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Transfer learning based deep convolutional neural network model for pavement crack detection from images

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Abstract

The road is a path that supports to connect different places. It plays a crucial role in our day-today life. Improper maintenance, overloading, climate conditions, and some other elements create distress on the roads. The common distresses are Potholes, cracking, and rutting. Manually detecting the distresses means human inspection is a messy and long time-consuming process. In recent past accidents on road is on the increase due to improper maintenance of road. Efficient methods of detecting pavement damages using image processing, machine learning and deep learning techniques have been a trending research topic. Image processing algorithms mainly include edge detection, region growing methods, and threshold segmentation operations for processing the pavement images and extracting crack information from the images. Machine learning methods of pavement crack detection adapts neural networks, supervised and unsupervised learning algorithms with pavement crack image as input. With Deep learning techniques, it has been possible to detect pavement cracks with greater accuracy. In this paper, we review the deep learning methods of pavement crack detection and propose a novel method to detect pavement cracks using Deep Learning with transfer learning. We also analyzed the performance of the proposed model for different network architectures namely, Google net, Alexnet and Resent and inferred that Google net gives better performance in detecting pavement cracks.

Keywords: Pavement Crack, Deep Learning, Machine Learning, Crack Detection.

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1. Introduction

A Pavement Management System (PMS) is defined as “set of methods or tools that assist decision-makers in finding optimum methods for providing, evaluating, and maintaining pavements in a service condition over some time”[2]. The reliability of the performance prediction and the usability of the maintenance suggestions depend on the accuracy of pavement condition evaluation, which should be able to provide an objective rating of pavement condition. After initial construction, the pavement is open to traffic, it should be subjected to periodic maintenance treatments throughout the life cycle to achieve long time service. Those treatments mainly include routine maintenance, preservation, minor and major rehabilitations. Determining the current performance condition of the pavement is the first step towards effective treatment arrangements. Therefore, the development of highly reliable automated pavement condition evaluation tools benefits not only the pavement condition evaluation departments but also the maintenance implementation and capital allocation agencies. Pavement condition data usually include different types of distresses, roughness, rutting, skid resistance, and structural capacity. Usually, raw data from original collection devices are incomplete, ambiguous, and contain excessive noise. Moreover, the time intervals and methods for data collection vary among each data collection activity, and the environmental conditions are significantly different from each region. All these factors make the development of highly reliable pavement condition evaluation tools challenging but valuable. Pavement surface distresses are the results of the joint effects of environmental influences, pavement aging, and traffic loading. As important indicators of pavement performance over time, pavement surface distresses are commonly evaluated manually. However, considering the many problems induced by this traditional method, many agencies have replaced manual evaluations with automated and semi-automated devices for pavement performance data collection and evaluation. The automated pavement condition survey can be considered as systems that include automated pavement condition data collection, pavement distress identification, and quantification using software and computer-based technologies. Following are the necessities of Deep Learning Technologies (DLTs) in automated PMSs: (1) Accurate and timely investigation and assessment of pavement condition are significant for the efficient supervising of current in-service pavements for the benefit of pavement management municipalities and agencies. (2) Manual pavement condition investigations are time consuming and less detailed than automated pavement condition survey and evaluation. (3) Pavement condition evaluation tools in current automated PMSs should be updated in pace with rapidly developed technologies to enhance the efficiency and accuracy of the systems. (4) The recently developed Deep Learning techniques (DLTs), have great potential of being integrated into automated pavement condition investigation and evaluation tools to improve the overall performance of the system.

Deep Learning is a state-of-the-art technology that has witnessed eye-catching advancement in recent years. The main implementation method of Deep Learning is via Deep Neural Networks, which use several hidden layers for multi-level feature extraction. The hierarchy features of the input image can then be obtained for further interpretations. As one important branch, Deep Convolutional Neural Network (DCNN) adopted the methodology of ”weights sharing”, which made the object recognition more efficient when using this technique.

2. Pavement surface distress

Surface distresses in a pavement can be caused by several factors such as environmental effects, heavy traffic, bad materials, and poor construction. Some of the pavement distresses are fatigue cracking, transverse cracking, longitudinal cracking, potholes, and block cracking.

2.1. Fatigue Cracking

The formation of fatigue cracking can be considered as the result of two main reasons. Firstly, the interconnection of cracks at the surface, which is initiated as a result of excessive tensile stress beneath the asphalt layer. [2] These can eventually result in one or more longitudinal cracks at the top surface of the road. This process is commonly named 'classical' or 'bottom-up' fatigue cracking. The cracks can also be caused by periodic traffic loads, where tensile stress leads to fatigue cracking that has patterns similar to the back of an alligator, so fatigue cracking is also known as "alligator cracking". The cracked areas of different severity levels are measured. Low severity fatigue cracking indicates the affected area has few connecting cracks, moderate severity represents fatigue cracking with a complete pattern, high severity fatigue cracking indicates the cracked area has an interconnected cracking pattern as shown in figure 1.

Figure 1: Sample Fatigue cracking on the pavement surface a) low severity b) moderate severity c) high severity

2.2. Transverse Cracking

Transverse cracks are characterized by cracks that are in the direction perpendicular to the flow of traffic. Transverse cracks can either be caused due to temperature changes or may be caused due to load on the road [2]. Temperature induced cracks can also be caused due to shrinkage of the asphalt binder due to aging that may lead to layer's movements. Joints or gaps on the overlay that are not filled may develop transverse cracks when loaded. Transverse cracking is measured by recording the number of occurrences and the total length of all cracks in different severity levels. The severity levels are classified as low severity (mean cracking width less than 6mm), moderate severity (mean cracking width exceeds 6mm but is less than 19mm), and high severity (mean cracking width exceeds 19mm) as shown in figure 2.

2.3. Longitudinal Cracking

Longitudinal cracking [2] is when cracks propagate along the traffic direction, hence perpendicular to the transverse cracking. The severity levels are classified based on the same principle as transverse cracking. According to the difference in occurrence location, longitudinal cracking can be classified

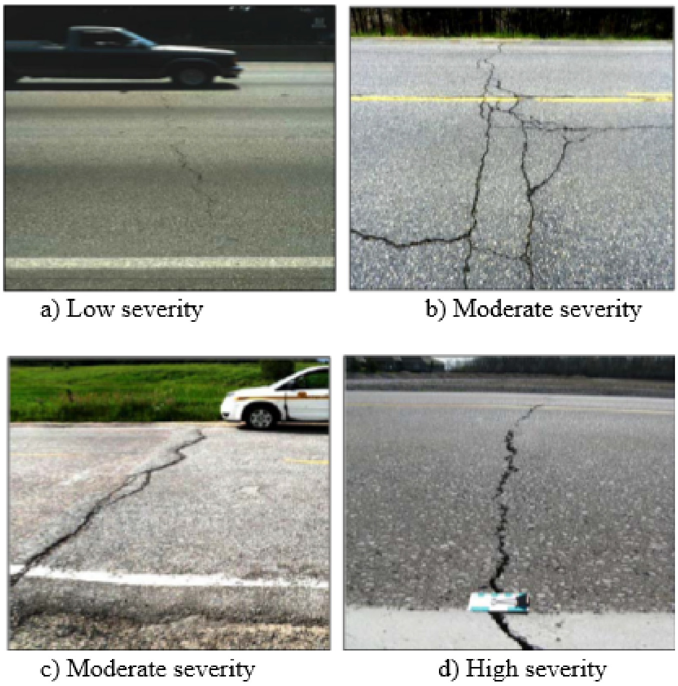

Figure 2: Transverse cracking on the pavement surface showing a) low severity b) and c) moderate severity d) high severity

as either wheel path longitudinal cracking or non-wheel path longitudinal cracking. Both wheel pathway and non-wheel pathway longitudinal cracking are recorded by the length with the unit of meter for every severity level. Low severity cracks are less than 6mm in width while high severity cracks can be wider than 19mm as shown in figure 3.

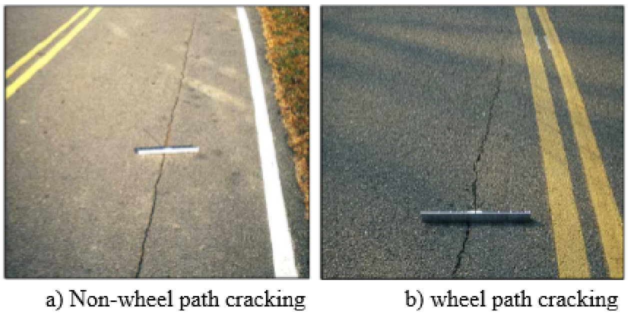

Figure 3: Longitudinal cracking on the pavement surface

2.4. Potholes

Potholes are small and bowl-shaped defects on the surface of pavement that penetrate through the hot mix asphalt (HMA) layer down to base layers. Many reasons contribute to the formation of potholes, such as the propagation of crocodile cracking which is featured by the interlocked and fatigue fractures. The presence of water inside these potholes can further lead to serious damage such as washing the larger areas of the pavement when several vehicles passing through. [9] However, they can expand if not treated in time. Severe accidents tend to happen due to the invisibility of the potholes to the drivers, thus causing hazards both to road users and their vehicle suspension systems.

Potholes are measured by recording the number as well as the square meters of the areas for every severity level. The depth is recorded as the maximum depth concerning the pavement surface. Low severity potholes have depths that are less than 25 mm; moderate severity potholes have measured depth that ranges from 25mm to 50mm; high severity potholes refer to those that have measured depths more than 50mm as shown in figure 4.

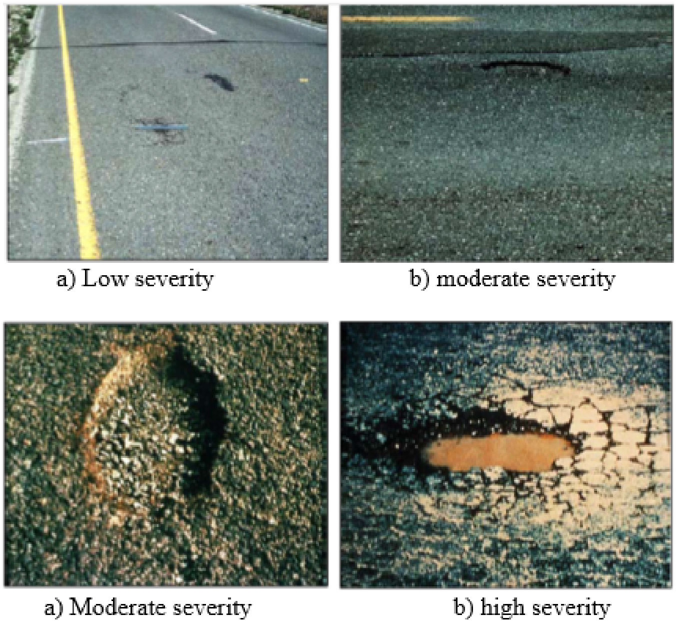

Figure 4: Potholes on the pavement surface

2.5. Block Cracking

In block cracking, a series of cracks are interconnected to each other and shape into a rectangular form. These cracks are simply connected to the longitudinal cracks which are perpendicular to the transversal path of a pavement. The closer spaces among the cracks indicate more advanced aging caused by shrinkage and hardening of the asphalt with time. [9] Block cracking must be repaired in a timely fashion, otherwise, it can accelerate moisture infiltration and roughness. Block cracking is measured by recording the square meters of the cracked area for each severity level. The severity of block cracking is classified into three levels: low severity indicates the mean crack width does not exceed 6 mm; moderate severity indicates the mean crack width ranges between 6mm and 19mm, and high severity indicates the mean crack width exceeds 19mm as shown in figure 5.

Figure 5: Block cracking on the pavement surface

3. Related Works

In [2], the authors proposed a transfer learning based model for pavement damage detection from pavement surface images using deep residual network. Authors used 71 images to train the network which were collected from the Crack Forest data set and testing was done on 47 images of it. The deep residual network classifies all pixels in road images into cracks and background. To achieve high efficiency, relatively small training images were used in transfer learning which a method of learning is by varying the weights of pre-trained CNN. The results of this paper show that compared to existing algorithms, the deep residual network model performs better with recall value of 84.9% and a precision value of 93.5%. Although the current CNN performed well in terms of identifying the presence of cracks at region-level, they had a limitation in terms of detecting cracks at pixel-level. Sufficient pixel-level accuracy that can quantify the width, shape, and length of the crack is required to be able to replace expensive sensors and manual inspection with vision-based algorithms.

In [9], the authors developed a model to classify road crack images using the transfer learning and deep convolution neural networks (DCNN). They analyzed the performance of the proposed model based on the learning method and regular term coefficient. The transfer learning utilizes the network structure of Faster R-CNN in designing a pavement crack detection model that performs better. The current model performs well for images of the pavement with limited damages and whose background is simple.

In [14], the authors proposed a crack detection system that is based on a Convolution Network trained on square image patches with given ground truth information. They trained the network to classify patches as pavement with cracks and pavement without cracks. They termed non cracked pavement images as negative patches and cracked pavement images whose center pixel is a pixel representing crack or in the close vicinity of crack as positive patches. The system proposed by them was cost ineffective when it comes to real time implementation.

In [8], the authors developed a system for detecting damages in roads automatically from captured images based on the YOLO v2 deep learning framework. The authors used 7240 pavement images that were captured using mobile cameras, to train the network and tested their model with 1,813 road images. They stated that their system serves as a better civil infrastructure monitoring system that could be applied in identifying pavement damages that require immediate repair. The objective of the proposed method is to use YOLO v2 framework in a Deep convolutional network for identifying the crack in the pavement and assign the corresponding class name. Their proposed system took 18.20 hours to train YOLO v2. The limitation of the model was that it failed to identify the cracks present on the left of the image and also those images which were not labeled correctly were misclassified. In addition the network failed to predict cracks that had bounding boxes overlapping each other.

In [3], the authors presented a detailed study on different techniques and methodologies used in detecting cracks based on classifiers namely Support Vector Machine (SVM), decision tree, and Convolutional Neural Network (CNN) that exist in literature. The authors created a dataset consisting of image based algorithms for operations such as "smoothing, intensity normalization, saturation, and crack detection". The type of crack is either identified using individual pixels or group of pixels. The authors have adapted twin intensity threshold technique for segmentation of the cracks from the pre-processed pictures. It is limited to SVM (support vector machines) and CNN (convolution neural networks) only.

In [10], the author developed a system to detect crack in concrete structures using pre-trained network. The SDNET dataset comprising of about 56 thousand images of Bridge Deck, Walls and Pavements, including images taken from varied locations and conditions forms the dataset that trains the network. For the purpose of training the authors have considered 90% of the dataset and have used the remaining 10% for testing their proposed model. From the results of their experiments, it is observed that Google Net and ResNet18 resulted in a significant improvement in the performance for Bridge Deck and Walls while for pavement surface images they showed only little improvement.

With the objective of localizing cracks on concrete surfaces, the authors used Mask R-CNN and obtained their respective masks which was used to acquire other properties for further analysis. This tool overcomes the limitations of manually monitoring and identifying the cracks on the pavements at regular intervals and has the advantage of faster processing, reduced cost and increased safety of the person. For the purpose of training the Mask R-CNN to detect damages in the concrete surfaces they framed a database of masks from the standard dataset consisting of images of cracked concrete surfaces using ground truth images. The authors achieved a precision of 93.9% and a recall of 77.5% when the trained model was subjected to testing.

In [11], the authors proposed a structured framework called Crack Forest, a novel structure for detecting cracks on roads using random forest algorithm. The method includes, redefining the tokens that contains a crack to give a clear information about the cracks with intensity inhomogeneity by applying the integral channel features; generating high-performance crack detection system by using a random structured forest that helps in identification of complex cracks; and describing the characteristics of cracks and separating them from noises efficiently. Experimental results show that the proposed model of crack forest methodology performs better than existing crack detection models. The proposed system performs well on images and experimentation on video has not been done. The system fails to measure the width of the crack detected.

In [4], the authors proposed a road crack detection technique which is based on DLT's and adaptive image segmentation. A Deep CNN is trained to predict whether crack is present in the test image or not. The images which consists of cracks are processed using a smoothing filter called bilateral filtering, which effectively reduces noise in the pixels. At last, the required features are obtained from the pavement surface using a method called adaptive thresholding. The network proposed by the authors has the ability to classify images effectively with an accuracy of 99.9% using the thresholding technique. In addition, machine learning-based crack detection techniques have come in to existence, and the features obtained by the artificial neural network are far more superior to the local features which are used in conventional methods. Although the proposed image segmentation technique performs effectively, it suffers from the drawback of inefficient segmentation of noisy color images.

In [13], the authors carried out image acquisition by using an area arrayed camera, which reduces the use of the camera environment. The authors used area arrayed cameras and Adaboost algorithms to realize, identify and classify road cracks. The pavement crack detection is based on a statistical method. The whole system can be divided into two, sample training, and image detection. In the sample training, the authors used the Adaboost technique to extract and train the Haar feature texture from the negative and positive samples of road cracks. Automatic pavement assessment using neural networks have been proposed in [6, 7] and using wavelet transforms has been dealt in [12].

It is inferred from the study of the related work on pavement crack detection, that deep learning has an edge over the traditional methods of crack detection in performance [5]. Here we propose a deep learning methodology to automatically detect cracks in pavement and classify the cracks based on the severity.

Methodology

The block diagram of the proposed methodology of crack detection in pavement using convolutional neural network is given in figure 6. Data Labeling: In many cases, labelled data is acquired

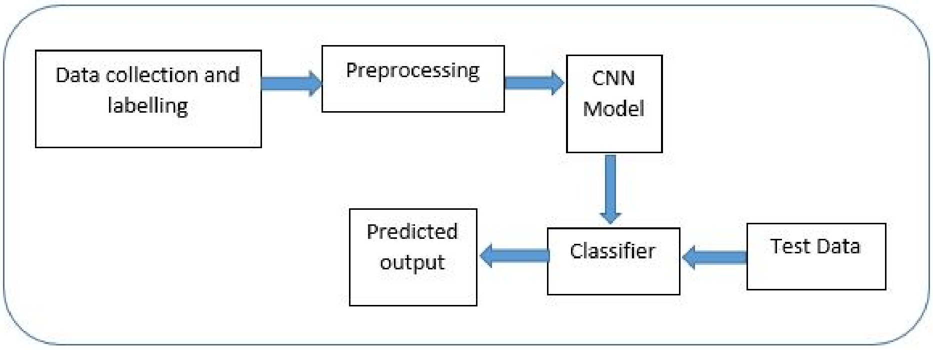

Figure 6: Block Diagram of the proposed methodology of pavement crack detection

during data acquisition process. Labeling could be performed based on three categories namely existing labels, crowd based, weak labels. Deep learning systems require massive amounts of data to make a reliable learning patterns. So in order to make ease of complexity the data is labelled into different classes based on number of classifications. Data labelling is also known as data segregation. By segregating the data into different classes, the network can easily get to know about data set and how the patterns are being generated while training the data set.

3.1. Choosing Retrained network

A pre-trained network such as Alex net, Google net, Resent etc., that has been trained to classify images is used in the proposed model to extract the features for the new tsk. Mostly these pre-trained networks are made to learn the features using a subset of the Image Net database. These networks have the ability to classify the input images into one of the 1000 categories which includes animals, fruits, human beings, musical instruments. Implementing Transfer learning using pre-trained network performs faster computation when compared to training a network from scratch. Retrained networks have various properties that should be configured while applying a particular network to a classification problem. The important characteristics are 'network speed, size and accuracy'. Choosing a network is generally a trade-off between these characteristics. Some of the pre-trained networks available in the MATLAB tool are Alex net, Google net, and Resnet-101. Not every pre-trained network contains the specifications with respect to the application and hence it should be Re-Designed as per the application to meet the project outcomes. This Re-Designing of network is done in fully connected layers where for each and every Retrained network the number of classifications differ based on the parameters chosen for the corresponding application.

3.2. Setting training options

Setting training options refers to tuning the parameters. Tuning refers to initializing the learning rate, choosing optimizer, initializing Epochs and choosing the verbose etc. These are the mandatory things before performing the training and these options will decide the accuracy and efficiency of the network.

3.3. Resizing of data

The input layer of the pre-trained networks accepts only fixed image size as input. But in real-time all the images will not be of the same size, depending upon the camera and resolution the size of the image changes thus creating different sized images. Hence images are resized to input matrix size of the pretrained network.

3.4. Initializing learning rate

To train the network, the Initial learning rate is given as a combination of initial learn rate and a positive scalar as comma separated value. The default value is 0.01 and 0.001 for the 'sgdm' solver and 'rmsprop' solver respectively. The 'adam' solvers also use a default value of 0.001. For optimum training the learning rate has to be chosen properly. Too low learning rate takes a long time for training and too high learning rate may lead to a suboptimal result.

3.5. Choosing optimizer

There are three commonly used optimizer for training a network. They are stochastic gradient descent with momentum (SGDM), RMSProp and Adam. In the case of sgdm optimizer, the momentum value is given as the name and the corresponding value as the argument. For the RMSProp optimizer, Squared Gradient Decay Factor that represents the decay rate of the squared gradient moving average is given as name and corresponding value as the argument. In the case of Adam optimizer, two decay rates one for gradient decay factor and another for Squared Gradient Decay Factor' are specified as name-value pair arguments.

3.6. Setting Epochs

An epoch is a measure of the number of times all of the training data are used once to update the weights. For batch training, all of the training samples pass through the learning system simultaneously in one epoch before weights are updated. During the training phase, the number of epochs required for training the network are specified as name and value pair where the name is 'Max Epochs' and the value is a positive integer. Each step taken to minimize the loss function in a mini-batch gradient descent approach is referred to as an iteration. Application of the training algorithm for the entire set of training data is referred to as one epoch.

3.7. Choosing Verbose

To know the status of the training progress, an indicator termed verbose, is displayed in the command window when given a value of 1 denoting True and will be disabled when given a value 0 denoting False.

4. Experimental Results

For testing the model for pavement crack detection, images captured through mobile camera with a resolution are used. Sample pavement crack images of different types given as input images to the network are shown in figure 7.
Table 1: Type of pavement cracks images and the splitup of data into training and testing data.

Table 1: Splitting Of Data store In To Training And Testing Data

CLASS	NO OF IMAGES	TRAINING	TESTING
NON-CRACKED	50	30	20
CRACKED	50	30	20
POTHOLES	36	21	15

Table 1 contains the details of the number of images taken to perform the training and testing data. Total 136 images were taken in which 50 images are non cracked, 50 images are cracked and 36 are pothole images. 60% of data set is taken for training and remaining 40% data is taken for testing. The data store is divided in to training and testing data by using randomized function. Deep Network Designer toolbox is used in MATLAB to adapt the network to classify the collection of images by re-designing the pre-trained neural networks. Deep Network Designer has a tool for transfer learning in which learned features from previously trained networks are applied to a new task with less number of training images. The following are the features of the deep network designer toolbox:
1) It provides an interface for designing and implementing deep neural networks with algorithms, pre-trained models, and apps.
2) It facilitates the use of convolutional neural networks in classification and regression of image and time-series.
3) It uses features such as automatic differentiation, custom training loops and shared weights that can be used to develop architectures such as generative adversarial networks (GANs) and Siamese networks.

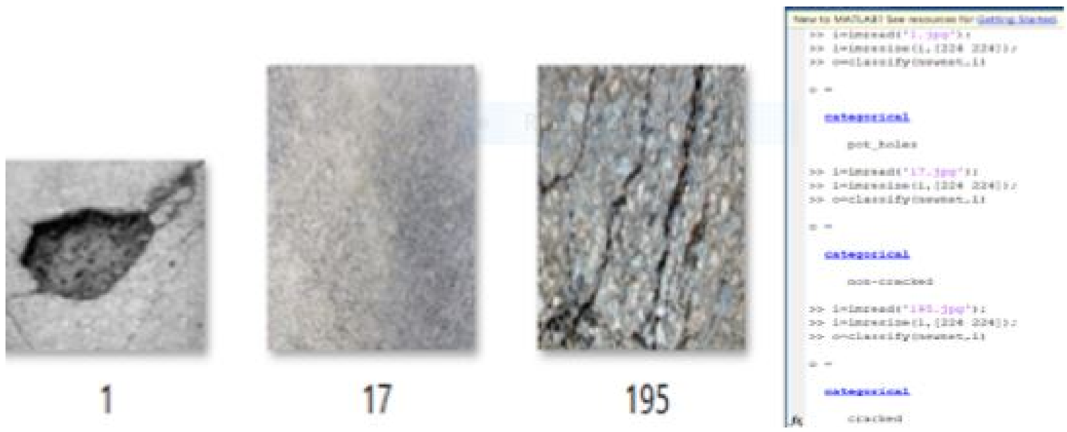

Figure 7: sample pavement images and the corresponding predicted output of the proposed model

During network training, if the plots value is set as training progress in the training options, the training metrics is displayed as a graphical figure every iteration, after the initiation of network training. If the plots value is set as validation data in the training options, the validation metrics is displayed as a figure every time when the train network validates. Figure 8 shows plots of the training progress. There are three accuracy plots shown in blue color, corresponding to training accuracy, Smoothed training accuracy and Validation accuracy. Training accuracy represents the classification accuracy obtained with each mini-batch. Smoothed training accuracy refers to the accuracy obtained when a smoothing algorithm is applied to the training accuracy. This results in less noisy curve that aids in spotting the pattern. Classification accuracy that is obtained using the entire validation set is referred to as validation accuracy.

The loss function associated with the training accuracy, smoothed training accuracy and validation accuracy are correspondingly termed as Training loss, Smoothed training loss and validation loss. When the final layer performs the task of classification, the loss function associated with the layer is termed cross entropy loss.

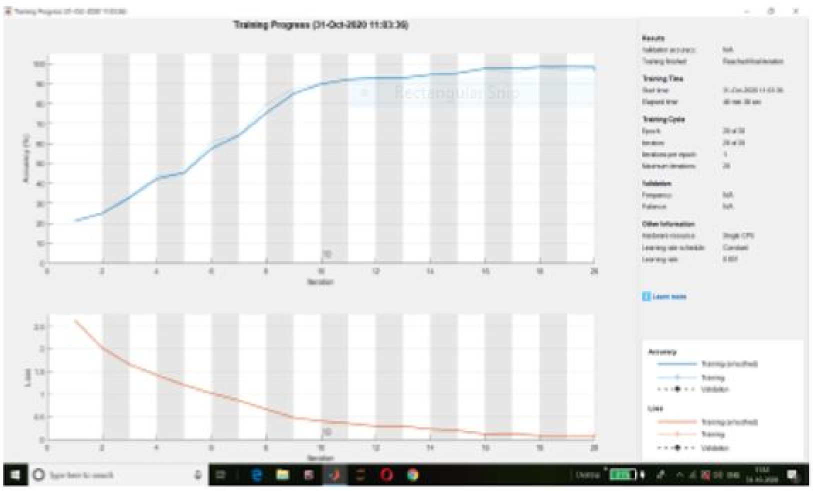

Figure 8: The training progress plot of a network

A desirable training options are used to make the network stable so that the network will give high accuracy in classifying the data. The results of the project are shown below:

Table 2: Summary of performance parameters and pavement condition prediction for different networks

NETWORK	EPOCHS	LEARNING RATE	ACCURACY	LOSS	PREDICTION
ALEXNET	20	10^{-4}	75%	1.5	RANDOM
GOOGLENET	20	10^{-3}	100%	0.1	ACCURATE
RESNET	20	10^{-3}	95%	0.1	MODERATE

Table 2 shows the performance details of ALEXNET, GOOGLE NET, and RESNET. Among them, GOOGLE NET is considered an efficient and stable network in training and classifying the data. In terms of performance RESNET also classifies as effective as GOOGLE NET but RESNET consumes more time and CPU RAM compared to GOOGLE NET.

The confusion matrix is a matrix of predicted class in the rows and the true or the actual class in the columns. The predicted class is the classification output of the system and the true class corresponds to the target that is expected as output. The cells that form the diagonal of the confusion matrix are the observations that are classified correctly. The off diagonal cells are those that represent incorrectly classified observations. Both observations and total number of observations percentage are given in each and every cell. The column which is on the far right of the plot gives the percentage of all examples obtained that belong to each class that are incorrectly and correctly classified. These values are also called as the precision values, and false rated. The row which is at the bottom of the graph gives the percentages of all examples which relates to each and every class i.e, classified into correct and incorrect data. These values are also called as recall values (or true positive rate), and false rate of negative values, respectively. The cell which is in the bottom right of the graph gives overall accuracy. Finally, the optimum network is defined by finding Accuracy, Specificity, and Sensitivity.

In case of real-time implementation of this project, a web-cam can be fixed to the bottom of the vehicle to capture the images and will be classified by passing them to the transfer learned network.

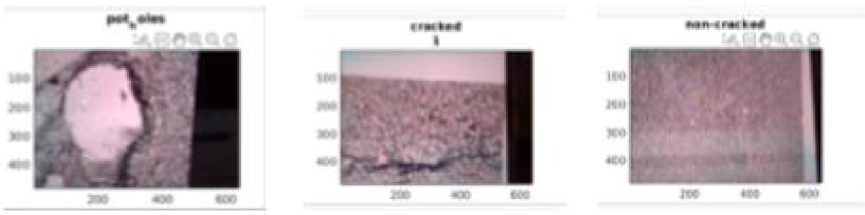

Figure 9: Real time data acquisition using webcam

The figure 9 shows real-time execution using web-cam. Firstly, the webcam settings will be initialized and then a snapshot from a webcam view is taken as an input image and passed on to the pre-trained network to classify the data. The class label and score of an image is plotted as the title for the preview of the snapshot. If it is performed in a loop with some delay then it can be used in the real-time scenario.

4.1. Performance Measures

True Positive (TP): A true positive test result is the condition when the crack present in the pavement image is identified as crack present.
True Negative (TN): A true negative test result is the condition when the system predicts as no crack when actually there is no crack.
False Positive (FP): A false positive test result is the condition when the system predicts as crack is present when there is no crack present in the pavement image.
False Negative (FN): A false negative test result is the condition when the system predicts as no crack when there is crack present actually in the pavement image.
Sensitivity: Sensitivity measures the ability of a test to detect the condition when the condition is present. It is given by equation 1.

$$Sensitivity = TP/(TP + FN)$$

Specificity: Specificity measures the ability of a test to correctly exclude the condition (not detect the condition) when the condition is absent and is given by equation 2.

$$Specificity = TN/(TN + FP)$$

Accuracy: A performance measure that gives a comparison of the measured values with a known standard in order to estimate the performance of the system. Measurement accuracy is identified as "the difference between the measurement of a factor and the accepted value for that factor from a trusted external source, or the percentage by which the two values differ". It is given by equation 3.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

Figure 10 represents confusion matrix chart for the pavement crack detection system output and the ground truth label. Rows denote the true class namely, cracked, non-cracked or potholes and the columns represent the system predicted class as to whether the pavement image contains cracks or potholes. Diagonal cells of the confusion matrix represents observations that have been correctly classified and off-diagonal cells correspond to observations that have been incorrectly incorrectly classified.

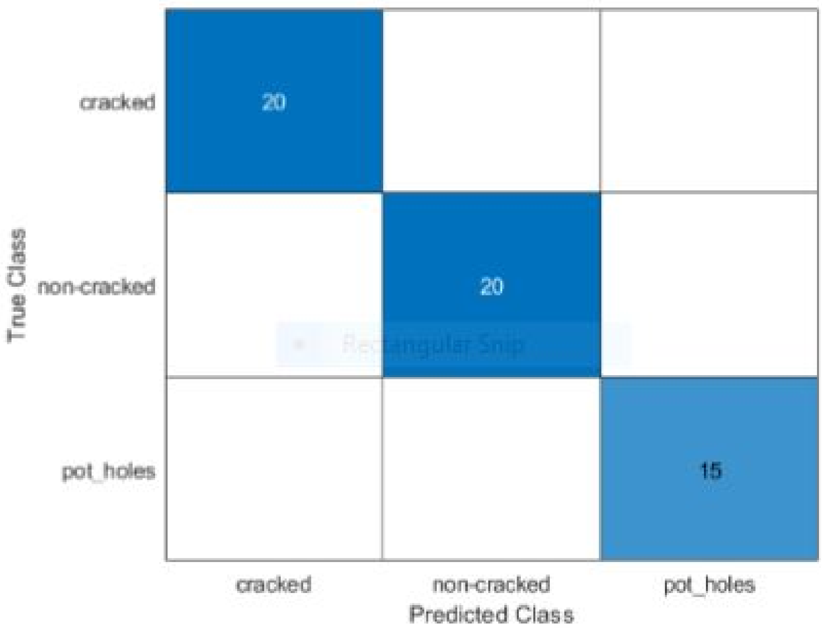

Figure 10: Confusion matrix chart for pavement crack detection system

Table 3: Comparison of number of epochs taken by different networks to reach 100% accuracy with less number of data

Table 3: Performance Analysis Of Networks

NET	**NO OF EPOCHS TO REACH 100% ACCURACY**	**NO OF EPOCHS TO REACH 0 LOSS**
ALEXNET	16	16
GOOGLENET	6	8
RESNET-101	18	19

Table 3 contains the performance of the pre-trained network in terms of achieving 100% Accuracy and zero loss. In Alexnet accuracy reaches 100% within 16 epochs and loss converges to zero in 16 epochs. In GOOGLE NET accuracy reaches 100% within 6 epochs and loss converges to zero in 8 epochs. In RESNET-101 accuracy reaches 100% accuracy within 18 epochs and loss converges to zero in 19 epochs. Among all these networks GOOGLE NET has taken less no of epochs to reach 100% accuracy and zero loss. Hence, GOOGLE NET is considered as efficient among the three networks.

5. Conclusion

Deep learning being the current state-of-art technology in developing models where feature extraction and classification with highest accuracy is required, is utilized in our proposed automatic pavement crack detection system. We have reviewed several machine learning techniques that correlate with deep learning which are efficiently used for pavement crack detection. Results of crack detection in pavement using deep learning are carried out and discussed in a detailed manner. Observed results proved the effectiveness of discussed methods in detecting cracks and compared to competing networks. In DLTs discussed, transfer learning technique with advanced pre-trained network GOOGLE NET has a high rate of accuracy and has an advantage over other nets because of its number of layers, higher adaptability for each iteration, and reduced loss.

6. Future Scope

In case of real-time implementation of this project, a camera can be fixed to the bottom of the vehicle to capture images of pavement and will be pre processed in MATLAB tool for enhancing the quality of images. Whenever an image gets captured it can be tagged with the GPS (Global Positioning System) to detect the coordinates of the location.

Advantages are: 1) In addition of GPS, PMS (Pavement Management System) can automatically find out the location of the damaged roads. 2) It reduces the time consumption and number of workers required to take action on the pavement distress. 3) Improves the working capacity of the project.

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