PROJECT REPORT

On

SURFACE CRACK DETECTION

Table of contents

Sr. No.	Contents	Page No.
1	List of Figures	3
	List of Tables	4
2	**Chapter 1**	
	Introduction	5
3	**Chapter 2**	
	Review of the related Literature and Present Scenario Gap findings and Problem Statement	8
	Scope and Objectives of Project	14
4	**Chapter 3**	
	Block Diagram	15
	Explanation of Block Diagram	16
5	**Chapter 4**	
	Implementation and Experimental Results	18
6	**Chapter 5**	
	Conclusion and Future Scope	22
7	References	23
	Dataset Samples	25

LIST OF FIGURES

Fig 3.1- Steps followed in implementation

Fig 4.1- Training and validation accuracy plot for Basic model

Fig 4.2- Training and validation accuracy plot for Wider model

Fig 4.3- Training and validation accuracy plot for Deeper model

Fig 4.4- Training and validation accuracy plot for Batch normalization model

Fig 4.5- Training and validation accuracy plot for Global average pooling model

Fig 4.6- Crack is detected on given input

Fig 4.7- No Crack is detected on given input

Fig 6.1- Sample images for positive and negative class

Fig 6.2 -Sample images for positive class

Fig 6.3- Sample images for negative class

LIST OF TABLES

Table 2.1- List of publication and authors

Table 4.1- Comparison of models based on accuracy

CHAPTER 1: INTRODUCTION

Texture analysis is utilised in a wide range of domains and applications, ranging from texture classification (for example, in remote sensing) to segmentation (for example, in biomedical imaging), as well as picture synthesis and pattern recognition (e.g., for image in painting). Texture is a property that is used to divide and classify images into regions of interest. In an image, texture offers information about the spatial distribution of colours or intensities. The spatial distribution of intensity levels in a neighbourhood defines texture. As data is transformed into meaningful, usable insights, supervised machine learning is applied. It allows businesses to use data to better understand and prevent undesirable consequences while also increasing intended goals for their target variable.

Crack classification is a method of applying machine learning algorithms to identify a certain crack type. Crack detection is the process of detecting or recognising the presence of a crack, whereas crack classification is the process of classifying the crack based on the feature retrieved from the crack region.

Crack detection is critical for discovering cracks and determining the health of a structure during a building inspection.

Cracks are a key source of concern for structures safety, durability, and serviceability. Buildings, bridges, roads, pavement, railway tracks, automobiles, tunnels, and aircraft all have cracks. The presence of a fracture reduces the value of civil infrastructure, necessitating its detection. The reason for this is that as cracks develop and spread, they tend to reduce the effective loading area, resulting in an increase in stress and, eventually, failure of the concrete or other structures. Because reinforced concrete constructions are always constrained, and buildings deteriorate over time, cracking appears unavoidable in all sorts of structures, including concrete walls, beams, slabs, and brick walls. Cracks in concrete parts, in particular, allow dangerous and corrosive chemicals to enter the structure, compromising its structural integrity as well as its aesthetics.

The reason for this is that as cracks develop and spread, they tend to reduce the effective loading area, resulting in an increase in stress and, eventually, failure of the concrete or other structures. Because reinforced concrete constructions are always constrained, and buildings deteriorate over time, cracking appears unavoidable in all sorts of structures, including concrete walls, beams, slabs, and brick walls. Cracks in concrete parts, in particular, allow dangerous and corrosive chemicals to enter the structure, compromising its structural integrity as well as its aesthetics.

Overloading, seepage, inappropriate or inadequate road surface drainage, lack of proper maintenance, lack of proper design, bad weather conditions, and other variables are all major causes of pavement deterioration and degradation. Road distresses disrupt and negatively impact traffic flow and safety, resulting in poor road performance. They also raise gasoline prices, cause traffic delays, and are inconvenient for all road users. Early detection of road cracks is critical because preventive structural maintenance and appropriate repair procedures can be implemented before the condition worsens and the pavement fails. Pavement maintenance saves a lot of money since it prevents the pavement from failing. So, main purpose is to detect crack on the surface by using various image processing techniques and machine learning methods.

Various machine learning models like CNN, DNN can be used. Also there are different classifiers like SVM, Decision Tree, Random forest is used in the feature extraction.

Pavement Distresses, whether minor or major, are a concern to the person and can become dangerous if left unattended for an extended length of time when their condition deteriorates. As a result, proper, timely, and selective maintenance becomes a fundamental element that extends the life of the pavement while also lowering maintenance costs.

CHAPTER 2: RELATED WORK

No	Publication	Authors
1	Road crack detection using convolutional neural network Bhat et al. / Indian Journal of Science and Technology 2021;14(10):881–891	Sharmad Bhat, Saish Naik, Mandar Gaonkar1, Pradnya Sawant1, Shailendra Aswale1, Pratiksha Shetgaonkar1
2	Road crack detection using deep CNN IEEE 2016	Lei Zhang, Fan Yang, Yimin Daniel Zhang, and Ying Julie Zhu
3	Automated road crack detection using CNN, 2018 IEEE International Conference on Big Data (Big Data)	Vishal Mandal, Lan Uong, Yaw Adu-Gyamfi
4	Sample and structured guided Network for road crack detection, IEEE 2019	Siyuan Wu, Jie Fang, Xiangtao Zheng, Zijie Li
5	Road Crack Detection using a Single Stage Detector Based Deep Neural Network, 2018 IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems (EESMS)	Carr, Thomas Arthur; Jenkins, Mark David; Iglesias, Maria Insa; Buggy, Tom; Morison, Gordon
6	Feature Pyramid and Hierarchical Boosting Network for Pavement Crack Detection, IEEE January 2019	Fan Yang, Lei Zhang, Sijia Yu, Danil Prokhorov, Xue Mei, and Haibin Ling
7	Road Crack Detection Using Deep Convolutional Neural Network and Adaptive Thresholding, IEEE 2019	Rui Fan1, Mohammud Junaid Bocus2, Yilong Zhu, Jianhao Jiao1, Li Wang, Fulong Ma, Shanshan Cheng, Ming Liu1
8	An integrated machine learning model for	Abbas Ahmadi, Sadjad

	automatic road crack detection and classification in urban areas, International Journal of Pavement Engineering 2021	Khalesi & Amir Golroo
9	Concrete crack detection based on well-known feature extraction model and YOLO v2 network, Applied science, 2021	Shuai Teng, Zongchao Liu, Gongfa Chen, Li Cheng
10	Automatic Pavement Crack Detection Based on Structured Prediction with the Convolutional Neural Network, IEEE 2018	Zhun Fan, Senior Member, IEEE, Yuming Wu, Jiewei Lu, and Wenji Li
11	Deep convolution neural network for crack detection on asphalt pavement, ICoNSET 2019, IOP	N A M Yusof, A Ibrahim, M H M Noor, N M Tahir, N M Yusof and N Z Abidin, M K Osman
12	Road Crack Detection and Classification Using Deep Learning, International Research Journal of Engineering and Technology (IRJET), 2021	Harshal Bhoir1, Amitkumar Pandey2, Rushikesh Patil3, Aparna Bhonde
13	Review and analysis of crack detection and classification techniques based on crack types, International journal of applied engineering and research, 2018	Sheerin Sitara, N. Kavita, S. Raghuraman G.
14	Building Crack Due to Lombok Earthquake Classification Based on GLCM Features and SVM Classifier, 2019 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)	Gede Pasek Suta Wijaya, Chaerus Sulton, Ida Bagus Ketut Widiartha, Ni Nyoman Kencanawati
15	Fully Automated Road Defect Detection Using Street View Images, conference 2017	David B. Abou Chacra, John S. Zelek

Table 2.1 List of publications and authors

There has been a lot of research done in this area. Above is a list of the publication and its writers.

In this paper, image processing is employed to detect road cracks using a convolutional neural network [1]. We can distinguish between crack and non-crack photos using this method. The purpose of this research is to examine and compare various crack detection methods and technologies. They created a CNN-based model with a variety of layer types and activation functions. Pre-processing techniques include greyscale conversion and image scaling. The testing process detects whether or not the image has cracks. After that, the model is compared to other models in the same domain. ResNet, VGG 16, and VGG 19 were employed as comparison models. Training time, accuracy, validation accuracy, loss, and validation loss are all used to make the comparison. Furthermore, the model assesses whether or not the discovered crack is of the longitudinal type. For CNN, they were able to reach a 0.99 accuracy rate.

The supervised deep learning method is employed in this research work to detect road cracks using deep CNN [2]. For classification, the ConvNet model achieved 0.8686 precision, 0.9251 recall, and an F1 score of 0.8965. In comparison, SVM and boosting ConvNet were utilized, and they discovered that boosting is ineffective. It was discovered that using the suggested deep learning framework, the learnt deep features improve crack detection performance.

The YOLO v2 model is utilized for automated road crack identification using CNN [3]. 9053 photographs were taken with a smartphone mounted on the car. CNN is used to assess distress. In this study, they used a deep learning framework to detect and classify different types of cracks automatically. The F1 score for detection without crack class prediction was 0.8780, and for classification with crack class prediction was 0.7394. The distress analyzer they devised is more accurate in evaluating alligator cracks but suffers with transverse cracks, it was discovered. The discrepancy in crack detection accuracy was primarily due to inaccurate crack labelling in the picture, background image, and shadow formation. Google street photos can be used for crack information in the future.

This research introduces a sample and structured guided network for detecting road cracks [4], as well as a sample and structured guided network for detecting road cracks. Self-attention method is employed in the Unet model to improve stability by encoding 2-order information. Test technique is utilized on 4 dataset image processing procedures such as contrast enhancement to improve generalization capabilities among local region into final features. Photographed photographs, on the other hand, are not labelled.

An application of residual network to automatically detect road and pavement surface fractures is proposed here: road crack detection utilizing single stage detector based DNN [5]. CrackForest dataset was trained using a feedforward ResNet architecture. The research reported in this study focuses on fracture detection in photographs of road and pavement surfaces. RetinaNet is the name of the neural network that was used. RetinaNet is based on a ResNet-based Feature Pyramid Network that achieves the accuracy of a two-stage detector in a single-stage detector.

Pavement fracture detection using a feature pyramid and hierarchical boosting network [6], To deal with difficult examples, a hierarchical boosting module is developed, which reweights samples in a hierarchical manner. For crack identification, it combines context information with low-level features. A new method of calculating average intersection union is proposed. For edge detection, the sematic segmentation method was applied to 5 crack datasets. However, it was limited in terms of computer resources and the number of photos available for the crack dataset.

An adaptive picture segmentation, adaptive thresholding method is utilized here to detect road cracks using deep CNN and adaptive thresholding [7]. It was discovered that 99.55 percent accuracy was attained. Middle East University provided the dataset, which included 40000 photos. Image segmentation based on clustering is also employed. They achieved a precision of 99.92 percent for picture classification in this study. 98.70 percent accuracy was attained for pixel level segmentation. However, some color photos with noisy pixels cannot be segmented successfully. As a result, deep neural network can be trained to segment semantically significant regions. We can design an app in the future that takes into account more facts about fractures and types. The severity of the situation can be measured further.

An integrated ML model for automatic road crack detection and classification in urban environments [8], an integrated model is suggested in this study to detect road cracks and classify them into different categories. Various techniques and algorithms, such as picture segmentation, noise reduction, feature extraction, crack classification, heuristic algorithm, Hough transform technique, and heuristic equation, were used to achieve the best results. Various classification models are compared, and a hybrid model is proposed. The dataset utilized was taken from the Tehrun Urban Area. Traverse cracks, longitudinal cracks, diagonal cracks, block cracks, and alligator cracks were detected as a result of this. The accuracy of this hybrid model was 93.86 percent. Severity can be calculated for future work.

The CNN model is employed to detect concrete cracks using a well-known feature extraction model and the YOLO V2 network [9]. They discovered that YOLOv2, ResNet is the best in terms of computing and speed in this study. They reached a precision of 0.89 with these, and the dataset utilized consisted of 990 RGB concrete crack photos.

A convolutional neural network (CNN) is utilized to learn the structure of the fractures from raw images without any preprocessing in automatic pavement crack detection based on structured prediction with CNN [10]. Crack detection is represented as a multi-label classification problem, using small patches collected from crack images as inputs to produce a huge training database, a CNN trained, and crack detection modelled as a multi-label classification problem. The method is compared to five other ways after being evaluated on two public databases.

This research proposes a deep convolutional neural network (DCNN) architecture for crack identification on asphalt pavement [11]. In a deep convolutional neural network, three convolution layers were used. They were able to detect the presence of cracks with a precision of 99 percent, recall of 98 percent, and accuracy of 99 percent. Overall, 94.5 percent accuracy was attained. Traverse, longitudinal, and alligator cracks have been observed. However, there was an issue with the background noise. As a result, the pixel method can be modified in the future to classify different types of cracks.

YOLO is utilized to discover and classify road cracks using a deep learning algorithm [12], and cracks have been identified. Picture Resizing, CLAHE Filtering, and Image Standardization were performed to the existing image collection for data pre-processing. YOLO (You Only Look Once), the deep learning model utilized, was able to effectively find and recognize more than one type of crack for a given image with good accuracies. The resulting image outputs were transformed to a downloadable text file so that the user could easily access information about the photographs evaluated. The user will receive an output file that includes a report on accuracy, photographs with cracks or without cracks, and images taken from several Japanese cities. The data is collected using a camera, and seven different types of cracks have been found, including longitudinal, construction, and pothole cracks.

This study includes a survey on various cracks, as well as a review and analysis of crack detection and classification algorithms based on crack types [13]. For easier identification, the wavelet processing approach and singular value decomposition are used to enhance the image. The outcomes can be assessed using quantitative measurements.

Building crack classification due to the Lombok earthquake using GLCM features and SVM classifier [14]. In this study, they used GLCM features and SVM classifier to classify cracks into mild, moderate, and severe categories. Instead of utilizing quantitative measures such as height and width, they discovered that GLCM features such as energy, contrast, homogeneity, correlation, and entropy give high results. Morphological filtering was utilized in this study, and two datasets were used: CDLE and MTU. Based on the results of the experiments, the suggested method has successfully classified two crack classes (moderate and severe), with 94.44 percent accuracy, 88.89 percent precision, and 100.00 percent recall. While the accuracy, recall, and precision for three crack classifications (mild, moderate, and severe) were 81,48 percent, 81,41 percent, and 88,09 percent, respectively.

They recognized deteriorated roads from street view pictures and pinpointed cracks within them using fully automated road fault detection [15]. Computing fisher vectors on local SIFT, contour weights to determine severity predicts the distress region. It was possible to reach a precision and accuracy of 93%. Gaussian voting is used to locate areas of deterioration on the road. For crack detection, an ultra-metric contour map is used. However, the classifier developed for the KIIT dataset did not generalize well. As a result, it will be able to be trained and evaluated on PCI data in the future.

GAP FINDINGS AND PROBLEM STATEMENT

GAP FINDINGS

- From the above literature review following were the gap findings:
- Not Enough data to train the models accurately.
- Many datasets had an imbalance in the data as there no enough images present for different types of cracks.
- Alternative denoising techniques can be proposed, as there was problem with noisy background.
- Algorithm can be more generalized in detecting severity level as it is not calculated in research work.

PROBLEM STATEMENT

Building a CNN model based on historical data which will be able to detect whether the crack is present in the image or not, when we provide any image to the model.

SCOPE AND OBJECTIVE OF THE PROJECT

SCOPE

Cracks can be seen on various Buildings, bridges, roads, pavement, railway tracks, automobiles, tunnels, and aircraft. The presence of a fracture reduces the value of civil infrastructure, necessitating its detection.

Crack detection and classification techniques combined with quantitative analysis are essential for determining the severity of a crack. Manual inspections might take a long time and require additional people. This isn't the best approach, thus to automate the process, various machine learning methods can be employed to detect cracks and then determine their severity levels.

OBJECTIVE

- To study different machine learning methods for crack detection.
- To detect and classify the cracks on the surface into binary classes based on image processing by using supervised learning method with the help of CNN model.
- To present, compare and analyze recently findings in the surface crack detection.
- To simulate and compare the proposed scheme outcomes with existing crack detection approaches.

CHAPTER 3: METHODOLOGY

BLOCK DIAGRAM

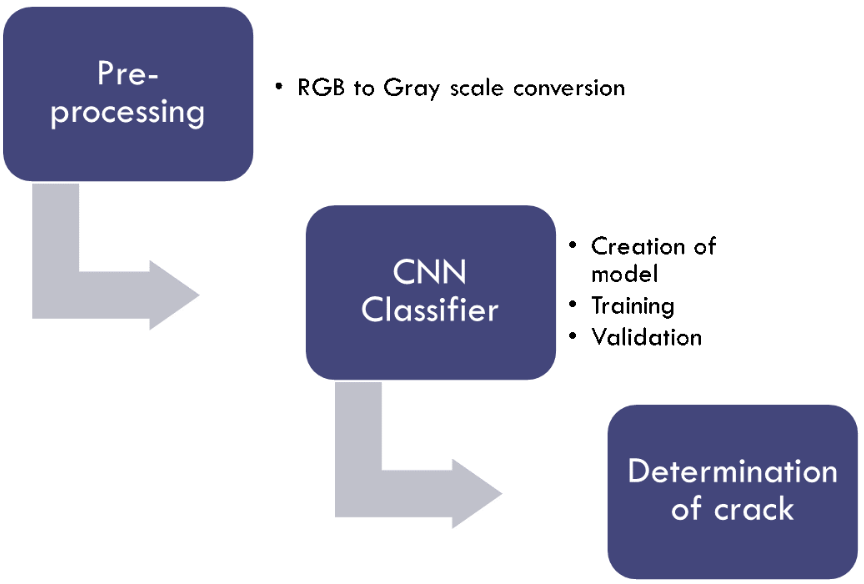

Fig. 3.1 Steps followed in implementation

EXPLNATION

There are 3 main steps which are listed below in crack detection and classification:

1. Pre-processing – The actions taken to format images before they are utilized in model training and inference are known as image preprocessing. This covers resizing, orienting, and color corrections, among other things. This phase includes two steps gray scale conversion and resizing of image.

2. CNN classifier

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take an image as input, assign importance (learnable weights and biases) to distinct aspects/objects in the image, and distinguish one from the other. This method can be used in classification purpose.

3. Determination of crack.

Training and testing model is performed to determine whether the crack is there in the image or not. Output size is set to 127*127 pixel.

First images are being collected from various sources in the form of database. After the collection images, the database goes through several preprocessing techniques like gray scale conversion and resizing of data. The conversion of color image into a grayscale image is converting RGB to values (24 bit) into grayscale values (8 bit).

In the classification phase, the processed images undergo through the layers of classifiers where in the image are classified as crack or no crack.

During testing phase, images with crack and no crack are detected and classified into two types as crack or no crack.

Basic CNN model consists of 3 convolution layers where each convolution layer is followed by max pooling layer. The output produced by this layer goes thorough flatten layer followed by two dense layers in order to improve the accuracy. The model is built by adding more layers like dense layer, ReLu in between to test it and to compare it with the basic model. Sigmoid function is used as activation function in the model for generating output.

Training and testing are set to 70:30 and accuracy graph is plotted for training loss as well as validation loss of the model. As there are total 40,000 images in total, which are labeled as positive and negative classes. In testing phase, model is used to classify the crack or no crack in the given image.

CHAPTER 4: IMPLEMENTATION AND EXPERMENTAL RESULTS

DATASET DETAILS

- This dataset is taken from the website Mendeley Data - Crack Detection.
- The datasets contain images of various concrete surfaces with and without crack.
- The image data are divided into two as negative (without crack) and positive (with crack) in separate folder for image classification. Each class has 20000 images with a total of 40000 images with 227 x 227 pixels with RGB channels.

Initially, CNN model is implemented using 3 basic layers, then in wider and deeper model 2 more convolutional layers have been added. Then in batch normalization model, normalization layer is used to map the features in the same distribution. Then global average pooling layer is added in next model as it reduces the problem of overfitting the data.

CNN model is implemented Training and Validation Scores of CNN models:

- Basic model

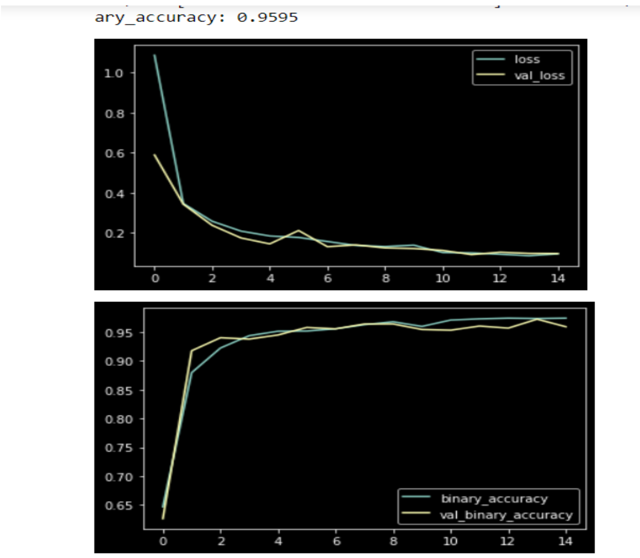

Fig 4.1 Training and validation accuracy plot for Basic model

- Wider model

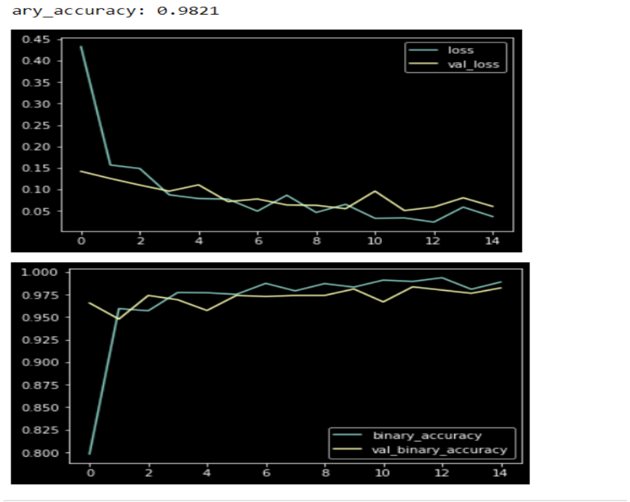

Fig 4.2 Training and validation accuracy plot for Wider model

- Deeper model

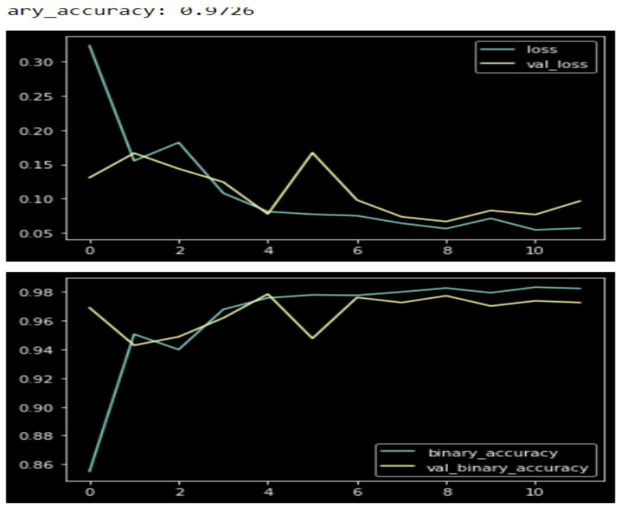

Fig 4.3 Training and validation accuracy plot for Deeper model

- Batch normalization model

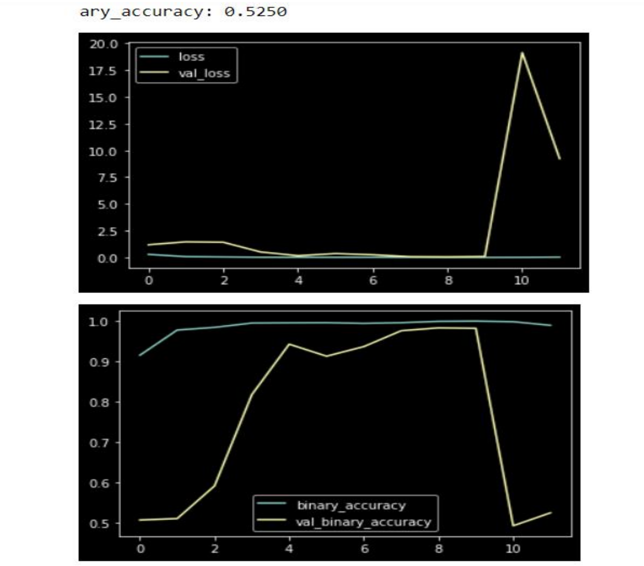

Fig 4.4 Training and validation accuracy plot for Batch normalization model

- Global average pooling model

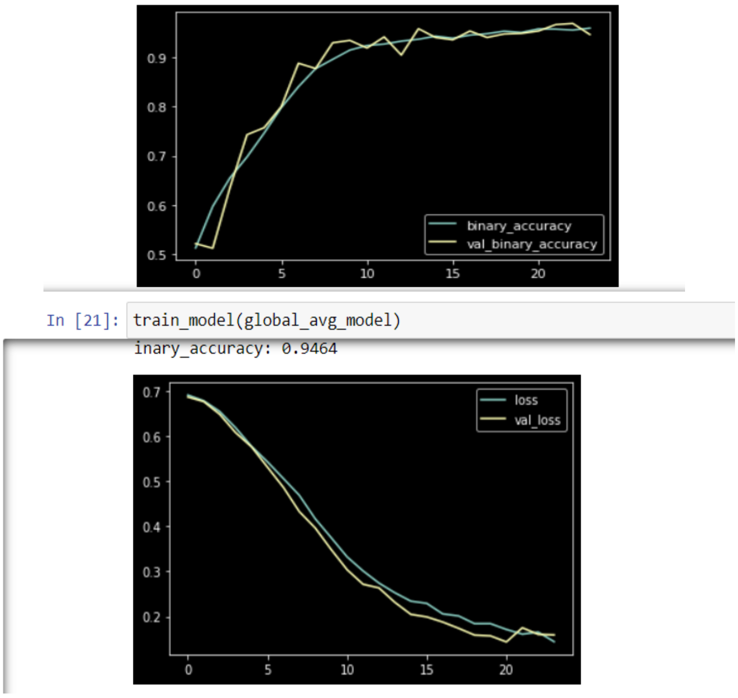

Fig 4.5 Training and validation accuracy plot for Global average pooling model

Cracks detection

- Crack detected

Fig 4.6 Crack is detected on given input

- No crack detected

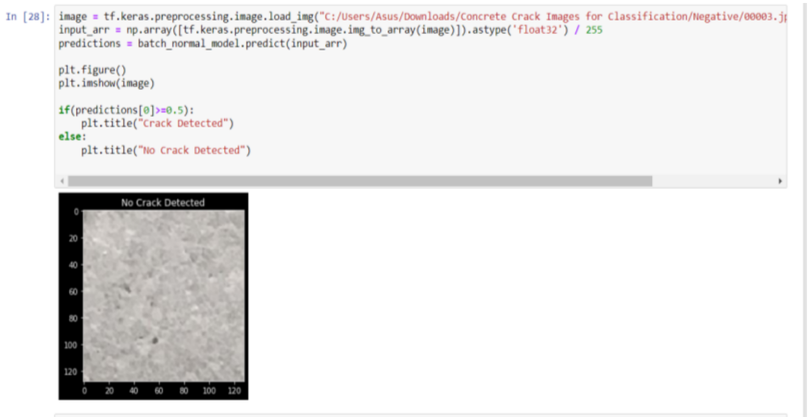

Fig 4.7 No Crack is detected on given input

RESULTS

Model	**Accuracy**
The basic_model	96.722% accuracy.
The batch_normal_model	98.333% accuracy
A global_avg_model	96.556% accuracy

Table 4.1 Comparison of models based on accuracy

CHAPTER 5: CONCLUSION AND FUTURE SCOPE

In this project, the cracks are detected in two classes by using image processing techniques. CNN model is used as classifier for crack detection. Here, positive means crack is detected, whereas negative means no crack in image.

Initially, CNN model is implemented using 3 basic layers, then in wider and deeper model 2 more convolutional layers have been added. Then in batch normalization model, normalization layer is used to map the features in the same distribution. Then global average pooling layer is added in next model as it reduces the problem of overfitting the data. Later the models have been tested and compared with the basic model.

In future work, an alternative strategy can be used and be tested. Different type of cracks can be detected and classified. Severity level of crack can be calculated. Also app can be developed and GUI can be created for easy navigation.

REFERENCES

[1] Road crack detection using convolutional neural network Sharmad Bhat1, Saish Naik1, Mandar Gaonkar, Pradnya Sawant1, Shailendra Aswale1, Pratiksha Shetgaonkar1, Indian Journal of Science and Technology 2021;14(10):881–891

[2] Road crack detection using deep CNN IEEE 2016, Lei Zhang, Fan Yang, Yimin Daniel Zhang, and Ying Julie Zhu.

[3] Automated road crack detection using CNN, 2018 IEEE International Conference on Big Data (Big Data), Vishal Mandal, Lan Uong, Yaw Adu-Gyamfi.

[4] Sample and structured guided Network for road crack detection, IEEE 2019, Siyuan Wu, Jie Fang, Xiangtao Zheng, Zijie Li.

[5] Road Crack Detection using a Single Stage Detector Based Deep Neural Network, 2018 IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems (EESMS), Carr, Thomas Arthur; Jenkins, Mark David; Iglesias, Maria Insa; Buggy, Tom; Morison, Gordon.

[6] Feature Pyramid and Hierarchical Boosting Network for Pavement Crack Detection, IEEE January 2019, Fan Yang, Lei Zhang, Sijia Yu, Danil Prokhorov, Xue Mei, and Haibin Ling.

[7] Road Crack Detection Using Deep Convolutional Neural Network and Adaptive Thresholding, IEEE 2019, Rui Fan1, Mohammud Junaid Bocus2, Yilong Zhu, Jianhao Jiao1, Li Wang, Fulong Ma, Shanshan Cheng, Ming Liu1.

[8] An integrated machine learning model for automatic road crack detection and classification in urban areas, International Journal of Pavement Engineering 2021, Abbas Ahmadi, Sadjad Khalesi & Amir Golroo.

[9] Concrete crack detection based on well-known feature extraction model and YOLO v2 network, Applied science, 2021, Shuai Teng, Zongchao Liu, Gongfa Chen, Li Cheng.

[10] Automatic Pavement Crack Detection Based on Structured Prediction with the Convolutional Neural Network, IEEE 2018, Zhun Fan, Senior Member, IEEE, Yuming Wu, Jiewei Lu, and Wenji Li.

[11] Deep convolution neural network for crack detection on asphalt pavement, ICoNSET 2019, IOP, N A M Yusof, A Ibrahim, M H M Noor, N M Tahir, N M Yusof and N Z Abidin, M K Osman.

[12] Road Crack Detection and Classification Using Deep Learning, International Research Journal of Engineering and Technology (IRJET), 2021, Harshal Bhoir1, Amitkumar Pandey2, Rushikesh Patil3, Aparna Bhonde4.

[13] Review and analysis of crack detection and classification techniques based on crack types, International journal of applied engineering and research, 2018, Sheerin Sitara, N. Kavita, S. Raghuraman G.

[14] Building Crack Due to Lombok Earthquake Classification Based on GLCM Features and SVM Classifier, 2019 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA), Gede Pasek Suta Wijaya, Chaerus Sulton, Ida Bagus Ketut Widiartha, Ni Nyoman Kencanawati.
[15] Fully Automated Road Defect Detection Using Street View Images, David B. Abou Chacra, John S. Zele.

DATASET SAMPLES

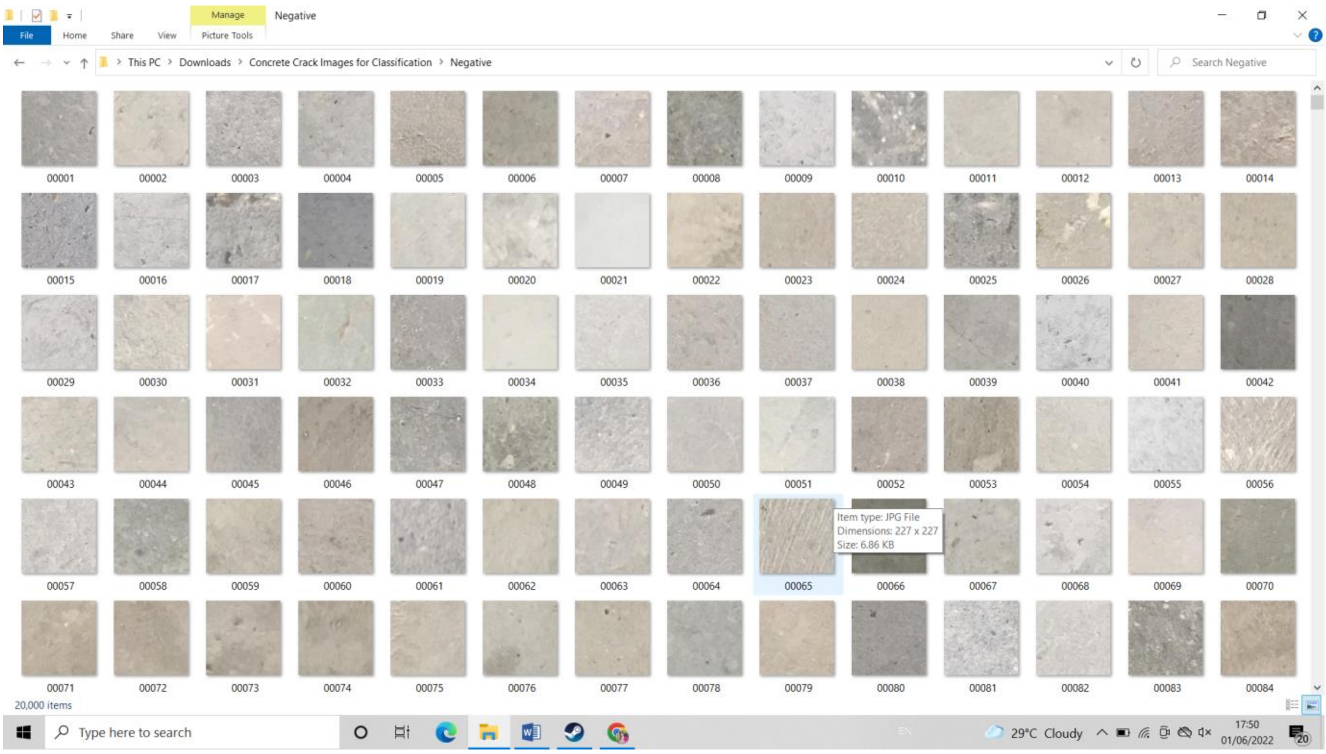

Fig 6.1 Sample images for positive class

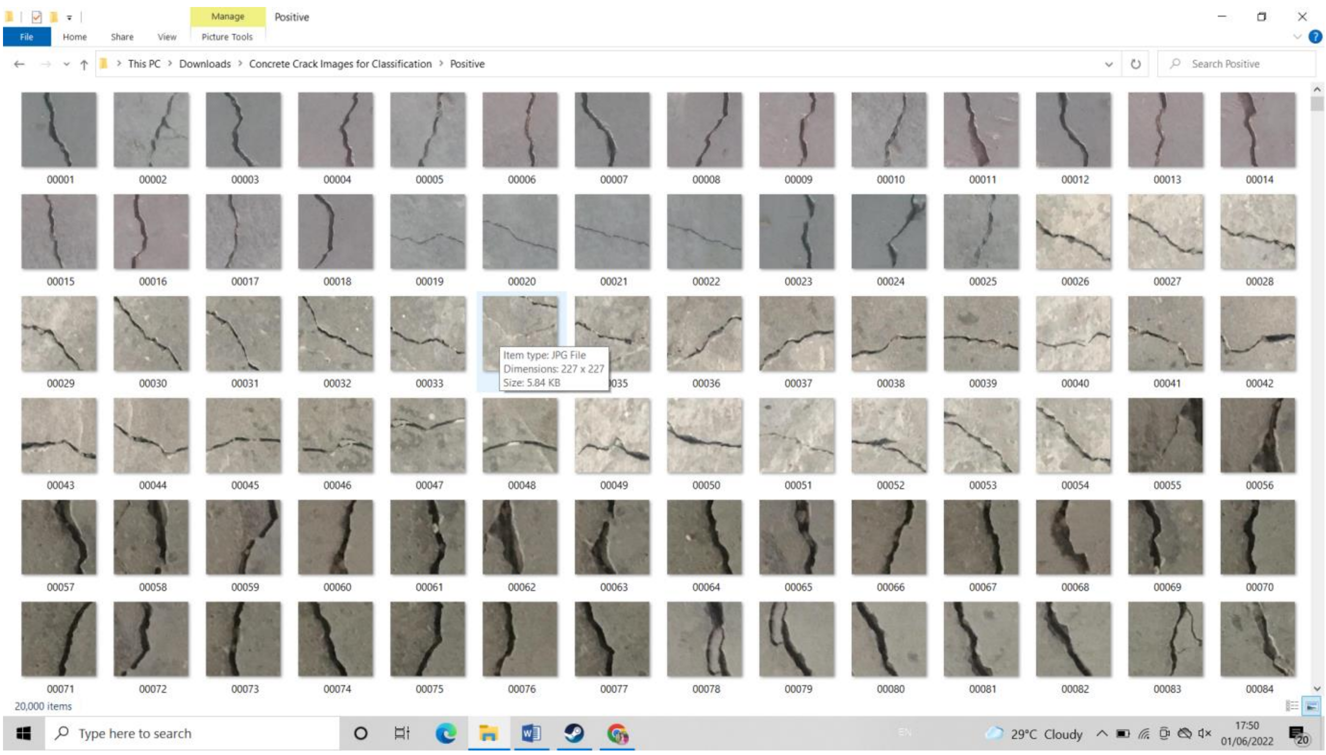

Fig 6.2 Sample images for negative class

```
plt.show()
```

<Figure size 432x288 with 0 Axes>

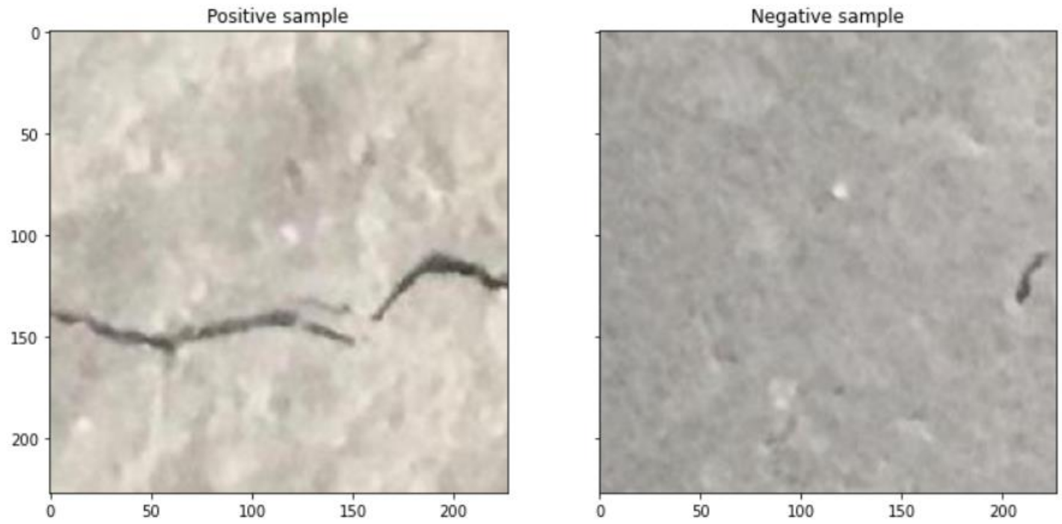

Fig 6.3 Sample images for positive class and negative classes