DETECTION AND CLASSIFICATION OF ROAD DAMAGE USING R-CNN AND FASTER R-CNN: A DEEP LEARNING APPROACH

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THESIS DECLARATION

I announce hereby that I am rendering this study document under Md. Shohel Arman, Lecturer, Department of Software Engineering, Daffodil International University. I therefore state that this work or any portion of it was not proposed here therefore for Bachelor's degree or any graduation.

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ABSTRACT

Road surface monitoring is mostly done manually in cities Being an intensive process of time consuming and labor work. The intention of this paper is to research on road damage detection and classification from road surface images using object detection method. this paper applied multiple convolutional neural network (CNN) algorithm to classify road damage and find out which algorithm perform better in road damage detection and classification. We classify damages in three categories pothole, crack and revealing. For this work we collected data from street of Dhaka city using smartphone camera and prepossessed the data like image resize, white balance, contrast transformation, labeling. Our study applies R-CNN and faster R-CNN for object detection of road damages and apply Support vector Machine (SVM) for classification and gets a better result from previous study. We calculated loses using different loss function. We got the highest 99.08 % accuracy and the lowest loss is 0.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

The city road network is the core system of transportation. Many road accidents happened every day. The World Health Organization 2016 report showed that death rate in Bangladesh is 15.5 % because of road accident. Safety of transportation systems is a matter of concern for the government and for the general people with the comprehensive construction of roads. Road damage, particularly pothole or crack, not only represents discomfort but also a risk to s afety. One of the most important duties is road repair work of these problems for road safety. Road networks must be checked regularly in order to identify potential dangers and risks to maintain safety of road network. For real use, experienced workers are usually responsible for the detection of road diseases and this process is highly time consuming and costly. For this reason, we need a low-cost automated system to identify road damage. There are lots of automated systems to identify road damage based on sensor, this process is costly. Laser scanning continues to be the key technology for the acquisition of 3D road data. Through this paper we work on road damage detection and classification using image processing which low-cost intelligence system. In recent years, deep education in the field of computer vision has achieved remarkable results and has shown great effectiveness in many fields of research. This study we apply convolutional neural network algorithms for road damage object detection and classification we use SVM. Previously work done on road damage detection using image processing they use different algorithm. We apply R-CNN and faster R-CNN for this work and compare which algorithm works better for road damage detection.

1.2 MOTIVATION OF THE RESEARCH

Road damage is one of the main causes of road accident and effects on economy of a country. Experienced workers are usually responsible for the detection of road diseases. this process is highly time consuming and costly for this reason it is very difficult to maintain road safety for the development country. To solve this problem, we need a low-cost automated system to identify road damage which helps the government to solve road safety issue. There are lots of automated systems to identify road damage based on sensor, this process is costly. Deep learning base solution can solve the problem

1.3 PROBLEM STATEMENT

We found that many researches done previously in this field. They apply various CNN method and there is no common dataset on road surface like other object detection datasets. We collected data from street of Dhaka city using smartphone camera. We apply R-CNN and faster R-CNN for this work and compare which algorithm works better for road damage detection and classify road damage into three categories Crack, Pothole, Reveling.

1.4 RESEARCH QUESTIONS

The research question was

- RQ1: Which Convolutional Neural Network method perform better for deep learning base road damage detection?
- RQ2: Classify road damage in three categories.

1.5 RESEARCH OBJECTIVE

The objectives of this research are

- To find out the best performing Convolutional Neural Network method.
- To Classify the road surface damage in three categories.

1.6 RESEARCH SCOPE

The study gap was found in "Wang W, Wu B, Yang, S, & Wang, Z. (2018, December). Road damage detection and classification with Faster R-CNN. In 2018 IEEE International Conference on Big Data (Big Data) (pp. 5220-5223). IEEE" apply only Faster R-CNN and compare with pre train CNN model ResNet-101 and ResNet-152. In this study we compared R-CNN and faster R-CNN and try find out which perform better and classify road damage in three categories

1.7 THESIS ORGANIZATION

In the next chapter, we covered further study, including the research gap, on the same subject. Our proposed research methodology was covered in chapter three. We discussed the results of the analysis in chapter four. Ultimately, we addressed in Chapter Five the observations and suggestions, which include assumptions, limitations and future work.

CHAPTER 2

LITERATURE REVIEW

2.1 PREVIOUS LITERATURE

Multiple number of articles based on the task of road surface and road damage publishing and continuing to increase. A standard machine learning approach focused on Support Vector Machine (SVM) [1] has been developed for road pothole detection tasks. They extracted the image region function in this experiment focusing on the histogram and added non-linear SVM kernel to detect the target. The result showed that the pothole can be well and easily recognized in this study.

On paper while [3], a deep learning based, specifically Convutional Neural Network was used as a classifier to detect road crack damage from images. They build a classifier that is less influential by the noise from lighting, dark casting, etc. The benefits of this study are that it the current method, used by humans to perform the audit of road potholes [5] learning the feature automatically without carrying out any extraction and calculation process compared with conventional methods.

For automated crack detection a low-cost sensor and a deep Convutional Neural Network [4] were proposed. This experiment showed a Convutional Neural Network model that can learn from the features automatically without the extraction procedure of any feature. Before the model feed, the input images were annotated manually. Deep learning-a low cost strategy for the identification of road potholes to solve the problem.

N. Hoang developed an intelligence system [13] for pothole identification and tested it using two machine learning algorithms, including the least square support vector machine (LSSVM) and the Artificial Neural Network (ANN). The classification accuracy of LSSVM algorithm was approximately 89 per cent and the use of ANN was approximately 86 per cent.

A pothole detection system was developed by Ryu [14] to read images from an optical device installed in a car and a methodology was then proposed for detecting pothole from the collared data. The suggested method is used first for the removal of dark regions for the pothole using a histogram and the closing process with a morphology filter. The nominee pothole regions are then selected with different features, such as volume and compactness. Ultimately, when contrasting pothole and context, it is determined whether or not the applicant regions are potholes. With this method, the rating reliability of 73.5% was obtained.

Pothole identification vision-based approach is proposed by A. Akagic et al 2017 [15]. The method first separates the damaged areas from the color space of RGB and then segments the object on them. The quest then only takes place in the area of value derived (ROI). Their approach is appropriate for other supervised methods as a pre-processing stage. The reliability of their system relies on ROI exactness being obtained and 82% are correct.

2.4 RESEARCH GAP

We provided details on the research gap in Table 1 below and continued the study on the basis of this gap.

TABLE 1: LITERATURE REVIEW

Paper	**Year**	**Author**	**Objective**	**Data**	**Methodology**	**Conclusion**
Road Damage Detection and Classification with Faster R-CNN	2019	Wenzhe Wang, Bin Wu, Sixiong Yang, Zhixiang Wang	Provide a smart phone-based model to detect road damage	Road image of japan	Faster R-CNN	They achieve Mean F1-score is 0.6255
An Approach for Extracting Road Pavement Disease from HD Camera Videos by Deep Convolutional Networks	2018	Wei Xia	Extract road surface diseases in complex background from camera videos.	Building own dataset using labeling method	CNN	To minimize the manual workload, they provide a weakly controlled approach is built to generate road damage data set.
A Deep Learning-Based Approach for Road Pothole Detection in Timor Leste	2018	Vosco Pereira, Satoshi Tamura, Satoru Hayamiz, Hidekazu Fukai	A low-cost approach for detecting photo of road potholes through the use of a CNN.	Collect road image from south Africa, Bangalore and Rangoon	CNN	They achieve Mean F1-score is 99.60 %
Road Damage Detection Based on Unsupervised Disparity Map Segmentation	2019	Rui Fan and Ming Liu	Present a new algorithm for road damage identification based on unattended segmentation of	KITTI, ApolloScape, EISATS	Roll angle estimation	They were achieved through the minimum of power in terms of the stereo rolling angle and road disparity

			discrepancy maps.			
Convolutional neural networks based potholes detection using thermal imaging	2019	Aparna, Yukti Bhatia, Rachna Rai, Varun Gupta, Naveen Aggarwal, Aparna Akula	Implementation of information enhancement methods, a deep study approach to Convolutional Neural Networks was introduced, a new approach to thermal imaging in this problem area.	Use a thermographic camera to collect data	Thermal imaging	They achieve a 97.08 % accuracy

2.5 SUMMARY

Our study is motivated by the which method works better on our own dataset. We are going to apply in our study CNN based model R-CNN and faster R-CNN and the we compare which one perform better and classify image in three categories.

CHAPTER 3

RESEARCH METHODOLOGY

For this study we use convolutional neural network (CNN) for object detection. Our working procedure is in figure 1.

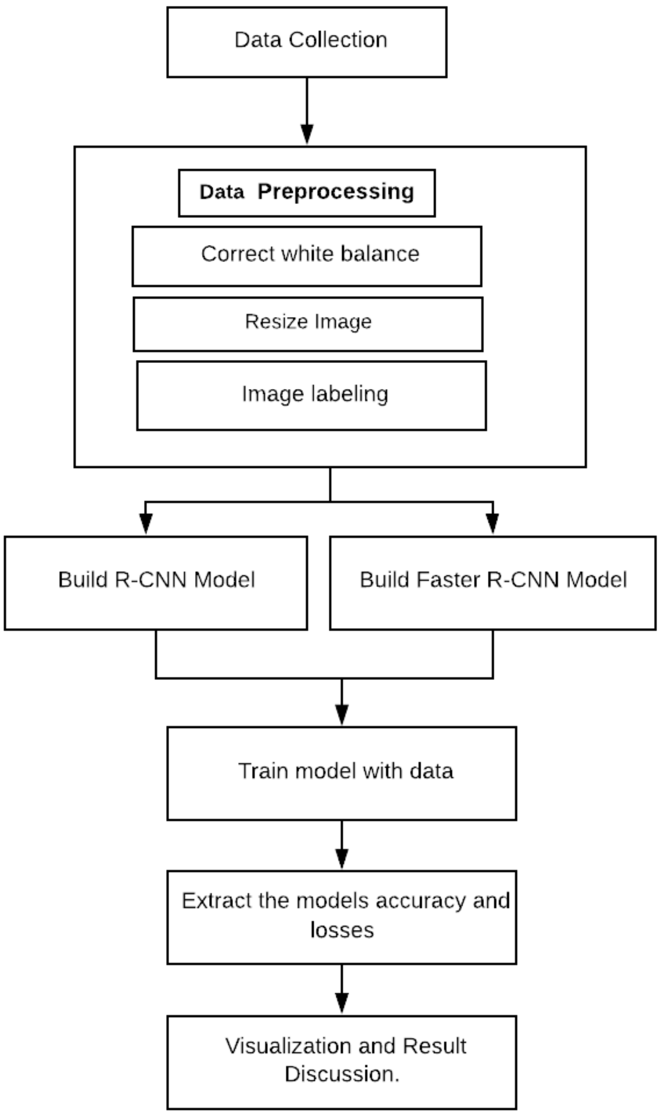

FIGURE 1: METHODOLOGY OF THE STUDY

3.1 DATA COLLECTION

In the road damage detection, there is no large-scale common dataset like other object detection dataset [6]. We go for build our own dataset with 1100 images. In this study we collect data from the street of Dhaka city using smart phone camera then we correct the image white balance and contrast transformation. Then resize image into 200 X 200 pixel. After that we labeling our image data with three category Crack, Pothole and Rivaling. Here is our sample data

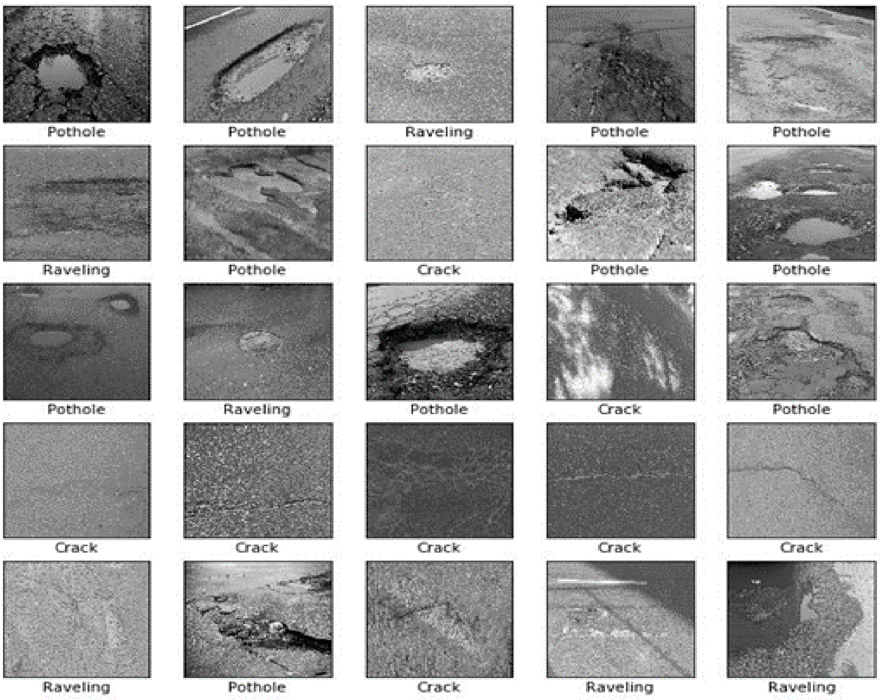

FIGURE 2: SAMPLE DATA

3.2 DATA PREPARATION

After collecting data of Dhaka city road surface, we resize image into 200 X 200 pixel and perform image white balance and contrast transformation then we use image labeling method to prepared our data set for our model. For labeling operation, we use open source image labeling tool LableIMG. We label our image data set into three class Crack, Pothole, Rivaling.

3.3 DEEP LEARNING BASED CLASSIFICATION

Artificial Neural Network classification is an incredibly popular way to solve the problem of pattern recognition. A fully connected neural network called a Convolutional Neural Network (CNN) was one of the essential components contributing to these tests. CNN's main advantage is that the important features are automatically detected without any human instruction. CNN model has two-part first part is for feature extraction and the second part works for classification. The first layer will attempt to identify edges and shape a model to detect the edge. Then instead layers may try to combine them in simpler ways. In first layer add filter to the image and try to extract the image edges. Second layer is polling layer also add filter to the image. This layer finds features more deeply from the image and each layer has RelU functionality which help to connect to the next neuron. Then flatten layer convert 3D image data to 2D data for classification.

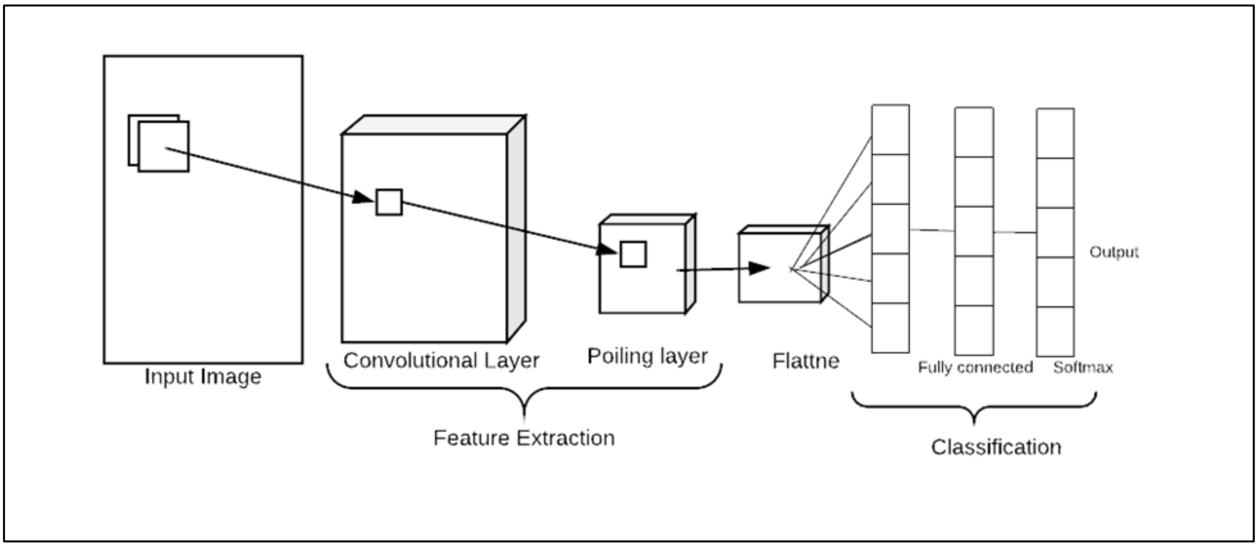

FIGURE 3: CONVOLUTION NEURAL NETWORK

3.4 R-CNN

In order to avoid the problem of picking a large number of regions, Ross Girshick, Jeff Donahue, Trevor Darrell and Jitendra Malik. proposed a method in which we use selective search to extract 2000 regions from the image and he called them regional proposals. So now you can only operate with 2000 regions rather than trying to identify a large number of regions. The selective search algorithm generates these 2000 region proposals. These proposals for 2000 candidate regions are twisted into a square and fed into a convolutional neural network that generates an output of 4096 features. The CNN is an extractor of features and the output layer includes the features collected from the picture then features extracted are fed into the SVM in order to identify the object's existence in the proposal for the applicant area.

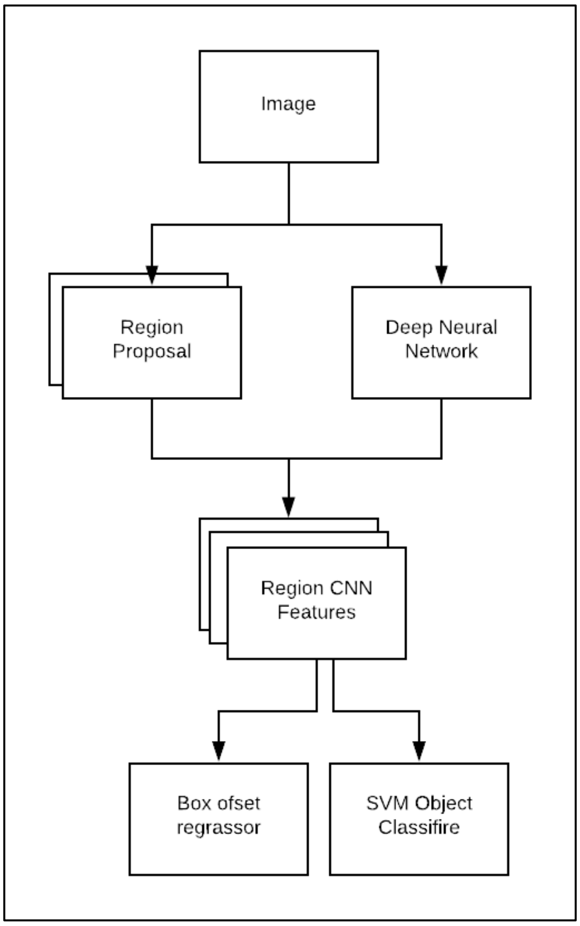

FIGURE 4:R-CNN WORKFLOW

3.5 FASTER R-CNN

Similar to the R-CNN, the picture is presented as a convolutional network input that gives a convolutional feature map. A different network is being used to predict regional proposals, in place of using a selective search method on the function graph. Then the predicted regional proposals are shaped using a RoI bundling layer to identify the object in the potential area and forecast the offset values for the border boxes.

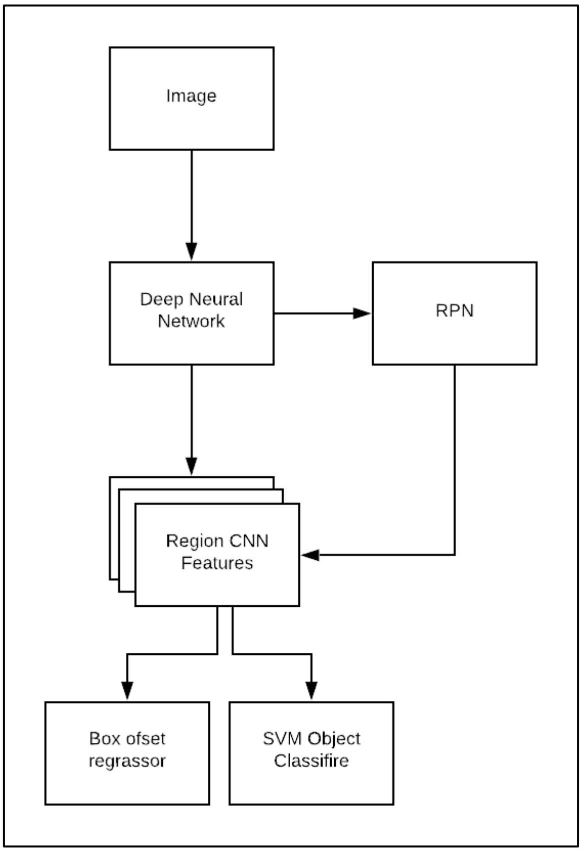

FIGURE 5: FASTER R-CNN WORKFLOW

3.6 EXPERIMENT

Our implemented model based on TensorFlow then the model was trained for 50 epochs 1100 of training dataset set and validate with 200 dataset and use optimizer to reduce the cost function [7], Our model has three convolutional and pooling layers and one fully connected layer. A Rectified Linear Unit (ReLU)activation function [13] is implied between the convolutional and pooling layers. The ReLU has the simplification form R[i] = max (i, 0) in its linear function in part. It maintains only the beneficial activation value by decreasing the negative component to null while the built-in max operator facilitates quicker calculation. Filter size 3, pooling size 2, Phase 1 and zero-padding are hyperparameters. In the last fully connected layer provides the classification of the input. We use Adam optimizer and for the losses calculation we used Categorical Crossentropy function, here N is the number of dataset and C is the total number of classes and probability predicted by the value of ***i*** observation to the value of ***c*** category**.**

$$SGC(p,t) = -\frac{1}{N}\sum_{c=1}^{c} 1_{y_i} \in C_c \log P_{model}(Y_i \in C_c)$$

3.7 SUMMARY

We are going to find out which Convolutional Neural Network method perform better for the road damage detection and classify road damage in three categories.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 ANALYSIS TECHNIQUE

Our analysis was done using python and numerical computation library by google TensorFlow and machine leaning library scikit learn and as an IDE we used Jupyter Notebook. Convolutional Neural Network method use for this research.

4.2 EVALUATION METRICS

We compare the actual values and the predicted values to calculate the accuracy of the R-CNN and Faster R-CNN model. Assessment indicators play a key role in building a model because it gives visibility into places that need change.

TABLE 2: EVALUATION METRICS

	Predicted class		
Actual class		Yes	No
	Yes	True Positive	False Negative
	No	False Positive	True Negative

Here,

- TP= True Positive
- TN= True Negative
- FP= False Positive
- FN = False Negative

Accuracy

Accuracy is the most natural indicator of performance. It is simply a ratio of correctly predicted observation to the total observations. For our faster R-CNN we got 0.998 that means our model predict road damage 99.8 % accurately.

$$Accuracy = TP + TN \div TP + FP + FN + TN$$

Precision

Precision is the proportion of positive measurements correctly forecast to the total positive analyses expected. this metric answer, the question of how much passengers have truly survived?

$$Precision = TP \ \div TP + FP$$

Recall

Recall the proportion of accurately projected positive results to all actual class observations-yes. The answer to the question is: How many objects did we mark of all who have really true?

$$Recall = TP \ \div TP + FN$$

F1 Score

F1 Ranking is the exact and remember weighted ranking. The score also takes into account all false positives and false negatives. It is intuitively less easy to understand than accuracy; but F1, particularly if you have an inconsistent class distribution, is usually more useful than accuracy.

$$F1\ Score = 2 * (Recall * Precision) \div (Recall * Precision)$$

4.3 VISUALIZATION

4.3.1 FASTER R-CNN ACCURACY

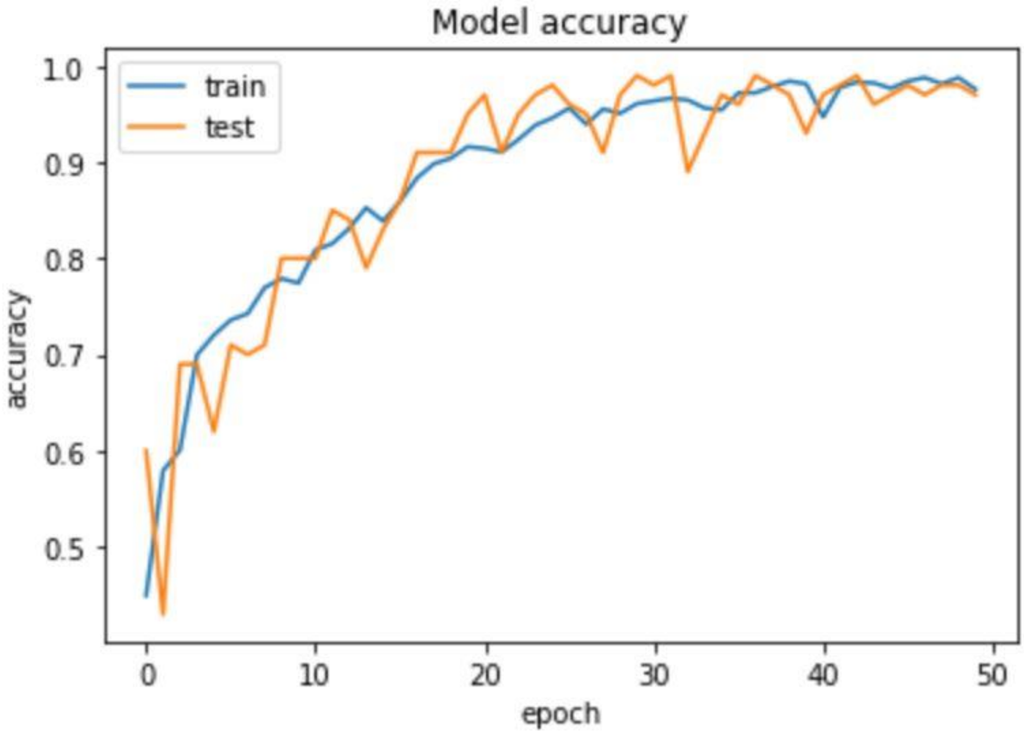

FIGURE 6: FASTER R-CNN ACCURACY

Two variable accuracy and epoch. We train our model with 50 epochs. From the graph showed that increases the accuracy with number of epochs.

4.3.2 FASTER R-CNN LOSS

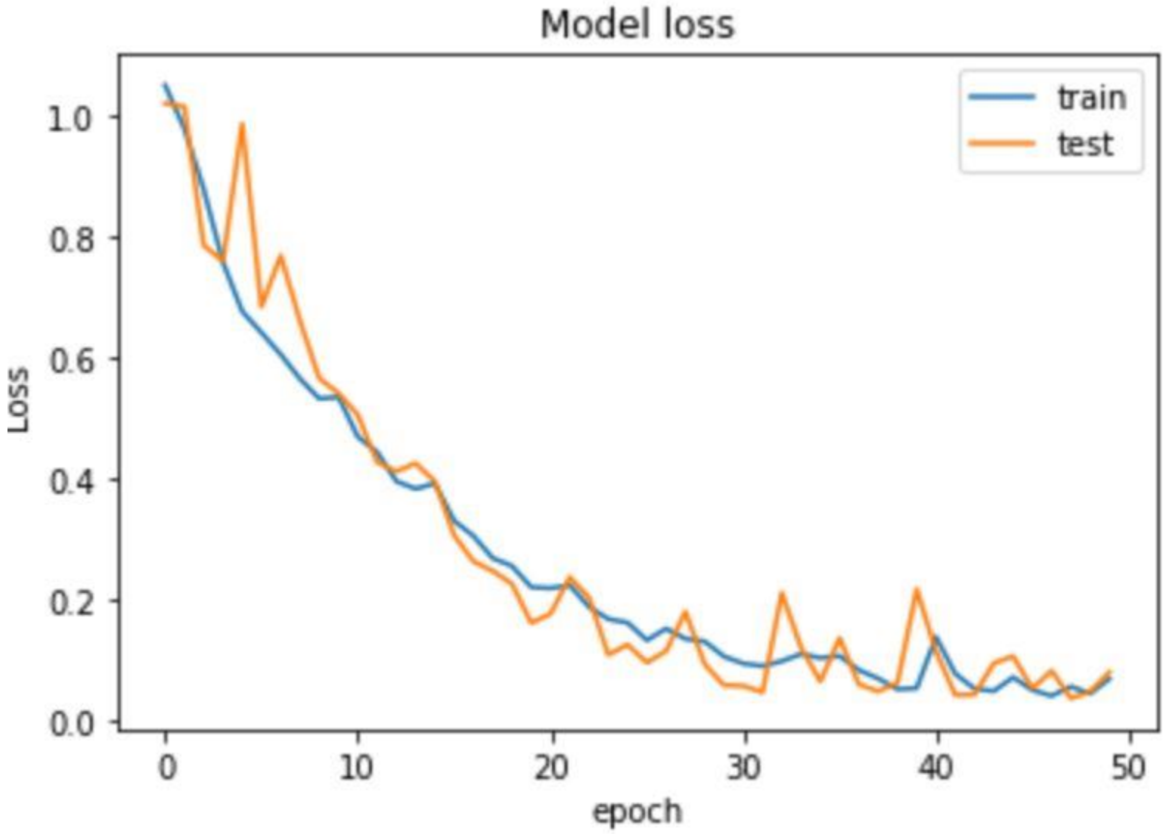

FIGURE 7: FASTER R-CNN LOSS

Two variable loss and epoch. We train our model with 50 epochs. From the graph showed that decreases the loss with number of epochs.

4.3.3 R-CNN ACCURACY

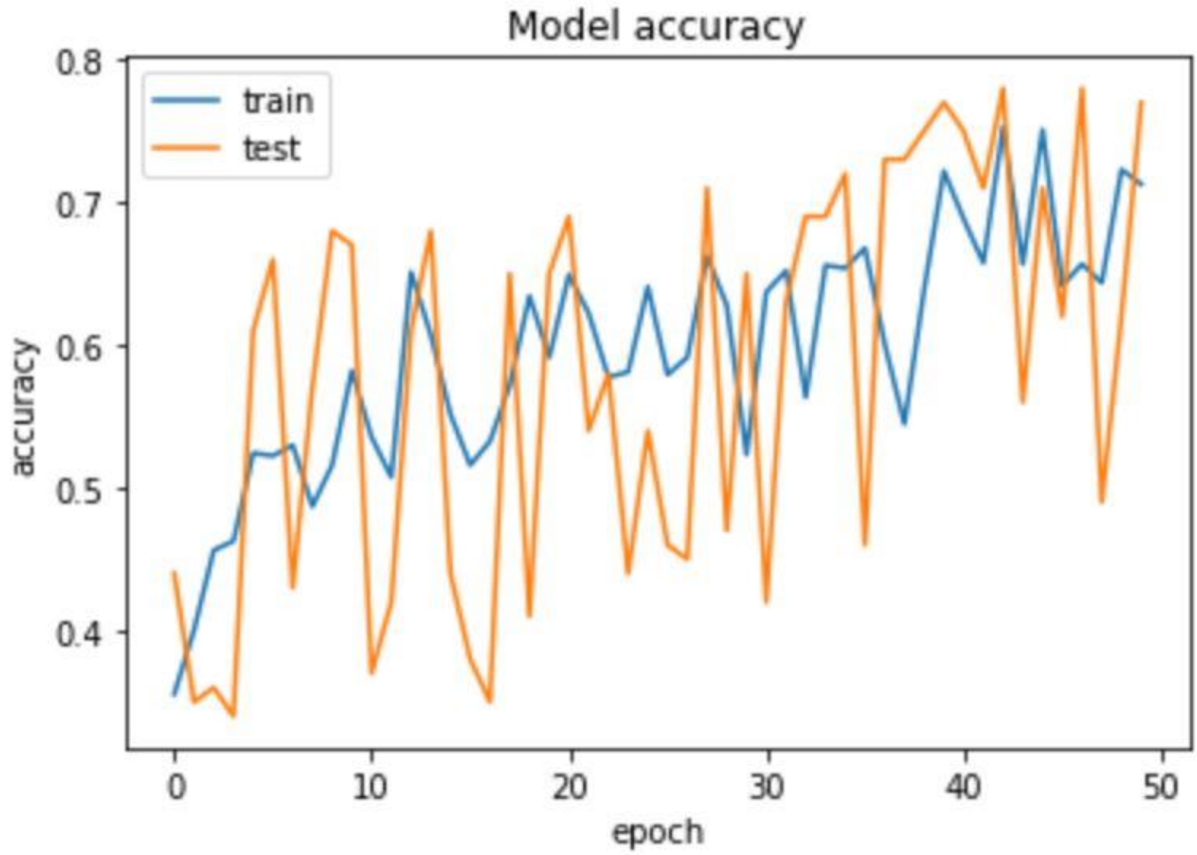

FIGURE 8: R-CNN ACCURACY

This model is not fit for road damage detection

4.3.4 R-CNN LOSS

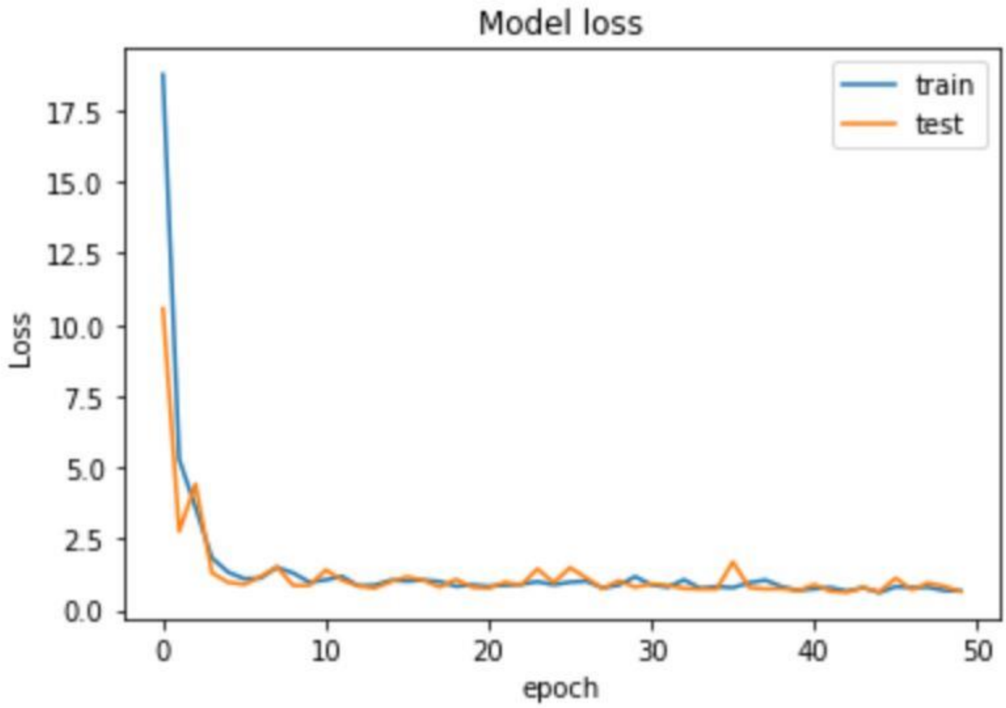

FIGURE 9: R-CNN LOSS

This model has higher late of loss so that this R-CNN model is not recommended for road damage detection.

4.4 EVALUATION METRICS TABLE

Here is the comparison table of accuracy and loss from our study result of the two method of road damage detection R-CNN and faster R-CNN.

TABLE 3 :ACCURACY AND LOSS

Algorithm	Accuracy	Validation Accuracy	Loss	Validation Loss
Faster R-CNN	98.02 %	99.80 %	0.03	0.01
R-CNN	71.44 %	76.01 %	0.70	0.63

4.5 F1 SCORE TABLE

Here is the Precision, Recall and the F1 score of the two CNN Model of Faster R-CNN and R-CNN

TABLE 4: F1 SCORE

Algorithm	Precision	Recall	F1 Score
Faster R-CNN	0.99	0.97	0.98
R-CNN	0.661	0.618	0.61

4.5.1 VISUALIZATION OF EVALUATION METRICS

Competitive evaluation metrics score visualization of faster R-CNN and R-CNN

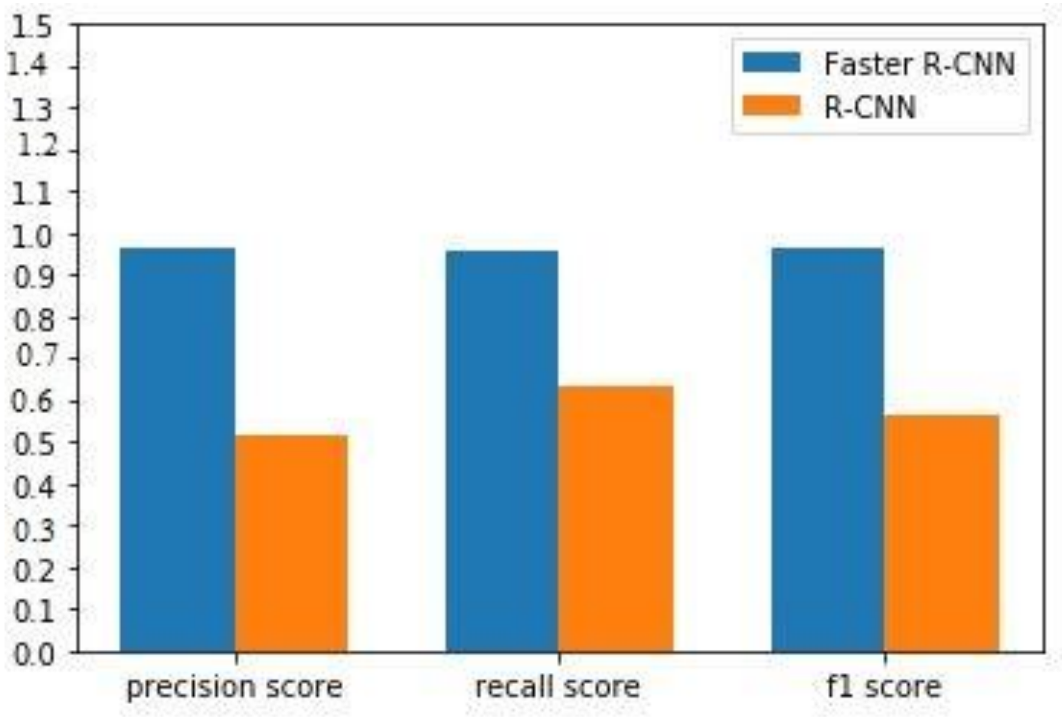

FIGURE 10 : EVALUATION METRICS

Here this graph showed that in every metrics result Faster R-CNN is better the R-CNN method.

4.5 CLASSIFICATION PREDICTION RESULT

After training of our model, we tested on our test data set. From previous discussion we already know that faster R-CNN works better the R-CNN. Here is the prediction result of faster R-CNN.

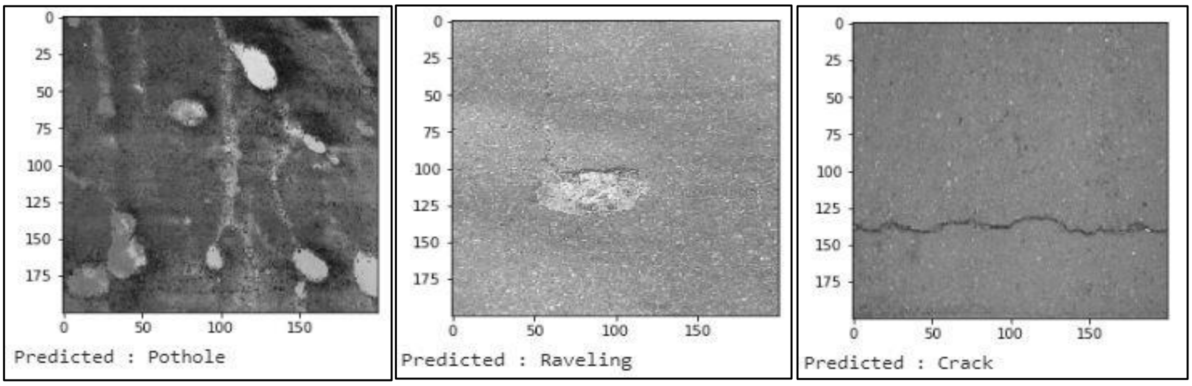

FIGURE 11: PREDICTION RESULT

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 FINDINGS AND CONTRIBUTIONS

The research goal of this study was to investigate which CNN model works better for road damage detection and classification. We collected data from the Dhaka city road surface. We collect total 1300 image of road surface then label image data into their classes Crack, pothole and rivaling. We tried to fit the data with R-CNN and Faster R-CNN model. We use 1100 image for training the test with 200 data then we evaluated our model with evaluation metrics. For evaluation we use F1 Score, Precision and Recall metrics. Evaluation result showed that Faster R-CNN better fit then R-CNN model and classification result is also better. The road damage detection using deep learning methods can help in the maintenance of the road conditions in low cost. We compare two CNN method to identify which work better for road damage detection and we develop a new dataset on specifically road damage image, hope this will help on future work on this field. In Further, this work can be extended to transportation system. Extend parameters to predict the repairing cost of road damage and which it can be figured out which area requires urgent repair work.

5.2 LIMITATION

It must be remembered that there are several limitations. In deep learning prediction need huge number of data but in road damage there is no common dataset for the work. It is very hard to collect road damage data.

5.3 RECOMMENDATIONS FOR FUTURE WORKS

Future work this dataset of road damage can help. Extend parameters to predict the repairing cost of road damage and which it can be figured out which area requires urgent repair work. To the best of my memory this is the first dataset of Bangladesh road damage.

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