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RESEARCH

Road condition assessment: A framework for automatic detection of surface flaws

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Road abnormalities such as cracks, unevenness, potholes, and manholes are increasing the number of road disasters in today's world, particularly in nations like India. Accidents and irreplaceable loss result from uneven and damaged roadways, as well as unneeded openings. The introduction of more Big Data sources through citizen recording devices has created a new foundation for public infrastructure management and control, as well as policy design. Roads that are maintained on a regular basis are less likely to be involved in accidents. However, manually inspecting road damage is costly, time-intensive, and requires a large amount of manpower. Automatically detecting and reporting the presence of potholes, manholes, and other anomalies such as cracks to the appropriate departments can aid in the recovery of road conditions. Detailed real-time performance object detection frameworks (YOLOv5 and RCNN) for detections of potholes are presented. The main objective of this manuscript is to propose a framework that utilizes machine learning and deep learning models for detecting surface flaws.

Keywords: Deep Learning, YOLO, RCNN, SVM, Big Data

Introduction

As the world's population grows, the strain on infrastructure has increased. Automobiles have been clogging the roads. It's becoming quite tough to keep track of this traffic. This is the key motivation for creating a vehicle that can aid the driver in a number of ways. On the roadways, one of the most pressing challenges is deteriorating road conditions. Driving can be challenging due to various factors, including oil spills, rain, natural wear and tear, and traffic accidents. Unexpected obstructions could lead to more collisions. Due to the terrible road conditions, the vehicle's fuel consumption increases, resulting in wasted gasoline.

Authorities are concerned about distress in asphalt pavements due to the need to prevent adverse conditions. These pavements are vulnerable to issues such as high traffic volume, weather exposure, aging, substandard materials, and inadequate drainage systems, which often lead to two primary types of failure: cracking and potholes. Potholes are depressions or cavities on the road surface that require immediate attention, as they can cause significant problems such as accidents, rough driving conditions, and damage to vehicles. Road accidents will become the sixth biggest cause of mortality in 2030, according to World Health Organization (WHO) predictions. The consequence of potholes piqued the curiosity of civil community scholars. Manual inspection methods are used in poor countries to detect potholes, resulting in erroneous estimates due to individual experience.

We offer a conceptual framework for a deep learning-based automated road defect identification system. We treat damage of a road as a single item to be detected in order to address the damage of the road type detection problem. Each of the various types of road damage is specifically considered as a distinct item. Then, we utilize one of the object identification algorithms (such as You Only Look Once [YOLO]) to study the visual patterns of each damage of road type by training it on the road damage dataset. A road defect recognition system alerts the driver to the presence of uneven roadways, cracks, and potholes along its path.

The primary objective of this paper is (a) to develop a framework for automated detection of road surface flaws. (b) Enhance Real-Time Performance. (c) Utilize Citizen Data for Scalable Solutions. (d) Benchmark Against Existing Methods. The novelty of this work lies in its integration of advanced object detection algorithms (YOLOv5 and RCNN) with citizen-driven Big Data sources to enable real-time, automated road defect detection and reporting.

The structure of the paper consists of six sections. Section 1 contains the introduction part. Section 2: the literature work. Section 3 the proposed methodology Section 4 implementation of the project. Section 5 describes about the results, and the conclusion was discussed in section 6.

Related work

A faster region-based convolutional neural network (R-CNN) algorithm for pre-training was utilized to ensure the process is both cost-effective and efficient. In their research, Hacıefendioğlu, Kemal, and Hasan BasriBaşağa (1) use deep learning to identify cracks in concrete roads. This study aims to identify cracks in concrete roads under various lighting and weather conditions. The research demonstrates the effectiveness of deep learning approaches, like faster R-CNN, in detecting cracks on concrete roads, offering a promising step forward for automated infrastructure inspection systems.

The researchers Satti, Satish Kumar et al. (2) used a unified technique to identify potholes and traffic signs. A support vector machine (SVM) classifier is utilized to differentiate between traffic signals and potholes, while a bounding box regression model is implemented to determine pothole dimensions. The hybrid characteristics from random sample consensus and accelerated segment test methods are applied to extract and align the most relevant features for identifying road traffic signs. Despite this, the proposed unified method effectively identifies both potholes and traffic signs, showcasing its potential to enhance road safety and support automated systems. However, a key limitation of the study is its reliance on a dataset with a small sample size. The research focuses on the importance of tailored solutions to address the difficulties of diverse road environments.

Davidovic, Marina et al. (3) projected in their study a new technique for detecting road problems Defects were categorized into three types based on geometric elements like points, lines, and polygons. Mobile mapping technology was used to identify road issues by applying point clouds and ortho mosaics as input data. The technique includes identifying point objects by analyzing point clouds alongside panoramic and ortho images. Utilizing ortho mosaics and panoramic photographs to map defects as point, line, and shape geometries, this study shows the efficiency of mobile mapping in identifying large-scale road infrastructure issues plus supporting precise defect detection and effective maintenance planning through geographic information systems (GIS) and AI-driven analytics.

We conduct real-time road surface recognition tests using a Raspberry Pi 3 B+, an MPU 9250, and a tripod dolly, employing machine learning techniques with long short-term memory (LSTM) and recurrent neural network (RNN) for surface detection. The proposed system utilizes an MPU 9250 and a Raspberry Pi 3 B+ sensor to collect data from six different road surfaces, facilitating a scalable, cost-effective RNN-based real-time road surface detection solution that typically identifies surfaces within 1 s.

Among the algorithms evaluated, the gradient boosting decision tree demonstrated superior accuracy at 97.92%, markedly exceeding the K-Nearest Neighbor (KNN) algorithm's lowest accuracy of 75.60%, thus reflecting a substantial improvement of 29.52%; this capability enables effective navigation of wheeled robot cars along smooth paths and underscores the feasibility of employing machine learning techniques on low-power devices for infrastructure and transportation purposes.

This article presents a novel method for detecting road surface irregularities using data from 3D force sensors in vehicle tires, demonstrating that the velocity prediction network (VP-NET) neural network offers superior accuracy and simplicity, while also highlighting a correlation between road conditions and noise levels in the sensor output, ultimately aiming to enhance road safety and optimize infrastructure management.

In their research, Arjapure et al. (4) showed that deep learning classifiers, especially convolutional neural networks (CNNs), are effective at finding potholes on roads. The system accurately detected potholes in road images with an 89.66% success rate using Python and OpenCV. This method greatly improves how we maintain roads, saves money, and enhances safety by detecting potholes in real time.

Arya, Deeksha et al. (5) proposed an approach based on a dataset of 26,620 images taken with smartphones from various countries to detect and classify different types of road damage. This approach was applied to evaluate the efficiency of the Japanese model for use in different countries. This method provides a practical tool for managing road maintenance in various environments while minimizing the need for extensive region-specific labeled datasets. The proposed research successfully results in the potential of transfer learning for road damage detection across diverse regions, offering a scalable and efficient solution for monitoring of automated infrastructure.

Wu, Chao et al. (6) implemented in their research a machine learning system for detecting road potholes. This research mainly focuses on the effectiveness of merging smartphone sensors with machine learning algorithms for automated pothole detection. The proposed model is developed using smartphone sensor data, employing traditional classifiers such as random forest classifier, likelihood ratio and support vector machine. Different techniques of machine learning are preferred over neural networks due to their lower data requirements. The proposed methodology gives a cost-effective, real-time solution for monitoring road conditions and provides a scalable method for managing and maintaining road infrastructure on a large scale. By using multiple classifiers and a large dataset, the accuracy and efficiency of the system can be improved.

In their research paper, Cao, Wenming, et al. (7), they examines 3 important types of methodologies used in road crack identification: machine learning, 3D imaging-related methods, and image processing. The review focuses on the progression of pavement defect detection methods, emphasizing image-based, sensor-based, and data-driven approaches. It also evaluates the 3D object classification performance of deep neural networks and tests various data representations for detecting 3D cracks. To enhance 3D crack detection, depth information is incorporated, providing a spatial structure to the cracks. The paper categorizes deep learning methods into three areas: object recognition, image classification, and pixel-level segmentation. The paper offers important insights into the current developments and future directions in pavement defect detection technologies. While this additional data improves the algorithm's accuracy, it also significantly increases computational costs. Although manual inspection is still in use, automated systems that leverage AI and machine learning are becoming more prevalent due to their ability to improve efficiency and accuracy in large-scale pavement monitoring.

The authors, Hsieh, Yung-An, and Yichang James Tsai, proposed in their paper (8) to gather and publish current information on machine learning-based crack detection approaches in order to assist researchers in swiftly determining their focus and direction. Eight deep learning models performance for crack segmentation was evaluated using consistent assessment methods and real-world 3D roadway images under various conditions. This paper investigates 68 machine learning-related techniques for crack identification, with a particular focus on pixel-level crack segmentation. The study emphasizes that both the quantity and quality of data play a crucial role in developing machine learning models and should be considered in future developments. A future performance evaluation framework is proposed to assess crack detection algorithms in a qualitative and objective manner. It highlights that while traditional methods are still valuable, deep learning models outperform them, especially when handling complex and large datasets. Faster, more reliable, and accurate data collection and labeling methods are also recommended. This study contributes to the evolving field of automated infrastructure monitoring and provides useful insights into selecting the most suitable machine learning models for crack detection tasks. The paper underscores the significant potential of machine learning, particularly deep learning approaches like CNNs, in automating crack detection for infrastructure maintenance.

Fan, Rui et al. in their publication (9) use disparity transformation and road surface modeling to detect potholes. The proposed method for pothole detection, combining disparity transformation and road surface modeling, demonstrates high accuracy and can be used in real-time road monitoring systems. This reliable detection algorithm integrates a disparity transformation technique with disparity map modeling to deliver accurate and efficient pothole detection. Dynamic programming and golden section search methods are applied to enhance the disparity. A dense disparity map is adjusted to differentiate damaged areas of the road from undamaged ones. Both real and simulated discrepancies are analyzed to precisely identify potholes. Since the standard pothole detection criteria may not always apply, a deep neural network is trained to recognize potholes in the transformed disparity map. This method provides a scalable, efficient solution for automated road maintenance, contributing to better road safety and reduced maintenance expenses.

The authors, by Kalliris, M., et al. (10), discover the use of acoustic measurements to detect wet road surfaces, a critical task for vehicle safety systems, mainly in advanced driver assistance systems (ADAS). This research suggests the machine learning algorithm application to examine acoustic signals recorded from road surfaces. Wet road surfaces have different acoustic features compared to dry surfaces, and the objective of this paper is to recognize these differences using data-driven methods. With machine learning models training on acoustic data, the author's goal is to develop a reliable method for detecting wet roads in the real-time environment. This paper (10) tells how machine learning can be utilized to improve the safety features in vehicles by enabling accurate detection of road conditions. This method could possibly be used in systems that warn drivers about hazardous wet roads, improving driving safety in adverse weather conditions.

In this paper (11), researchers Maeda, Hiroya, et al. used deep neural networks to identify and categorize road damage. The model utilized sophisticated CNNs for training on a dataset comprised of smartphone-taken photographs. By employing smartphone images, this innovative method offers an efficient and cost-effective approach to real-time road monitoring, showcasing its potential for scalability in infrastructure management and maintenance; the system's processing speed and accuracy were rigorously evaluated through tests on both a smartphone and a graphics processing unit (GPU) server, while the road damage was

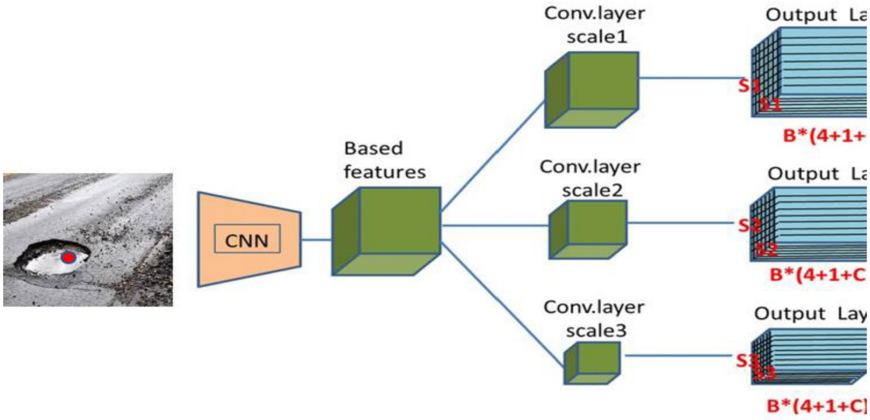

FIGURE 1 | Architecture of YOLO.

meticulously classified into eight unique categories, with the research conducted by Maeda et al. highlighting the remarkable efficacy of deep learning techniques, particularly CNNs, in the precise detection and classification of road damage captured through smartphone technology, thereby significantly advancing the domain of automated road inspection and setting the stage for the development of more sophisticated systems that leverage readily accessible tools like smartphones.

In their research, Song, H., Baek, K., & Byun, Y. present a basic method for identifying potholes with a smartphone in this research (12), and they utilize transfer learning to categorize the data. They introduce a fundamental approach for detecting potholes using a smartphone and employ transfer learning techniques to effectively classify the gathered data. The diverse road conditions complicate learning, but Song et al. show that machine learning effectively detects potholes using data from smartphone sensors, although it needs a varied dataset for success; this can enhance road maintenance and safety through accurate identification of damage.

Existing methodologies frequently depend on limited or geographically specific datasets, which constrains their scalability and efficacy in varied road environments; although numerous strategies employ deep learning for anomaly detection, they fall short in delivering real-time performance and fail to leverage citizen-driven Big Data sources for optimal road monitoring and maintenance, while current systems inadequately tackle the need for cost-effective and automated solutions suitable for extensive deployment, particularly in resource-limited regions such as India.

Proposed system

YOLO

Object detection is a key task in computer vision that includes recognizing objects within an image or video and accurately defining their locations. Unlike image classification, which only classifies an image, object detection provides additional spatial information by drawing bounding boxes around each detected object. Many deep learning models, including R-CNN, Faster R-CNN, Fast R-CNN, and YOLO, apply CNNs for object classification while concurrently employing regression techniques to forecast the synchronizing of the bounding boxes that enclose these objects. These models combine classification and localization in a unified framework, making them crucial for applications requiring both identification and spatial reasoning.

YOLO is an acronym that refers to "you only look once." The architecture of YOLO is given in **Figure 1**. This is the available fastest method, and it can even recognize objects in real-time stream video. We used this method to detect potholes because of its fast pace and high accuracy of image recognition (13, 14). Across a variety of detection datasets, it outperforms other detection algorithms. It is well-known for its high accuracy and ability to work in real-time at a frame rate of 45 frames per second. It strikes a good balance between speed and precision. It only wants one forward propagation run through the neural networks to create predictions; the algorithm "just looks once" at the image.

Proposed methodology

The application utilizes advanced image processing algorithms (15–17) to analyze the uploaded photos and identify potential potholes. This allows them to take photos of road defects directly within the application, whether in their local area or any other location they wish to report.

The proposed web-based application system is aimed at both citizens and municipal authorities to facilitate the monitoring and evaluation of road surface conditions. This platform allows citizens to capture the pothole image and submit it for processing. To access this platform, the user must create an account with a valid email address and password. After registering, users need to give permission to the app to use the device's location and camera.

After capturing and uploading a pothole image, the app sends the data to the server for analysis. The server processes the uploaded image and rapidly determines if a pothole is present (18–20). Within moments, the user receives a notification informing them of the result—whether or not a pothole has been detected. This seamless, real-time feedback ensures that citizens can contribute to road maintenance (21, 22) efforts efficiently and that authorities can promptly address road issues based on accurate, crowd-sourced data. It is logged into the system's database whenever a pothole is reported. On the backend, neural networks are used to identify potholes within images using the YOLO technique. Civic authorities can create an account on the app and sign in with their credentials. They are able to view potholes that have been reported by users in their specific neighborhoods. This web program accurately detects potholes (23, 24) and assists in their repair. When it comes to finding potholes in images, this method is fast and accurate. It can even identify many potholes in a single shot with ease.

The proposed methodology helps in the identification of potholes and also helps in the maintenance of urban infrastructure. Sometimes manual inspections are prone to human error and can take more time. Because of the automated web application process, it reduces the reliance on manual inspections for identifying pothole detection. This leads to more accurate and timely road repairs, potentially reducing the risks of accidents caused by the road damage.

Moreover, the real-time nature of the application confirms that potholes (25, 26) can be repaired quickly before they become costly or dangerous to repair. The data reported through citizen reports also allows cities to implement a more proactive approach (27–30) to road maintenance, recognizing problem areas before they worsen into major issues.

Workflow of the web application

A web application for pothole detection powered by the YOLO model.

The system architecture (as mentioned in **Figure 2**) includes a web application, an image processing model, and a server for handling requests and data storage.

YOLO algorithm for pothole detection

To begin, we consider a pre-processed image of a pothole and apply YOLO. The image is segmented as grid frameworks. The picture is then isolated into any number of matrices, depending on the image. Each grid goes through a localization and classification process. Every matrix's objectness or certainty score is determined. When no pothole is identified in the framework, the bounding box and the network's objectness estimation will be zero; if a pothole is located in the lattice, the objectness will be one, and the bounding box value will be the detected object's bounding value. It is necessary to construct what we anticipate in order to comprehend the YOLO computation.

In conclusion, we need to forecast an object's class and the bounding box that indicates the object's region. There are 4 descriptors for each bounding box (as mentioned in **Figure 3**): The bounding box's center (bx,by), height (bh), width (bw), and value pc correspond to an object's class (for example, pothole (1) or no pothole(0)). Furthermore, we want to predict the **pc** value, which represents the probability that an object exists within a given bounding box. As stated earlier, when applying the YOLO method, we do not focus on specific regions of interest in the image that might comprise an object. Instead, the entire image is processed in a single step. Rather, we're using a 19×19 lattice to divide the image into cells.

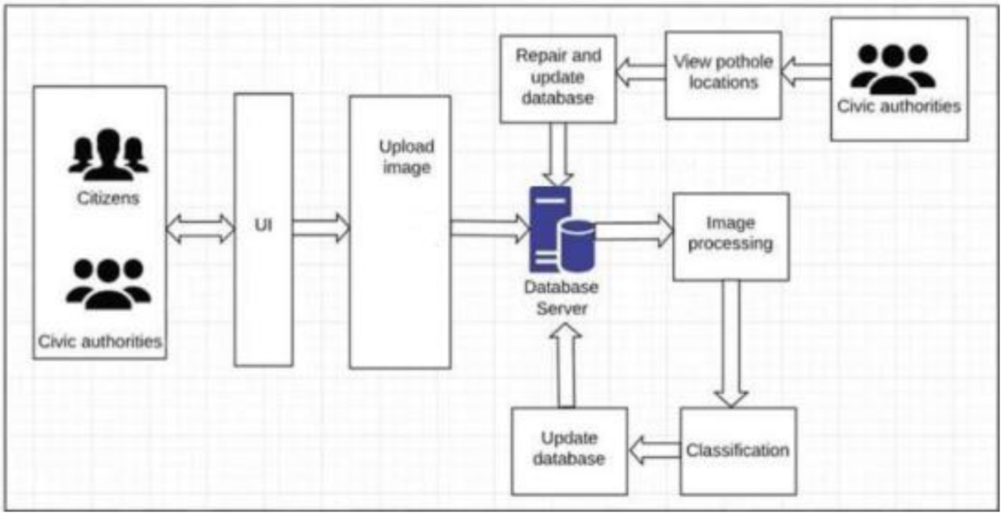

FIGURE 2 | System architecture.

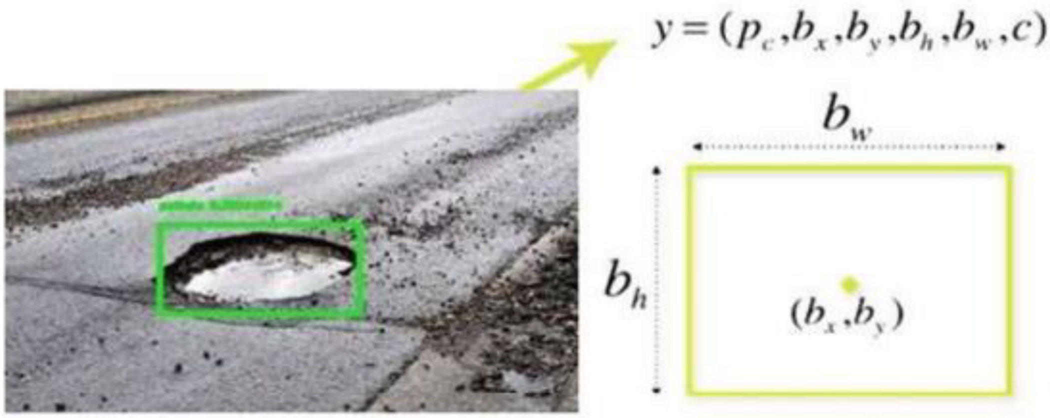

FIGURE 3 | Bounding box description.

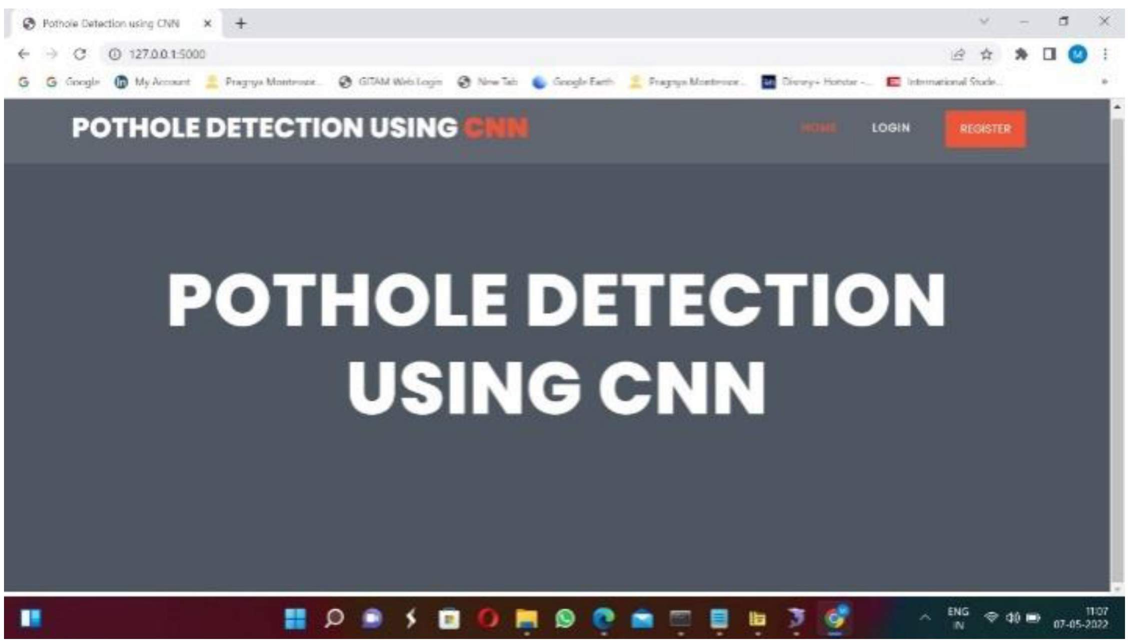

FIGURE 4 | Home screen.

Each cell is responsible for anticipating 5 boundary boxes. This results in a substantial total of 1805 bounding boxes for the single image, many of which will be empty. Consequently, we estimate the pc value, which is applied in a process termed non-max suppression to exclude boxes with a low pothole possibility and to retain bounding boxes with the largest shared area.

Implementation

1. User Registration: Citizens can sign up for the web application using an email address and password (refer to Figures 4 and 5).
2. User Login: Registered users will access the application by logging in with their email and password (refer to Figure 6).
3. Permission Access: User has to give permission of camera and storage.
4. Image Upload: User can upload the image of the pothole and then submit (refer to Figures 7 and 8)
5. Processing and results: Once the image is submitted, it is processed within seconds, and the user is then alerted with the value of potholes detected.
6. Logout.

Results and discussions

Output screens

The result is presented alongside the original image, allowing users to compare the processed output with the raw data. The

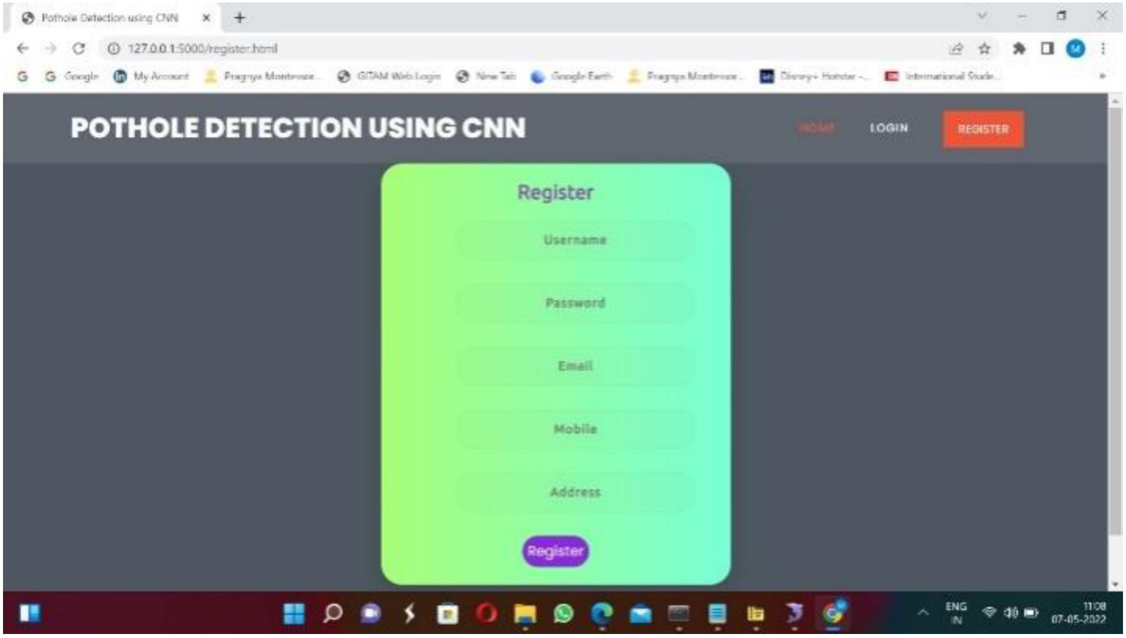

FIGURE 5 | Registration page.

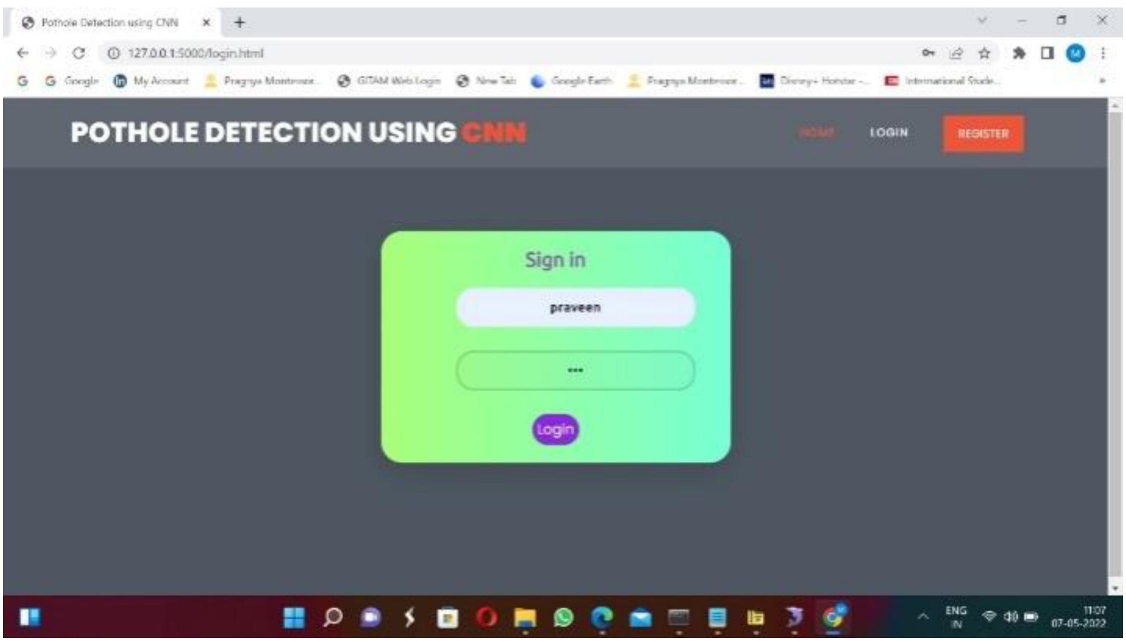

FIGURE 6 | Sign in page.

output interface of the system displays the processed image along with a clear indication of whether a pothole has been detected (see **Figure 9**). The user interface is designed to offer real-time feedback, ensuring that road conditions can be assessed promptly. If a pothole is found (see **Figure 10**), the system highlights its location on the image, visually marking the affected area to ensure easy identification. The highlighted pothole regions are typically outlined or marked with a distinct color or shape, providing a straightforward visual representation of the detected defects. This feature ensures that users can quickly and accurately assess the presence and location of potholes, facilitating efficient road maintenance and monitoring. Refer to **Figure 11**, which shows the image when the potholes are not detected on the roads.

The YOLO-based Python code for detecting road surface flaws

```
import cv2
import numpy as np
# Load YOLO model
net = cv2.dnn.readNet("yolov5.weights", "yolov5.cfg")
```

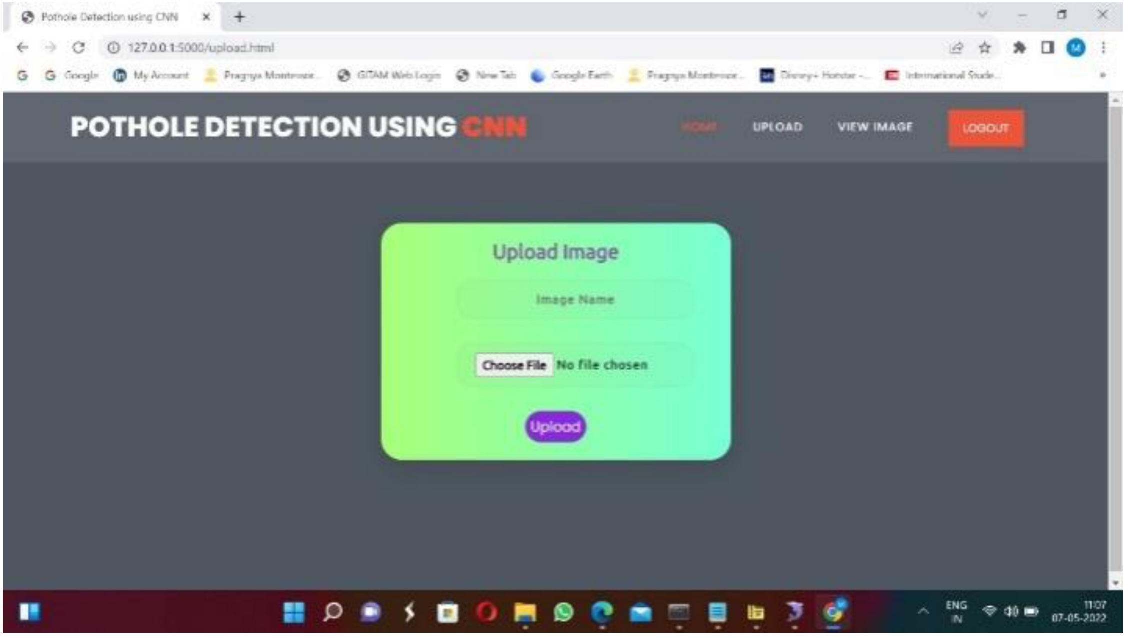

FIGURE 7 | Image uploading page.

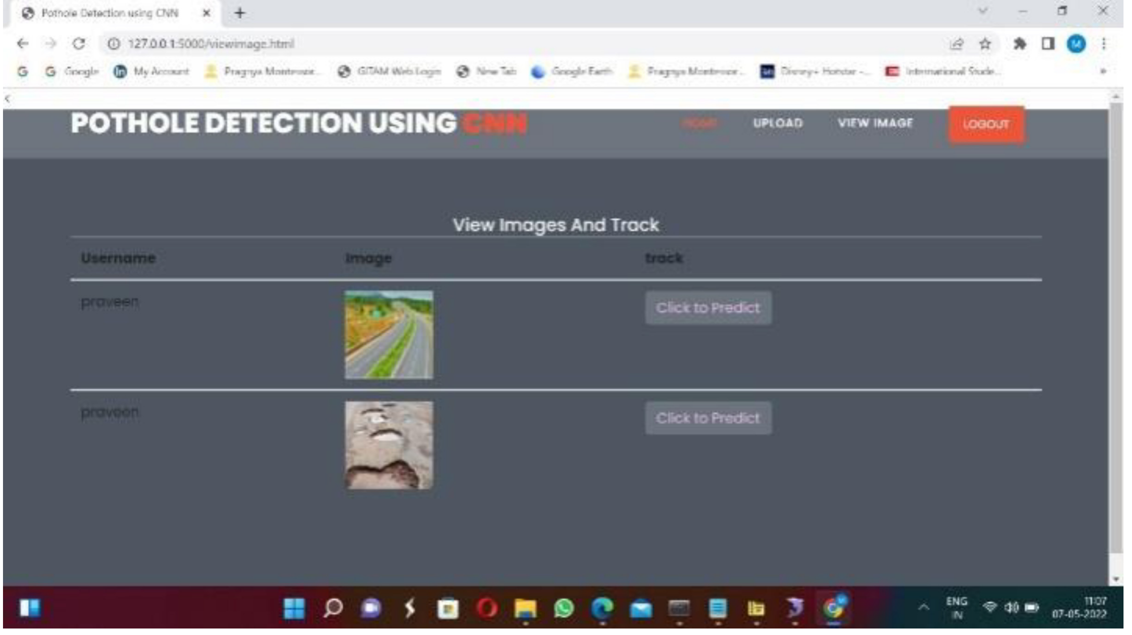

FIGURE 8 | Page that shows all the uploaded images.

```
# Load the COCO class labels YOLO was trained on
with open("coco.names", "r") as f:
    classes = [line.strip() for line in f.readlines()]
# Get layer names and output layers
layer_names = net.getLayerNames()
output_layers = [layer_names[i - 1] for i in net.getUnconnectedOutLayers()]
# Load an image of a road
image_path = "road_image.jpg" # Replace with the path to your road image
image = cv2.imread(image_path)
height, width, channels = image.shape
# Pre-process the image
blob = cv2.dnn.blobFromImage(image, 0.00392, (416, 416), (0, 0, 0), swapRB = True, crop = False)
net.setInput(blob)
# Perform detection
outs = net.forward(output_layers)
# Initialize lists for detected bounding boxes, confidences, and class IDs
boxes = []
confidences = []
```

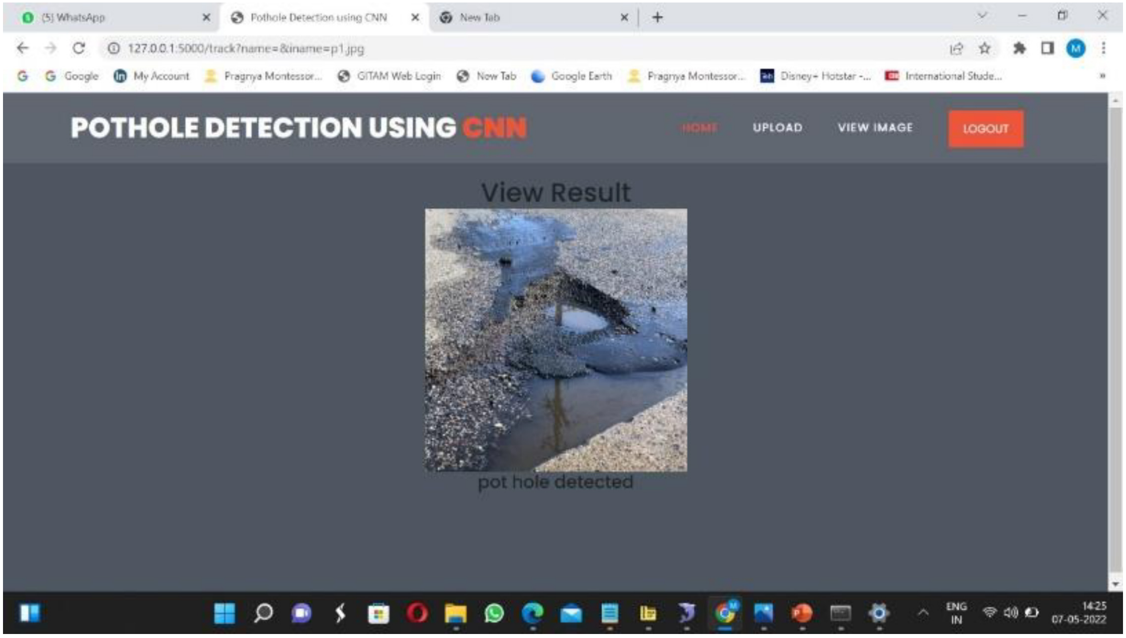

FIGURE 9 | Pothole detected.

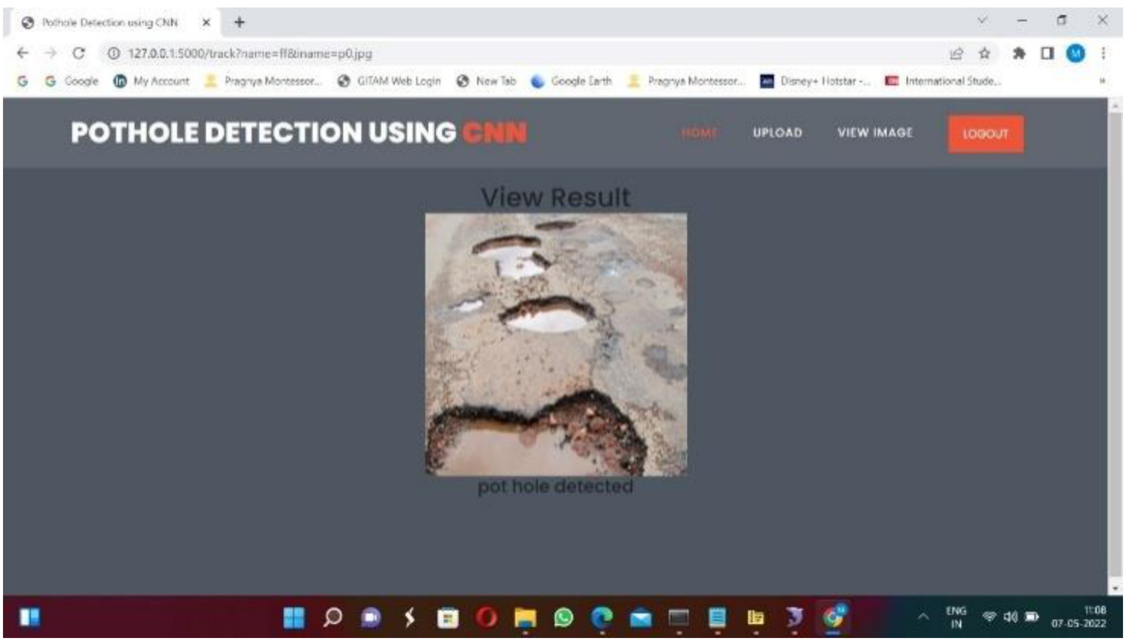

FIGURE 10 | Result when a pothole is detected.

```
class_ids = []
# Parse detection results
for out in outs:
    for detection in out:
        scores = detection[5:]
        class_id = np.argmax(scores)
        confidence = scores[class_id]
        if confidence > 0.5: # Confidence threshold
            center_x = int(detection[0] * width)
            center_y = int(detection[1] * height)
            w = int(detection[2] * width)
            h = int(detection[3] * height)
            # Calculate top-left corner of the bounding box
            x = int(center_x - w / 2)
            y = int(center_y - h / 2)
            boxes.append([x, y, w, h])
            confidences.append(float (confidence))
            class_ids.append(class_id)
# Apply Non-Maximum Suppression
indices = cv2.dnn.NMSBoxes(boxes, confidences, 0.5, 0.4)
# Draw bounding boxes and labels on the image
for i in indices.flatten():
```

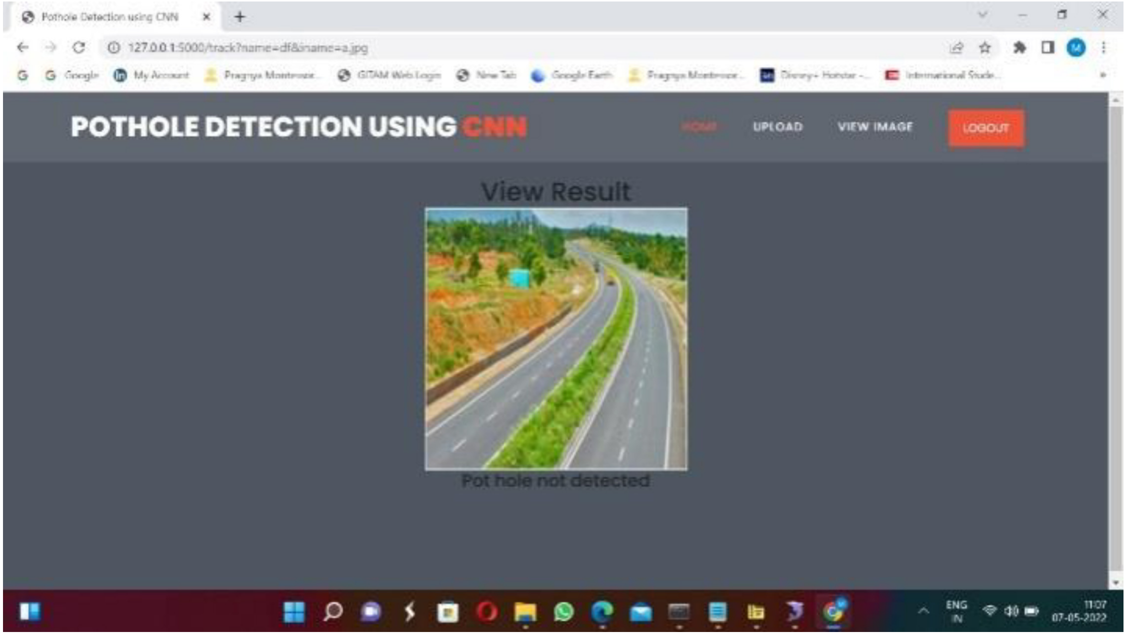

FIGURE 11 | Result when pothole is not detected.

```
    x, y, w, h = boxes[i]
    label = str(classes[class_ids[i]])
    confidence = confidences[i]
    color = (0, 255, 0) # Green for bounding boxes
    cv2.rectangle(image, (x, y), (x + w, y + h), color, 2)
    cv2.putText(image, f"{label}: {confidence:.2f}", (x, y - 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)
# Display the output image
cv2.imshow("Road Flaw Detection", image)
cv2.waitKey(0)
cv2.destroyAllWindows()
# Save the output image
cv2.imwrite("detected_road_flaws.jpg", image)
```

Conclusion and future scope

We looked at a variety of pothole-detecting methods before settling on the optimal YOLO technique. In accurately identified photos, the app detects potholes with a 76% accuracy rate. Duplicate storage and pre-processing burdens are minimized, as users directly upload pothole images to the app. It assists municipal officials in prioritizing remedial efforts.

This methodology could be further improved by incorporating a global positioning system (GPS) module, enabling users to compare various conditions of roads and select the shortest route with optimal surfaces. A feature could also be added to generate color-coded maps indicating the road surface conditions severity. The pothole detection model's efficiency could also be enhanced through backward learning, allowing the system to become increasingly accurate over time.

Conflicts of interest

The author declare that the research was construed as a potential conflicts of interest.

Author contributions

The author agrees to be accountable for the content of the work.

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