Road Surface Guard: AI Paved Safety

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Abstract

Pothole detection is a critical aspect of road maintenance and safety, with the potential to prevent accidents and reduce infrastructure repair costs. Early detection and timely repair of potholes can help prevent accidents and reduce maintenance costs. Deep learning techniques have shown success in several computer vision tasks, including object detection and segmentation. The proposed system leverages Convolutional Neural Networks (CNNs), You Only Look Once (YOLO) object detection algorithm and Light Detection and Ranging (LiDAR) technology to identify and locate potholes in real-time. The system's architecture comprises data collection from vehicle-mounted cameras, image preprocessing, and a deep learning model for pot-hole detection. A labeled dataset of road images with annotated potholes is used to train the model, allowing it to learn the distinctive features of potholes, such as shape, depth, and texture. These images are then utilized to train a CNN-based model using deep learning techniques. The trained CNN model is then employed to detect pot-holes in real-time road images captured by vehicle-mounted cameras. Evaluation of the proposed system on diverse road surfaces and lighting conditions demonstrates its robustness and accuracy. It achieves a pothole detection rate of over 90%, outperforming traditional methods. The system's ability to provide instant alerts to drivers and municipal authorities enhances road safety and expedites pothole repair efforts. The proposed approach can be integrated into existing road monitoring systems, aiding in the timely identification and remediation of road hazards, ultimately improving road safety, and reducing maintenance costs.

Keywords: Deep Learning, Convolutional Neural Networks (CNNs), Light Detection and Ranging (LiDAR), Real-time Monitoring, Vehicle-mounted Cameras.

I. Introduction

Potholes pose significant challenges to road safety, vehicle maintenance, and traffic management. Timely detection and repair of potholes are crucial to mitigate these challenges. Traditional methods of pothole detection rely on visual inspections conducted by road maintenance crews, which are time-consuming, expensive, and often prone to human error. The current methods have limitations in measuring information such as volume and depth of potholes, lighting, and shadow conditions, providing the exact shape of potholes. To address these limitations, computer vision and deep learning technologies have emerged as promising tools for automating pothole detection. By mounting cameras on vehicles, our system continuously monitors road conditions, instantly detecting and alerting drivers, and municipal authorities to the presence of potholes. By utilizing LiDAR's ability to capture precise topographical data and recognize the unique characteristics of potholes, this model aims to present an approach to pothole detection, one that offers improved accuracy and efficiency compared to traditional methods. Pothole detection has several steps beginning with data preprocessing in which image enhancement is done along with data augmentation. Then we move on to feature extraction using CNN and transfer learning we fine-tune the model. The key objectives of this study include the development of a LiDAR-based pothole detection system, the evaluation of its performance across various road conditions, and an assessment of its potential impact on road safety and maintenance. The outcomes of this model contribute to the enhancement of intelligent transportation systems and road maintenance practices. Our proposed solution not only improves road safety by promptly identifying road hazards but also streamlines repair efforts, reducing infrastructure maintenance costs. Hence, our system serves as a solution for the integration of technology into infrastructure management, addressing the challenges posed by potholes more effectively than ever before. In pothole detection, the success of the model heavily relies on the quality of image data preprocessing. Properly prepared data not only streamlines model training but also ensures that the model's performance is robust and reliable. These preprocessing steps are particularly vital for addressing the challenges associated with pothole detection, such as varying lighting conditions, diverse road surfaces, and pothole appearances. By standardizing, normalizing, and augmenting the data, machine learning models are better equipped to identify and locate potholes accurately, contributing to safer road conditions and more effective road maintenance. Along with detecting the pothole reporting of the potholes is equally important. Traditional methods for repairing the roads and covering of potholes is very time-consuming process i.e. it would take a lot of time to even locate where the potholes exist. The outcome of our model is not giving the public an opportunity to report the potholes to the officials for the rapid action for repairing the roads and covering potholes.

II. Literature Survey

Review of Recent Automated Pothole-Detection Methods by Kim et al. [1] pothole detection was mainly performed via visual inspection by human experts. Automated pothole-detection methods apply various technologies that converge basic technologies such as sensors and signal processing. The automated pothole-detection methods can be classified into three types according to the technology used in the pothole-recognition process: a vision-based method, a vibration-based method, and a 3D reconstruction-based method.

A review on automated pavement distress detection methods by Coenen et al. [2] the distresses and related detection methods are presented. This review also includes commercial solutions. Thereafter, a gap analysis is conducted which is concluded that the distresses related to pavement micro-texture need serious additional research to be implemented in a cost-effective fashion. Depth-related distresses are detectible well, but rely on expensive tools.

Review of Pavement Defect Detection Methods by Wenming et al. [3] three major types of methods used in road cracks detection: image processing, machine learning and 3D imaging based methods. Image processing algorithms mainly include threshold segmentation, edge detection and region growing methods, which are used to process images and identify crack features.

A Review on Negative Road Anomaly Detection Methods by J. Dib et al. [4] The main limitation to obstacle avoidance nowadays has been negative road anomalies which is the term we used to refer to potholes and cracks due to their negative drop from the surface of the road. This has for long been a limitation because they exist in different, random, and stochastic shapes. Today’s technology lacks the presence of sensors capable of detecting negative road anomalies efficiently as the latter surpasses the sensor’s limitations rendering the sensing technique inaccurate

Pavement asset management systems and technologies: A review by Peraka et al. [5] T he objective of this review paper was to collect and report several current state-of-the-art developments in PAMS and the associated embedded processes, majorly focused on data collection procedures, analytical techniques, decision making tools, and processing methods.

Developing a near real-time road surface anomaly detection approach for road surface monitoring by Shahram et al. [6] The processing smartphone sensors to monitor road surface conditions is technically challenging due to dissimilar sensor properties, different smartphone placement, and different vehicle mechanical properties. This study aimed to develop a hybrid method using threshold based and Machine

Learning approaches for near real-time detection and classification of road surface anomalies using smartphone sensor data with higher-level accuracy. The proposed algorithm has self-adapting and self-updating capabilities to adapt itself to any type of smartphone and the dynamic behaviors of various vehicles and road surface conditions.

Indian pothole detection based on CNN and anchor-based deep learning method by Mallikarjun et al. [7] The main contribution of this paper lies in collecting the pothole data in different Indian traffic conditions and detecting of the same using a vision-based method by defining the performance of deep learning methods like sequential convolutional neural network (CNN), and anchor-based You only Look Once3 (YOLOV3) and analyzing the models in terms of resources and performance of detection. The experiments were conducted on both models and a conclusion was drawn to bring out the benefits of the model with 98% accuracy using CNN and 83% precision using Yolov3.

Computer vision for road imaging and pothole detection: a state-of-the-art review of systems and algorithms by et.al [8] Computer vision algorithms have been utilized for 3-D road imaging and pothole detection for over two decades. Nonetheless, there is a lack of systematic survey articles on state-of-the-art (SoTA) computer vision techniques, especially deep learning models, developed to tackle these problems. This article first introduces the sensing systems employed for 2-D and 3-D road data acquisition, including camera(s), laser scanners and Microsoft Kinect. It then comprehensively reviews the SoTA computer vision algorithms, including (1) classical 2-D image processing, (2) 3-D point cloud modelling and segmentation and (3) machine/deep learning, developed for road pothole detection.

Detection of Potholes Using a Deep Convolutional Neural Network by Lim et al [9] A deep convolutional neural network based on YOLOv2 with a different architecture and two models is proposed and can obtain a significant increase in performance over YOLov2.

Pothole Classification Model Using Edge Detection in Road Image by Baek et. al [10] It detects all objects except potholes using an object detection algorithm. The detected object is removed, and a pixel value of 255 is assigned to process it as a background. In addition, to extract the characteristics of a pothole, the contour of the pothole is extracted through edge detection. Finally, potholes are detected and classified based by the (you only look once) YOLO algorithm.

Pothole Reporting System by Alissa et al [11] Potholes cost motorists around 6.4 billion dollars annually, thus demonstrating the need for a system to aid with the detection and reporting of potholes. The four systems we needed to consider for the implementation of this project were the power system, the sensing system, the data processing system, and the reporting and logging system. The logging and reporting system, located on an android mobile device, will store the pothole locations on a cloud server.

Detection of Pothole in Real-Time Using Android Based Application by Tejeshwari et al [12] The project conducts a study into the use of the internet of things to detect and report potholes on roads. The paper assembles an open hardware equipment and sensor to experiment the detection and reporting of potholes using GPS Tracker devices. The project presented the architectural design and system to detect, report and manage potholes and other road obstacles using GPS Tracker.

Pothole Detection, Reporting and Management using Internet of Things: Prospects and Challenges by Ebenezer et al [13] The paper conducts a study into the use of internet of things to detect and report potholes on roads. The paper assembles an open hardware equipment and sensor to experiment the detection and reporting of potholes using IoT/IoE enabled devices. The paper presented the architectural design and system to detect, report and manage potholes and other road obstacles using IoT.

Real-time machine learning-based approach for pothole detection by Alexander et al [14] This study presents a comparative study of machine learning models for pothole detection. The Test dataset was isolated entirely from the Training and Validation datasets, and a stratified K-fold cross-validation was applied to the Training dataset. The Random Forest Tree and KNN showed the best performance on the Test dataset with a similar accuracy of 0.8889.

Convolutional neural networks-based potholes detection using thermal imaging by Aparna et al [15] The objective of this work is to analyze the feasibility and accuracy of thermal imaging in the field of pothole detection convolutional neural networks approach of deep learning has been adopted. The results show that images were correctly identified with the best accuracy of 97.08% using one of the pre-trained convolutional neural networks based residual network models.

III. Proposed System

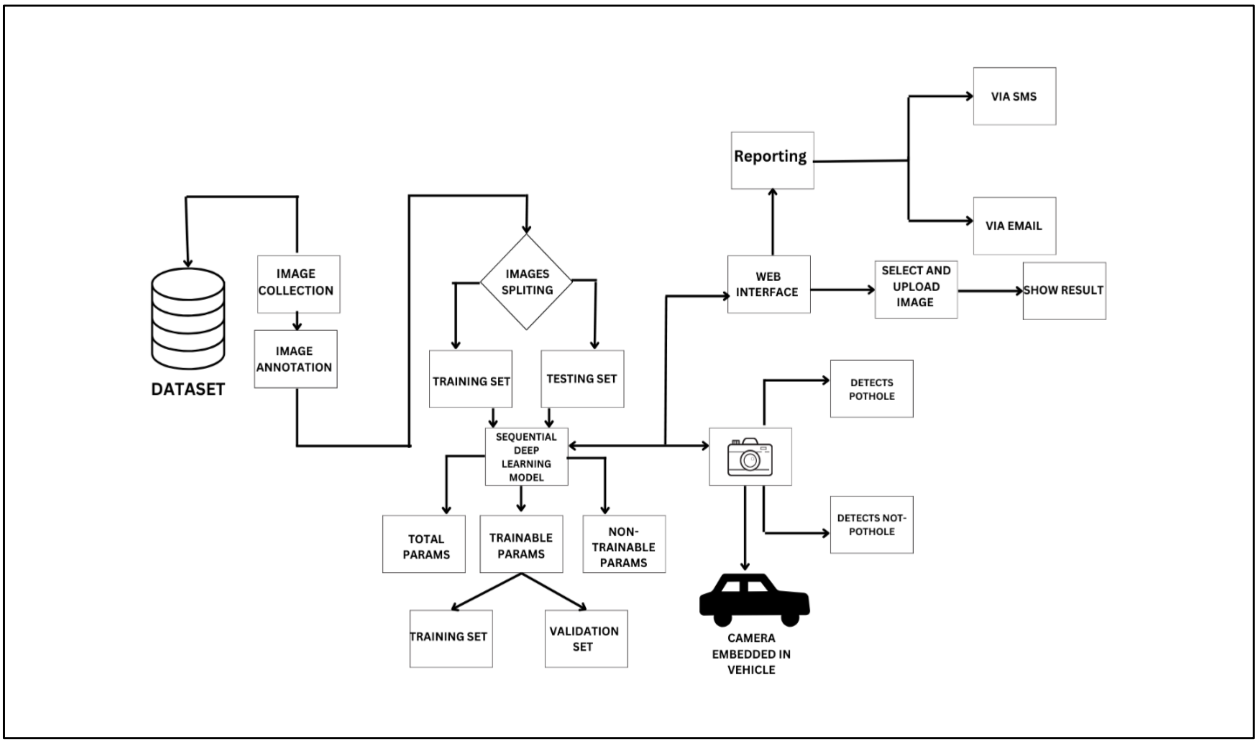

Figure 1: System Architecture of the proposed system

Pothole Detection:

Dataset:

The datasets have been taken from Kaggle. Dataset 1 consists of plain road images and other dataset consists of pothole images.

Data Pre-Processing:

Before the data is trained the images need to be pre-processed. The pre-processing is needed as it we have multiple images of various sizes and many other elements in the image other than just the pothole. The images have been resized into an array and now every image is of the same size and the image with the same quality and clarity. Resizing the images help in maintaining the consistency, taking up less memory space and in increasing the computational efficiency. Before training the model, the labels need to be created for the images on the dataset and the entire data is then combined into a single array of values and divided into training and testing data.

Methodology

The goal of the model is to perform binary classification, specifically for detecting potholes. The model outputs probabilities or scores that can be interpreted as the likelihood or confidence that the input image belongs to the positive class (pothole).

The model is a CNN, a type of neural network commonly used for image classification tasks. It consists of convolutional layers with tunable parameters, max-pooling layers for down-sampling, a variable number of convolutional layers, flattening layer to convert 2D features to a 1D array, a dense (fully connected) layer with tunable units, dropout layers for regularization, and a final dense layer with a sigmoid activation function for binary classification.

A sequential model (as shown in Figure 2) is a type of neural network architecture used for building and training deep learning models, particularly for tasks related to sequences of data. It is commonly used for tasks such as natural language processing, time series analysis, and other sequential data problems. The key characteristic of a sequential model is that it processes data in a sequential order, making it well-suited for tasks where the order of the input data matters. Sequential models are often composed of multiple layers of neurons, and the data sequentially flows through these layers, passing from one layer to the next.

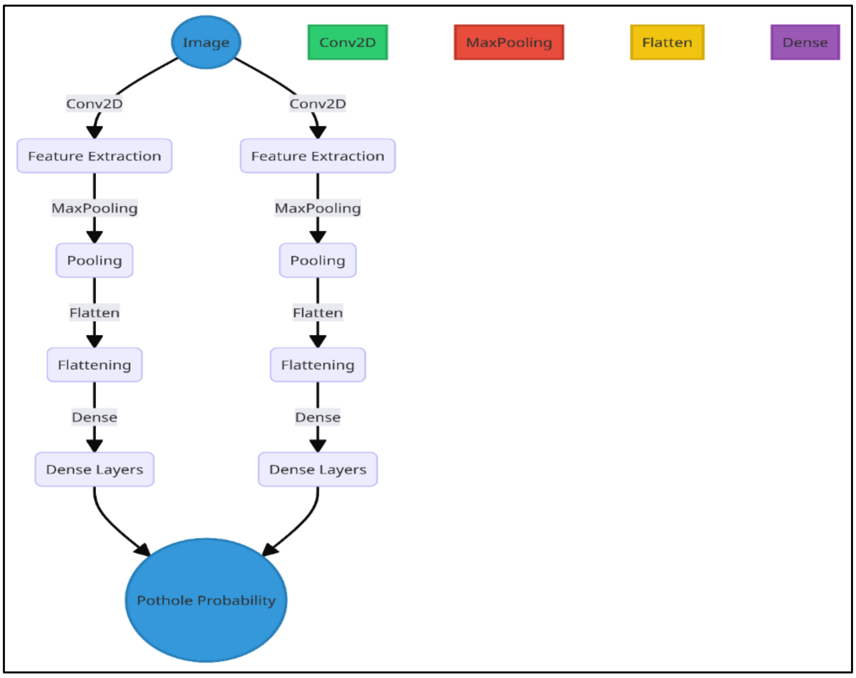

Figure 2: Sequential model Layers

Conv2D layers are essential for capturing spatial hierarchies in data, making CNNs well-suited for tasks like image classification, object detection, and segmentation.

Max pooling is a down-sampling or sub-sampling operation often used in convolutional neural networks (CNNs) to reduce the spatial dimensions of the feature maps while retaining the most important information. Max pooling is particularly popular for image recognition tasks, but it can be applied to various types of data.

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Search: Running Trial #3

Value             |Best Value So Far |Hyperparameter
112               |32                |conv_1_filter
3                 |5                 |conv_1_kernel
1                 |4                 |num_layers
80                |48                |conv_2_filter
5                 |5                 |conv_2_kernel
128               |80                |dense_units
0.2               |0.1               |dropout_1
0.0001            |0.01              |learning_rate
32                |128               |conv_3_filter
5                 |5                 |conv_3_kernel
112               |128               |conv_4_filter
3                 |3                 |conv_4_kernel
128               |80                |conv_5_filter
5                 |5                 |conv_5_kernel
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Figure 3: The image shows how the data is being processed in the various layers of the sequential model for pothole detection

The dense layer, also known as a fully connected layer, is a fundamental component in neural network architectures, such as feedforward neural networks and deep learning models like multilayer perceptron (MLPs). Dense layers play a crucial role in learning and modeling complex patterns in the data.

A flattened layer is a type of layer commonly used in neural networks, especially in deep learning models like convolutional neural networks (CNNs) and feedforward neural networks. Its primary purpose is to transform multi-dimensional data into a one-dimensional vector, which is essential when transitioning between convolutional and fully connected (Dense) layers or when the network requires one-dimensional data as input.

Keras Tuner Bayesian Optimization tuner for hyperparameter tuning

In the proposed system, Keras Tuner's Bayesian Optimization tuner serves (shown in Figure 4) as a powerful tool for fine-tuning the hyperparameters of Convolutional Neural Networks (CNNs) to enhance the accuracy and effectiveness (as shown in Figure 3) of the pothole detection system. This tuner streamlines the process of searching for the best hyperparameter configuration by employing Bayesian optimization techniques. To use it, you first define a function that constructs your CNN model, with hyperparameters as arguments, and returns a compiled Keras model. Next, you specify the hyperparameter search space, including parameters such as the number of layers, filter sizes, learning rates, and dropout rates. You configure the Bayesian Optimization tuner to optimize a chosen objective (e.g., accuracy or F1-score) and set the maximum number of trials. The tuner will iteratively explore various hyperparameter combinations, training multiple models, and ultimately provide you with the best configuration. After obtaining the optimal hyperparameters, you can train and evaluate the model on your pothole detection dataset, ensuring that it meets the desired performance metrics. Once satisfied, you can deploy the tuned model in a real-world setting to detect potholes with improved accuracy and reliability.

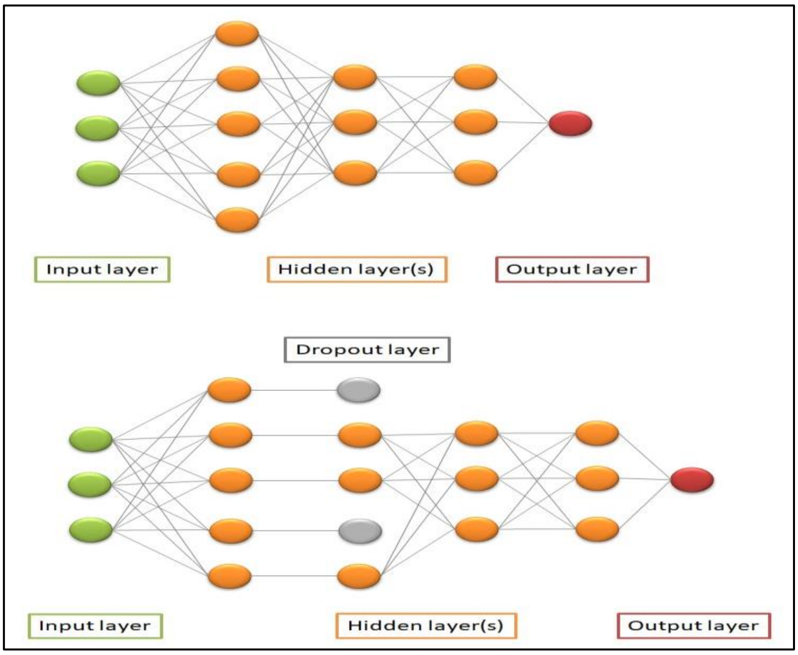

Figure 4: Tuning the Hyperparameters and Layers of Neural Network Deep Learning

Model Training

"epochs" refer to the pivotal stages of the model training process of pothole detection. As the training dataset, composed of images depicting road surfaces with and without potholes, is passed through the neural network, each complete pass through this dataset is termed one epoch. The choice of the number of epochs is a crucial hyperparameter, influencing how well the model learns to identify potholes.

Too few epochs might result in an underfit model that fails to capture intricate patterns, while an excessive number of epochs can lead to overfitting, where the model learns the training data too well, including its noise, at the expense of generalization to new data. To address this, practitioners typically monitor the model's performance on a validation dataset during training and may employ early stopping, which halts training if the model's validation performance plateaus or deteriorates.

Selecting the right number of epochs is a critical balancing act, ensuring that the model attains an adequate understanding of pothole features while preventing overfitting.

The model is trained for 5 epochs per trial during the hyperparameter search. The best model, as determined by the tuner, is then trained on the entire training set for an additional 5 epochs. The training is performed using the Adam optimizer with a binary cross-entropy loss function, common choices for binary classification problems.

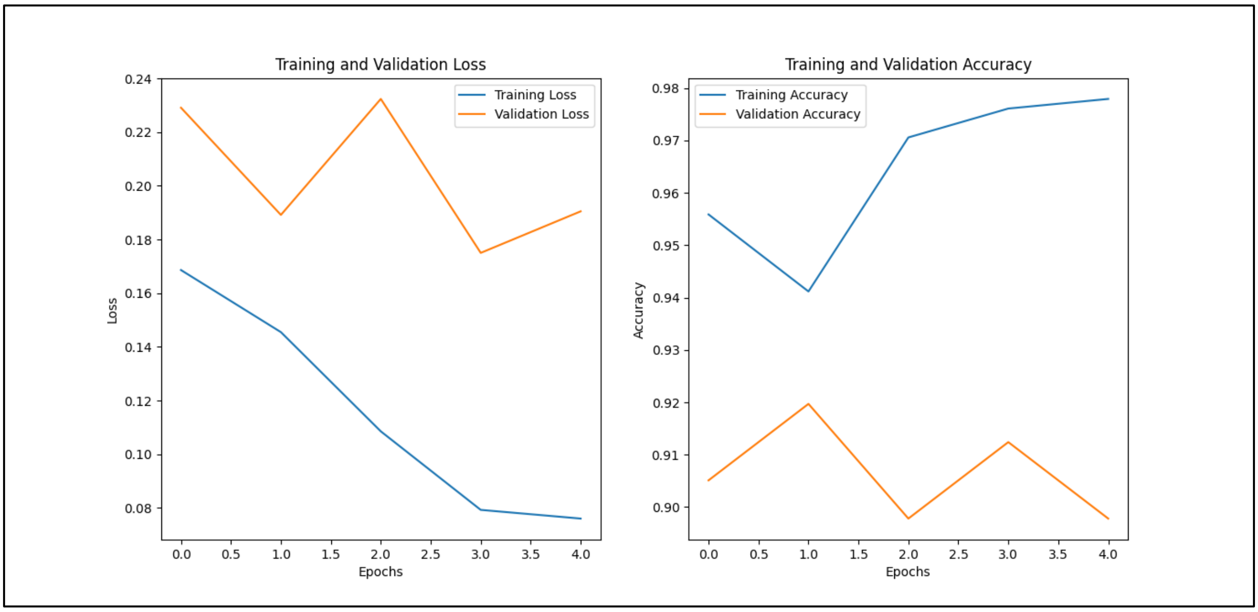

Figure 5: Loss and Accuracy from multiple Epochs

Adam optimizer

The Adam optimizer plays a pivotal role in pothole detection, particularly when training Convolutional Neural Networks (CNNs) to recognize and classify potholes in images or video frames. When building a pothole detection model, one of the key considerations is how to efficiently adjust the model's weights and biases during the training process. The Adam optimizer, with its adaptive learning rate and momentum, offers a solution.

In the context of pothole detection, the Adam optimizer is used as part of the model training process. The steps generally involve designing a CNN architecture to extract features from images, defining an appropriate loss function (often binary cross-entropy for classifying potholes), and choosing essential hyperparameters like the learning rate. The model is then compiled, specifying the optimizer as 'Adam' or by customizing hyperparameters within the optimizer.

During training, the Adam optimizer efficiently adjusts the model's parameters to minimize the chosen loss function, enabling the CNN to learn the distinctive features and patterns associated with potholes. To enhance the model's performance and avoid overfitting, techniques like early stopping and model checkpoints can be employed. After training, the model is evaluated on a validation dataset to fine-tune hyperparameters, and it is eventually tested on an independent dataset to assess its real-world performance. The efficient weight updates and adaptability of the Adam optimizer contribute to the model's ability to make accurate pothole detections, making it a crucial component of the pothole detection system. Once the model demonstrates satisfactory results, it can be deployed in real-world applications, such as in vehicle-mounted cameras, where it continuously monitors and detects potholes on the road, contributing to improved road safety and infrastructure maintenance.

Pothole Reporting:

The potholes can be detected by the vehicles but the major problem of potholes would be solved only when the potholes will be covered and proper roads will be maintained.

To handle this issue and for the authorities to act fast for repairing the potholes, the concept of reporting the potholes to the authorities is needed. The reporting activity can be done with the help of the web interface through which you can send the information regarding the pothole via a SMS or an Email.

In the message to the authorities the user information, name and email id will shared as well as the location coordinates of the potholes, so that the authorities can reach the exact location to repair the roads.

In the SMS message the users can send their details along with the location coordinates to the authorities, this is possible through the SMS API named Twilio. In the Email the users can send the message to the authorities with their email-id and the location coordinates of the pothole and the image of the pothole which would help the authorities understand the severity of the road condition.

IV. Results

After several epoch's and hyperparameter tuning the model considers the best trained model for the further processing and it takes up the validation set. The validation set has new data this allows the model to assess how well it generalizes to unseen data.

A confusion matrix (shown in Figure 6) is a table that is used to evaluate the performance of a classification algorithm. It shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for a given classification task. The numbers in the matrix represent the number of instances in each class that were classified as the other class. The number 72 in the second row of the first column indicates that there were 72 instances that were plain road but were classified as pothole.

The overall accuracy of the classification algorithm can be calculated as follows:

$$\textbf{accuracy} = \textbf{(TP + TN) / (TP + TN + FP + FN)}$$

The accuracy is 90.3%. This means that the classification algorithm correctly classified 90.3%.

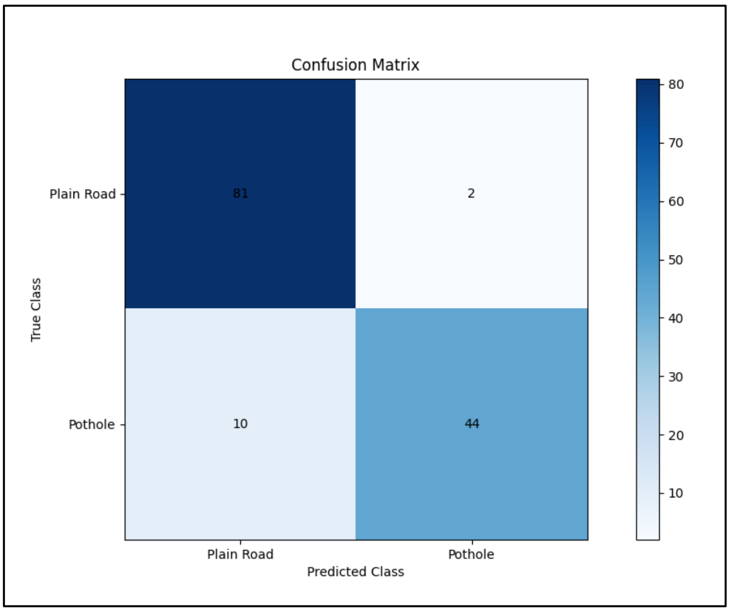

Figure 6: Confusion Matrix

Following training, the model's performance is assessed on a separate validation dataset, using metrics like accuracy, precision, recall, and F1-score. The F1-score is the harmonic mean of precision and recall hence it is the best among all four measures because it combines both precision and recall into a single metric. Binary Cross-Entropy loss continues to play a role as an indicator of how well the model generalizes to unseen data. In summary, Binary Cross-Entropy is an essential tool in pothole detection, facilitating the development of models that reliably and accurately identify potholes in images, contributing to safer roads and improved infrastructure management.

A true positive is an outcome where the model correctly predicts the positive class. Similarly, a true negative is an outcome where the model correctly predicts the negative class.

A false positive is an outcome where the model incorrectly predicts the positive class. And a false negative is an outcome where the model incorrectly predicts the negative class.

There are four very common metrics for evaluating machine learning models and their performance. The metrics we will go through are Accuracy, Precision, Recall and F1 Score.

Precision is the proportion of positive predictions that are correct, while recall is the proportion of actual positive cases that are correctly identified.

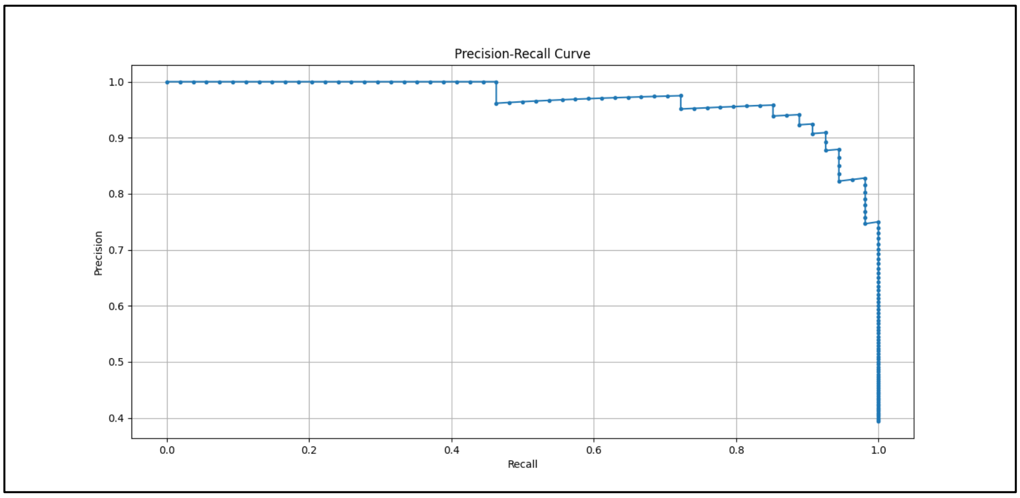

Figure 7: Precision- Recall curve

The curve (in Figure 7) shows that as the threshold increases, precision increases while recall decreases. This is because a higher threshold means that the model is more likely to classify an instance as positive, which will increase precision but decrease recall. The area under the curve (AUC) is a measure of the overall performance of the model. A higher AUC indicates a better model. In this case, the AUC is 0.82, which is a good score. It measures the proportion of correctly classified instances (both True Positives and True Negatives) among the total number of instances. It indicates the proportion of correctly identified positive instances among all instances predicted as positive. Precision addresses the model's ability to avoid false positives. It measures the proportion of correctly identified positive instances among all actual positive instances. Recall focuses on the model's ability to identify all positive instances.

Classification Report:

	precision	recall	f1-score	support
Plain Road	0.97	0.82	0.89	83
Pothole	0.78	0.96	0.86	54
accuracy			0.88	137
macro avg	0.87	0.89	0.87	137
weighted avg	0.89	0.88	0.88	137

Figure 8: Classification report of the proposed system

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The web interface for reporting the potholes:

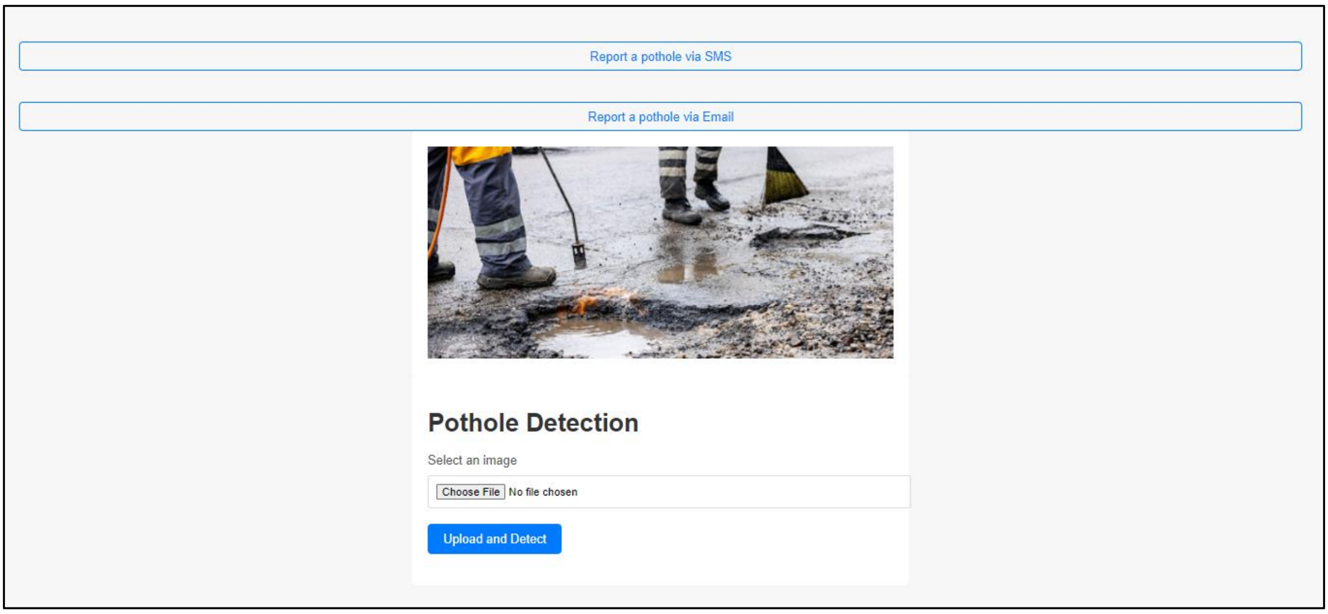

Figure 9: Interface for reporting and understanding how the model is working

To understand for the working of the model we can test the image by uploading the image file and clicking on upload and detect , output says either pothole detected or no pothole detected

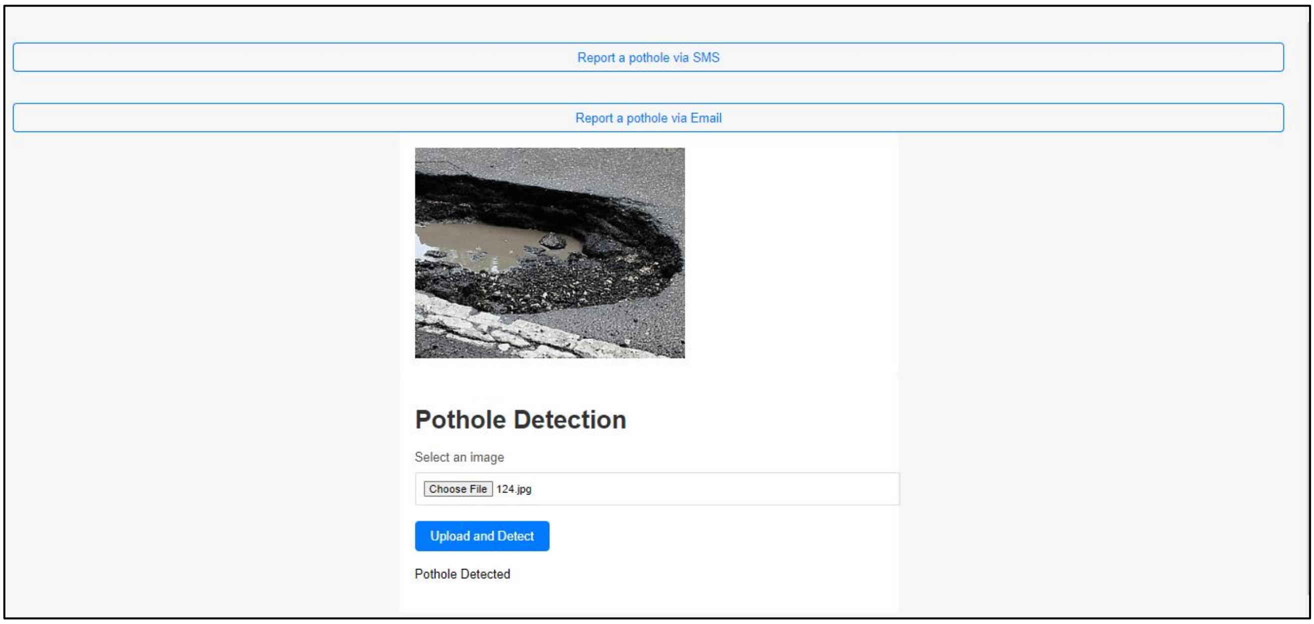

Figure 10 : The model detects the uploaded image as an pothole and displays the message

Reporting can be done via an SMS or an E-Mail :

With the SMS the enterted information looks as such :

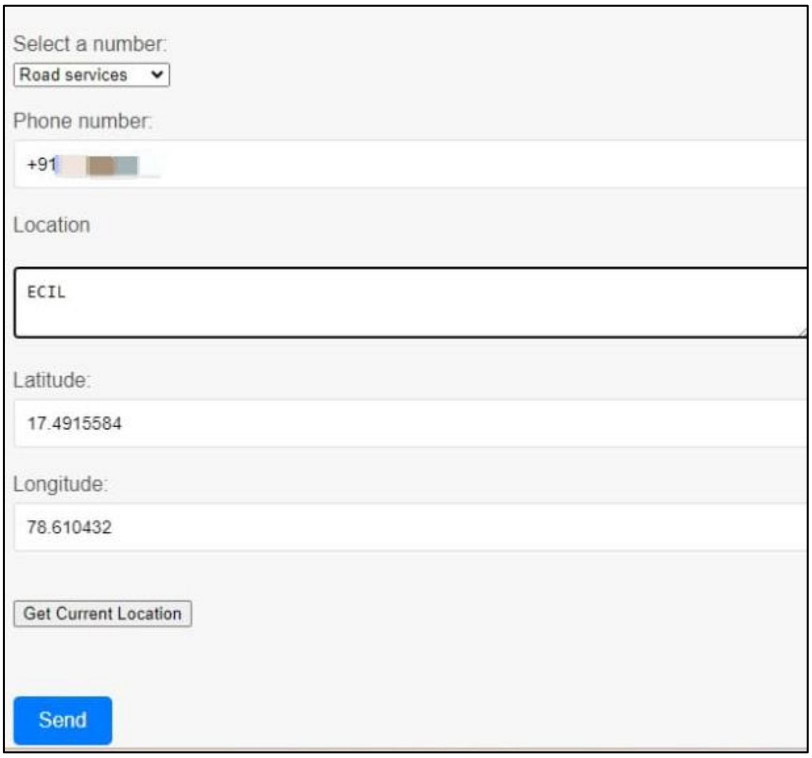

Figure 11 : Image of the web-interface for reporting via SMS

With the E-Mail the enterted information looks as such :

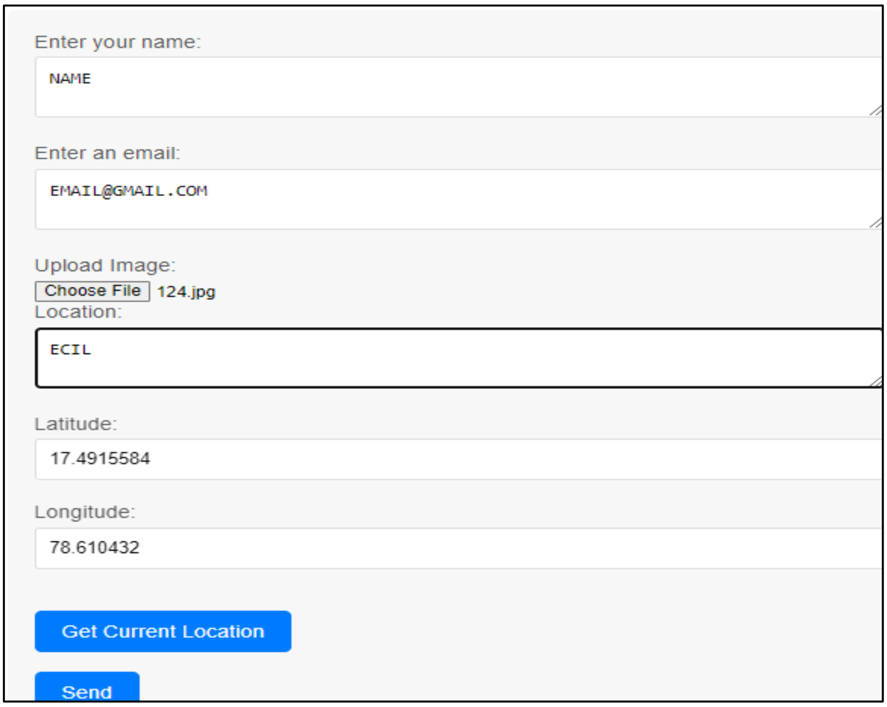

Figure 12: Image of the web-interface for reporting via E-Mail

Conclusion

The main aim of the model is to detect potholes on the roads and notify them without any human interference. No manual intervention is required to spot and report the potholes. It can be detected automatically with the help of Deep Learning Techniques. Our pothole detection system helps the society in promoting road safety and reduces the difficulties in detecting the pothole and reduces the usage of human power and hence saves time. Therefore, by filling the pothole accidents which occur on the road may be reduced. The image captured and the geographic location that is longitude and latitude of pothole detected will be sent to the concerned government authorities mail and SMS. The authorities can see the image and if they click on the link sent through e-mail, they can check out the location of the pothole detected in the map. In this paper, we have developed an innovative method to find potholes easily using CNN. After collecting a suitable amount of data containing the images of potholes under various conditions and weather, and implementing augmentation techniques on the data, convolutional neural networks approach of deep learning has been adopted, that is a new approach in this problem domain using thermal imaging. Also, a comparison between the self-built convolutional neural model and has been done. The results show that images were correctly identified with the best accuracy using one of the pre-trained convolutional neural networks.

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