CNN-Based Road Damage Detection

Geethamahalakshmi G[1]

1 Easwari Engineering College

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Abstract

Monitoring road degradation is an important activity that can assist in reducing maintenance costs and preventing accidents. In picture recognition tasks, road damage detection using Convolutional Neural Networks (CNNs) has exhibited outstanding results. In this paper, a CNN-based robot was tasked with identifying various types of road surface deterioration. Gathering and preprocessing images of damaged road surfaces, constructing and instructing the CNN architecture, and evaluating the CNN's performance on a test set are all part of this approach. Our suggested method is extremely accurate, around 90%, at detecting various types of road degradation, including cracks, potholes, and bumps. The findings demonstrate how CNNs can be utilized for identifying road degradation and improving road maintenance and safety.

G. Geethamahalakshmi[1], and **Sanju Hannah Samuel**[2]

[1] *Assistant Professor, Electrical & Electronics Engineering, Easwari Engineering College*

[2] *Student, Easwari Engineering College*

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1. Introduction

Poor metropolitan road conditions could drastically impact the quality of vehicles, the effectiveness of driving, and the security of traffic. An important area of study within the field of intelligent transportation involves evaluating road conditions. It is a difficult job because of a variety of disturbing elements, such as the challenge of distinguishing between various road conditions and of building up rare road damages. To increase the precision and effectiveness of damage identification, a convolutional neural network (CNN) model for road damage identification has been built employing various road features. The road management will soon be able to take corrective action as a result of the greater rates of damage, cracks, and potholes owing to the CNN model's ability to recognize distinct patterns. The primary goals are to create a neural network-based system to analyze road damage identification and provide warnings to road administrators. We can train such patterns and develop a model that can identify them using a deep CNN. Despite this, due to the wide road network plus the lively outdoor environment, it can be challenging to assess the condition of the roads. The majority of the existing road damage assessment techniques are performed by certified inspectors, and it's subjective, laborious, costly, and time-consuming. Furthermore, recent study has only engaged just a handful of academics and has primarily focused on discovering road degradation (such as cracking).

The goal of roadway surface management is to enhance asphalt condition to reduce accidents. When rain penetrates into a damaged area, the surface of the road is liable to various damaging conditions. The water is then interprets the condensed earth beneath the pavement, leading to soil erosion, which could lead to detrimental repercussions such as sinking of an area on the ground surface. Furthermore, if the condemned area or road is not restored, the roadside texture will deteriorate even further, affecting vehicle steering and enhancing the likelihood of accidents. In an effort to reduce accidents, various methods have been adopted to regulate road conditions, and it has been recently implemented. Recent advancement in technology, such as machine learning techniques and deep learning techniques, is involved in the field of image processing, and these techniques are adopted in the recent development areas similar to image processing; it contains usage of a sensor technique for identifying the road conditions and has resulted in high detection performance. Methods for image processing have been widely applied in research on the detection of road surface deterioration, resulting in extremely high detection accuracies. Numerous studies focus solely on whether or not damage exists. However, in the actual world, in order for road management from a government agency to take significant action, they must first understand what sort of damage exists. Furthermore, in several of these previous studies, the researchers used a variety of ways to obtain their own data. There is no base for road damage detection because there is no publicly accessible standard road damage dataset.

To identify areas of road damage, this programme employs a computation methodology such as a convolutional neural network (CNN), which contains various layers in the technique. This technique is used as a detection tool for precise road surface maintenance since it can identify road deterioration at the pixel level. With the advent of deep neural networks, image processing technologies have recently taken considerable strides. Among the different neural network structures, topologies depending on the convolutional neural network (CNN) are commonly employed. CNN-based algorithms are becoming more popular in the Image Net Large Scale Visual Recognition Competition (ILSVRC), focusing on classification and detection issues. In addition, the algorithms outperformed standard image processing methods in handling regression difficulties, identifying objects, and semantic segmentation. Semantic segmentation, for example, is a neural network structure that splits input picture data into pixels or instances with a unique meaning and is solely created in the manner of an autoencoder with only convolutional neural networks. As a result, it is also known to be a fully convolutional neural network.

2. Literature Survey

In accordance with Wita Dewisari Tasya and Fadhil Hidayat in[1], the seriousness of road damage demands to be identified in establishing decisions concerning when road repairs will be carried out. The identified damage could be used to construct the pavement condition index (IKP). The goal of this research was to enhance the calculation of the pavement condition index using interpolation to determine the reduction factor and corrected total reduction factor. Amr Abdelraouf, Mohamed Abdel-Aty, and Yina Wu introduced a system in [2] to identify rain as well as road surface conditions using roadside traffic cameras.

To address the primary issue, Dong Chen, Nengcheng Chen, Xiang Zhang, and Yuhang Guan suggested a reflectometry method for real-time pothole observation [3]. To create many prototypes, devices for testing, on the prototypes, the acceleration signal was installed and measured using a new technique of image processing and implemented in the new signal processing technique called the edge type. Findings have been obtained, and spatiotemporal messages are quickly communicated to the sensory server through the Internet of Things' narrow band. Yao Wei and Shunping Ji developed ScRoad Extractor, which was intensively used on the road side mount and will be used in the scribble extractor, in [4].

The road label propagation algorithm has demonstrated that it takes into account both the algorithm-based approach of the buffer technique used in the line and path networks and the color and vital characteristics of the megapixel network approach. A new mask control approach is proposed for generating the masks, and it contains various classifications of road, non-road, and unknown. Because road boundaries are basic map features, accurate and full extraction of these boundaries is critical to building HD, Jingjing Yan, Shunping Ji, and Yao Wei introduced a new approach, which regularized the new approach in the form of a framework known as the extraction framework in [5], adopted a graph neural network (GNN), and quickly accessible road centerlines. The technique approaches the convolutional neural network (CNN), and a GNN-based approach reduces the issues facing on either side of the inferences present in the width of the system in the graph technique., Yachao Yuan, Md Saiful Islam, and Yali Yuan introduced in [6] an EcRD: an Edge-cloud driven Road Damage detection & warning framework method. They showed that the suggested EcRD is capable of identifying the damages on the road side in all dangerous and hazardous situations and from the edge and multi-type road damages at the cloud by comparing it to the state of the art.In [7], a Road-Mask R-CNN mobile damage detection model technique is used.

We also see in [8] that Wenda Li, Michael Burrow, Nicole Metje, and Gurmel Ghataora presented a vehicle-mounted pointed laser system that allows for the automated, quick, and low-cost assessment of fretting, a primary mode of local road damage. A strong approach was introduced, using a variety of pre-processing methods and processing of signals as an algorithmic approach that checks the histograms of laser-measured distances from the road surface in order to account for variations in road texture. The results proved that the system can measure road stress to the levels of precision required for road management planning, programming, and preparation. In [9], Rui Fan, Umar Ozgunalp, Brett Hosking, Ming Liu, and Ioannis Pitas demonstrated a robust pothole identification technique that is highly precise and computationally effective. To discriminate among damaged as well as undamaged road regions, an extensive disparity mapping was employed. To improve this efficiency, the transformation parameters were calculated using the golden segment search and latest programmable techniques. Potholes were accurately spotted through examining the variations between actual and modelled disparity maps. Finally, the identified potholes' point clouds are retrieved via the rebuilt 3D road surface.

In [10], Akanksh Basavaraju, Jing Du, Fujie Zhou, and Jim Ji propose to investigate several multiclass supervised machine learning approaches for efficiently classifying the techniques, using various sensors and data obtained from smartphones. This paper identifies the three methods as: smooth road, potholes, and severe transverse cracks. They hypothesise that incorporating characteristics from all three dimensions of the sensors yields more precise results, outperforming models that just employ one axis, and the usage of neural networks delivers much enhanced data classification.

The pothole picture dataset was annotated and trained with YOLOv4, and the results were evaluated using recall, prediction, and mAP at [11]. In [12], the research was expanded by Patrik Jonsson, Johan Casselgren, and Benny Thörnberg into video surveillance of a road section, enabling the classification of region segments of weather-related road surface circumstances such as wet, snow-coated, or ice. Infrared photos were captured with an infrared camera outfitted with an array of optical wavelength filters. The photos were primarily utilised to create multivariate data models and to classify roadway conditions in each pixel. This approach vastly outperformed conventional single-point road status classification techniques. In [13], the paper focuses on the importance of CNN and LSTM networks, which help to drive and implement traffic monitoring and aid in density estimation. Results show the accuracy and speed of the system.

3. Proposed Methodology

3.1. Model Overview

Roads are an important part of worldwide transportation systems. They are, however, subject to damage over time due to natural disasters such as floods, earthquakes, and landslides, and human activities such as construction, heavy traffic, and inadequate maintenance. The effects could cause danger to cars, pedestrians, and other travellers, as well as increase road maintenance costs. As a consequence, it is vital to detect and rectify these flaws as quickly as possible so as to prevent accidents and ensure road safety. In recent years, various technologies, including computer vision, have been developed for automating the process of identifying road damage, which may save time, money, and boost safety. We updated the parameters of the model in accordance with studies of aspect ratios and damaged region sizes in our training dataset. To overcome the problem of uneven data distribution of various classes, we added specific data augmentation procedures (contrast transformation, brightness correction, and Gaussian blur) prior to training. Our experiments suggest that our technique can achieve a Mean F1-Score. In this research, we propose a CNN model system for identifying road damage using the YOLOv5 object recognition technique. YOLOv5 is an innovative object recognition system that can distinguish and classify several objects in a photograph in real time.

The YOLOv5 algorithm is going to be used to identify and classify different types of road damage conditions such as potholes, cracks, and abnormalities. This algorithm is implemented in a robot that is tested on roads, from which the road administrators would get a proper instant analysis of the road on which the testing is done. Basically, the road damage detection robot is taken for analysis to the road that is controlled via IOT, where, after the analysis of the field, details such as counts of each pothole, crack, and abnormality, as well as the location and severity of each pothole, crack, and abnormality, are detected. Potholes are quite severe on many roads, which would cause unexpected accidents and should be taken into consideration, for which when detected, a message notification with the location will be sent to the respective engineer. This would help the road engineer to do accurate analysis and take the right action without spending much time on analysis. This would be much helpful for road engineers and administrators. Fig. 1 and 2 represent the block diagram representation of the identified system.

Block Diagram

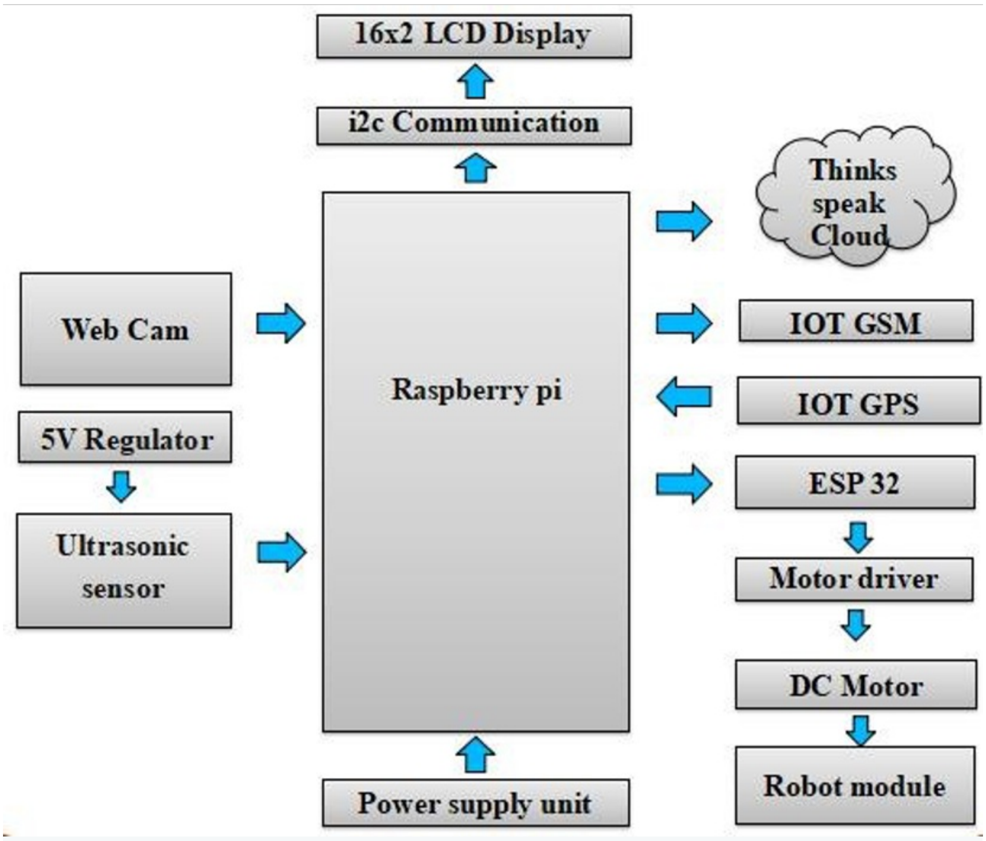

Fig. 1. Block Diagram Representation – Part 1

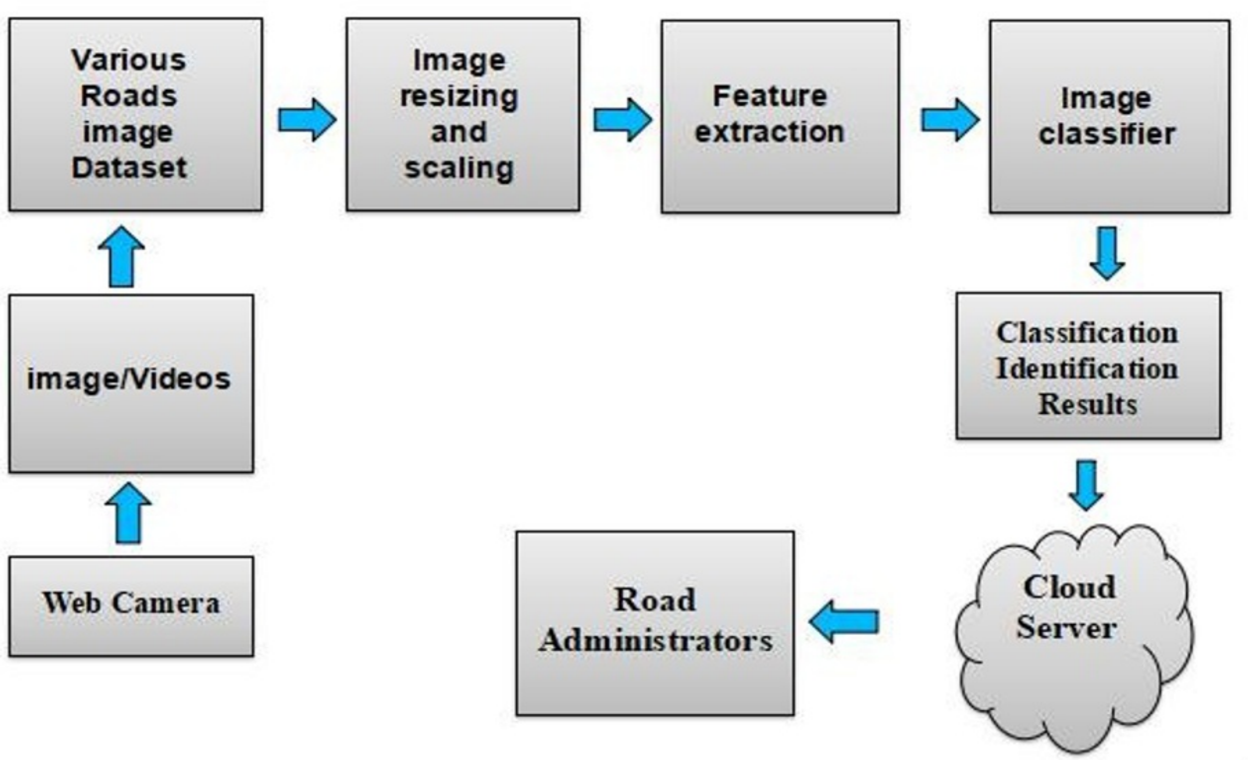

Fig. 2. Block Diagram Representation – Part 2

Modules Explanation:

The proposed system for road damage detection using different features would involve the following modules:

Software Modules:

Data Collection: From a variety of sources, including freely accessible datasets, online databases, and our own data gathering, we will assemble a sizable dataset of photos featuring various kinds of road damages. Labels specifying the type and place of the damages will be added to the dataset as annotations.

Data Preprocessing: To enhance the efficiency of the YOLOv5 algorithm, the data gathered shall be preprocessed to eliminate any unwanted noise and artifacts, compress and crop the photos to an appropriate size, and standardize the pixel values.

Model Training: A set of training has been set up, which has a validation set, and a testing set that must be created from the preprocessed data set. Transfer learning will be used to train the YOLOv5 algorithm on the training set. We will start with a pre-trained model and make adjustments to it on our data set to increase its performance. To fine-tune the hyperparameters and avoid overfitting, we will make use of the validation set. Finally, we will use metrics like recall, precision, and F1 score to assess the model's performance on the testing set.

Model Deployment: On a stream of live footage from a camera positioned on a moving vehicle, trained YOLOv5 models will be used. In real time, the system will identify and categorize various kinds of road damage, giving the necessary information to the road authorities.

Hardware Modules:

Hardware modules such as Raspberry Pi 4, Web Cam, HC05 Bluetooth Transceiver Module, Ultrasonic sensor, ESP 32, and L293D Motor driver are used in this technique.

Raspberry Pi 4:

It consists of a 64-bit quad-core processor, which has 4Kp60 hardware video decoding, dual-display capability, a capacity of 4K resolutions through two micro-HDMI connectors, and RAM with a capacity up to 4GB. Bluetooth 5.0, Gigabit Ethernet. It also contains dual-band in the range of 2.4/5.0 GHz wireless LAN, a USB port of 3.0, including PoE capabilities. This is the main processor for controlling the embedded system.

Web Cam:

The normal HSD 720P 30FPS digital webcam is used, which is used in capturing the live inputs from the road on which the robot is taken for analysis.

HC05 Bluetooth Transceiver Module:

The HC05 Bluetooth module that can easily transmit UART data wirelessly over Bluetooth is used. In addition to an edge connector, the Bluetooth module has a 2.4GHz ISM band frequency, PIO control, and an integrated antenna. It is possible to set up the HC-05 Bluetooth module as either a master or a slave. This connects the robot as well as the controller app used to control it.

Ultrasonic sensor:

It measures the distance from the target end and hits with ultrasonic sound waves and reverts back the sound into an electric signal. Ultrasonic waves receive signals very quickly. Mainly, this technique is used to detect the pothole depth.

ESP 32:

The ESP32 is an inbuilt chip microcontroller with built-in Wi-Fi.

L293D Motor driver:

The L293D is a 16-bit IC that has a common motor driver or motor drivers, which permits DC motors to be driven in either direction. It allows the simultaneous control of either side of DC motors. A single L293D IC will control either side of DC motors. This helps to run the robot.

Therefore, we could summarize by saying that our proposed system would analyze in an accurate and efficient manner to detect the potholes, cracks, and irregularities, which would be very beneficial for the road engineers.

4. Results and Discussions

4.1. Data Set

The dataset was taken from different roads and separated into four different classifications based on the detection, which is shown in Table 1.

Table 1. Dataset Classification

Classification Made	Testing Images
Good roads	1000
Damaged roads	1000
Cracks	1500
Potholes	1000

For testing in each case, there was a set number of pictures given, and from that, a few were validated based on that the accuracy and the loss were predicted.

Accuracy and Loss:

Among the numerous architectures, the YOLOv5 architecture was chosen, whereas the YOLOv5 method is intended to recognize and classify many items in a single image in real time with great accuracy. It uses a deep neural network architecture that has been trained on massive datasets of labelled images. The YOLOv5 method employs a single neural network architecture to process the entire image in a single pass. To increase its performance and reduce the amount of labelled data required, the YOLOv5 algorithm is trained utilizing a combination of supervised and unsupervised learning approaches such as transfer learning and self-supervised learning. After the input photographs are provided, the training will take place in a set format that is one step in length. Each learning rate determines the step size at every stage, with the goal of minimising loss. One observes that Epoch indicates the number of sessions the complete batch of datasets has been trained. Based on the training and testing, the F1 score confidence is derived, which is roughly 0.156, with a confidence level ranging from 0.4 to 0.82. Fig. 3, 4, and 5 represent the confidence curve and the accuracy and loss curve of the system.

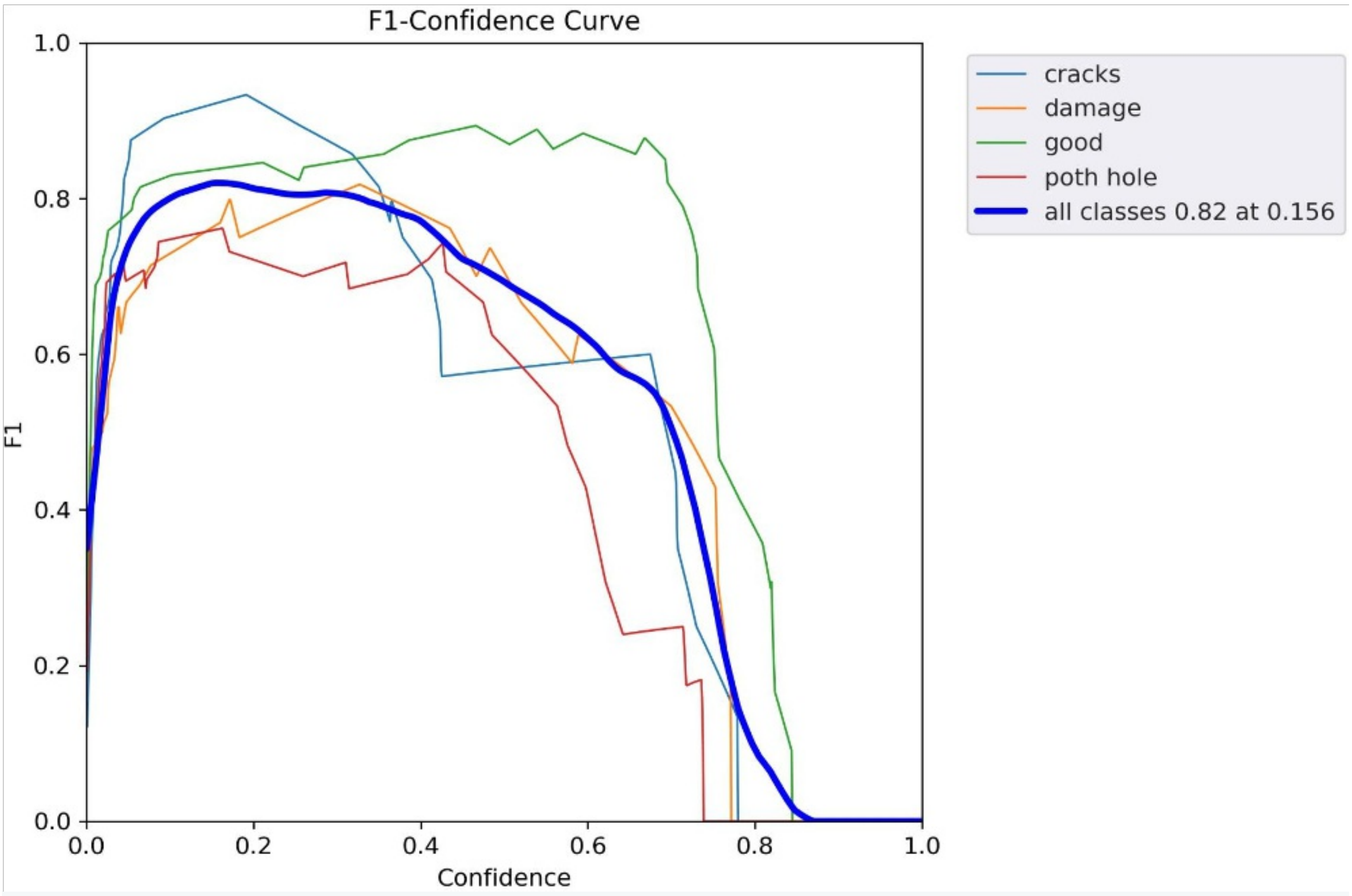

Fig. 3. F1 – Confidence curve of the system

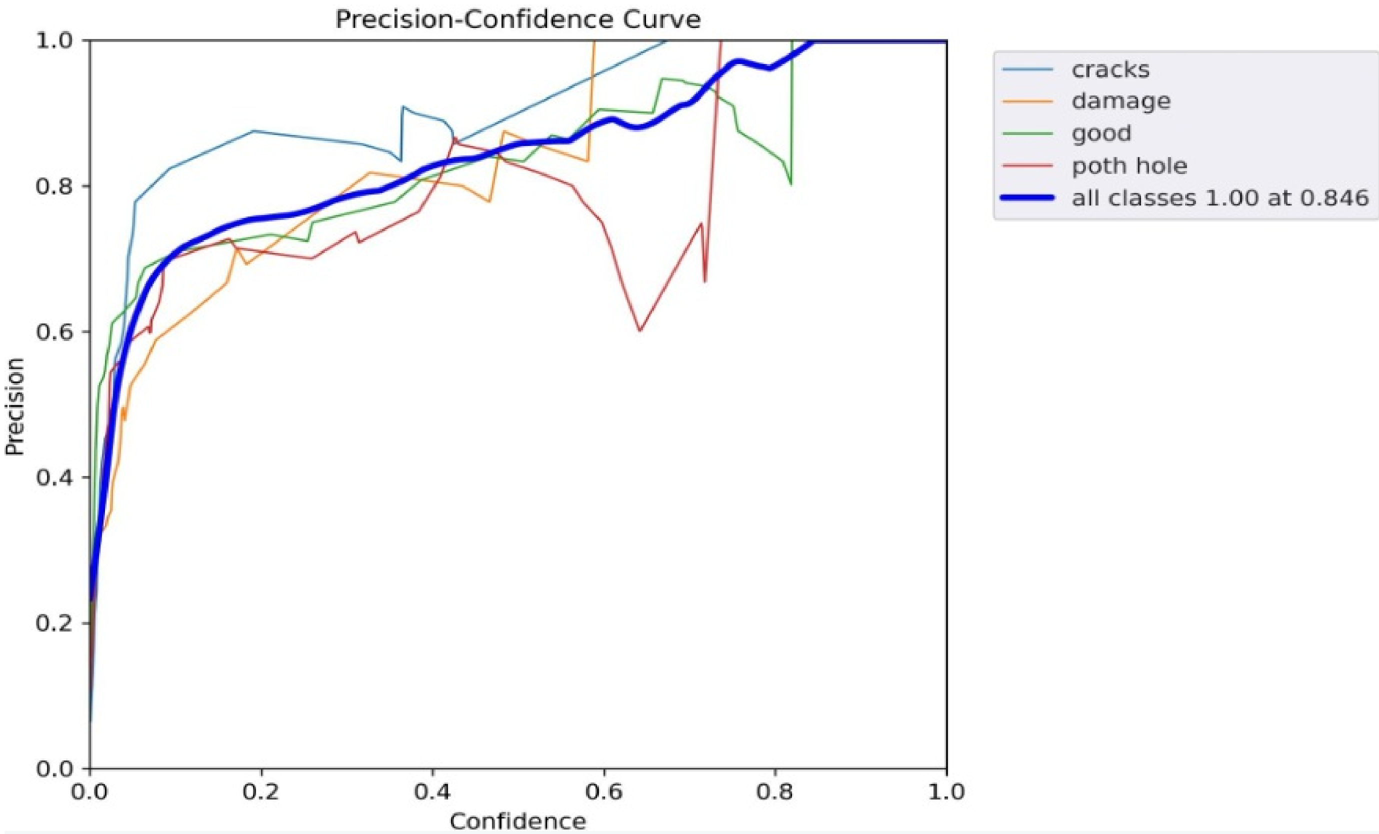

Fig. 4. Precision-Confidence Curve of the system

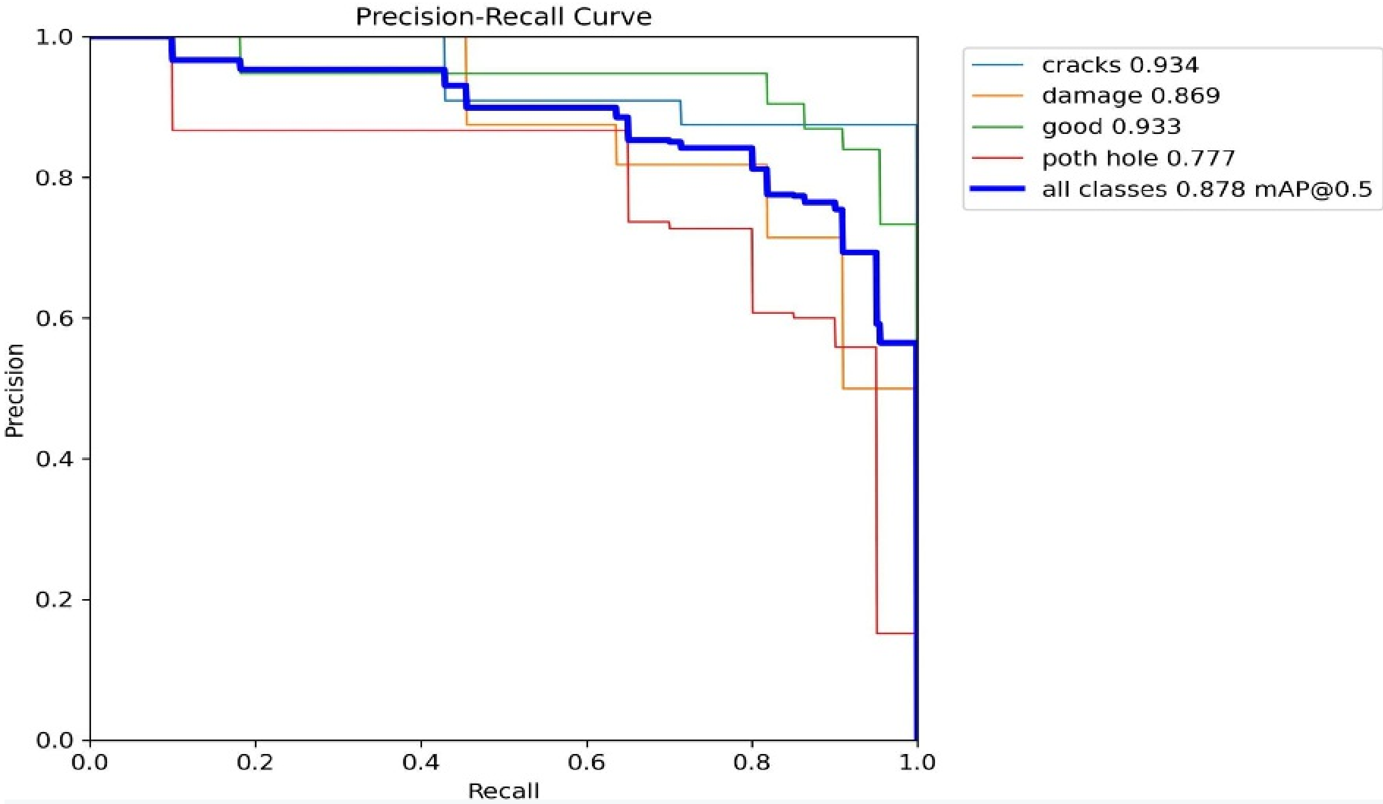

Fig. 5. Precision – Recall Curve of the system

Implementation of the Model:

For our proposed system, code developed is saved in a txt.format. The proposed code was developed for both training and for prediction. The respective data sets and codes are all saved in a folder for easy access. The code respective for the training will be run first in cmd.exe, where in this process the dataset will be trained in various epochs which are, in batches, based on various classifications.

As shown in Fig. 6, which represents one set of batches that goes under training, this process would take some time. Based on that, the accuracy and loss will be predicted. Once trained, we can move on to the next step, which is where the system could give us the right output.

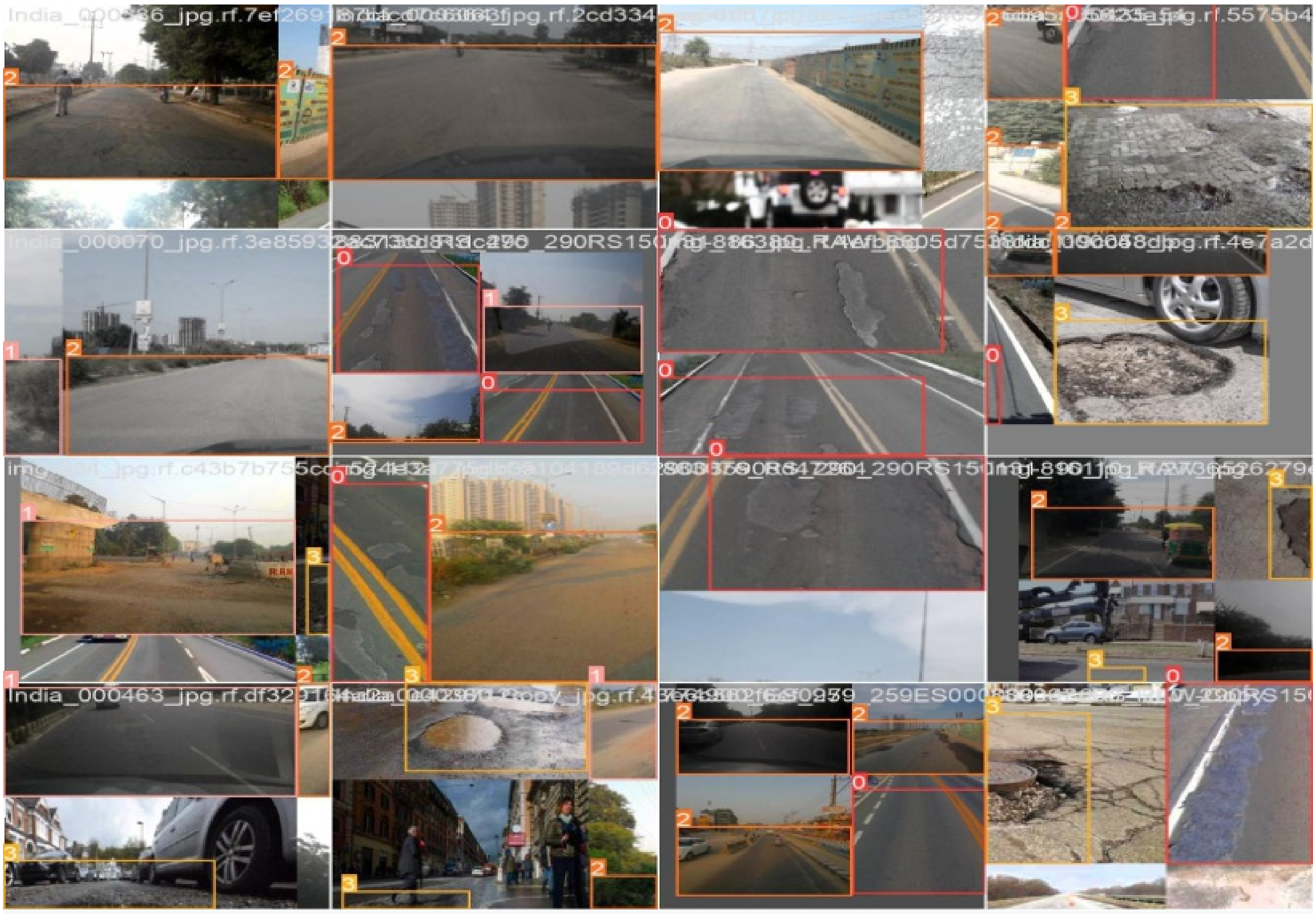

Fig. 6. Training Process

Once the training is completed, the next step is to run the prediction code, which would give us the output from which the system could predict the right one and do the analysis via web camera.

In Fig. 7, we could see the hardware setup of the road damage detection robot, where it is made as such to run through the road easily for analysis.

As seen in Fig. 8, each class was effectively recognized, and in this way, from the field. There, we could see that the precise range of the prediction and the appropriate advice would be provided at the same time to motivate the engineers and administrators of the roads to take the appropriate action.

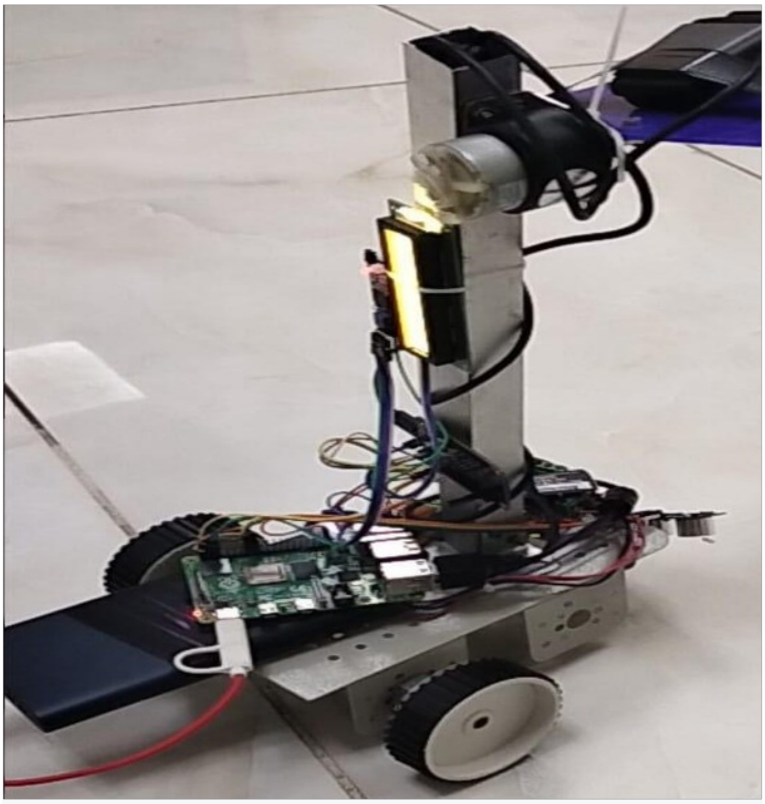

Fig. 7. Hardware setup

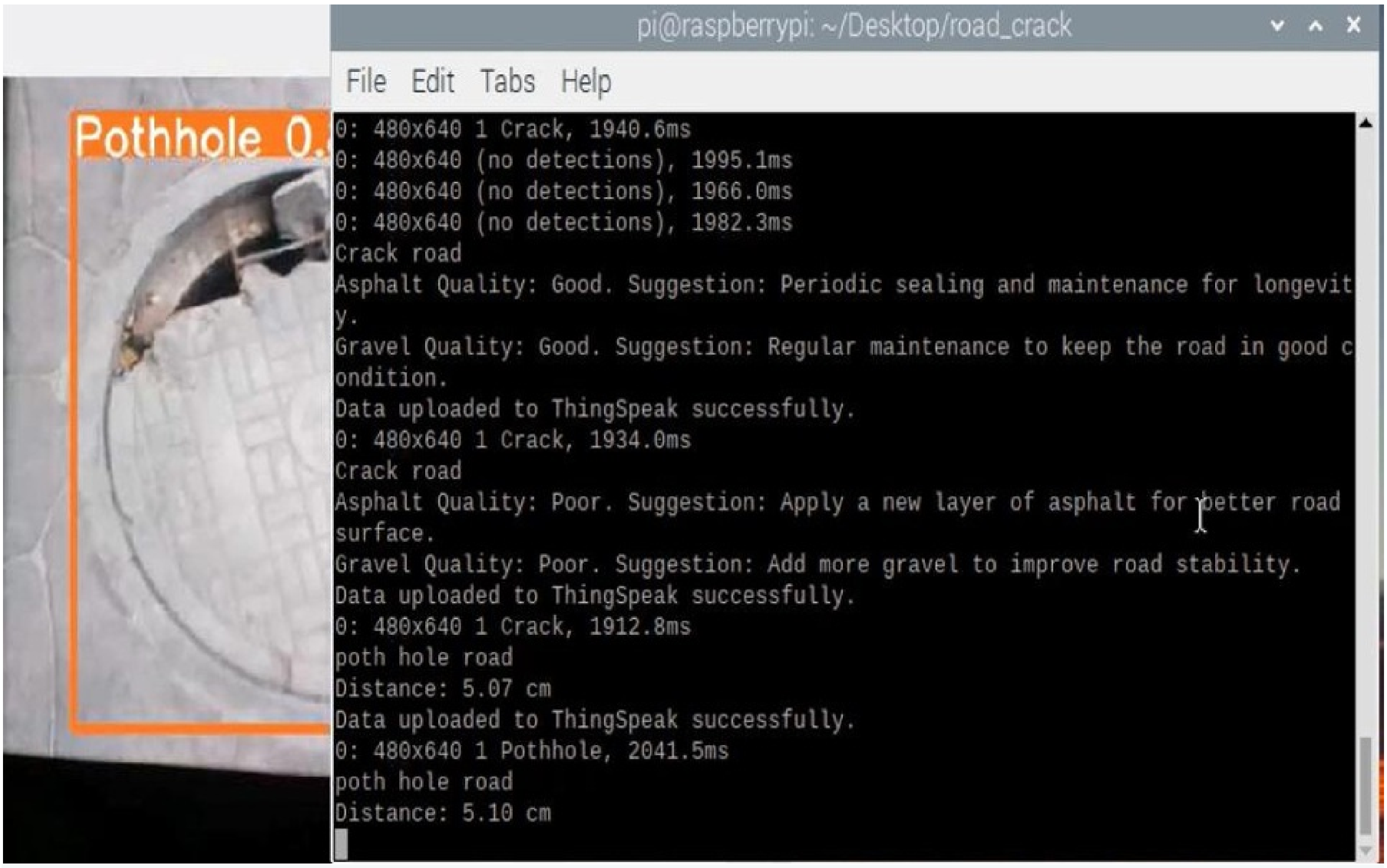

Fig. 8. Sample output after prediction

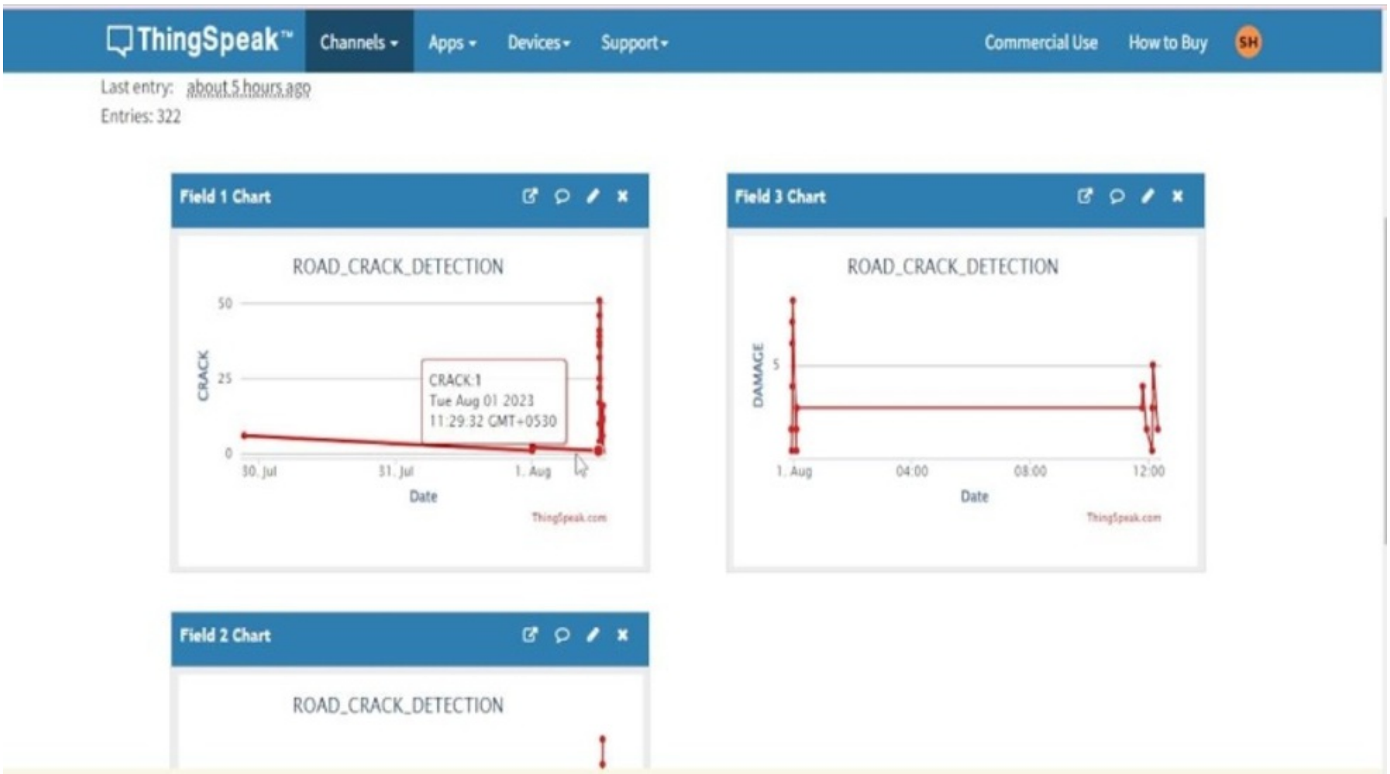

Fig. 9. Graph generated after analysis

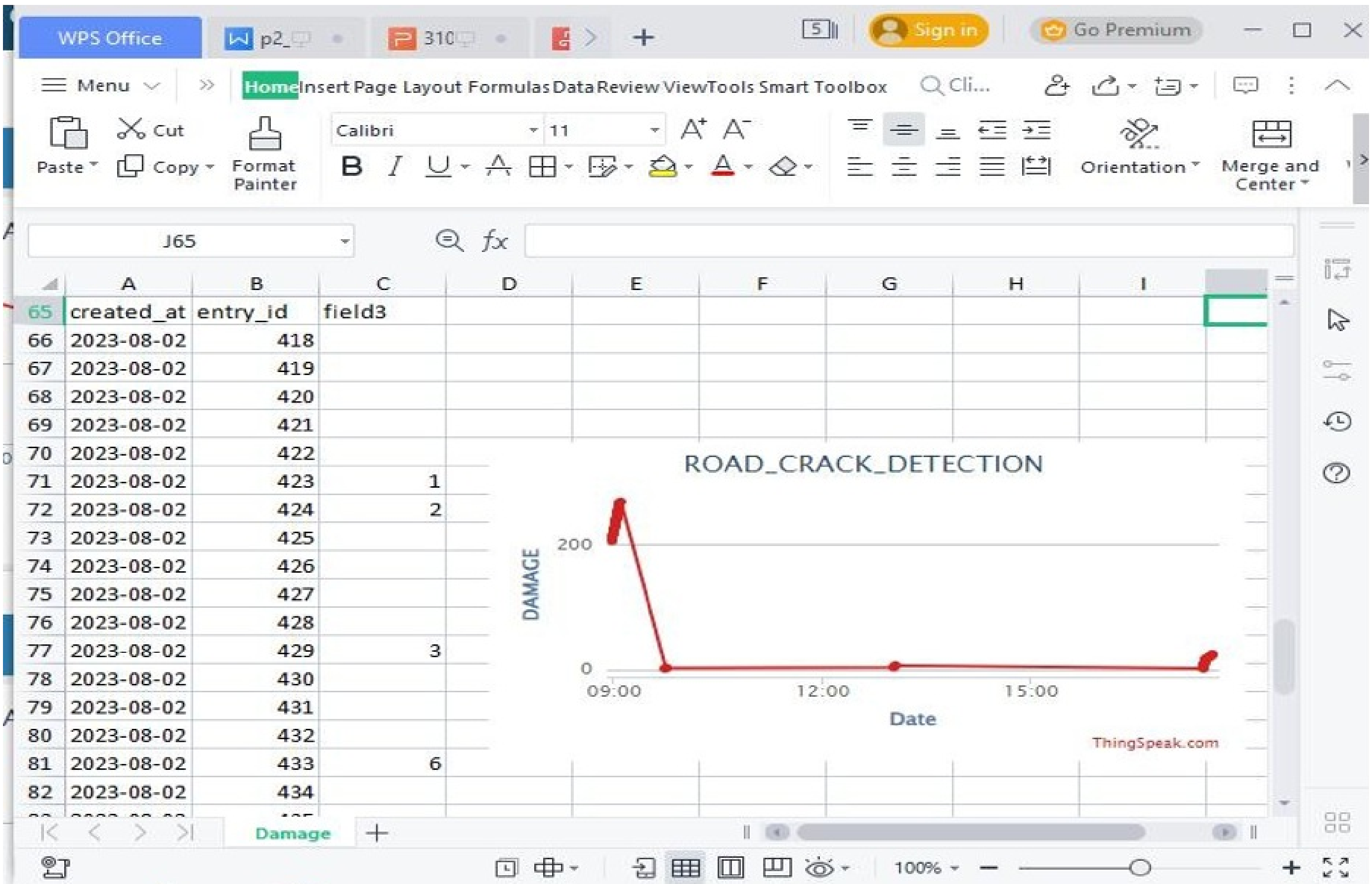

Fig. 10. Analysis report for damages detected in a field

The analysis will be carried out with respect to the count and severity based on the various inputs captured upon the prediction of the sets of inputs captured by the web camera via the system. A graph for each class will be formed in the IoT cloud based on the analysis data projected by the system, as shown in Fig. 9. The study report can then be exported, allowing engineers or road administrators to evaluate the specifics in Fig. 10.

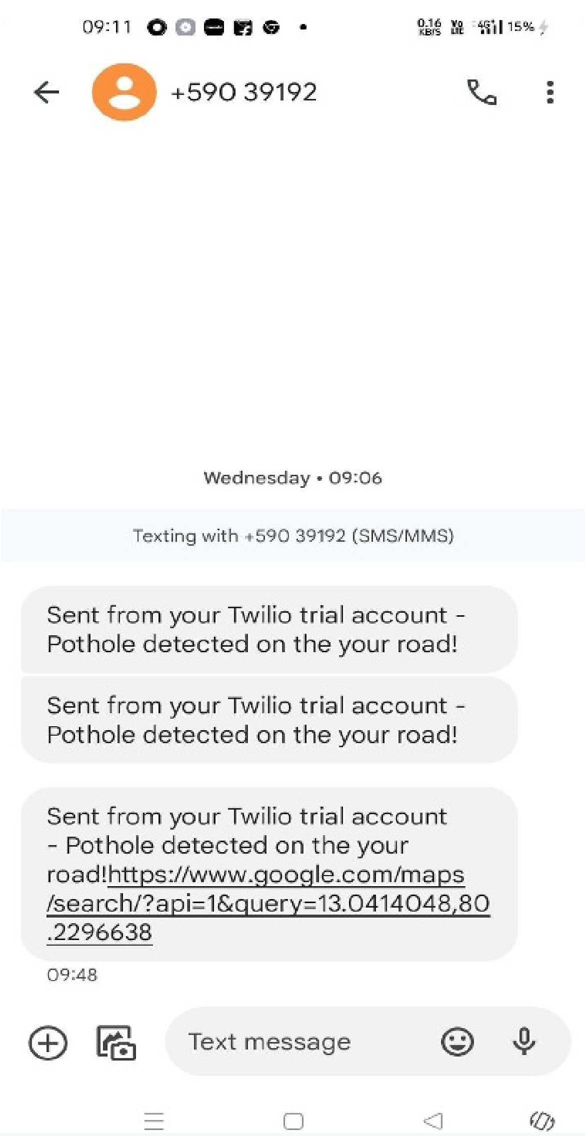

Fig. 11. Alert message on potholes with location

In Fig. 11, we could see that the alert messages on the severity of the potholes with location will be shared to the respective engineers and administrators to be aware of it. Hence we could get to know how much helpful the system will be for the respective road engineers and administrators.

5. Conclusions

Finally, we suggested a robot system for detecting road damage via the YOLOv5 object detection algorithm. The technology is capable of identifying and categorizing various kinds of road damage in real-time, improving road safety while reducing inspection time and expenses. To improve its performance, the system can be implemented on mobile devices and improved over time. The proposed method has tremendous application potential in maintaining roads and safety.

6. Future Scope

There are various changes that might be made to this method. The preliminary findings are quite positive. New acquisition campaigns are required to enrich the dataset and strengthen the convolutional neural network. Also, investigate and add new light-weight models or methodologies for learning, which may operate better with limited information for hazardous road damage identification in future work, and compare the benefits to the current architecture. Furthermore, to improve, we could develop a smart vehicle in which we could add more features and make predictions, and develop with predicting the required amount of materials required for clearing the damage, and could be developed with the help of navigation too.

References

1. ^*V. Vassilev, Road Surface Recognition at mm-Wavelengths Using a Polarimetric Radar, IEEE Transactions on Intelligent Transportation Systems, 23(7), 6985-6990, (2022).*
2. ^*A. Abdelraouf, M. Abdel-Aty and Y. Wu, Using Vision Transformers for Spatial-Context-Aware Rain and Road Surface Condition Detection on Freeways, IEEE Transactions on Intelligent Transportation Systems, 23(10), 18546-18556 (2022).*
3. ^*D. Chen, N. Chen, X. Zhang and Y. Guan, Real-Time Road Pothole Mapping Based on Vibration Analysis in Smart City, IEEE Journal of Selected Topics in Applied Earth Ob-servations and Remote Sensing, 15, 6972-6984, (2022).*
4. ^*Y. Wei and S. Ji, Scribble-Based Weakly Supervised Deep Learning for Road Surface Ex-traction From Remote Sensing Images, IEEE Transactions on Geoscience and Remote Sensing, 60, 1-12, (2022).*
5. ^*J. Yan, S. Ji and Y. Wei, A Combination of Convolutional and Graph Neural Networks for Regularized Road Surface Extraction, IEEE Transactions on Geoscience and Remote Sensing, 60, 1-13, (2022).*
6. ^*Y. Yuan, M. S. Islam, Y. Yuan, S. Wang, T. Baker and L. M. Kolbe, EcRD: Edge-Cloud Computing Framework for Smart Road Damage Detection and Warning, IEEE Internet of Things Journal, 8(16), 12734-12747, (2021).*
7. ^*J. Dong et al., Pixel-Level Intelligent Segmentation and Measurement Method for Pave-ment Multiple Damages Based on Mobile Deep Learning, IEEE Access, 9, 143860-143876, (2021).*
8. ^*W. Li, M. Burrow, N. Metje and G. Ghataora, Automatic Road Survey by Using Vehicle Mounted Laser for Road Asset Management," IEEE Access, 8, 94643-94653, (2020).*
9. ^*R. Fan, U. Ozgunalp, B. Hosking, M. Liu and I. Pitas, Pothole Detection Based on Dispar-ity Transformation and Road Surface Modeling," IEEE Transactions on Image Pro-cessing, 29, 897-908, (2020).*
10. ^*A. Basavaraju, J. Du, F. Zhou and J. Ji, A Machine Learning Approach to Road Surface Anomaly Assessment Using*

Smartphone Sensors," IEEE Sensors Journal, 20(5), 2635- 2647, (2020).

11. ^*M. Omar and P. Kumar, "Detection of Roads Potholes using YOLOv4, International Con-ference on Information Science and Communications Technologies (ICISCT), Tashkent, Uzbekistan, (2020).*
12. ^*P. Jonsson, J. Casselgren and B. Thörnberg, Road Surface Status Classification Using Spectral Analysis of NIR Camera Images, IEEE Sensors Journal, 15(3), 1641-1656, (2015).*
13. ^*Rakesh S, K. Jeyageetha, Nishant S, D. Nageswari, R B R Prakash, S. Suma Christal Mary, 8th International Conference on Communication and Electronics Systems (ICCES), IEEE (2023).*