DEEP LEARNING APPROACH TO CLASSIFY ROAD DAMAGE OF BANGLADESH USING CONVOLUTIONAL NEURAL NETWORK

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This Thesis report has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering.

APPROVAL

This thesistitled on "Deep Learning Approach to Classify Road Damages of Bangladesh using Convolutional Neural Network", submitted by Hasnur Jahan, ID: 181-35-2297 to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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ABSTRACT

Road damages are a big issue for a developing country like Bangladesh. Manually maintained road damages are costly and time-consuming. So, it's a need of time to make a system that will automatically classify the road damage to let the authority understand which roads are mode damaged and which one is less. It's also needed for drivers to safely drive a car on the road. Developed countries already made a system that is not affordable for Bangladesh. So, I have decided to make a system that will help the authority to classify road damages at a low cost. So, I have used transfer learning of convolutional neural network which will help to make a system to classify road damages at low cost, because transfer learning is a system where we can reuse the code. There I have used 5 models of convolutional neural networks and all of them were transfer learning methods. They are Xception, InceptionV3, VGG16, VGG19, and DenseNet201. All the model's model accuracy, model loss, confusion matrix, and classification results have been generated. But among all of the five models, VGG16's gives the highest accuracy score of 92%. In the future, I will work on detecting road damage and will increase the dataset to get higher accuracy and with other classification types of roads damages.

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CHAPTER 1
INTRODUCTION

1.1 BACKGROUND

Road damages are the state on those the road structure's functions are not capable to give out the vehicles according to the expectation of the vehicle. Normally road damages are created by uneven maintenance, poor maintenance, behaviors of road users. Around the world every year a huge amount of cost is implemented for fixing road damaged. Road damages are dangerous for people and traffic. According to Dhaka Tribute, in Dhaka cities, half of the roads have been damaged in 2017. And every day about 18 people are killed by road accidents due to road damage. Among the world, South Asian countries faced the problem of road damage most. Bangladesh is one of those countries. For road construction, proper monitoring is a need. Because without monitoring it's hard to detect where there has been road damage and where there has not. After detecting road damage, the management needs to understand the type of road damage and which road damage is most needed to repair. If the management does not monitor properly, then it will become hard for them to detect the most construction demanding road damage. So, the constructions of road damages are a time-consuming and costly process. But it is very necessary to maintain road damages. Because road damages have an impact on the human body along with the impact on the vehicle.

In other countries, they have already developed some processed to detect and classify road damage to understand the type of road damages. There has a global road damage detection challenge 2020 (GRDDC 2020) dataset which is available online. It contains 26336 road images. The dataset has been made on road images from India, Japan, Czech Republic. Worldwide competitions have been held on the dataset and participants have been implementing different types of machine learning techniques on the dataset. There are several algorithms and techniques which are used to solve the challenges. In different works, researchers have used different types of algorithms and most of their works are based on deep learning. Because it's an image processing-based work. So, with deep learning, it's easy to detect and classify road damage from a road surface.

So, for classifying road damages from images deep learning is a very popular method. Why classification technique is important? Because it is very important to teach a model which one is a damaged road and which is not. What type of damages have there? Is the damaged road being allowable for a pass or not? One can get all the question-answer from these questions. In a standard classifying format, there have at first 2 types of road damages and they are cracks and others. Among cracks, there have two types, longitudinal and Lateral. Among them, there have more classifications also. And in other types, there have rutting, bump, pothole, separation white line blur crosswalk blur. All of these road damages types are classified with different class names. They are decided into 8 class named D00, D01, D10, D11, D20, D40, D43, D44 (table-1). For classifying road damages people approaches with both machine learning model and deep learning method. Different researchers classified road damages into different types. Some researchers only classified the cracks and some researchers classified them into other types.

TABLE 1: STANDARD CLASSIFICATION OF ROAD DAMAGE

Damage type			Detail	Class Name
Crack	Linear Crack	Longitudinal	Wheel mark part	D00
			Construction joint part	D01
		Lateral	Equal interval	D10
			Construction joint part	D11
	Alligator Crack		Partial pavement, overall pavement	D20
Other Corruption			Rutting, bump, pothole, separation	D40
			White line blur	D43
			Crosswalk blur	D44

In my work, I have approached with a convolutional neural network which is also known as CNN of deep learning our work is in my work, I tried newly to make a classification among 3 types of roads where there have clean that means it is a non-damaged road also. So, during classifying road damages, I used the 2 types of road damages and clean road. We have named the clean road which has no damage as a non-damaged road. That means there have 3 types of roads among which I made the classification. So, they are- crack, pothole, and non-damaged road. We used five Convolutional Neural Networks which are all transfer learning methods. They are VGG16, VGG19, DenseNet201, InceptionV3, and Xception for classifying road damages and non-damaged roads.

1.2 MOTIVATION OF THE RESEARCH

Road damages problems are one of the major problems which caused every year a lot of people's death. Roads which are damaged create a problem for people during traveling. It is very hard to maintain every road damage so fast for a developing country like Bangladesh. Detecting road damage manually is time-consuming and costly. If there have a system for the authority to classify the road damages to find out which is more dangerous then many losses of life and property can be prevented. In other countries, they have already developed some system which is used to detect and classify road damages. Like there has global road damage detection challenge 2020 (GRDDC 2020) dataset on which competition held to develop a system for detecting and classifying road damages. They are used in the country. The developed systems are low-cost and time-saving. The authority is using the system and correcting the road at a low cost and easily by saving time. But we have found that there has only one work based on our country's road damages. By inspiring that we have to think of making a road damages data set from the road damages of the Dhaka city. Dhaka is a populated city and there have many road damages which are waiting for cured by the authority. And it's time and money-consuming for the authority. So, to help the authority to detect the road damages we have made a system which will help the authority to detect road damage easily. And by classifying them they will be able to find out which one is more in need of services. From our work, they will be able to classify the road where there does not need repair or the Non-Damaged Road. So that they will be able to easily rank the most dangerous damages and non-damaged roads and can repair the damaged road easily. So, the motivation behind the work is to make a low-cost system for our country which will give the best results on basis of the dataset from the country's road.

1.3 PROBLEM STATEMENT

We know that road damages are quite problematic for people of any country. Early, many works on road damages have already been done. Many authors of the researcher work with different types of algorithms such as Deep Convolutional Neural Network, CNN, embedded system, and many more. Some approaches with the state to the art solutions also. Some approaches classify road damages into 2 types, and some classify them into 8 colors. For classifying the type of road damages, they applied SVM, Random Forest, decision tree, and many more. They collected the data with different systems. Some used customized datasets and some used Global data which is available. Other countries worked with their road's dataset. But in Bangladeshi climate and situation, is different from others. So, the research is appliable for their own country. For our country Bangladesh we want to apply deep learning models on the dataset created from our country's road. And try to make 3 types of classification. They are potholes and cracks and non-damaged roads. Because in our county's perspective other types of damages are not so much available.

1.4 RESEARCH QUESTIONS

The research question was

- ❖ Q1: Which model performs better for classifying road damages?
- ❖ Q2: What type of damages are there?

1.5 RESEARCH OBJECTIVE

The main objective of my paper is to classify the road damages types from a road surface at a low cost. Also wanted to get a better result so that our model can be more appliable. Our thesis goas are:

- ❖ Creating an automated system.
- ❖ For creating a low-cost system that is affordable for a developing country like Bangladesh.
- ❖ Classify road damages to understand the damage type.

❖ To get more accurate results.

1.6 RESEARCH SCOPE

Research's main scope is as follows:

❖ To develop a method on basis of the Bangladesh road damages dataset that can classify road damages.
❖ Will help the Bangladesh authority for having a system that will be low cost and will easily classify road damages and non-damaged roads. So, it will help the authority to repair soon and will decrease people's sufferings

1.7 THESIS ORGANIZATION

In the first chapter, a particular part on road damage detection system and its usage, the background behind the work, motivation of the research, problem statement, research questions, research objective are discussed. The other parts related to our research are as below:

In the next chapter I will discuss, the literature review where we can see some researcher's studies which have already been done on the same field of road damages, their used methodology, lacking and on the base of their work comparison among my work and their work. In their chapter, we will discuss the methodology of our work. In the methodology of my work, I will discuss data collection, pre-processing of data and will analyze our work. The results of the methodology will be discussed, in chapter four. The last chapter is the ending chapter. Here I will give the conclusion part where there will be the total summary of my work. Here I have discussed what work I will do in the future for the betterment of the work.

CHAPTER 2
LITERATURE REVIEW

2.1 INTRODUCTION

In a literature review, a researcher reviews the previous work, research, conference paper, books, article, etc. with that one can find out what work has already been done on the topic, summarize the whole topic, find out what lacking in the work. after analyzing they can work on limitations and overcome the limitations to get better results.

2.2 PREVIOUS LITERATURE

The idea of repairing damaged roads started from the time when people started traveling on the roads built for their travel. Because the roads are used by people after they are built and the roads are ruined after a long day of use. On-road damage, many researchers have already done their research and applied different types of machine learning algorithms to classify road damages. Some of the works are classification tasks along with detection. So, for my work, I have focused on the classification parts only.

As the convolutional neural network has good capabilities of image processing, Gioele Ciaparrone and el at [1] proposed two convolutional neural network models for classifying road damages. At first, the problem was tried to solve by approaching semantic segmentation. Later it was tried to solve the problem with the method of object detection. And they get that the 2^{nd} process can be a support system for humans to make a valid decision.

Embedded system is well known for road damage detection by deep convolutional neural networks. For low convolutional neural networks, Siyu Chen and et al [2] used a deep convolutional neural network. For faster computing speed they used TensorFlow, mobinet. And before applying all of them they used OpenCV to resize the image dataset by 300*300. They collect their dataset by capturing road images by setting the camera on the windshield of the car. They used the system for helping the authority by inventing a low-cost system.

Menghini L. and et al [3] evaluated the conditions of the road pavement by a Deep neural network. They used YOLO V5 and a faster R-CNN deep neural network algorithm to detect pavement distresses automatically and for identification with localization. They used the data set from the competition of GRDDC2020. In the future, they want to apply automatically localizing instead of non-destructive remote sensing technology.

A competition was held on the dataset of Global Road Damage Detection (GRDD Dataset). The goal was to get state of an art solutions from the dataset. The dataset was made by global Deeksha Arya and et al. [5] they collected the data from Japan, India, and the Czech Republic. In this paper, they show that try to get the best solution among the participants and the winning team approaches with ultalytics-YOLO(u-YOLO) model. By Appling augmentation in test time, they try to improve the robustness of the model.

Md. Shohel Arman and et. al. [7] approaches with an object detection method to detect road damages. With R-CNN and Faster R-CNN, they detect road damages. And they applied SVM (Support Vector Machine) for road damage classification. They got 98. 88% accuracy with the 0.01 lowest loss. For preventing the repairing cost, they want to extent parameters in their future work.

Hiroya Maeda and et al [11] worked for road damage detection using a deep neural network. For that work, they used images collected through smartphones sated on a vehicle dashboard. For annotation, they used manual annotation which was similar to PASCAL VOC. They classified road damages into 8 types. By using SSD Inception and SSD MobileNet they got all the results. In the future, they want to detect damages that are of a rare type.

Then they [9] also worked to detect road damages using a neural network. They manually annotated 163664 the data which is collected with a smartphone camera installed above a car. Using Server of GPU compared the runtime speed and accuracy. They try to make data classified into 8 categories. And their recall and precision are greater than 71 percent and 77 percent by using inception V2 and MobileNet.

With faster R-CNN Wenzhe Wang and et al. [12] detected road damage and also made a classification. They applied data augmentation techniques here where contrast transformation gaussian blur and brightness adjustment were used. Data was collected by mounted phone in a vehicle. They achieved an F1-score mean of 0.6255 in the competition. In the future, they want to optimize network structure and want to try other techniques to improve the performance.

Yanbo J. Wang and et al. [13] worked with faster R-CNN and SSS object detection algorithms for applying a deep proposal on road damage detection and classification. Here imageNet Pre-trained Resnet 1010 and VGG-16 for backbone models of faster R-CNN and SSD used. For better results, they used single model prediction. They obtained their data with a smartphone mounted on a vehicle. Their main aim was to reduce the cost of road management and maintenance.

With decteron2 and Faster R-CNN Vung Pham and et al. [14] detected the road damage and classified the. They used the X101-FPN base model for faster R-CNN and default configuration of Detectron2's applied. Their dataset was the Global Road Damage Detection Challenge 2020 (GRDDC 2020). They aimed to detect road damage at a low cost in a timely. In the future, they want to visualize the intermediate features which are extracted by this model.

Janpreet Singh and et al [16] worked-on road damage detection with mask R-CNN. They also classified them. The dataset was from IEEE BigData Cup Challenge 2018. The paper was written for the competition. The images were captured with smartphones from 7 cities of Japan. They tried to detect the various types of road damage. They classified the road damages into 8 classes.

Xiaoguang Zhang and et al [17] explore the tricks for detecting road damage using a one-stage detector. They used Yolo v4 for the detection of road damages and used CGAN for data augmentation. Their dataset was collected from Global Road Damage Detection Challenge 2020 (GRDDC 2020). The work was for the international conference which was on big data. Their accuracy was comparatively high and have good efficiency. This has provided them with a way of applying it in real life. They have applied only one model in the future they want to apply more models.

For reflection and classification of alligator crack and the surface of the road Panop Khumsap and et al [18] used novel feature extractions. For crack detection, they used the WEKA crackIt toolbox. For classification, they used naïve Bayes, SVM, and decision trees with 10-fold cross-validation. They used that method to distinguish between 2 types of surfaces among reflection, cracks, potholes, alligators. To drive automatically in the future, they want to use navigation robots and make the road safer.

Using crack detection N. A. M. Yusof and et al [19] wanted to detect asphalt pavement cracks and classify them. For detection, they used a deep convolutional neural network. The pixel gride size of the images was 1024x768 to 32x32. They assumed if the crack has then the value will be 1 and if not, the value will be 0. They have collected their dataset with a digital camera named Nikon Coolpix S6150 on a condition of natural lightening. Their system was a fully automated crack detector. And their accuracy was above 94.25%. In the future, they want to detect and classify the block crack images in a real situation.

2.3 CONCLUSION

There have many types of algorithms used. For having a good result, they applied feature extractions, augmentation, annotation, and many more techniques. Forget better accuracy and real-time performance. In our work, we also tried to detect road damage in real-time and classify them.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 RESEARCH METHODOLOGY

We have applied Xception, InceptionV3, DenseNet201, VGG16, VGG19 convolutional Neural Network methods for our work on a dataset collected with a smartphone.

3.2 DATA COLLECTION

There has already an available dataset on the internet on which much works has been done. Like GRDDC 2018, 2020, and so on. There have datasets that have been collected from India, Japan, the Czech Republic, etc. There have more other dataset resources available on the internet which are from different countries. But there has no dataset available on Bangladesh's road damage dataset. So, we have thought to collect data from Bangladeshi roads. For this work, I have collected datasets only from Dhaka City(Figure 1).

Figure 1: All type road damages sample picture

3.3 DATA PREPROCESSING

After collecting data from the different roads of Dhaka city we have approached to preprocess our dataset. This is a step where we prepare data for the train to the machine so that the machine can learn the data easily. Creating a machine learning model is the most important part. When we approach a process of machine learning with data, we do not have formatted and clear data. And if the data is raw then we need to apply more preprocessing processes to the dataset. The processed data increased the accuracy of the model. So, for our work at first, we have collected the dataset from the road of Dhaka city. I have classified roads into 3 types (Figure 3). There have 2 types of road damage and one type of road where there has no road damage. After collecting road pictures, I have divided the data into train and test sets. In the training dataset, there have 80% data and in the test set, there have 20% data. And in both of the training datasets, there have three folders of three types of datasets. They are potholes, cracks, and non-damaged roads. In the test dataset, there has a total dataset wherein the crack there have 94 data, in the non-damaged road there have 102 data and, in a pothole, there have 113 data. In the training dataset, there has a total dataset wherein crack there have 372 data, in the non-damaged road there have 410 data and, in pothole there have 451 data. So, there has a total of 1542 data in the dataset (Figure 2).

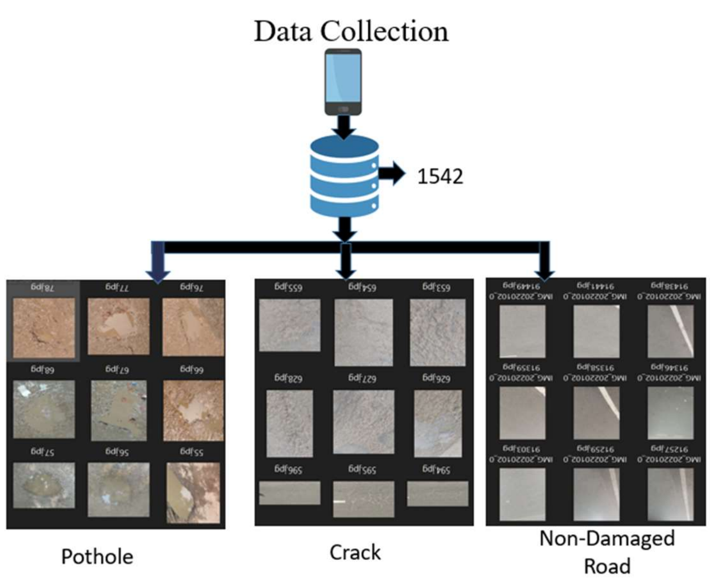

Figure 2: 3 Types dataset sample

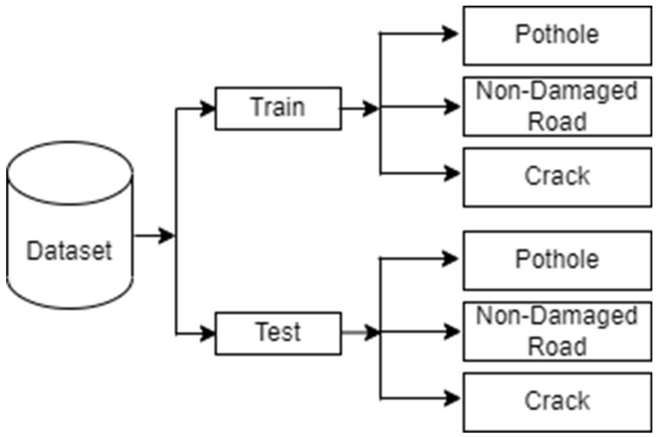

Figure 3: Dataset Labeling

3.3.1 Data Normalization:

I have used min-max normalization for re scaling the value. So, using the method I have re-scaled the pixel value from 0 to 225(figure 4).

3.3.2 Data resizing:

For get a better result data re-sizing is one of the biggest tasks in image processing. I have re-sized the dataset into (224, 224) format (figure 4).

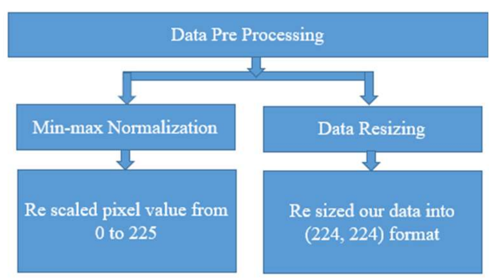

Figure 4: Dataset preprocessing diagram

3.4Convolutional Neural Network

As for our data classification, I am using all the models of convolutional neural networks. So, here the CNN's (Convolutional neural network) basic idea is explained (figure 5).

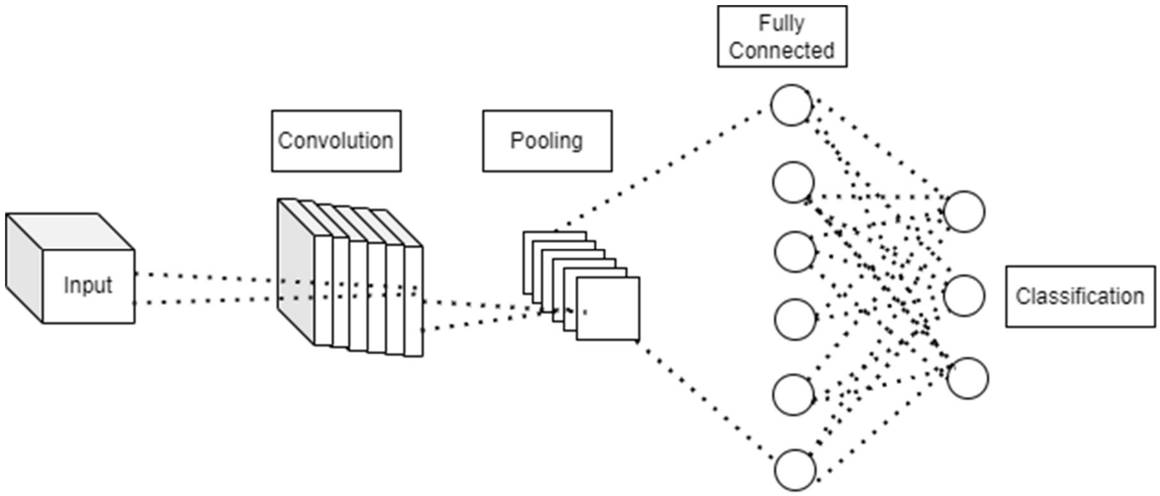

Figure 5: Convolutional neural network's basic architecture

After taking input convolutional layer is the first layer that is used for extracting features. In this stage, the image is resized into (M*M) size.

Then the next layer is the pooling layer. Here the previous image's size is reduced for decreasing the calculating cost. And in a max-pooling layer from the feature map, the largest element is taken.

Then the time is for a fully connected layer. They are the last layer before the output layer. Here the images are flattened which is gotten from the previous layer. Here the classification process is beginning.

After connecting to the fully connected layer overfitting may occur. So, for overcoming this problem dropout is used. Here it is decided which data may be fired and which data will go for further steps.

One of the most significant parameters is the activation function. ReLu, Softmax, tanH is some of the generally utilized activation functions.

For my work I have used Softmax activation Function.

3.5 VGG16

It is a convolutional neural network. In 2014 Andrew Zisserman and Karen Simonyan of oxford university introduced it. It is an improved format of AlexNet. The AlexNet architecture is improved by replacing the previous large Kernel Size with the multiple kernel size 3*3. And the improved one is the VGG16. It is one of the most important evaluation matrixes. All secret layer's activation mechanism is ReLu. In our used architecture of VGG16, we have used an input layer. Then Functional Step. The output of the functional step will enter into the dropout step and at last, there has the output level (figure 6).

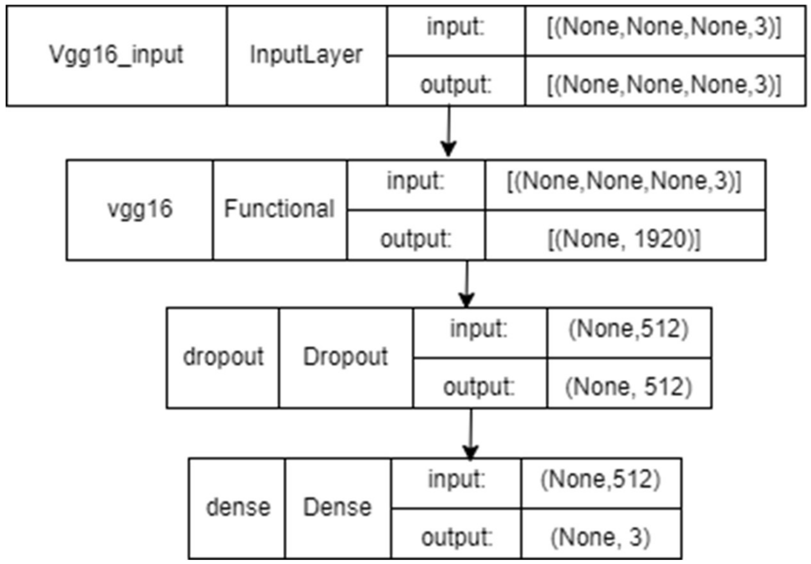

Figure 6: VGG16 Architecture

3.6 VGG19

VGG19 is one of the improved formats of AlexNet architecture. It's a transfer learning method that is used for good classification methods. For other frameworks, weights are easily available. Here in our proposed model at first, there have Inputlayer, then there has a functional layer. After that Dropout, the layer is used, and at last, the output layer comes after the dense layer (figure 7).

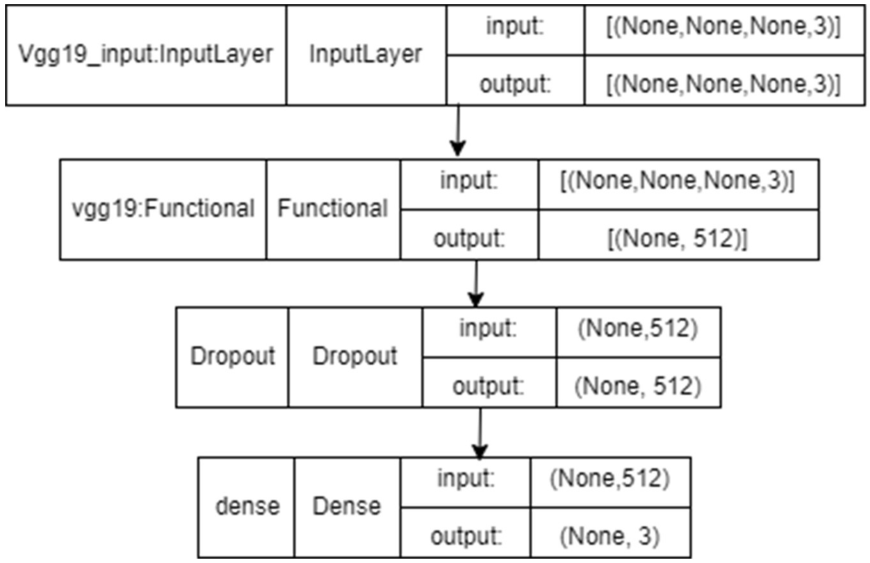

Figure 7: VGG19 model architecture

3.7 DenseNet201

Transfer learning is an effective way to get a great result from less data size in a problem of classification. And further the results of the model can be improved with hyper tuning. In the proposed model I at first there have InputLayer, then a functional layer, drop out and at last, there has the Dense Layer (figure 8).

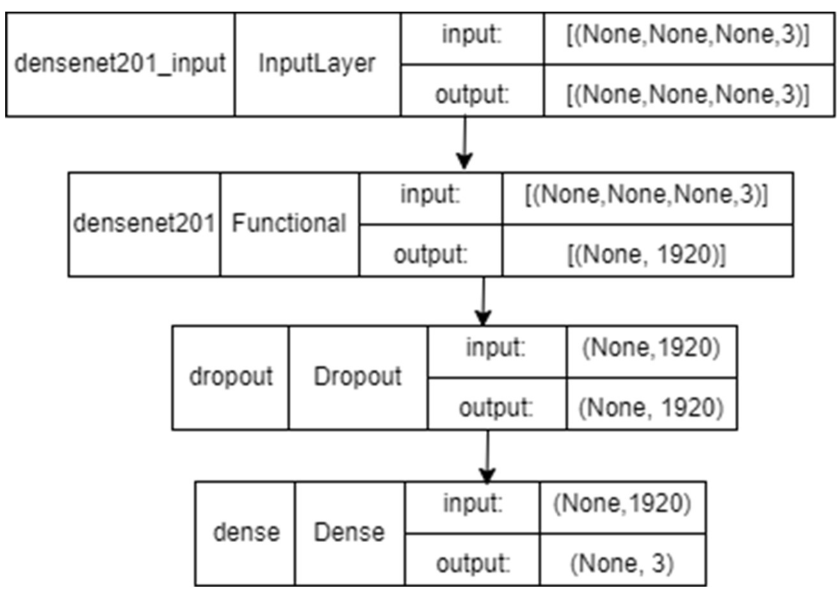

Figure 8: DenseNet201 model architecture

3.8 Xception

It is a convolutional neural network that involves separable convolutions which is depthwise. This model is inspired by the inception model. The outlook of xception is extreme inception. That refers extreme version of the inception module. In my xception model, there have an InputLayer at first, then there has the functional layer, then the dropout layer and at last, there has the dense layer (figure 9).

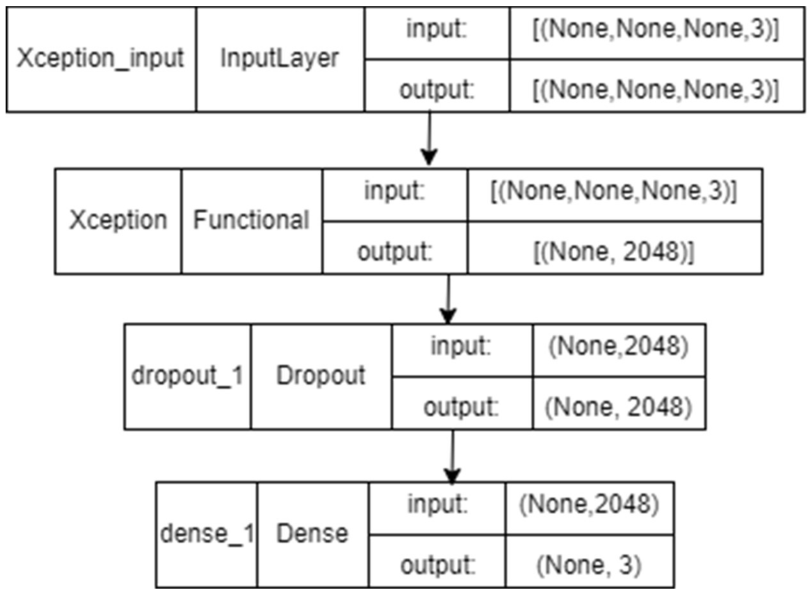

Figure 9: Xception model architecture

3.9 InceptionV3

It's also a convolutional network that is a part of the inception family. It is used for the classification of the image. Inception V1 is the basic model of Inception V3. Google team expanded the model. Like the other model we proposed there at first the inputLayer then the functional layer, then the dropout layer, and at last the dense layer (figure 10).

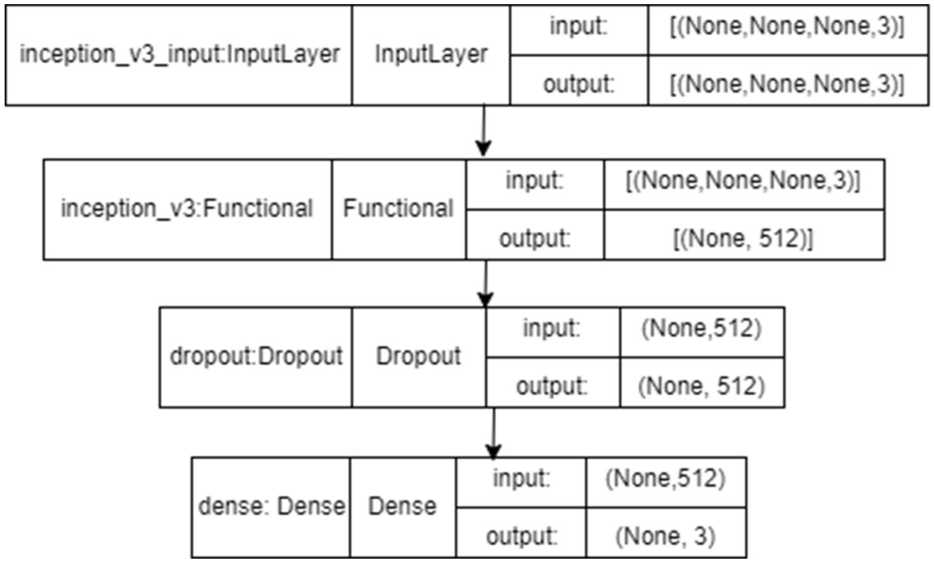

Figure 10: InceptionV3 model architecture

All the methos which I have used are pre-trained convolutional neural Network's using transfer learning approach. For every method I have used same types of activation function along with other parameter. At first the batch size for my used method is 16 as there have 3 output classes. I have used 20 epochs for the work. As optimizer I have used Adam optimizer whose learning rate was 0.00001, and used loss function named categorical_ crossentrophy. As the activation function I have used Softmax activation function.

3.10 Transfer Learning:

All the proposed methods in the work are the transfer Learning of vision models. Making a shortcut for re-using the model weights which is pre-trained is known as transfer learning. It is the system of a neural network to solve one problem using the trained model of another problem. The transfer learning processes can detect the generic features of photographs. It achieved the state performance of state to the art and still, the system remains effective.

3.11 Evaluation Methods

I have plotted the confusion matrix for evaluating the results. For evaluation, it needs the true positive, true negative, false positive, and false negative values.

Here, true-positive is correctly predicted actual value

True-negative is correctly rejected

False-positive is incorrectly predicted that the value is positive

False-negative is incorrectly rejected.

3.11.1 Accuracy:

The accuracy of the model determines that how accurately a machine can predict the results. When all classes are equally important then it is important. In my work, all classes are equally important. So, the accuracy is also important to identify the accuracy of the model.

$$\text{Accuracy}=\frac{True\ positive\ value+True\ Negative\ Value}{True\ positive\ value+True\ Negative\ value+False\ positive\ value+False\ Negative\ Value}..(1)$$

3.11.2 Precision:

It is a term that finds out the performance of a model in machine learning. Precision is calculated by dividing the true positive value by the all-positive value.

$$\text{Precision} =\frac{True\ positive\ value}{True\ positive\ value+false\ positive\ value}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

3.11.3 Recall:

measurement of the perfectly-identified true positive is called recall. The recall is calculated by dividing the true positive value by a total existing related document.

$$\text{Recall} =\frac{True\ positive\ value}{True\ positive\ value+fals\quad Negative\ value}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(3)$$

3.11.4 F1 score:

Test accuracy's measurement is called as F1 score. By using precision and recall F1 score is calculated.

$$\text{F1 score} = 2*\ \frac{Precision*Recall}{Recall+Precision}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots(4)$$

For all the five models named Xception, InceptionV3, DenseNet201, VGG16, VGG19 method I have shown the model accuracy slope along with model loss. In model accuracy slope the accuracy is found out from the perspective of Training accuracy and Validation accuracy. For model loss also the loss is found from the perspective of training accuracy and validation accuracy. For both graphs on the x-axis, there has the epoch number and, on the y-axis, there has the number of accuracies.

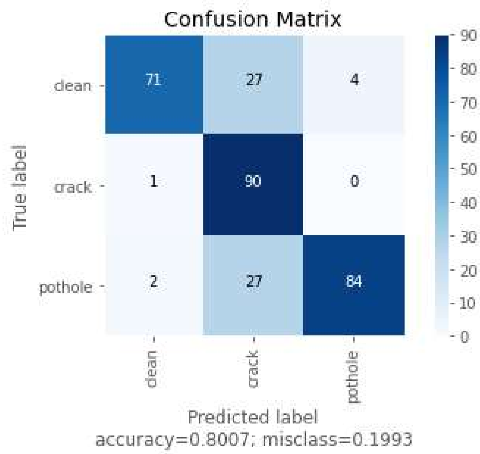

Figure 11: Confusion Matrix of Xception

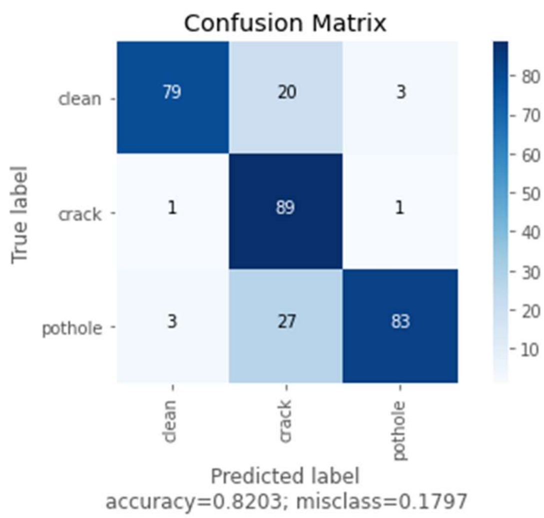

Figure 12: Confusion Matrix of DenseNet201

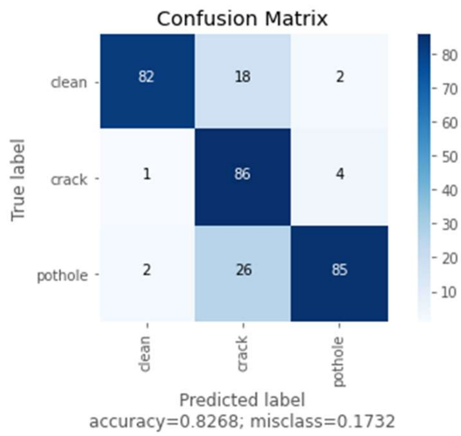

Figure 13: Confusion Matrix of InceptionV3

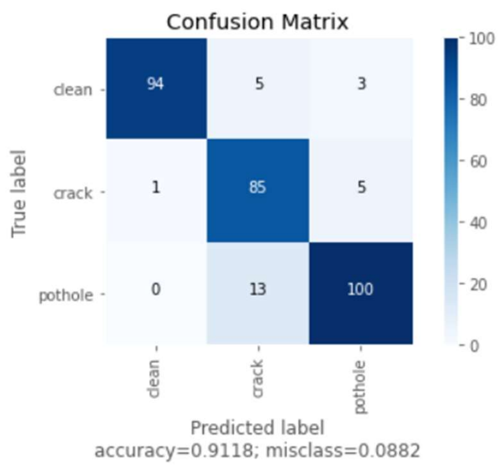

Figure 14: Confusion Matrix of VGG16

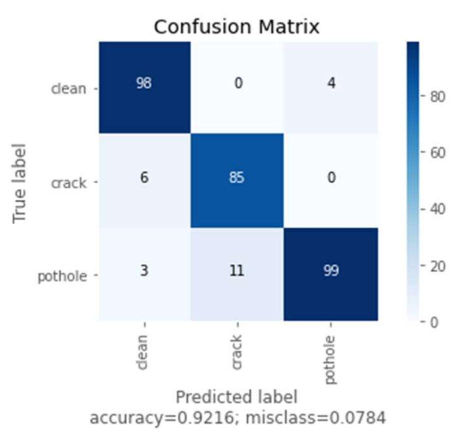

Figure 15: Confusion Matrix of VGG19

CHAPTER 4
RESULTS AND DISCUSSION

4.1 INTRODUCTION

The road damage classification process is described in that part. After the data collecting and preprocessing part, I have described the models and which I have applied for classification technique. There I will describe the results of the model.

4.2 RESULT DISCUSSION:

After implementing the convolutional neural network models on our dataset, we have gotten the model's accuracy and model's loss plotting graph. Training accuracy and validation accuracy are compared for gaining the graph of all the model's accuracy and model's loss.

4.2.1 Xception:

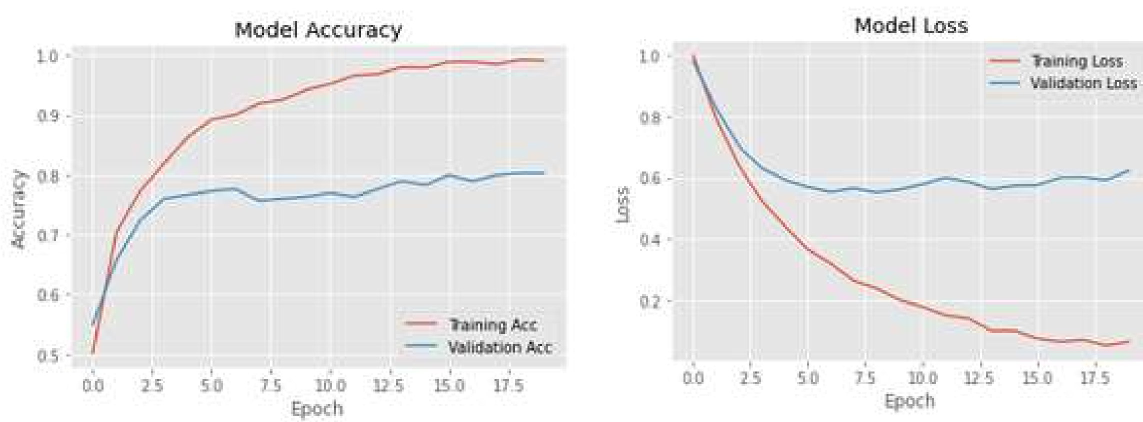

Figure 16: Model accuracy and model loss of Xception

4.2.2 InceptionV3:

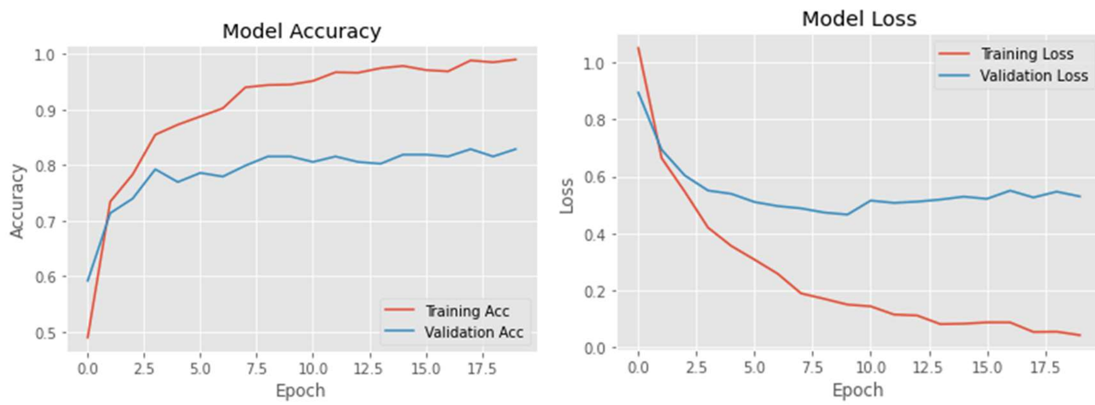

Figure 17: Model accuracy and model loss of InceptionV3

4.2.3 DenseNet201:

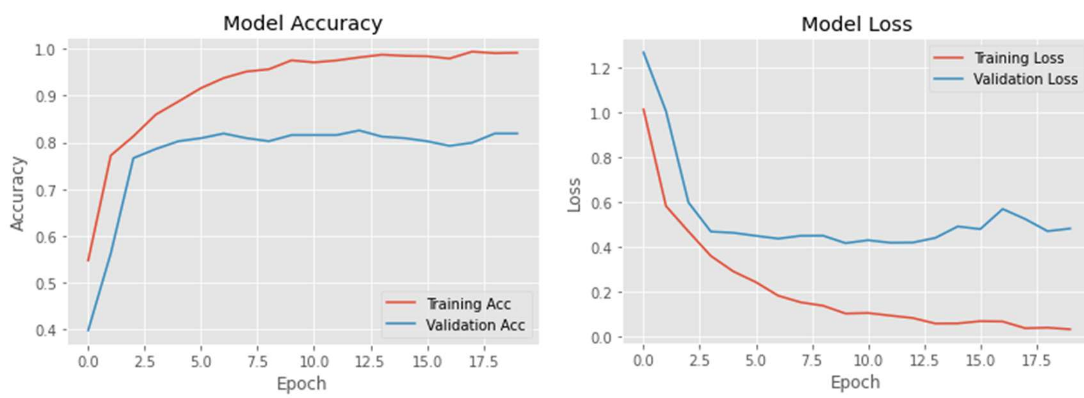

Figure 18: Model accuracy and model loss of DenseNet201

4.2.4 VGG16:

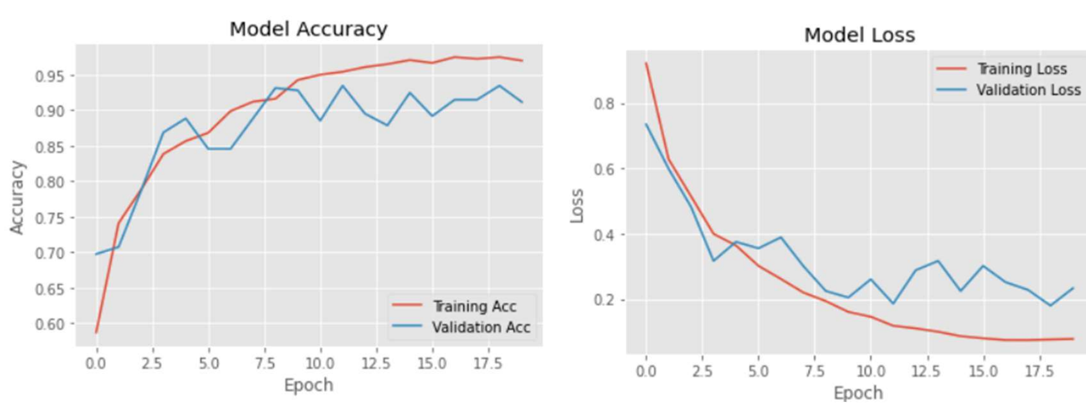

Figure 19: Model Accuracy and Loss of VGG16

4.2.5 VGG19:

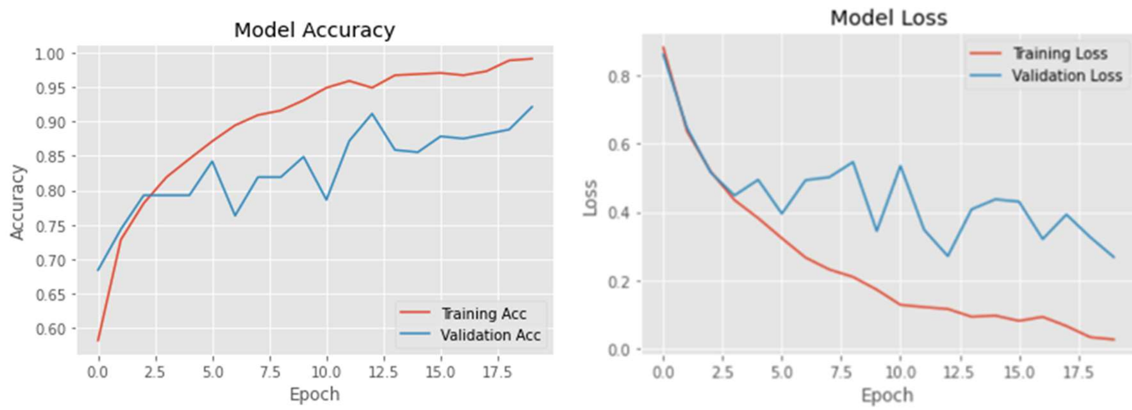

Figure 20: Model accuracy and model loss of VGG19

TABLE 2: CLASSIFICATION RESULTS OF USED MODELS

Name of the model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Xception	86%	81%	81%	80%
InceptionV3	86%	83%	83%	82%
VGG16	92%	91%	91%	91%
VGG19	92%	92%	92%	92%
DenseNet201	85%	83%	82%	82%

In table [2] there has the classification report of 5 models which I have implemented for the classification method. For xception the accuracy result is 80%, for InceptionV3 accuracy is also 82%, for VGG16 the accuracy is 91%, for VGG19 accuracy is 92% and for DenseNet201 accuracy is 82%. So, there we can see the accuracy of VGG19 is highest than any other model. So, we can say that it's a better model than other models.

After gaining the results I have visualize the comparison of the accuracy in (figure 21) and confusion matrix results in (figure 22).

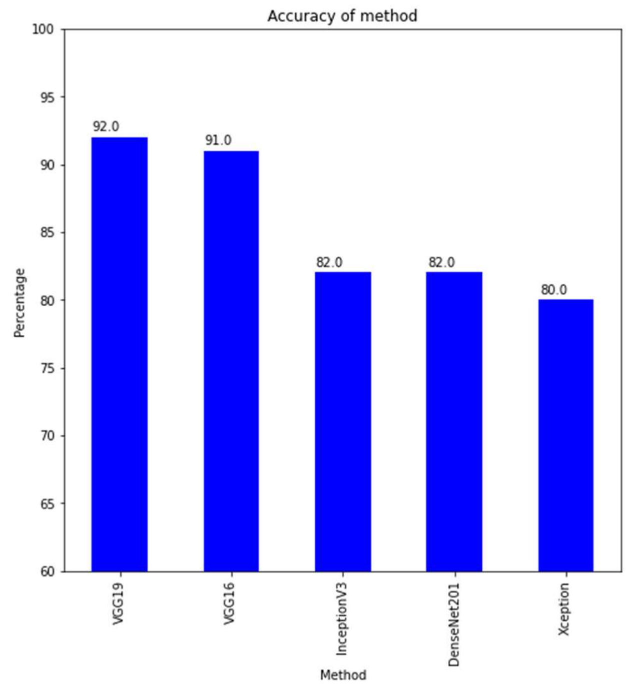

Figure 21: Comparison between Accuracy of all the applied models

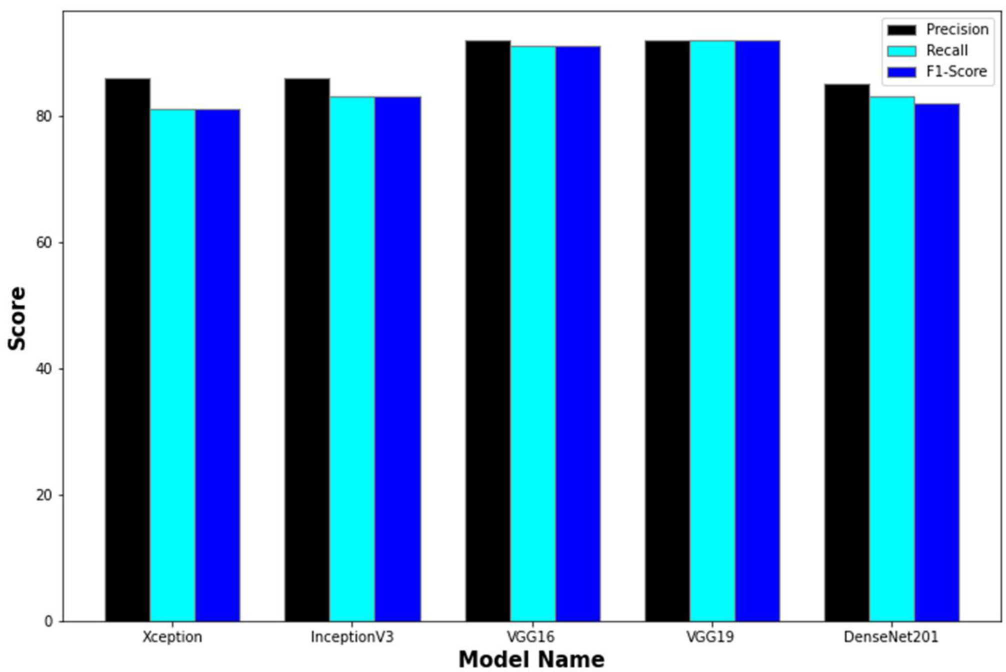

Figure 22: Comparison between Precision, Recall and F1-Score of all the applied models

CHAPTER 5
CONCLUSION AND LIMITATIONS

Road damages are a highly concerning issue because it is harmful to people along with vehicles. Manually maintained road damages are costly and time-consuming. For maintaining road damages, it will helpful for authorities if they can apply the automated system to classify which types of road damages are more dangerous and which types of damages are less dangerous. It will also help the drivers to avoid the road which is damaged, because it's harmful to the vehicles and can be injurious to the people and goods in the vehicle. So, from that idea, they can decide that which damage is most in need to repair, and which is less in need. In other countries, there have already built systems. By for a country like Bangladesh, it is difficult to use a system of high cost. So, with my work, I have tried to make a system that is a system of low cost. For the work, I have used the deep learning method. From deep learning, I have used the transfer learning method of a convolutional neural network. Transfer learning will make the system a low-cost system because with that it is possible to reuse the code. I have used 5 models of convolutional neural networks and all of them were transfer learning methods. They are Xception, InceptionV3, VGG16, VGG19, and DenseNet201. All the model's model accuracy, model loss, and classification results have been generated. But among all of the five models, VGG19's accuracy is higher. It gives an accuracy score of 92%, precision score of 92%, recall rate of 92%, and F1 score of 92%.

Limitations: in the work, the model's accuracy is not satisfactory. It may be because of a small dataset which is on basis of Dhaka city. Further, I will try to increase the dataset to get higher accuracy. And in my next work, I want to detect road damage along with other type of classifications of road damages.

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