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Image-based Road Pothole Detection using Deep Learning Model

Priyanka Gupta
Department of CSE
MITS, Gwalior, India
guptapriya071@gmail.com

Manish dixit
Department of CSE
MITS, Gwalior, India
dixitmits@mitsgwalior.in

***Abstract*—Road pothole detection is essential to ensure any engineering structures' health. Manual pothole detection and classification is very human-intensive work. Several sensor-based techniques, laser imaging approaches, and image processing techniques have been deployed to less the intervention of humans in road inspections. Still, these approaches have some limitations, such as high cost, less accuracy, and risk during detection, as Machine learning-based approaches require manual feature extraction for the prediction. Therefore, this proposed work aims to use deep learning modes for better pothole detection results. Several pothole datasets are available online, and deep learning-based methods require lots of data for the training; therefore, pothole images are collected from the different datasets and combined into one dataset to train the model. Augmentation is also applied to the dataset for better training, as augmentation provides images with different angles, and by fine-tuning the model consequently, records with about 98 % accuracy.**

Keywords— Deep learning, Convolutional Neural Network, Pothole Detection, Image Augmentation, Image Enhancement

I. Introduction

Road accidents are one of the leading causes of death, disability, and hospitalisation globally, particularly in India[1]. According to the World Health Organization (WHO), at least one person out of every ten people who died on the world's roads is from India. The cost of vehicle accidents is borne by the victims and their families and the economy in terms of premature deaths, injuries, disabilities, and lost potential income. In 2020, 366138 road accidents caused the deaths of 1,31714 people and injured 3,48,279 individuals[3]. Potholes can be one reason for these accidents; they cause discomfort and sometimes lead to vehicle accidents. Potholes can be formed due to wear and tear, weathering of roads, effects of temperature variations, and high-water pressure. Roads and other large-scale structures should be inspected frequently. Traditional inspection methods are time-consuming and need extra human interventions[2]. With the advancement in technology, several intelligent systems are introduced for inspection, which is less time-consuming and provides a low-cost system with fewer human interventions[10].

A convolutional neural network (CNN) based pothole detection method is suggested to address these problems. Deep learning based method decreases computation time and produces an exact dimension of features in these tasks[4][5][6].

A. Motivation and challenges

Real-time road inspection in complex environments such as low- illumination environments, no reachable areas are crucial. Several methods have been developed for pothole detection because of the computational time it needs. An efficient inspection system that detects potholes in images is required for the roads' fast treatment. In this situation, a pre-processed dataset and robust technique are the basic need of the current inspection system. This work is done for better results in road pothole detection with less computational time. This research compares the accuracy of an existing pothole detection method with the proposed transfer learning-based method.

Fig. 1. Sample of pothole images [1][2]

The primary contribution of this research may be summarized as follows: First, using digital image processing technology, the image dataset is deliberately pre-processed and augmented for better results. Second, the CNN model is trained using the dataset, and parameters are optimised for better accuracy. Finally, the performance of the suggested methods was validated using a dataset with good results.

II. Related work

Computer vision-based technologies have been widely implemented for real-time pothole detection[7][8][9] on roads, including wide cracks. Here some pothole detection techniques are discussed with their pros and cons as road's potholes always need urgent treatment for safety purposes.

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Sunil et al. [14] suggested a pothole detection and warning system based on mobile sensing called pothole detection system (PDS). It detects pothole using the Machine learning approach by gathering data from moving vehicles, and data from the vibrations and the GPS sensors. This method was first implemented in the Noida sector, and 80% of road defects need urgent treatment.

Hadistan et al. [15] have also proposed a low-cost, sensor-based detection approach with a warning system for pothole detection on roads. But it can work with the 4% distance range from the sensor.

Ravi et al. [16] proposed a deep learning-based classification approach for pothole detection. This proposed model classified the pothole images, and after the classification, images are passed through the detection model for the bounding box generation across the potholes. The YOLOv3 model is used to detect the pothole and achieves 89% accuracy for testing. It can be increased by using a more comprehensive dataset containing images of different lighting conditions and cutting down the labor and time by using public transport for data collection.

Aparna et al. [1] suggested a convolutional neural network-based method for pothole detection using thermal images, but it achieved only 64.42% accuracy. This article implements a variant of the pretrained Resnet model, and ResNet50 and ResNet101 give better accuracy.

Hoang et al. [17] proposed the least squares support vector machine (LS-SVM) and the artificial neural network based method for pothole identification. In this work, the classification accuracy rate for the LS-SVM method is 89%, while the ANN algorithm's accuracy rate is around 86%.

K. an. et al. [18] tested several pre-trained pothole detection models, giving 97% classification accuracy with colored images and 97.5 % with grayscale images. Different models such as Inception_v4, Inception_ResNet_v2, ResNet_v2_152, MobileNet_are experimented, and results show models are 96.5~97.5% accurate.

Gajjar et al. [19] presented a deep learning-based real-time pothole detection method. Three models, including faster R-CNN, SSD, and YOLOv3, have trained on the dataset, while results show that YOLOV3 provides better results and performs best in real-time.

Ahmed et al.[20] proposed a smart pothole detection method using deep learning, which is based on dilated convolution. This paper modified the VGG16 model for better results and less computational power. Some convolutional layer has been removed, and different dilation rates have been used for the modification. This proposed method uses modified VGG16 as a backbone for the Faster RCNN and gives better mean precision and shorter inference time.

III. Proposed Methodology

This research proposes a method for pothole detection. This section explains the entire process of the proposed methodology. As shown in figure 3, The general flow of the proposed methodology is that the dataset has been collected to train the model. In the first step, prepare the dataset by collecting pothole images from various sources. As for better model training for pothole detection, a good amount of dataset is required. In the second step, a model is required for pothole detection. For this work, the deep learning model is used to achieve better results as it is the methodology that can be used to solve most problems like object detection and classification. In this study, several pretrained models have experimented on the pre-processed dataset. Still, the ResNet50 model performed well compared to another variant of the ResNet model for road pothole detection. In the third step, train the model with specific data, validate the model with the remaining data, and visualize the results.

A. Pothole dataset

As some standard pothole image datasets are available for road potholes so in this study, the author combined two open datasets [12][13] and acquired some images from a smartphone with a high-resolution camera of 2448x3256. For better model training, raw images of the pothole with a sensible variety of image variations, including lighting, shadow, and so on, capable of possibly triggering false alarms, are acquired from roads using a high-resolution camera. The main focus was to increase the diversity of the dataset so that the model learns from different perspectives. The dataset has two classes named positive and negative with a total of 1281 images, of which 929 images have potholes and 352 non-pothole images of variable size, so further pre-processing is required for a better dataset.

B. Pre-processing and data augmentation of the dataset

To carry out the proposed work, this article used deep learning on the pothole dataset, and it requires a huge volume of pre-processed data to train the model. The captured data needs pre-processing as images has to be the same size. Some images require cropping for the images because some images have unuseful information.

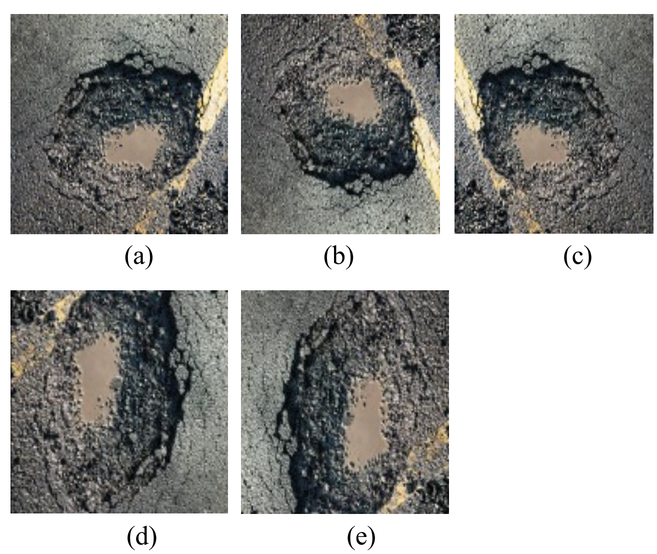


Fig. 2. (a) Original image (b) FlipVertical (c) FlipHorizontal (d) Rotate 90^0FlipVertical (e) Rotate90^0 Flip Horizontal

Image augmentation is typically required to boost the performance of deep models to build a robust classifier with very little training data. To increase the size of the dataset, images are augmented in different scenarios such as horizontal flipping, vertical flipping, rotation90^0 with horizontal flipping, and rotation90^0 with vertical flipping. Model training by the variety of image variations gives good results. The dataset is augmented with horizontal and vertical flipping and rotation. Figure 2(a) shows the original image, and Figures 2(b)(c)(d), and (e) are the corresponding augmented images.

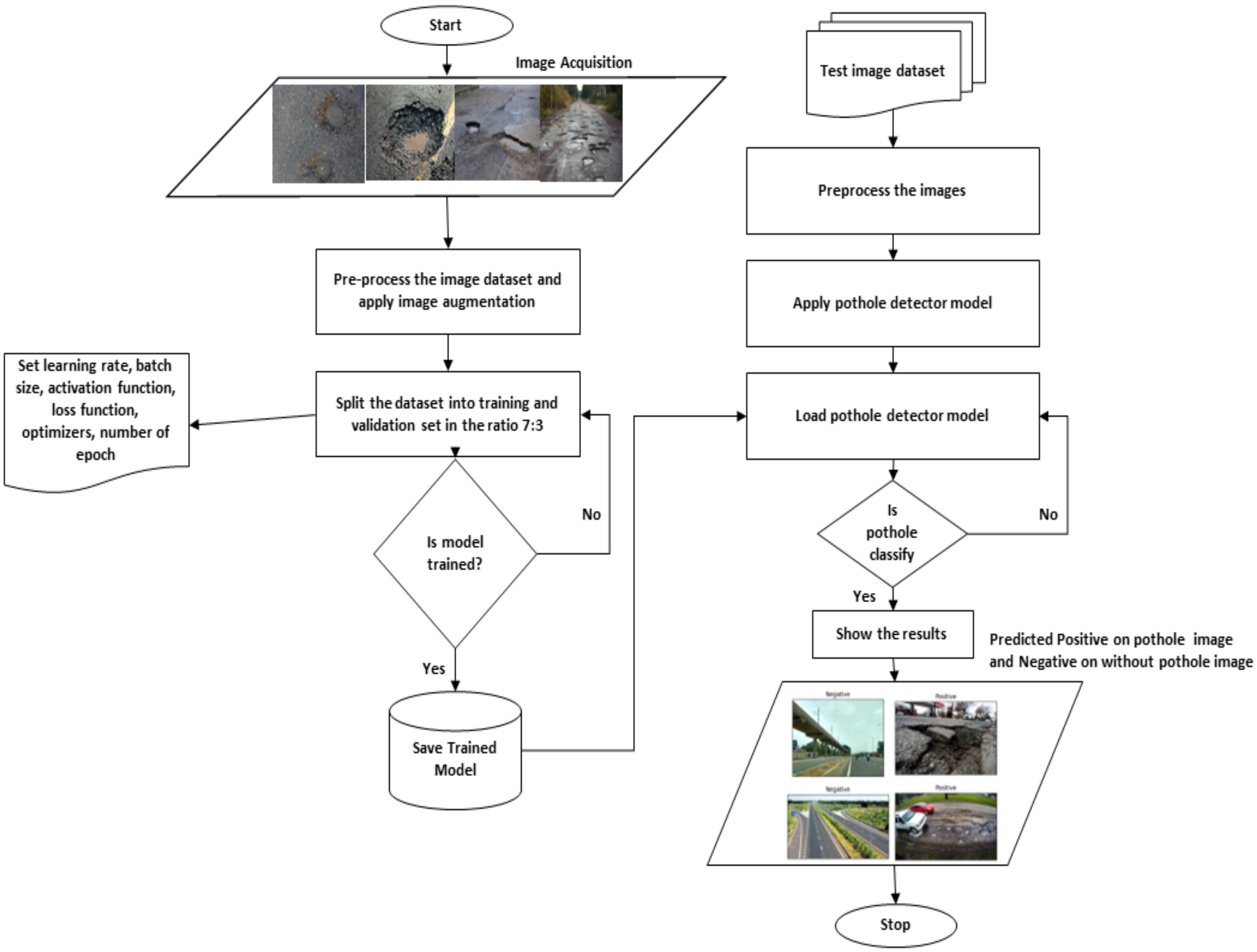


Fig. 3. Flow chart of the proposed methodology

C. Deep learning model and transfer learning

A CNN model is made up of some convolutional units and an FCL. Convolutional blocks contain a convolutional layer, an activation function, and with variants of pooling layer. A convolutional layer performs a convolution operation to the output to extract the features from the preceding layers using a set of filters or kernels. The recent deep architecture of CNN, such as AlexNet, Inception, VGG16, and ResNet, has improved prior-art configurations by adding weight layers.

Transfer learning

Most previous studies proposed pothole detection techniques that used CNNs trained from scratch for pothole detection. On the other hand, transfer learning has improved a pothole detector's training efficiency and accuracy. It can create accurate models while saving time. In this method, rather than creating a model from scratch, choose a model already trained in a similar and much larger dataset to solve similar problems. To classify the potholes images, one pretrained model is imported, and then apply fine-tuning to the model to accomplish the given task.

Residual Neural Network Model (ResNet)

The ResNet was proposed by He et al. [97], which placed first in the ILSVRC-2015. One of the versions of ResNet is ResNet50, with 48, 1, 1 convolutional, average, maxpooling layer respectively.

It included residual connections amongst layers, supporting the reduction of loss, preservation of knowledge gain, and improvement of training efficiency.

The convolution of its input plus residual connections gives the final output. Figure 4 shows the basic architecture of ResNet50, which is a broadly used convolutional architecture pre-trained on ImageNet [15]

. In this proposed work, ResNet50 has been selected for pothole detection. ResNet50 model pretrained on ImageNet has been choosen over different model because of better accuracy for classification.

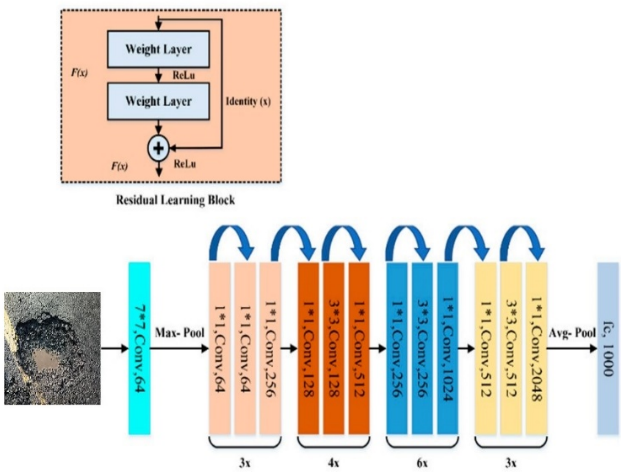


Fig. 4. ResNet50 architecture[11]

Transfer learning is performed on the last layer for the pothole classification (i.e., whether the image has a pothole or not). Dense layers are added at the bottom of the model, and the Softmax activation function is used at the last layer with two outputs, as our model has only two outputs (i.e., a pothole image and a non-pothole image). Model performance is affected by the model's parameters, so fine-tuning parameters such as learning rate and optimizer can increase the model performance. This work selects the ADAM optimizer as it gives higher accuracy than the SGD optimizer. The categorical cross-entropy is an excellent choice for classification tasks. The only activation function recommended for use with the categorical cross-entropy loss function is Softmax. When adjusting model weights during training, the cross-entropy loss is used. The goal is to minimise the loss, which means that the smaller the loss, the better the model. Cross-entropy is defined as

$$L = -\sum_{i=1}^{n} t_i \log (p_i) \tag{2}$$

Where t_i is the truth lebel and p_i is the Softmax probability for the i^{th} class.

D. Experimental design, Metrics, outcomes, and analysis

i. Experimental setup

This experiment is done by using a laptop with 8 GB RAM, an i7 core processor, and a 4GB NVIDIA GPU processor, as well as Window10 OS. The model training is done after complete implementation on the Visual Studio code platform. The image dataset is randomly divided into 70% and 30% images for training and validation, respectively. Models are also trained without GPU, but it takes too much time. As a result, training time decreased significantly by switching to a GPU environment.

ii. Evaluation metrics

Several measures [11] are used to evaluate the pothole detection approaches. In this work, accuracy is calculated to evaluate the proposed method. Accuracy evaluation of the proposed method is calculated by the following:

Accuracy [Acc]: Accuracy can analyse the classification model's correctness. It implies how comparable a result is to being correct. The ratio of correctly classified classes and the total number of testing classes is termed accuracy

$$Acc = \frac{Tp+Tn}{Tp+Fp+Tn+Fn} \tag{1}$$

tp, tn, fp, and fn are true positive, true negative, false positive, and false negative. These are explained as follows:
Tp= predicted pothole, and actually, it has potholes.
Tn= predicted non-pothole, and actually, it is non-pothole.
Fp= predicted pothole, and actually, it is non-pothole.
Fn= predicted non-pothole, and actually, it has potholes.

iii. The outcome of the different dataset

Figure 4 shows the experimental outcome of the collected dataset. Positive indicates that the image has potholes, and negative indicates that the images do not have potholes. In figure 4, it is easily shown that potholes are classified clearly with a positive and negative labels.

Fig. 5. Results visualisation on the combined dataset

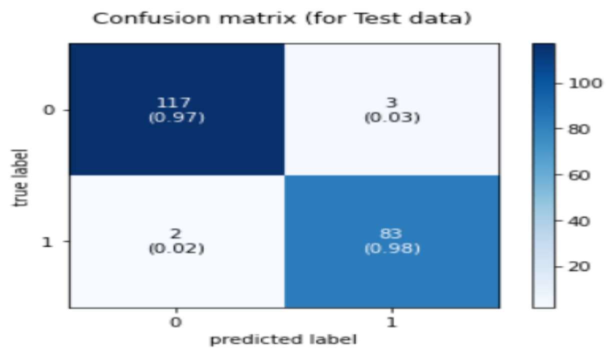
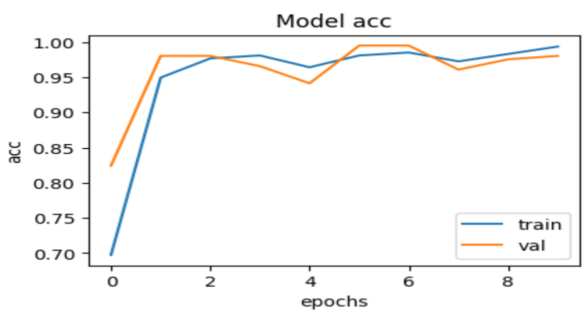


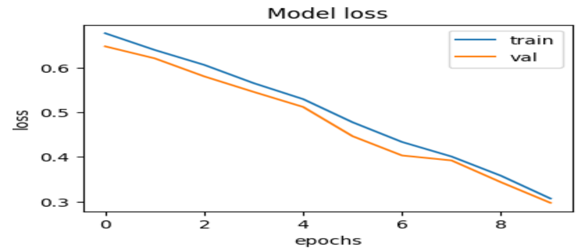
Fig. 6. Confusion matrix of the dataset (pothole-0 and non-pothole-1)

iv. Result analysis

Figure 5 depicts the accuracy of the result by the confusion matrix. In figure 5, 0 indicates pothole, and 1 indicates non-pothole. 117 images are clearly classified as potholes, and 83 images do not have potholes. On the other hand, 2 images were wrongly classified as potholes, and 3 are wrongly classified as non-pothole. Results show that image size 224x224 gives better results with validation accuracy of 98% and validation loss of 18.92%.



(a)



(b)

Fig. 7. (a) Model accuracy as per epoch (b) Model loss as per epoch

Figure 6 shows the performance graph of the proposed method. Figure 6a shows the accuracy analysis, and figure 6b shows the loss analysis of the method per epoch.

TABLE I. COMPARISON WITH THE PREVIOUS METHOD

Model	**Pretrained Model**	**Optimizer=Adam, Image size= 224x224**			
		Training		**Validation**	
		Accuracy	**Loss**	**Accuracy**	**Loss**
CNN-based Resnet50 [1]	Yes	90.05	25.11	91.77	24.07
Our Proposed Method	Yes	**99.37**	**18.69**	**98.05**	**18.72**

Table 1 summarizes the results of previous models used for pothole detection and the recent fine-tuned model. The experiment shows training accuracy of 99% and loss of 18.69% by dividing the dataset into 70:30 ratio for training and validation. Table 2 shows the comparison of different previously proposed methods on different datasets. Hoang [17] used LS SVM on road images and got 87 % accuracy. Ryu et al[22] uses 90 images that were selected from the video clip and got 73.5% accuracy. An et al [18] implemented different deep learning models on 3186 images and achieved 96.5 to 97 % accuracy for pothole detection.

TABLE II. COMPARISON WITH PREVIOUSLY PROPOSED METHODS

S. No.	Reference	Method used	Dataset	Image size	Accuracy (%)
1	Hoang et al. [17]	LS-SVM and NN using steerable filter-based feature extraction	Total 200 images of roads	150x150	87
2	Ryu et al. [22]	Segmentation, candidate extraction, and decision	Total 90, 2D road images were selected from the video clip	1280x720	73.5
3	An et al. [18]	ANNs(InceptionV3, ResNet_v2_152,MobileNet_v1)	Total 3186 images of potholes	224x224	96.5~97
4	Aparna et al. [1]	CNN-based Resnet50 model	Road thermal images	224 x 224	97.08
5	Proposed work	Resnet50 using transfer learning	Smartphones and camera images of potholes	224x224	98.05

IV. CONCLUSION

Pothole detection using deep learning methods can assist with better road maintenance, particularly in developing countries with limited resources. For this aim, the proposed convolutional neural network-based system using images can compare with existing pothole detection techniques. The proposed ResNet50 model with transfer learning has achieved 98.05% accuracy, the highest ever reported compared with the previous ResNet model, which achieved 97.08% accuracy.

Furthermore, after classifying an image as a pothole, the proposed work can be further extended to detect the region of potholes and segment the pothole image by labeling the pothole dataset. Parameters such as pothole severity can be detected, allowing it to be determined which area requires immediate repair work.

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