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Intelligent Deep Learning Based Pothole Detection and Alerting System

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Abstract

Potholes are a common problem in roads and highways around the world, which can cause severe damage to vehicles and create safety hazards for drivers. In recent years, deep learning algorithms have been increasingly used for automated pothole detection. This research offers a deep learning-based algorithm that can detect potholes early using photos and videos, reducing the likelihood of an accident. This model is basically based Faster Region-based Convolutional Neural Network(F-RCNN) and You Only Look Once Version 3(YOLO V3). It also discuss the challenges in detecting potholes, such as variable lighting conditions and noise in the data, and how these challenges have been addressed in previous research. Finally, we provide a comparative analysis of the performance of different deep learning algorithms for pothole detection based on accuracy. There are various pothole identification models that combine the accelerometer with machine learning techniques, but there are fewer pothole detection models that use simply machine learning techniques to detect potholes. The findings of this study suggest that deep learning algorithms can provide accurate and efficient pothole detection solutions that can help road authorities to maintain and repair roads, reduce vehicle damage, and enhance road safety.

Keywords: Pothole Detection, Deep Learning, Image Processing, Annotation, Faster RCNN,YOLO V3,Accuracy.

Introduction

Potholes are a hollow structural damage to the road that can cause serious traffic accidents and reduce road efficiency. Manual road condition assessment is a difficult task because it is a time-consuming and labor-intensive process. India has the world's second-largest road network. As a result, the road network is critical to Indian economic development and social functioning. According to the report, the Road Transport sector GDP grew at a close to 10% annual average rate over the last ten years, compared to a 6% annual GDP growth rate overall. And according to government of India statistics, from 2013 to 2016, potholes claimed 11,836 lives and injured 36,421 people. Pothole problems are difficult to resolve because floods, disasters, heavy rainfall, and other natural disasters occur almost every year in almost every location. The government of India is currently constructing roads at a rapid pace. However, road maintenance is a difficult task due to poor drainage and overloaded vehicles. The most important step in maintaining road conditions is detecting potholes with high accuracy.

Several studies have been conducted in recent years to detect potholes in the road automatically. Lin J, et al. proposed using SVM (Support Vector Machine) for pothole detection[1]. The image region was extracted using the histogram of the image, and a simple kernel SVM was used to locate the pothole. Using this method, the target was easily identifiable. Deep learning based on CNN (Convolutional Neural Network) is used to classify potholes and cracks in images. A CNN model was created that was unaffected by noise caused by incorrect illumination and shadows [2]. Hiroya Maeda et al. [3] created a system that detects road damage using CNN methods on phone images. To solve the problem, deep learning algorithms were applied to a large dataset for pothole detection. The accuracy and speed of the road damage detection system were commendable. Some researchers have used deep neural network-based binary classification [4] to classify road images. Whether they belong to normal road images or pothole images. Before the system can perform classification, the features of the images must be fed into it. For detecting road cracks, a new neural model called Cracknet [5] has been proposed. The difference between this and other neural models is that pooling layers are not included. This method was very effective in detecting cracks and uneven surfaces on the road.

In this paper, a method for building a precise and effective pothole detecting system using deep learning algorithms is proposed. Using Yolo V3 (You Only Look Once) and Faster R-CNN algorithms, an intelligent deep learning system is created. Here, pothole detection schema contains two parts: (1) Data preprocessing and (2) prediction of potholes in static and dynamic situations using deep learning algorithms. In the first section, training datasets and test datasets are selected from the subsets of all accessible data that relate to the schema. To create these datasets, labelling the images is necessary, and after that, these image files are converted into train. record file that will serve as the model's input. The prepared data is supplied to deep learning models in the second section, which will train and anticipate potholes based on it. Finally, the YOLO V3 and Faster RCNN model, according to the experimental results, performs best in terms of speed and is also acceptable in terms of accuracy for all image sizes. In terms of time requirements, YOLO V3 performs incredibly well and the most accurate performance comes from faster R-CNN.

Literature Survey

Based on the literature review, there are three categories of pothole detection systems. Vibration-based techniques are economical, they are unable to detect potholes located in the middle of the road. The 3D reconstruction methods necessitate sophisticated and expensive equipment. In contrast, the vision-based system is an enhanced version of conventional pothole identification technologies, as it can more accurately detect potholes.

In the most recent years, technology has advanced significantly. Vibration-based techniques include ways for gathering unusual vibrations produced in the cars as they are travelling over irregularities in the road. The vehicle's vibrations are recorded using an accelerometer. The primary drawback of vibration-based techniques is that the vibrations generated by potholes on the road can solely be gauged while the vehicle is in motion over them.

D. Wiratmoko, et al. [7] employed a Convolutional Neural Network to develop a classification and monitoring system for identifying potholes on village and city roadways. The method involves processing photos through a Convolutional Neural Network, which is subsequently downsized twice to produce small images with distinct weights. The inspection tool's output is used to determine the presence or absence of a pothole on the road. The experiment successfully identified potholes with a 92.8% accuracy rate using the CNN algorithm. But it failed to give correct results in terms of detecting potholes on roads.

Aparna, et al. [8] utilized thermal imaging to demonstrate a Convolutional Neural Network system for detecting potholes. After adjusting various parameters, such as the learning rate and batch normalization twice, the self-designed CNN architectures produced test accuracies accordingly. Additionally, the authors examined several pre-trained ResNet models, utilizing the ResNet101 pre-trained model on a pixel image to produce the outcomes. The test accuracy achieved was 73.06%. However the accuracy was not good enough and the losses were also high, but the proposed method has the potential to be expanded further to determine the size of potholes after identifying them in an image.

Using deep learning techniques, P. Ping et al. [9] proposed a pothole detecting system that includes a camera installed on the dashboard of a vehicle. The YOLOv3, Faster RCNN, SSD, and HOG with SVM models are trained and evaluated using a pre-processed dataset. The YOLOv3 model fared the best, with an accuracy of 82%, when the results of all four models were compared.

Finding dry and wet potholes on roadways is a challenge that is addressed by A. Dhiman et al. [10]. The suggested model uses a Mask RCNN with a transfer-learning based approach, with weights trained using CCSAD frames. But the created model could only locate dry potholes. In order to recognize potholes in difficult terrain, the authors gathered a range of datasets and trained the network using photos from each dataset individually.

A. Dhiman et al. [11] address the difficulty of distinguishing between dry and wet potholes on highways. The suggested model makes use of a transfer-learning technique. Using Mask RCNN, weights were trained using CCSAD frames. Nevertheless, the proposed model could only identify dry potholes. To recognize potholes in difficult conditions, the authors collected a range of datasets and trained the network using photos from all of the different datasets collectively.

In contrast to the cameras being put on the public transportation buses, a sensorbased network called "BusNet" [12] is suggested for the monitoring of road conditions. It uses a number of inexpensive, quick, and sensitive sensors as well as GPS. Due to environmental circumstances that might harm the sensor and degrade the BusNet's functionality, this technology is not perfect in every situation. Due to the availability of cameras that are accessible, affordable, and practical, computer vision and image processing-based approaches have gained popularity over the past few years and have successfully replaced traditional manual inspection methods for pothole identification. Because of the uneven pothole textures, pothole structures, road bumps, manholes, and shadows, etc., image processing-based pothole identification is still a difficult task. For this issue, various computer-vision-based methods for pothole detection and classification have been investigated. This paper is being proposed in order to fulfill the limitations by increasing accuracy and the visibility problems.

Data Preparation

Labeled images are necessary to create the training data because they include the location and name of the object that will be identified by the model. By manually drawing a rectangle bounding box around each training image's object, the images are tagged. It could be time-consuming to locate the exact location of these bounding boxes for each training image. We will use an image labelling tool like LabelImg to get around this. By simply drawing a line across a pothole to mark an object, this tool makes tagging potholes easy. In the process of data preparation, a dataset is created using LabelImg, which transforms a JPEG image file into XML with labels for potholes. And then this XML file is converted into CSV records which has image details. A train.record file is generated from CSV file which is used as input to the model.

After each image has been labelled, a.xml file is created for it that provides the bounding box's top-left and bottom-right coordinates. The model that will forecast the location of the potholes is then supplied these coordinates.

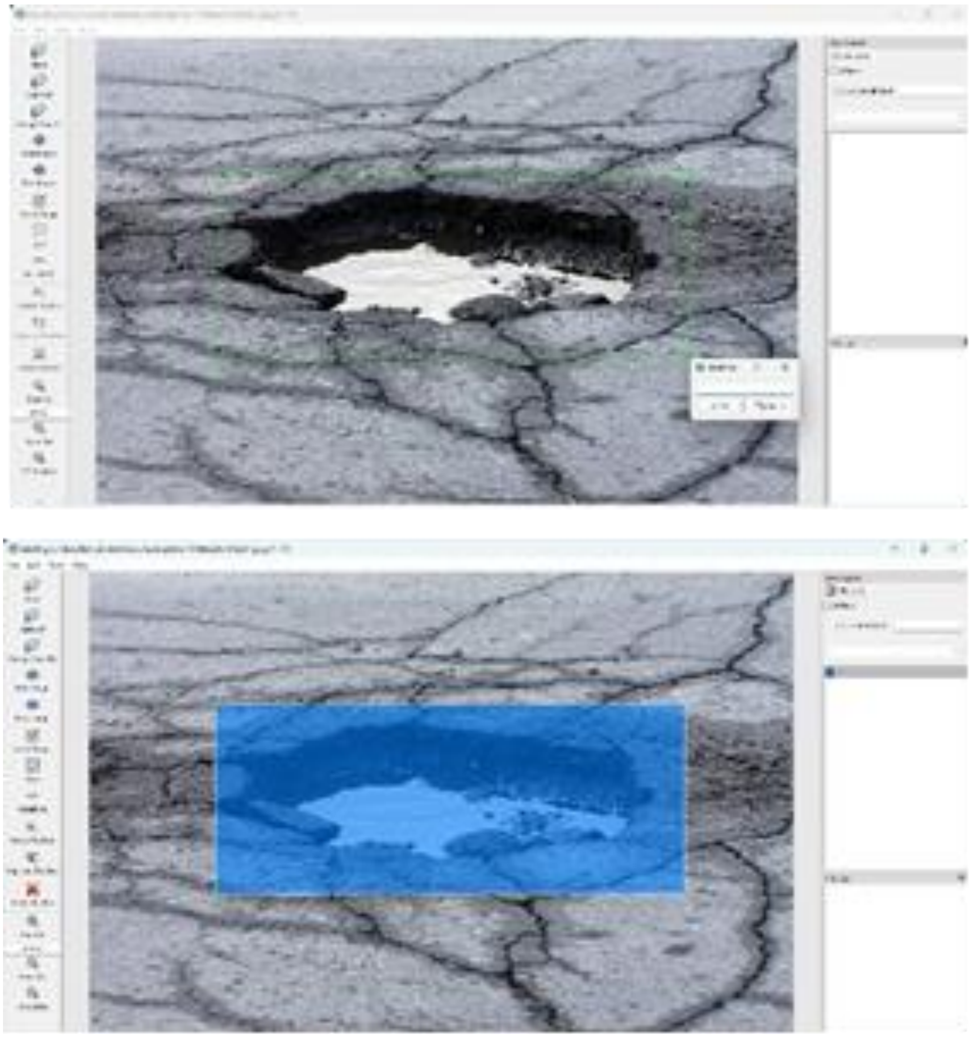

Figure 1: Detecting potholes manually using LabelImg

A dataset of 2036 images has been made, 652 images will be used as test data, leaving 1384 images in the overall dataset as training data. Table 1 is a list of the comprehensive statistics of the dataset.

TABLE 1 Comprehensive Statistics of the Dataset

Index name	**Description**
Image size	72dpi*72dpi
Total Categories	2
Total dataset size	2036
Training dataset size	1384
Test dataset size	652

Methodology

After pre-processing the data, a system is developed for the detection of potholes in videos and images so that users of the online application can report problems by uploading the video or image. YOLO V3 and Faster RCNN algorithms are applied to the system. An exclusive configuration file has been made specifically for the training. The hardware configuration determines how long it takes to train the model. After testing was completed, more code was built to record video and detect potholes in both the image and video streams. Although the system performs well in tests, it still has room for improvement.

A. Faster RCNN

An object detection model, Faster R-CNN (Region-based Convolutional Neural Network), has been applied in a number of computer vision applications, including pothole detection. Faster R-CNN is a two-stage object identification model that employs a classifier to categorize the suggested regions and a region proposal network (RPN) to create region proposals. Based on the features that were extracted from the input image, the RPN creates a set of rectangular regions of interest (ROIs). The class and bounding box coordinates of each object are then predicted using these ROIs as input into a model.

In order to use Faster R-CNN for pothole identification, the model must first be trained on a dataset of photos with potholes. The coordinates of the potholes in each image should be identified in the dataset. The classifier is trained using the labelled dataset to find potholes in new images.

To use Faster R-CNN for pothole detection, the input image's features must first be extracted. Convolutional neural networks (CNNs), like ResNet or VGG, are used for this. The RPN is then fed the features, producing a set of ROIs.

The next stage is to determine whether or not each ROI is a pothole. A classifier that has been trained on the labelled dataset is used to accomplish this. The classifier foresees the likelihood that each ROI will have potholes. The ROI is identified as a pothole and its bounding box coordinates are outputted if the probability exceeds a predetermined threshold.

When potholes are found, they can be noted on the image or used to create a map of all the potholes in the region. Authorities can utilize this information to determine the priority for pothole monitoring and repair.

In conclusion, Faster R-CNN is a pothole detection model with strong object detection capabilities. The model may be used to identify potholes in new images and videos by training it on a dataset of annotated images with potholes. In order to prioritize pothole monitoring and repair, authorities can utilize the model to create maps of the region's potholes.

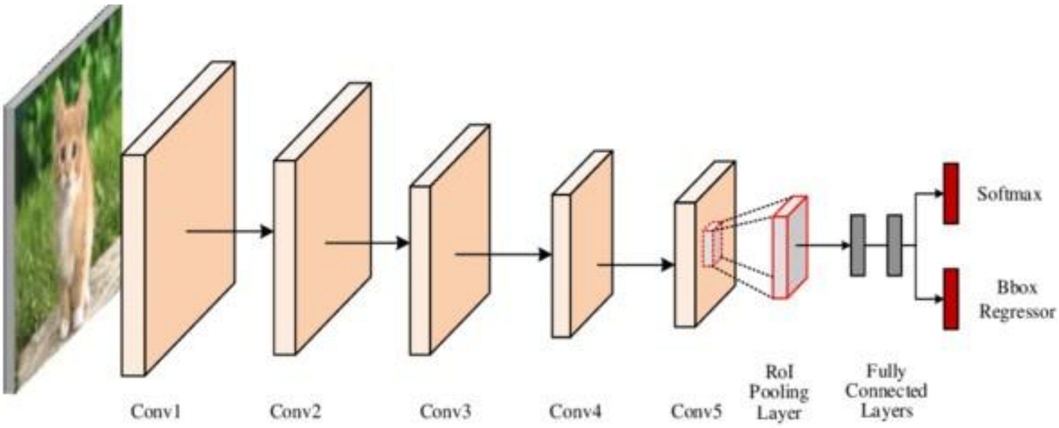

Figure 2: Faster RCNN Architecture

B. YOLO V3

YOLO v3 is a powerful object detection algorithm that can be used to detect potholes in videos as well as images. Processing videos with YOLO v3 for pothole detection involves using the algorithm to analyze each frame of the video and identifying any potholes present.

The ability of YOLO v3 to process frames rapidly and precisely is one of the main benefits of employing it for pothole identification in videos. This is crucial in applications like driverless vehicles, where real-time pothole detection is necessary to protect passengers and other road users.

The algorithm must be trained on a dataset of images that contain potholes in order to use YOLO v3 for pothole detection in videos. After trained, the algorithm may be used to analyze each frame of the video and detect any potholes. In this project, earlier the collection of images containing potholes has been trained using faster RCNN.

The YOLO v3 algorithm provides a potent tool for pothole detection in videos. Realtime video applications can benefit from pothole detection that is accurate and dependable because to the algorithm's training on high-quality data and the proper threshold settings.

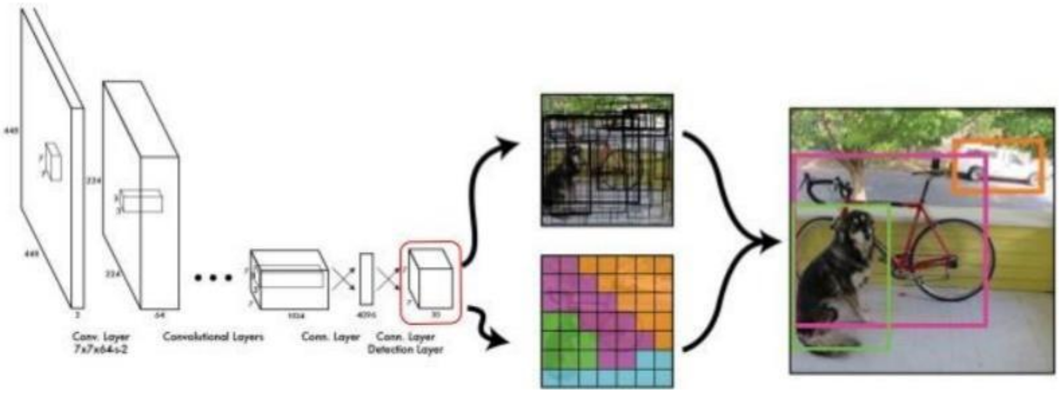

Figure 3: YOLO V3 Architecture

A model for detecting potholes in video/images has been identified, allowing the contractors and citizens work alongside to reduce the potholes. The model is built with the Inception v2 framework and fine-tuned. A specific configuration file was developed for the training. There is only one class in the configuration file (pothole). Training the model takes some time, depending on the hardware arrangement. Following training, the testing procedure was completed, and some further code was built to record video and detect potholes in both video and picture. The system tested well; however it may be improved further.

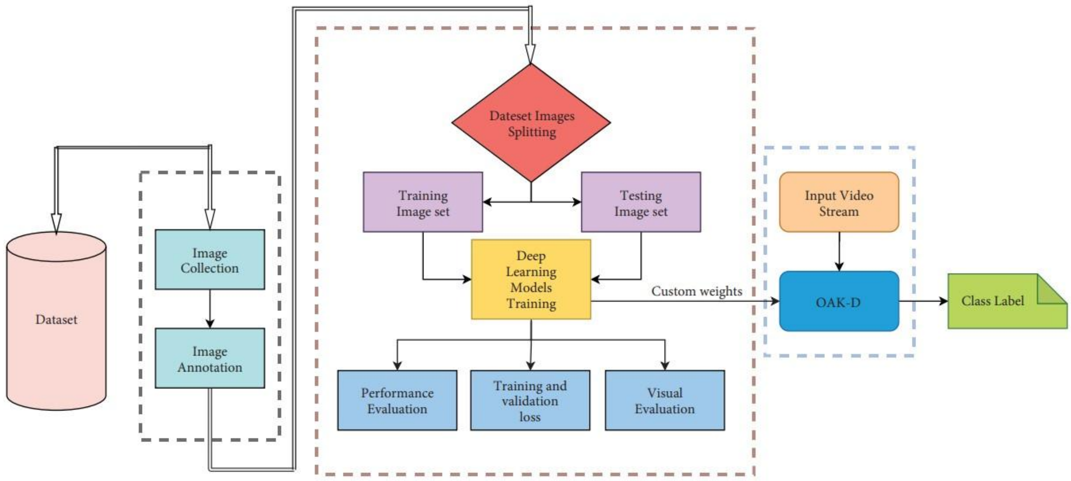

Figure 4: Flow of Methodology

Results and Discussion

As shown in the figure.12, YOLO V3 along with Faster RCNN accurately detect the pothole dimensions in the video as well as in the image. The accuracy of detecting potholes using this model i.e; YOLO V3 and Faster RCNN is much more than any other models discovered so far. The accuracy of the model proposed is between 85% to 90%.

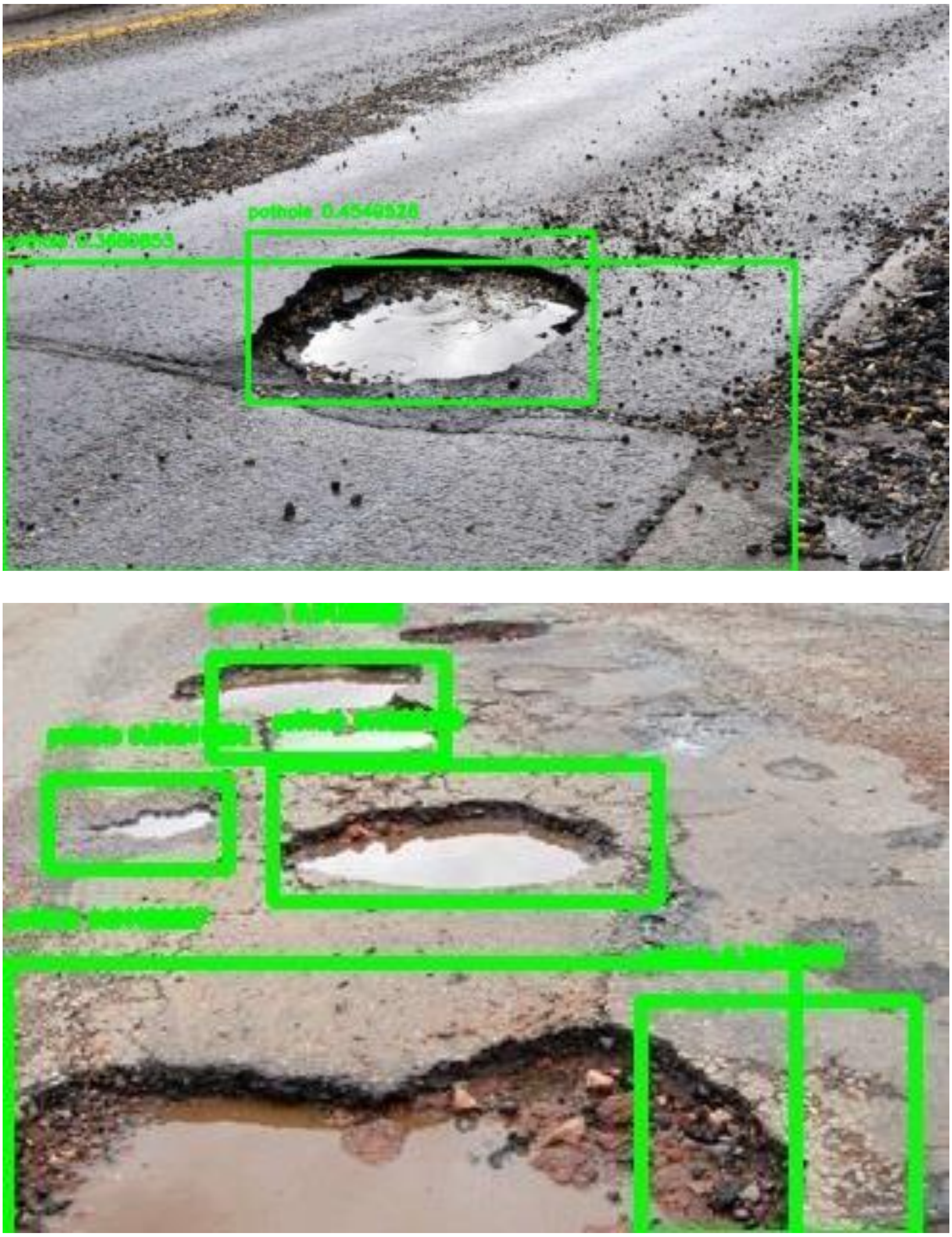

Figure 5: Pothole detection in video and images using the proposed model

The comparison between the existing models and proposed model has proved that YOLO V3 and Faster RCNN model performs the best by over riding maximum of limitations.

Table 2: Comparison between different models

Model	Accuracy
SSD (Single Shot Detector)	40%
YOLO V3	80%
YOLO V3+Faster RCNN	90%

Conclusion

The proposed technique can assist road maintenance authorities in developing quick and efficient measures for road infrastructure repairs. Preprocessed dataset, YOLOV3, and Faster R-CNN are used to train and test the models. An accessible data was picked before converting labelled picture files to train. The models will utilize this record as input. The system produces incredibly good results in the experiment data, with an accuracy of 90%. Furthermore, the model will determine the position of the pothole and upload it to a map (as represented in the website developed by using this model) so that the users can complain about the potholes on road by uploading the captured images on website. Future projects involve attempts to improve the system and make it more user-friendly. The proposed model can further be enhanced using the global positioning system (GPS), which can identify and locate pavement defects by a camera installed on the car and alerting the driver to a pothole on the road in front of the vehicle.

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