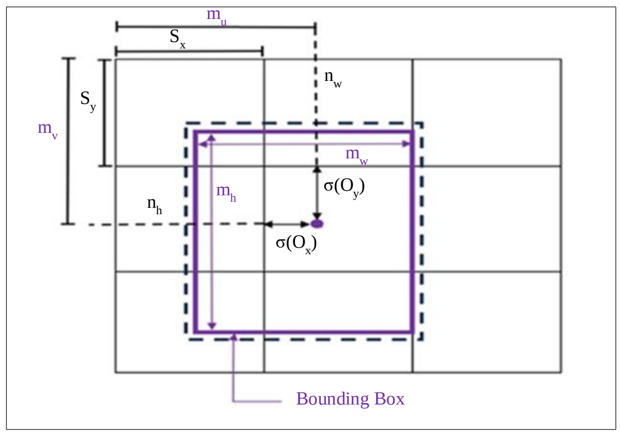

Fig. 7 YOLO bounding box

$$B = box\ (m_u, m_v, m_w, m_h) \quad (1)$$

$$m_u = \sigma(o_x) + s_x \quad (2)$$

$$m_v = \sigma(o_y) + s_y \quad (3)$$

Figure 7 shows how YOLO detects objects by using a bounding box. Four coordinates (mu, mv, mw, mh) are used to get the bounding box around the object. In equations (2) and (3), mu and mv represent the centre's coordinates, the offset from the cell's origin by sx and sy, and any offset from the image's origin given by σ (ox) and σ (oy) [4].

$$m_w = n_w e^{\,Ow} \quad (4)$$

$$m_h = n_h e^{\,Oh} \quad (5)$$

Equations (4) and (5) show *mw* and *mh* represent the width and height of the bounding box based on *nw* and *nh* which predicted the bounding box width and height. The formula can be used to get the confidence score (C) given in Equation 6 [4]:

$$C = P(object) * IoU \quad (6)$$

Where IoU stands for Intersection over Union between the ground truth and predicted box, the probability that the detected object is a member of a particular class is denoted by P(object). Equation 7 shows IOU, which can be defined as,

$$IOU = Intersect\ Area / Union\ Area \quad (7)$$

The loss function of YOLOv8 combines localization loss (L_{loc}) with classification loss (L_{cls}). The total loss is defined in equation 8 [5]:

$$L = \lambda_{loc} L_{loc} + \lambda_{cls} L_{cls}\ , \quad (8)$$

Where L is a loss function, the relative significance of the localization loss and the classification loss is controlled by the hyper-parameter λ_{loc} and λ_{cls}, respectively.

4. Result

4.1. Analysis Prediction Result

The inference is made on a subset of the dataset having 729 images consisting of 1185 total instances across all classes. These instances belong to the nine mentioned classes such as No Parking, Pothole, Speed Limit, Crosswalk, etc. The trained model's performance is evaluated using precision, recall, and mean average precision at Intersections over Unions (IoU) with a threshold of 0.50 (mAP50).

During this process of evaluation, each image takes 0.3 milliseconds of preprocessing before making it before it is fed into the model for inference. The inference stage takes 2.5 milliseconds per image to generate a prediction. Post-processing takes 2.7 milliseconds per image. During this stage, the model's predictions are processed to remove redundant detections using Non-Maximum Suppression (NMS) and generate the final set of results by filtering out low-confidence detections.

Table 2. Result of evaluation metrics

Sr. No	Class Name	Precision	Recall	mAP@50
1	Pothole	0.60	0.32	0.39
2	Traffic light	0.95	0.9	0.95
3	Crosswalk	0.97	0.83	0.89
4	Stop	0.87	1	0.99
5	No parking	0.76	1	0.97
6	Speed breaker	0.93	0.78	0.89
7	Turn right	0.54	0.75	0.8
8	Turn left	0.73	0.67	0.77
9	Speed limit	0.98	0.98	0.98

Table 2 presents a detailed analysis of the trained model, highlighting its performance across various classes. Notably, the overall mean average precision is 85.1%, with a precision of 81.6% and recall of 80.4%, indicating a commendable level of performance even if only 60 epochs are executed for model training. Equation 7 shows the Intersection over the Union (IOU) formula. In evaluation, the mAP is one of the most important metrics. Mean Average precision is represented by the area under the precision-recall curve given by Equation 11 and shown in Figure 8.

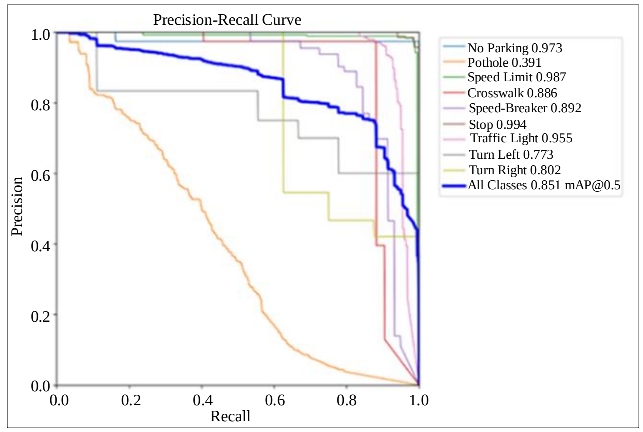

Fig. 8 Precision-recall curve

$$\text{Precision} = \frac{\text{True positive}}{(True\ positive + False\ positive)} \quad (9)$$

$$\text{Recall} = \frac{\text{True positive}}{(True\ positive + False\ negative)} \quad (10)$$

Figure 9 shows the Precision-Confidence curve across all the classes. The Precision Formula is given in Equation 9. Precision is all about the percentage of true positive predictions among all correct predictions.

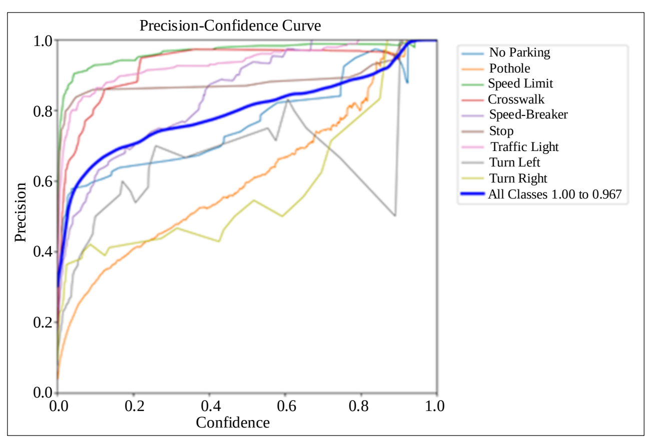

Fig. 9 Precision-confidence curve

$$Mean\ average\ precision = \frac{1}{k} \sum_{i=1}^{n} (precision_i) \quad (11)$$

Figure 10 represents the recall confidence curve across all the classes. Recall the formula given in Equation 10. Recall is the model's capability to detect all correct instances in the dataset.

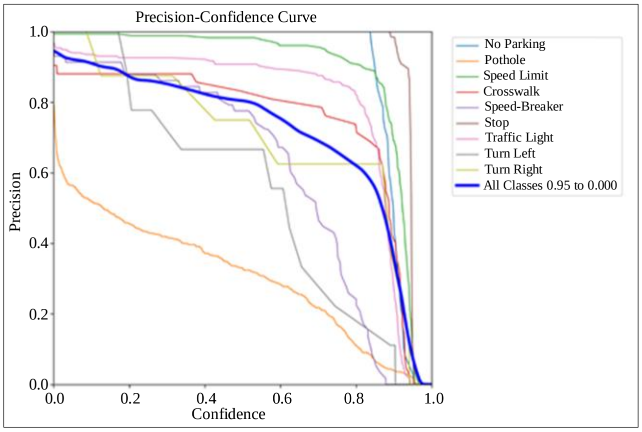

Fig. 10 Recall-confidence curve

Predictions about potholes and traffic signs like speed limit, traffic lights and crosswalks with the confidence score are shown in Figure 11. The images used for prediction are quite challenging as they contain different objects along with the intended object class.

Fig. 11 Sample prediction made by the trained model

4.2. Integration of Model with Graphical User Interface

The user interface is created for users which is locally hosted for users on a laptop. To use the web app, the user must register into the system with a valid email id and phone number. Once an account is created, the user can log in again with email and password. Upon logging into the application, a welcome message will appear, accompanied by the user's name, as depicted in Figure 12.

Users need to click on the video button on the top-right side and upload the video. After clicking on the video button, the user will be redirected to the page represented in Figures 13 and 14, where the user has to upload the video and get output regarding the presence of potholes or traffic signs along with voice alert and confidence score. Figure 13 shows that the input video consists of potholes, which are marked with the help of a bounding box. Along with the rectangular box class name pothole is written on top of the box along with the confidence score about the detection.

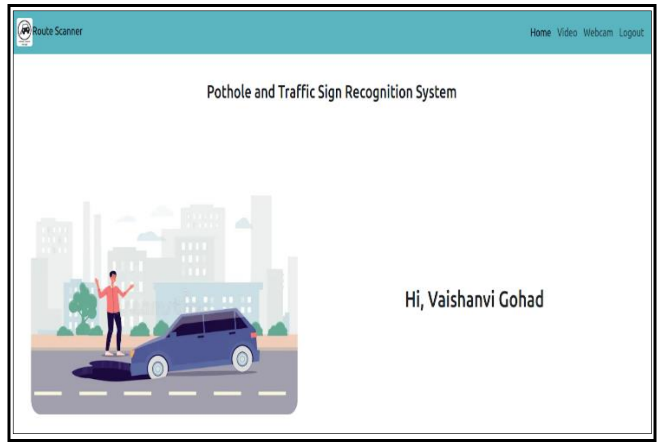

Fig. 12 Home page of the web app, which shows a welcome message to a user who is currently logged in

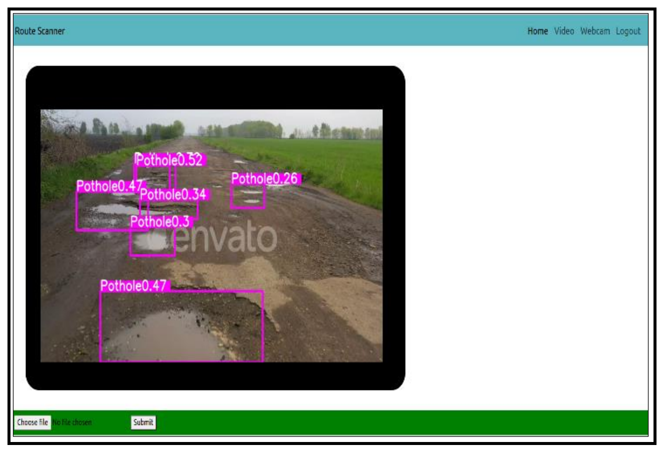

Fig. 13 Input video and get output regarding the presence of potholes along with voice alert and confidence score

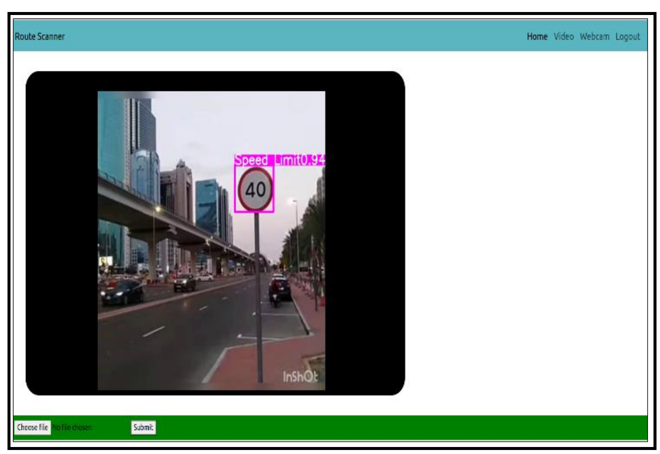

Fig. 14 The application detects the speed limit and confidence score from the input video, along with a voice alert to the driver

At the same time, information about the potholes will be notified to the road authority so the road maintenance team can take proper action regarding repairing the road damage. In Figure 14 speed limit is detected from the input video, as well a voice alert is given to the driver. A bounding box is drawn around the symbol of the speed limit, and on top of the box class label, which is the speed limit along with the confidence score for detection, is written. A dashboard is created to display all the collected data on potholes along with their location represented in Figure 15.

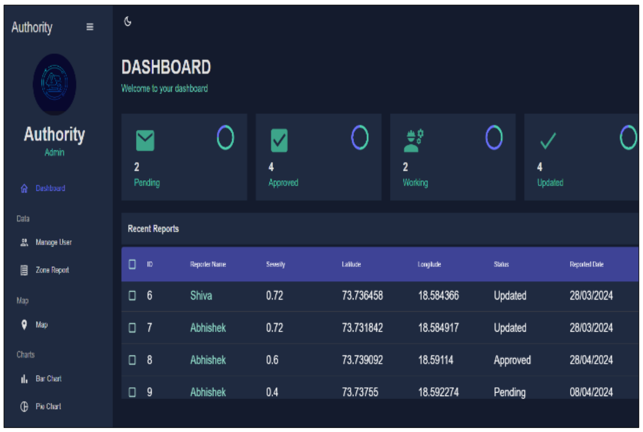

Fig. 15 Authority's dashboard

Figure 16 demonstrates the mapping of potholes on Google Maps with markers. The authorised person would remove this marking after repairing the road through the marker.

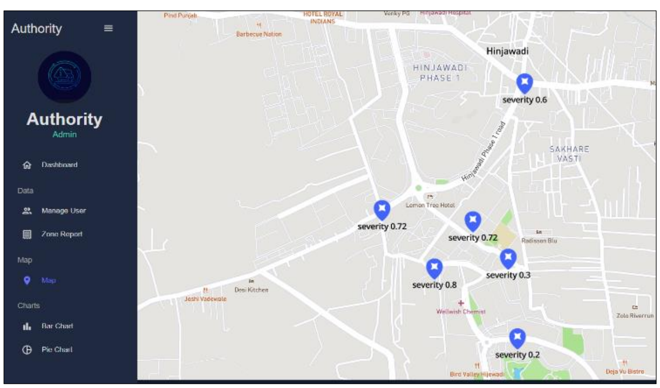

Fig. 16 Map showing pothole locations' marking on the dashboard

Figure 17 helps the road maintenance team to understand how many complaints of potholes are recorded monthly out of how many are resolved, approved, pending or updated. Ultimately, this dashboard will help the road maintenance team to keep track of all the complaints reported.

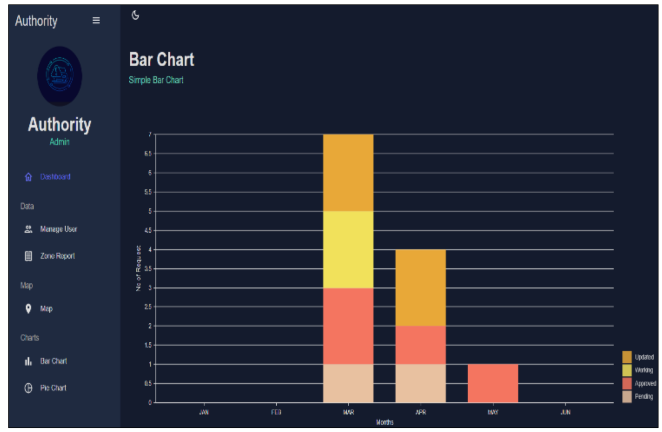

Fig. 17 Visualization of the pothole complaints

5. Conclusion

This paper proposes a novel approach which addresses two major factors that lead to road accidents: damaged roads due to potholes and driver unawareness of traffic signs. The developed system focuses on improving travel safety and road maintenance with the help of a web application. The YOLOv8 object detection algorithm trained on a dataset encompassing nine distinct classes, including potholes, traffic lights, crosswalks, and various traffic signs. The experimental result shows that the proposed system's mean, average, and precision are optimal.

This system beats other existing systems by detecting various classes of the dataset by using a single algorithm and eliminating the need for hardware sensors for data collection, as images in the dataset are collected from online sources such as Kaggle and Roboflow. The collected dataset consists of diverse images under varying lighting conditions, weather effects, and road surface materials. Simultaneously, the system gives voice alerts of traffic signs and potholes, which helps in preventing road accidents. By automatically reporting pothole locations to a road maintenance team's dashboard, the system eliminates the necessity for manual inspections. Once authorities repair reported potholes, they can mark the complaints as resolved, prompting the removal of the corresponding mapping on Google Maps. In this way, the developed system can help in reducing road accidents, continue smooth traffic flow and prevent vehicle damage.

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