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Road pavement Distress Identification and Classification using Deep Learning

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Abstract - *Safety on roads is necessary as most of the communications in India take over on roads. These road maintenances by engineers require a method to survey in faster way. Traditional methods of road distress identification is often time consuming and it is safety compromising technique. The report generation manually done may or may not be efficient which needs again re-verification. Therefore, an automatic detection of the distress is required which combines the recent technology to enhance the efficiency and also to less time consuming. The deep learning approach is trending research area which can be used in the image pattern identification and classification. The dataset includes the labeled distress images of different classes. The Resnet-50 pre trained model is used in this work to identify and classify the defects in the distress images. The model after being trained, performance metrics is obtained which depicts the training, validation accuracies and losses for the model. The plot of model accuracy shows that model is trained well. The final classification list includes the images along with which class label the recognized image belongs to as cracks or no cracks.*

Key Words: **Classification, Deep Learning, Resnet-50, Road distress, Performance metrics, Transfer learning**

1. INTRODUCTION

Road maintenance is essential for driving safely and it is essential area for transportation in India. Maintaining a safe driving and accident avoidance situation is to monitor the degradation of road surface efficiently. That requires more of labor and knowledge on how maintenance is regulated. Usage of raw materials on construction of road, temperature of environment and wear and tear usage of road depends on the quality and lifetime of road. And after construction they need to be properly checked for safety purpose because one left can lead to severe damage to road surface and requires high cost and time for repairing. In the situation of the irregularities, shapes and not fixed texture patterns, detecting distress is a challenge in manual inspection. Visual inspections automation addresses the limitations of the human oriented visual approach so researchers have been moving towards the development of AI based and image processing based techniques. Surface distresses are tiny, thin things in images. There are many approaches developed and using real time data set of a location indeed helps in identification. Deep learning model automatically detect the distress which is less time consuming and effective compared to traditional methods. The model used here is variant of convolutional neural network called Residual Network (Resnet), also popular among VGG, Lenet, Googlenet, etc. The Residual block architecture provides a skip connection in order to avoid the problem of vanishing gradient problem. Regularization of the layers in the network skips the layers which causes performance issues. For our work we have used Resnet-50 which includes another layer for normal Resnet-34 model with 1x1 convolutions for restoring channel depth in the deep network. Here the work is comprised of steps that include transfer learning of Resnet-50 model, training on our image dataset, validating and testing providing the outcome of the model. A specified deep neural network Resnet-50 is used here to identify the distress on the image data set collected. There is a concept of transfer learning used here for pre-trained model to train on the given image dataset. The network classifies the types of distresses as Alligator, Transverse, Potholes, Longitudinal and No-cracks distress. The performance metrics during training is calculated which includes training and validation loss and accuracy according to the network trained. The classified output after testing is saved into the file so that engineers could easily identify distresses if searched in the file. The classified file includes the type of distress in the dataset that is mapped to correct type of distress class.

1.1 Problem Statement

Road distress is a complete or incomplete separation of surface into two or more parts, produced by breaking or fracturing. Automated identification and classification of cracks on the road has remained one of the high-priority research areas. Early inspection would be helpful for the initial identifications and maintain the roads to prevent further damage. However, there could be an approach that helps to identify the cracks and its types on roads using the trending practice, “Neural networks” which is based on deep learning. The problem with earlier works was due to less data the model developed would provide lesser accuracy of the system. The model trained on the enough images dataset should give as efficient method as possible. The use of transfer learning in the deep learning model enables to improve the performance while reducing time to build the model from scratch.

1.2 Motivation

The initial motivation to bring up this project is that transport system in current situation is eventually growing which also needs attention to maintain the roads in good condition. Sometimes, the problem is that the roads get built eventually without the use of good quality approaches and results in distress and other distress issues which makes ultimately difficult to identify and repair if left un-noticed. So if an effective approach is developed then the identification of cracks in the initial stages would help the engineers to rectify the repairs for the same and ultimately repair the distresses happened. Therefore, a deep learning model which replaces the manual inspection method is required to identify and classify the distress for smart future. Deep learning model enhances the training of image data which is large and works on real time data, providing high accuracy with large datasets. Usually when a new model needs to be developed from scratch needs time and varied weights and biases on huge dataset. Therefore the use of transfer learning comes into picture which motivates to use because of high saving training time and provides high accuracy as it had been trained on huge datasets. It is learning that considers the past trained knowledge to train any new data set.

1.3 Objective

1. The major objective of the study is to use pre-trained model based on deep neural network on our dataset to train and to detect road distress from the image dataset.
2. To use the trained model to classify the types of distress from the road images.
3. To check the performance of network chosen using performance metrics.
4. The data augmentation technique to increase and enhance features of the image dataset.

1.4 Related work

The proposed work [1] is based on a deep learning based convolution network (ConvNet). The system gets training using the image patches and also the ground truth information is provided in order to classify the images of cracks as crack present or not. The system uses a method which is on deep CNN, where the features automatically learn from manual interpreted images which are acquired by smart phone. Then the images are fed into neural network and based on training the data the algorithm is chosen as best among support vector machine and boosting algorithms in terms of performance metrics. The features extracted directly from the convnet layers give better results than the features which are selected manually. The work introduces 3 types of algorithms for comparison and convolution network comes out to be an efficient algorithm according to performance measures. For ConvNets precision, recall and f1 score respectively are 0.8696 0.9251 0.8965. The limitation observed in this approach would be collection of images around 500 taken from smart phone which are limited and the metrics could have been improved on increase in images collected.

In the paper [2] the deep learning technique which is convolutional neural network is used to automatically detect types of crack. The main intention of work is to assign class name to crack type correspondingly and then classify according to their class names giving best performance when used the algorithm. The approach uses 7,240 images for training it. The images obtained are from cameras of mobile. They are being verified based on 1,813 images of road. The system accuracy is measured according to the average f1score taking consideration of precision and recall. To attain classifying types of cracks, they used YOLO v2 algorithm for implementation which classifies according to the class name. The YOLO v2 shows result as precision 0.8851; recall 0.8710 and f1 score being 0.8780. Here, the limitation is that the system shows accuracy more in alligator cracks evaluation compared to transverse distress. It could be because of the less images dataset. Variation in accuracy after crack detection is caused because of label which is not correct in the image, dissimilarity among the distress and image in background; also due to formation of shadow is the limitation during implementation which was observed in the study.

In the research paper [3] automated Pavement Imaging (APIP) software is developed for assessing paving distress. The software algorithm developed for digital images allows the detection of linear, cross, and alligator cracking. It will automatically then calculates the size of the crack that is used to determine the magnitude of paved distress. This approach uses the concept of an ortho-image in order to process the image individually. The ortho-image is an image which is generated by the computer which is taken aerially having distortions from which are caused by terrain relief. There is also removal of tilts from camera. From tested samples, it is identified that the approach of photogrammetric gives results which are reliable. The output from APIP software is in a form of a report which has information of type, depth and harshness of the distresses. The algorithm is able to identify the type of distress. It also provides information about distress which is severe. The accuracy showed up to 90%.

In the paper [4] ANN algorithms, Back propagation and Self-Organizing Maps were used to recognize defects in the bridge images that are collected. BP and SOM algorithm were combined for improving performance of the network. The images are collected on the bridge to monitor the health. The reason to them chose above methods was because of efficiency on data processing. The images which are of gay scale type are converted to binary set of images in order to vary the background with the distress. The traditional algorithm is replaced by the SOM algorithm for the segmentation of image. Later features are passed into BP algorithm which gets trained. Then the result is obtained showing the combination of both algorithms in one system to get better performance over supervised learning algorithms. The performance and accuracy is calculated for each network algorithm separately and after combining both to check the better output obtained which seems SOM alone has true positive rate of 90% and BP has 60% for set of 200 images.

In paper [5], a method detecting cracks on image and measuring parameter is introduced that combines digital image processing into convolutional neural networks. The bridge images are collected and passed on to the deep neural network. For image processing semantic segmentation is introduced in the work. The features are extracted and passed on to the VGG network for faster training, using the graph of features; the length of crack is evaluated using number of pixels in image. The network structure is adjusted to improve the accuracy measure in classification. The processing is introduced as one of the parameter into CNN layer and they construct fresh image using a linear regression model from graph extracted to calculate length of crack. The proposed method shows 95% accuracy in classifying crack, and error less than 4% in measuring the length of crack.

In the paper [6], different machine learning algorithms were used in order to perform classification of road. The images are taken using accelerometer, gyroscope and GPS from smartphones. The three main class labels- smooth road, potholes, and deep transverse cracks are considered here for classification. The data collected from the sensors are considered among 3 axes rather than 1 axis along the coordinates to train the classifiers used. Here the machine learning algorithms used are SVM, decision tree and neural network for training. The dataset is separated as training, testing and validation data set before fed into the model and later is trained. The model generated is evaluated for the performance using metrics for all three machine learning algorithms. The activation functions used are tanh, relu and sigmoid functions during training. The trained model is tested using the test data and the labels are predicted. As there were manually collected data the data set formed is less and due to which there is slight difference in the performance metrics of the algorithms.

In this paper [7] there is comparison of the 3 different algorithms in order to classify the cracks on pavement. The algorithms used are genetic algorithms, multilayer perceptrons, and self-organizing maps. These algorithms are introduced for improving work's efficiency. Linear regression is used to detect the cracks. The projection technique was used for representing image. The class map and GA encoding method are used to obtain a classifier that will form crack-type map which will is of two dimensional matrixes. The classification model used the feature vectors components to check on the coordinates map space which is obtained. There were five hundred images selected which is of different type of crack. A projection-based approach is used to get binary vectors pair giving vectors with the required features thereby choosing MLP algorithm as best with accuracy of 98.6%.

In this paper [8] the cracks on concrete bridges is detected using the vision based approach. There is usage of convolutional neural network (1D-CNN) and long short-term memory (LSTM) method in this work. The proposed 1D-CNN-LSTM approach shows higher performance compared to other neural networks. The images contain some images of crack on bridges and some with no cracks for testing the model. The dataset used are divided into training, validation and testing images to check the model performance. The algorithm is trained with many training images after preprocessing phase where images are transformed according to frequency domain. The combination of two algorithms will perform well with the accuracy of 99.05%, 98.9%, and 99.25% for training, validation, and testing data.

In paper [9] the method was proposed which introduces a real time crack detector using deep learning algorithm and the Bayesian fusion algorithms. It is a crack segmentation and detection of the cracks method for the work. There were 1403 images collected from various sources like internet and also created own images, divided those images into 1000 training images, 100 validation and 3030 images for testing. They follow a method of samples to create boundary boxes of patches on images of cracks. The faster RCNN is used to as algorithm to detect cracks for training purpose and Bayesian algorithm is developed for image segmentation by removing false noises in the patch images. Many algorithms were considered for the comparison based on the image segmentation and the method faster RCNN gave results as F1 score being 0.6767, precision as 0.59. The average computation time per image of the segmentation is 0.06 for the Faster RCNN which is low compared to other methods taken for comparison.

In paper [10], an approach was carried out to detect the road cracks using deep learning neural network. The model used here is called Retina Net. The retina net model along with many models is used as backbone to learn from the feature maps. The other models consist of many models for comparison like, VGG19, resnet50, resnet101 and resnet152. The approach overcomes the limitation of 2 stage detectors which seem to be running slow compared to single staged detectors due to high computation cost. The images are collected from another work proposed which doesn't need processing it further. The samples are obtained from the method of augmentation to improve the number of samples obtained. The resnet models and VGG models converge faster than dense net models. The best average infer time is seen in the resnet models like RESNET50 has infer time as 0.29s, resnet101 0.36s and VGG19 as 0.5s.

In paper [11] the work proposed uses a feature mapping and faster RCNN to detect the crack on the concrete surfaces. The faster RCNN is the deep neural network which will be used to detect the cracks on the real time basis. The images taken are real time images of the roads. The images are taken from the technology called as drones. These drones will capture the images of concrete surfaces and the algorithm analyses where these cracks are detected, stores as reference images. Then later target image as the whole is taken from the drone. Then the algorithm called as feature mapping maps the features obtained from the target image and the reference image. If cracks found single image is obtained as output. The images taken are 2000 which are 22x227 pixels. Out of this 90% are randomly chosen as training and testing and validation images. The accuracy of the final model is 89.28%. The inspection receives a photo which will also show the crack locations.

In paper [12], Mask RCNN algorithm which is considered as deep neural based network, is used to detect the crack images of the surfaces like roads, bridges, bridges and surface structures. This a real time automatic crack detector which detects cracks from the dataset containing images. The threshold value is set for the final output which decides the mask for consideration. They collected 352 images from various sites. Then later data set is divided into 286images for training, 36 validating images and 20 test images. The pre-trained model is taken or consideration rather than training the model from the scratch. The model weights are already present when it is trained under MSCOCO dataset, and the learning rate considered is 0.001 to 0.0001. Loss function is calculated with the epochs considered. The model shows to be effective as it runs successfully giving crack detection of the images without considering the interferences in the image like noise, oil marks, objects and dirt etc.

The paper [13] shows the work of the crack detection on the pavement surfaces using the pre trained deep convolutional neural network (DCNN) model trained on the 'imagenet' data set. The concept of transfer learning takes place which includes pre trained model to learn the features of new data set and present the output. The new data set consists of hot mix and Portland concrete type pavement crack surfaces images. Various other machine learning classifiers are used for comparison and VGG16 DCNN presents a best performer. 1056 images were collected from the organization, 337 images had crack and 719 images had no crack. The types of cracks present in that database are transverse and horizontal cracks. The training, testing and validation samples are 760,212 and 84 respectively. The model is made to run on these data sets and then the classifiers are used to classify the labeled data to predict whether the crack or no crack. The activation function Relu used in the hidden layer and Softmax activation function is used in the output layer. Then the performance metrics including training, validation curves, accuracy and precision is evaluated. Out of many machine learning VGG16 with the single neural network gives accuracy of about 87% more compared to others.

The paper [14] shows the detection of crack on the concrete surfaces using improved version of VGG16 and cross entropy loss function. The 2 data sets were created one for crack classification and another for crack detection. The CC1500 contains the 1500 images, 1150 for training and 300 images for testing. Another data set is SDNET2018 contains 56000images with crack and non-crack images. Then the data processing takes place which includes labeling. The concept of transfer learning here too is used for the model Lenet-5. VGG16 model is optimized accordingly to the image of cracks. Then it is trained to learn the features to obtain best features. The Lenet-5 model detects the cracks and obtains the black and white images of crack. The model performs better for the various datasets provided compared to VGG16, UNET and percolation. One instance is, for Deep crack dataset F1 score is 90.1% for lenet-5 model, compared to other models.

In paper [15] the 2D and 3D information is collected to inspect the cracks. The work is automated using the images of distress. The data is collected using the 2 cameras to generate the 3D and 2D images of road. In the first step the road surface depth is analyzed and taken a 3D image using 2 cameras to obtain important features. The 2D images from the same surface are taken to compare the other images taken. A stereovision technique is applied for reconstruction of 3D image to recover the road depth. The intensity relaxation process is carried out after this to make the adjustment in the 2D images taken. After the pre-processing including reformatting the images are fed into feed forward neural network. Based on the probability check in reconstruction, the network is trained with a learning parameter of 0.01, 1500 epochs and provides accuracy of 97%.

2. PROPOSED METHOD

Here the design and the implementation of the work are discussed in subsections giving detailed explanation on the model used and the way it is used.

2.1 Dataset collection and processing

The image data set obtained is of Indian road. The image dataset used contains nearly 300 real images of road distress. The types of crack are analyzed according to the pattern and classified manually as Alligator, Transverse, Longitudinal, Potholes and No-crack images. These images are of random size and of 500X700 pixels with resolution of about 96dpi. The images need data augmentation which is a technique of expanding image data set by artificially performing variations on existing image data set. It represents the set of possible images that would be created by using techniques like transformation, rotations, cropping etc. The validation images considered here are used for image augmentation. The augmentation process is necessary for improving performance of the system because larger data sets are used for training it. The feature considered here for images to be trained by model, includes not only flipping images horizontally or vertically, but also image under illumination variations need to be learnt as feature. Therefore the techniques used here for image augmentation include horizontal, vertical flips, saturation, contrast and resizer. These techniques when applied on each set of distress types generate possible images and on the whole we obtain many images for training the model. The images are divided into validation, training and testing images. Totally there are 2569 images obtained after augmentation process. Then they are divided as 2058 training images, 251 validation images and 260 testing images. Training image data set consists of images that are

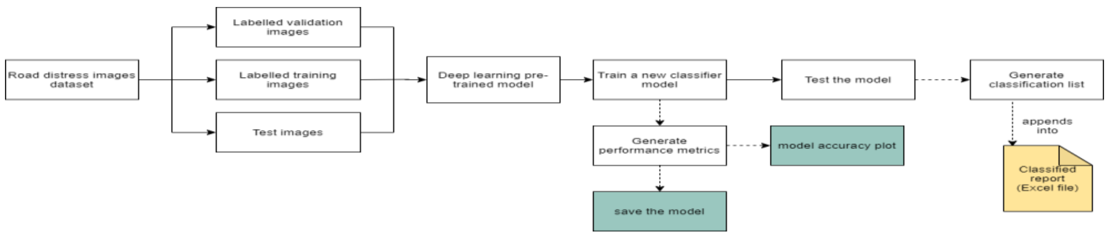

Fig -1: The high-level architecture of the proposed work using Resnet-50

used for model to learn to fit the classifier parameters and also used to build the system. Validation image dataset consists of set of images which will be required for classifier parameters adjusting like in case of changing the weights and bias accordingly during validating. Test image dataset is used to examine the performance of the new classifier generated and to check the correctness of system. The training and validation images include the types of distresses (with class labels) while testing images include images without class labels.

2.2 Transfer learning using Resnet-50

Transfer learning is majorly used in image processing and computer vision task. With the less training data transfer learning will enhance the performance of the system by saving the training time which would require more when trained from scratch. We are using this concept of transfer learning because the tasks are similar which uses the image data set and to identify the classes which it belongs to. The resnet-50 model has been pre trained on the "ImageNet" data set and the weights would have been adjusted already. The imagenet is a dataset of over 14million images consisting of various image categories labelled as balloon, dogs, etc. The dataset is split into training, testing and validation images. Therefore the model when trained with such similar images set, would gained experience and knowledge to train any new image data set given.

2.3 System analysis and implementation

The study utilizes the Deep Neural Network, which includes images of distress, and that automatically identify distress in paving images along with a variety of non-cracks and defects. The model chosen is Resnet which is variation of convolutional neural network contains several layers which can extract features from the pavement images and learn new features. The design and architecture is shown in figure 1. After categorization of selected distresses into training, validation and test set, running through the model network the model which is obtained is from Keras and Tensorflow both are popular and unique in their contribution towards machine learning to deep learning. The Resnet model uses the concept of CNN but with little difference in the layers. There is a pooling, padding, convolutions, and activations, fully connected layers which will be stacked along with the skip or identity connection to the residual blocks. The residual networks solved the problem of vanishing gradient by introducing these skip connections in between the residual blocks. There is residual mapping and identity mapping in between the residual blocks which is adding the value to the input to approximate the final function of the block. The vanishing gradient problem when obtained during residual mapping is solved by the help of identity mapping avoiding the weights of the network. This concept is used in the resnet-50 which has 50 layers having width, heights of multiple of 32, channel width of being 3. The Resnet architecture has 4 stages. The initial phase is performed as initial convolution and max-pooling with kernel sizes. This is the start of the first stage having 3 residual blocks of 3 layers each. The input and channel width gets reduced to half and doubled respectively for every stage of the residual block of CNN layers. The model has average pooling and flatten layer as last phase. The resnet-50 model when used after being trained for 'imagenet' dataset gets input size of 300x300 with channel width 3. The dense layer is set with 512 neurons for the input; activation function used is Relu and hidden dense layers of 512 neurons with same activation function. Finally the output is composed of 5 neurons, activation function as Softmax. The dropout is 0.3 and learning rate of 2e-5 set for the model. The Rectified linear (Relu) function is the activation function which is nonlinear activation function which is denoted in equation (1),

$$f(x) = max(0, x) \tag{1}$$

,where x is the input and f(x) is an activation function considers the positive values and if any negative values come up during training of the model, it is considered as zero. It solves the problem of vanishing gradient. The Softmax activation function is used at the output layer of the model to obtain the probability of the object belonging to each particular class. The mathematical function represented by equation (2),

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{2}$$

, where z is the input vector assigned to the function, Z_i is element of the input vector to the function which takes real, positive, negative or zero values. The exponential term is applied to each vector of the input, which may be fixed in the interval (0, 1). The summation ensures the valid probability distribution for K number of classes. The model pre-trained undergoes processing by all these activation functions for the new data set. The model is validated under epochs which are required to train accordingly so as to avoid over fitting of the model. After training, the performance metrics for the model are obtained; these are validation accuracy, training accuracy, validation loss and training loss across epochs.

The model is saved after the training and validation is performed. The model saved uses the test images and performs testing. The model tested will be providing us the list of each image probability tested over test images. For each images in the test images dataset, model checks and provides a list. For instance, the reference array made as [Alligator, Longitudinal, Nocrack, Pothole, Transverse cracks], the images are tested and if 'Nocrack' image had the most highest probability of classification predicted among many other distress, the image is set as 'Nocrack' and is matched into the final list. The final list is saved as Excel file for easy understanding and analysing of types of distress mapped accordingly to its class label.

3. RESULTS

In this section evaluation and the results that are obtained after being parameters are presented and discussed. The Resnet-50 model after being trained using 2058 training images and compared to validation images giving model performance metrics. The training and validation accuracy and losses are obtained for the model. The experiment is implemented with Keras.2.4.1 and Tensorflow 2.4.1 run on Google Colab with runtime and accelerator being GPU and python3. The models are trained with image dataset and number steps per epoch. The training and validation accuracy plot is shown in chart 1, showing the accuracy against the number of epochs considered for training and validation. The accuracy gets increased at the 3rd epoch with differences in both training and validation. Later from 4th epoch the accuracy starts to increase slightly reaching good accuracy point before epochs end.

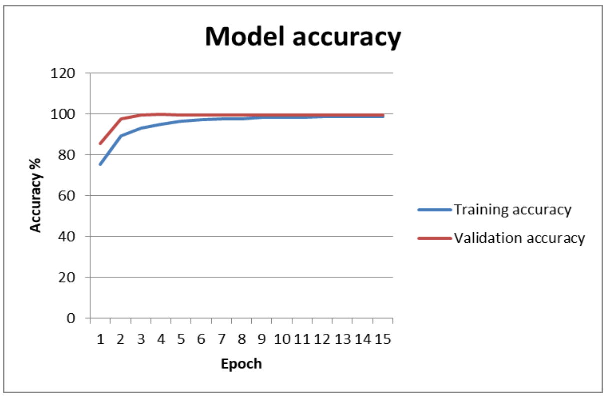

Chart -1: The Model accuracy of the proposed system in terms of percentage using resnet-50

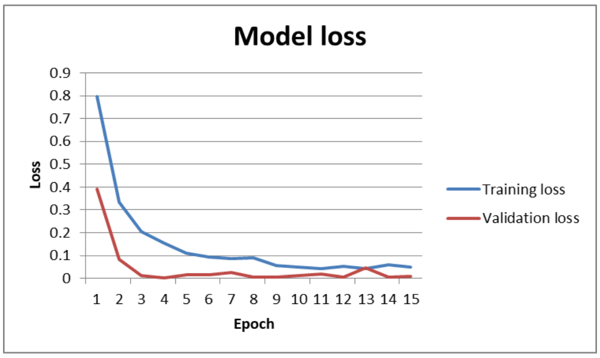

Chart -2: The loss function when calculated along the epochs during training and validation using resnet-50

The training and validation accuracy of the model shows 98.6% and 99.68% respectively with negligible differences in between which depicts there is no problem of over or under fitting of model. Similarly in chart 2, the loss of the model is shown in a plot which training loss is almost equal to validation loss. At the moment above 10th epoch model has an accuracy of 98.6% on the training set and 99.68% on the validation set. This means that we expect model to perform with 99.68% accuracy on new data. After the testing of model with the test images is completed, an array is generated for each type of cracks which among other types shows the probability higher. It means that that type of crack is depicted for the class label it belongs to. Then the distress image is classified into the list as shown in table 1 and stored in excel sheet for easy understanding of classification. The table 1 shows the class label name of 5 different types considered (Alligator, transverse, longitudinal, pothole and nocracks) and other column represent the test images being classified into their class labels. For all the test images chosen the list will be generated and are viewed in the Excel file. The Excel file can be used for easier reference and can sort the images according to the class labels correctly predicted by the model.

Table -1: The table represents the classified output of the types of distresses matched after class labels using Resnet-50 model

	Class label	Image file name
0	Alligatorcrack	AC(1).jpg
1	Longitudinalcrack	LC (33).jpg
2	Nocrack	NC (10).jpg
3	Transversecrack	TC (10).jpg
4	Pothole	PH (73).jpg
5	Pothole	PH (69).jpg

4. CONCLUSION AND FUTURE WORK

The work introduced the concept of transfer learning and deep learning which the trend is in the recent technology. The Resnet model which is a variant of convolutional neural network is used here for identification, detection and classification of road distress images. The data augmentation is introduced to improve the collected images dataset so that the model performance is improved. The types of cracks considered here are transverse, alligator, pothole, longitudinal and nocrack types. These types of distress are classified into their class labels. The pre-trained model resnet-50 is used to train and validate on the images presenting us the performance metrics. Then the test images are tested after the model is trained and validated giving the array of the probabilities of the image belonging to each class. The highest probability of the image belongs to that particular class and this helps to match the images to their classes in the Excel file obtained. It can be concluded that the selected resent 50 model successfully detects the distresses on images and then correctly classified according to the class labels taken efficiently. The proposed work can be extended to check on the length of crack in the image and to analyses the depth of the distresses. There are many other types of cracks on roads which can be considered for classification purposes. The work can further focus on the severity of the detected distresses. In future work we will try to train the Resnet-101 and resnet-152 models in order to check the performance on given data set.

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