A DEEP LEARNING APPROACH TO IDENTIFY SURFACE CRACK

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I. INTRODUCTION

Crack plays a critical role in evaluating the quality of concrete structures, which affects the structure's safety, applicability, and durability. A crack is one of actual damage on an entire concrete surface. There are different crack detections like surfaces, roads, buildings, etc. Cracks in concrete structures are primary indicators of possible structural damage and durability. Most of the developed countries conduct a regular crack assessment of civil engineering structures as part of infrastructure maintenance. Manual visual inspection is the most commonly employed method in practice for obtaining crack information such as the existence, location, and width, which can be used to prepare maintenance plans. Although crack information can be obtained from a manual visual inspection, it is labor intensive, costly, time-consuming, and often unreliable because the results depend on the experience and skill of the inspector.

Automatic crack detection is being developed in place of the slower subjective old human inspection processes for rapid and reliable surface fault analysis. As a result, a more secure survey approach is used [7]. Non-destructive testing benefits greatly from automatic fracture detection. It is difficult to measure deterioration objectively using manual examination [8]. Non-destructive testing techniques such as I infrared and thermal testing, (ii) ultrasonic testing, (iii) laser testing, and (iv) radiographic testing can be used to do automated crack detection [8].

Day by day the interest in image-based crack detection for non-destructive inspection is increasing. Some of the difficulties in image-based detection are because of the random shape and varying size of cracks and various noises such as irregularly illuminated conditions, shading, blemishes, and concrete spall in the acquired images. Because of its simplicity in processing, many image processing identification methods were proposed. These methods are divided into four types: integrated algorithms, morphological approaches, percolation-based methods, and practical techniques [8].

Many image processing techniques (IPTs) have been developed to identify concrete cracks [1-3], concrete spalling [4], and potholes and cracks in asphalt pavement [5-7] to get a better of the drawback of human-based crack identification methods. The IPTs can not only identify fractures in pictures [8, but also estimate their width and direction [9, 10]. The structural characteristics, such as histogram and threshold, are the easiest technique to identify fractures in pictures [10, 9]. To increase its performance even further, generic global transforms and edge detection detectors such as fast Haar transform (FHT), fast Fourier transform (FFT), Sobel, and Canny edge detectors [8, 7] were used. Although IPTs are excellent at detecting some particular pictures, their resilience is low because crack images collected from a concrete building in real-world settings may be impacted by elements such as light, shadows, rusty and rough surfaces.

Machine learning (ML) techniques are being used by academics to increase the performance of image-based crack assessment approaches [9]. The ML-based approaches extract crack characteristics using IPTs first, then determine if the extracted features represent cracks [10]. ML methods such as artificial neural networks (ANNs) and support vector machines (SVM) were used to identify concrete fractures, spalling, and other structural deterioration. However, because the efficacy of this approach is dependent on the extracted crack features, the findings have invariably been influenced by incorrect feature extraction employing IPTs.

The goal of this project is to keep track of structural health and ensure structural safety. The manual crack detection process is painstakingly time-consuming and suffers from subjective judgments of inspectors. Manual inspection can also be challenging to perform in the case of high-rise buildings and bridges. In this research, we use deep learning to create a straightforward yet highly accurate fracture detecting algorithm. Additionally, we evaluate the model on real-world data and see that the model is accurate in detecting surface cracks in concrete and non-concrete structures, for example, roads, buildings, etc.

The intensity inhomogeneity of the cracks and intricacy of the background, such as the low contrast with the surrounding pavement and potential shadows with comparable intensity, keep the task tough, nevertheless.

Extracting features is undoubtedly necessary when image processing techniques detect cracks in an image. Consequently, the use of image processing methods is also restricted because pictures taken on actual concrete surfaces are influenced by some noises caused by lighting, blur, and so on.

II. Review of Related Works

In recent years, researchers have begun to use neural networks to detect cracks automatically. The following is a brief overview of the application of different networks in crack detection.

Deeper Networks for Pavement Crack Detection (Leo Paulya, Harriet Peela, Shan Luoa, David Hoggb and Raul Fuentesa) Pauly et al. studied the influence of CNN depth and the position change between the training dataset and test dataset on pavement crack detection accuracy. The results show that increasing the network depth can improve the network performance, but when the image position changes, the detection accuracy will be greatly reduced. In this paper they demonstrated the effectiveness of using deeper networks in computer vision-based pavement crack detection for improved accuracy. They achieved 90.2% accuracy for 4 convolutional layers where the tasted dataset was random.

Crack Detection Using Enhanced Thresholding on UAV based Collected Images(Q. Zhu, T. H. Dinh, V. T. Hoang, M. D. Phung, Q. P. Ha)Hoang (2018a,b, pp. 1–4) almost achieves this by treating this as multi-class problem using SVM (Support Vector Machine) algorithm to detect “longitudinal crack”,“transverse crack”,“diagonal crack”,“spall damage”,“intact wall”(Hoang 2018a,b,p. 1). SVM creates a hyperplane that is a line which separates each class based on their characteristics ensuring that separation between classes is at the maximal distance possible. Hoang (2018a,b, p. 1) attained a test accuracy of 85.33% (14.67% error rate) using 100 image samples per class. Even though Hoang’s work in Hoang (2018a,b,4 D. B. Agyemang and M. Bader pp. 1–4) method treated the problem as a multi-class task, the researcher did not think about training their model to detect if the image is not a surface at all as the CNN cannot recognize if an image does not belong to its classes.

Automatic Bridge Crack Detection Using a Convolutional Neural Network(Hongyan Xu, Xiu Su, Yi Wang, Huaiyu Cai, Kerang Cui and Xiaodong Chen)Hongyan Xu, Xiu Su, Yi Wang (2019) proposed an end-to-end crack detection model based on the convolutional neural network (CNN), taking the advantage of atrous convolution, Atrous Spatial Pyramid Pooling (ASPP) module, and depth wise separable convolution. The ASPP module enables the network to extract multi-scale context information, while the depth wise separable convolution reduces computational complexity. They compared their model With or Without Atrous Convolution. the model without the ASPP module, the crack recognition rate of the model with the ASPP module is 5.77% higher which means the application of ASPP in crack detection can better fuse multi-scale image context information. The model achieved a detection accuracy of 96.37

Design of deep convolutional neural network architectures for automated feature extraction in industrial inspection(Daniel Weimer, Bernd Scholz-Reiter, Moshe Shpitalni)Weimer et al (2016) evaluated several deep-learning architectures with varying depths of layers for surface-anomaly detection. They applied networks ranging from having only 5 layers to a network having 11 layers. Their evaluation focused on 6 different types of synthetic errors and showed that the deep network outperformed any classic method, with an average accuracy of 99.2% on the synthetic dataset. Their approach was also able to localize the error within several pixels of accuracy Their approach to localization was inefficient as it extracted small patches from each image and classified each individual image patch separately.

Crack and Noncrack Classification from Concrete Surface Images Using Machine Learning(Hyunjun Kim, Eunjong Ahn, Myoungsu Shin and Sung-Han Sim)H Kim, E Ahn, M Shin, SH Sim used two main procedures: (1) interest point detection and (2) interest point description, for identifying concrete cracks using machine learning. They selected ve metrics (precision, recall, F1 score, accuracy, and computational time) to compare the methods of the SURF-based and CNN-based for detecting Crack and non-crack classification from concrete surface images. The classification performance of the CNN-based method is better in classifying actual cracks and crack-like non-crack objects. They used CCRs for identifying cracks and non-crack objects. In the training stage, concrete surface images with cracks and non-cracks were prepared, from which CCRs were automatically extracted using image binarization. After the CCRs were generated, they applied the SURF-based and CNN-based methods to the CCRs. The precision and F1 score were higher for the CNN-based method provided that sufficiently large minibatch sizes and CCR set sizes were used. The recall and accuracy of the CNN-based and SURF-based methods were largely the same. they used image binarization to extract crack candidate regions.

ROAD CRACK DETECTION USING DEEP CONVOLUTIONAL NEURAL NETWORK (Lei Zhang, Fan Yang, Yimin Daniel Zhang, and Ying Julie Zhu)Zhang et al. proposed a crack detection method based on deep learning, which seems to be one of the earliest works applying CNN to road crack detection. The pavement pictures are taken by smartphones, and the network model is built on the Caffe Deep Learning (DL) framework. They used support vector machines (SVM), Boosting and ConvNets. By comparing with traditional machine learning classifiers such as support vector machines (SVM) and boosting methods, the author proved the effectiveness of deep learning methods. Compared to the SVM, the Boosting method can detect the cracks with a higher accuracy.

Hoang (2018a,b, pp. 1–4) almost achieves this by treating this as multi-class problem using SVM (Support Vector Machine) algorithm to detect “longitudinal crack”,“transverse crack”,“diagonal crack”,“spall damage”,“intact wall”(Hoang 2018a,b,p. 1). SVM creates a hyperplane that is a line which separates each class based on their characteristics ensuring that separation between classes is at the maximal distance possible. Hoang (2018a,b, p. 1) attained a test accuracy of 85.33% (14.67% error rate) using 100 image samples per class. Even though Hoang’s work in Hoang (2018a,b,4 D. B. Agyemang and M. Bader pp. 1–4) method treated the problem as a multi-class task, the researcher did not think about training their model to detect if the image is not a surface at all as the CNN cannot recognize if an image does not belong to its classes.

After analyzing a few related works, we add logistic regression models with different settings and also use deep neural networks for getting better accuracy.

III. Dataset

We are using the Publicly available Surface Crack Detection. This data set was made publicly available on Kaggle.

In this project, we use 40,000 photos of the dataset, and the number of cracks and non-crack images is set to equal. The data set consists of 20,000 images of concrete structures with cracks and 20,000 images without cracks. The dataset is generated from 458 high-resolution images (4032x3024 pixel). Each image in the data set is a 227 x 227 pixels RGB image. Some sample images with cracks and without cracks are shown below:

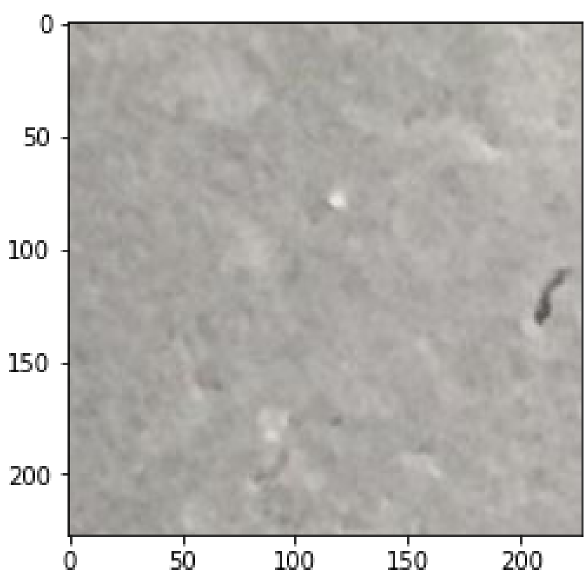

Figure: non crack

Figure: crack

Figure: non crack

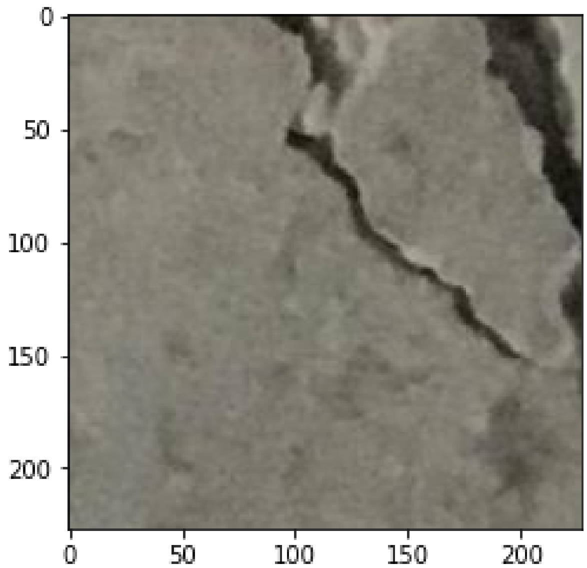

Figure: crack

In the databank, a series of large crack images are cropped into small images with 28*28 pixels, and then classified into images with cracks and without cracks manually. The training set and testing set are picked up from those small images randomly.We shuffle and split the data into train and test. The data downloaded will have 2 folders one for Positive and one for Negative. We need to split this into train and test. We randomly shuffle the data into the train and rest into Val where the train set has 35000 images and the test set has 5000 images.

IV. Proposed Architecture

The section summarizes the whole process of the proposed crack detection method. The figure is the general flow of the NN model and logistic model-based surface crack detection. But before training the models, a dataset should be established to generate training and testing sets. In the databank, a series of large crack images are cropped into small images with 28*28 pixels, and then classified into images with cracks and without cracks manually. The training set and testing set are picked up from those small images randomly. After extracting the features, the models are implemented. Through training the models using the training and testing sets, the CNN and logistic classifier for crack detection can be obtained accordingly. To verify the effectiveness of the trained models, a process of testing is implemented. And finally, the accuracy is calculated.

Figure: Flowchart of the proposed system

V. Methodology

A. Model

1) Deep Neural Network: A deep neural network (DNN) or deep net for short isan artificial neural network (ANN) with multiple layers between the input and output layers. Deep nets process data in complex ways by employing sophisticated math modeling. And we use single layer and multiple layers in different settings.

2) Logistic Regression: Logistic regression is a binary classification method. It can be modeled as a function that can take in any number of inputs and constrain the output to be between 0 and 1. This means we can think of Logistic Regression as a one-layer neural network. Simple. Logistic regression takes an input, passes it through a function called the sigmoid function then returns an output of probability between 0 and 1. This sigmoid function is responsible for classifying the input. And Logistic regression has no hidden layer.

B. Activation function

1) ReLU: ReLU stands for rectified linear activation unit and is considered one of the few milestones in the deep learning revolution. ReLU function is its derivative both are monotonic. The function returns 0 if it receives any negative input, but for any positive value x, it returns that value back. Thus, it gives an output that has a range from 0 to infinity. It uses this simple formula to transform its input:

$$f(x)=\max(0,x)$$

ReLU is used withinside the hidden layers in preference to Sigmoid or tanh as the use of sigmoid or tanh withinside the hidden layers ends in the notorious trouble of "Vanishing Gradient". The "Vanishing Gradient" prevents the sooner layers from studying vital statistics while the community is backpropagating. The sigmoid that is a logistic characteristic is extra preferrable for use in regression or binary category associated issues and that too simplest withinside the output layer, because the output of a sigmoid characteristic levels from zero to 1. Also Sigmoid and tanh saturate and feature lesser sensitivity.

2) Leaky ReLU: Leaky ReLU function is an improved version of the ReLU activation function. As for the ReLU activation function, the gradient is 0 for all the values of inputs that are less than zero, which would deactivate the neurons in that region and may cause dying ReLU problems. Leaky ReLU is defined to address this problem. Instead of defining the ReLU activation function as 0 for negative values of inputs(x), we define it as an extremely small linear component of x. Here is the formula for this activation function. Leaky ReLu is excellent at keeping off the saturation trouble, wherein a neuron can get "stuck" at certainly considered one among its excessive values. But the vanishing gradient trouble remains a project with leaky ReLu. A manner to deal with this in truly deep networks is to attach every layer to numerous different layers. This lets in for the gradient to "skip" a few layers that could in any other case dilute it.

$$f(x)=\max(0.01*x\ ,\ x).$$

This function returns x if it receives any positive input, but for any negative value of x, it returns a really small value which is 0.01 times x.

3) SoftMax: Logistic regression is a generalization of softmax regression (also known as softmax classifier) to the situation when we want to handle several classes. In logistic regression, we were able to determine the likelihood that a particular instance belonged to a single class. By taking into account different logistic regression models for each class, such the ones below, this might be expanded to include several classes. The logits o1, o2, and o3 are calculated using the equations below. Recall that the log of an event's success probability is what logit is. The numerical result is transformed to values between [0, 1] using the softmax activation function. Given that the output of the soft - max adds up to 1, the output can be thought of as a probability distribution.

VI. Background Study

The Deep neural network (DNN) model and Logistic Regression are used in this project to detect the surface crack.

All the experiments in this paper are performed on TensorFlow in the Windows system:

hardware settings: CPU: Intel (R) Core (TM) i7CPU@3.20 GHz, RAM: 16G, and GPU:

NVIDIA GTX1080Ti.

And we use custom model to train the data. The specific experimental steps are as follows:

Step 1- Data Loading:
Importing concrete surface crack images. A batch of data is randomly loaded from the training set (batch size: 20) for subsequent data processing.

Step 2- Image Preprocessing:
We use a built-in function in TensorFlow to adjust the size of the input image to the fixed size of the model. Then, do data augmentation via resizing, translation, and other operations. It is worth noting that, due to the use of TensorFlow's built-in function, a large number of pictures generated by data augmentation will not be saved to the local computer.

Step 3- Define the structure of the crack detection model:

We use custom models in this project. A single hidden layer is used in the First DNN settings where the activation function we use is Leaky Relu. And in settings2 we use the Logistic Regression Model and the activation function is SoftMax.

Step 4- Compile the model and start training:
Before training the model, it is necessary to specify the hyperparameters related to the network structure and select the appropriate optimization strategy. In this experiment, the batch training is 20. The dataset is randomly shuffled before each epoch of training to ensure that the same batch of data in each epoch of model training is different, which can increase the rate of model convergence. The learning rate plays a significant role in the training of the model. Choosing an appropriate learning rate can speed up the model's convergence speed; on the contrary, it may cause the loss value of the objective function to explode.

Step 5- Test the performance of the model:
Finally, we calculate the accuracy on test sets where the values are differing from one to another because we use a different model with different settings.

VII. Result

The Deep neural network (DNN) model, Logistic Regression, and convolutional neural network (CNN) are used in this project to detect the surface crack. After every 3500 iterations, the accuracy and loss are calculated for each setting. We can see the difference from the table. Using Multiple layers with the Relu function is not suitable for detection, and accuracy is only 49.08. But if we use Multiple layers with the Leaky relu function in the Deep neural network, the accuracy is 82.64%, which is far better than the 2nd setting. But if we use logistic regression for the detection of the surface crack, the accuracy rate is higher than the Deep neural network, which is 87.46%. Because there is no hidden layer in this model so that there is no chance of overfitting the model also it can work in binary class as well as multiclass very well.Logistic regression is less difficult to implement, interpret, and train. But If the number of observations is less than the number of features it may result in overfitting. Among them, the convolutional neural network gave the best accuracy of 98.33% loss is 0.06472. The results for different Models are given below:

Model Name	Accuracy	Loss
DNN (Single Layer and LeakyReLU)	79.22	0.458812
DNN (Multiple Layer and ReLU)	49.08	0.6835
DNN (Multiple Layer and LeakyReLU)	82.64	0.7105
Logistic (SoftMax)	87.46	0.418
Convolutional Neural Network (ReLU)	98.33	0.06472

After every 3500 iterations, the accuracy and loss are calculated for each setting. We can see the difference from the table. Using a Single layer with the Leaky Relu function is good for detection and accuracy is only 78.92 and loss is 0.4519. But if we use logistic regression for the detection of the surface crack, the accuracy rate is higher than DNN (Single layer) which is 87.76. Because there is no hidden layer in this model there is no chance of overfitting in the model.

The loss graph for each setting is given below:

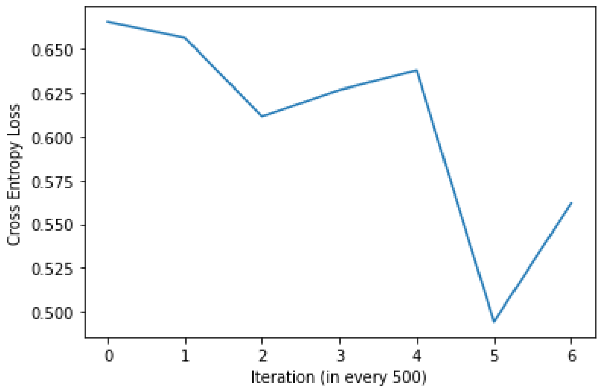

Figure: DNN (single layer)

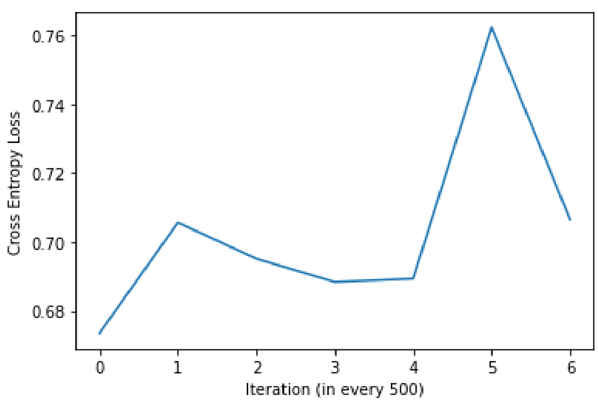

Figure: DNN (multiple layer)

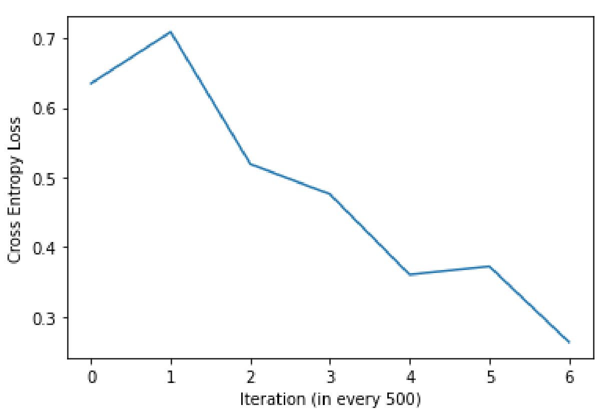

Figure: DNN (Multiple Layer and Leaky Relu)

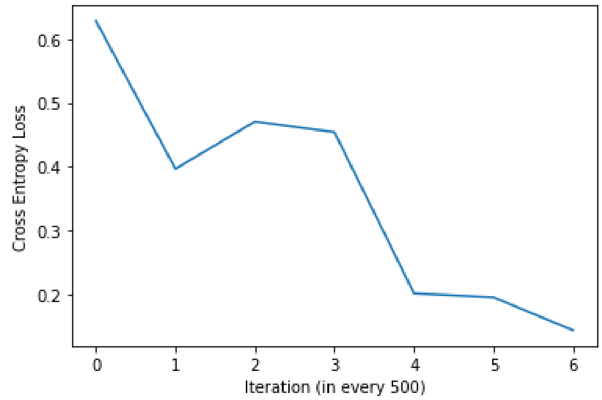

Figure: Logistic Regression Model

We also used a confusion matrix to evaluate the accuracy of the CNN model, precision, recall, and F1 score as performance measures. Primarily CNN is used for image and speech recognition applications as it is a subtype of neural networks. That is why CNNs are ideal for this application.

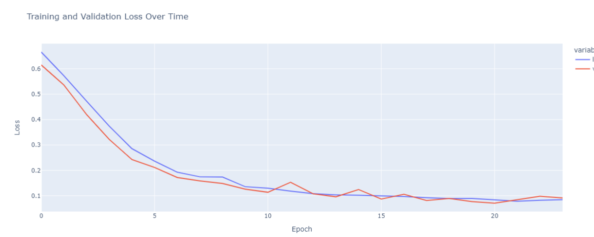

Figure: CNN model

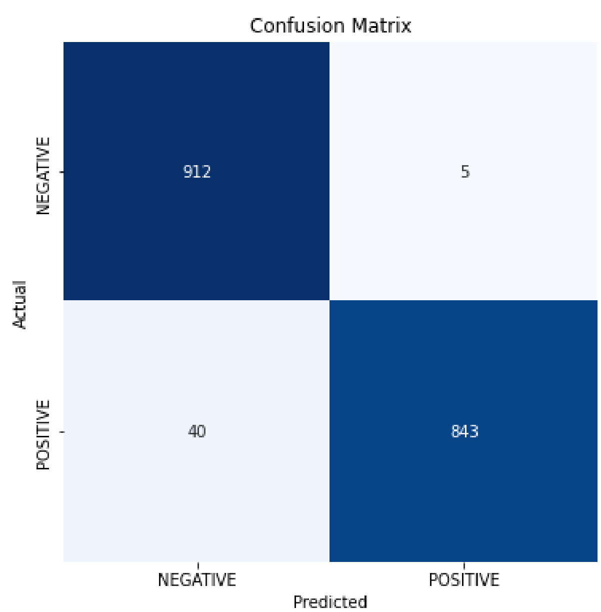

Figure: Confusion Matrix of CNN model

Classification Report of CNN Model:

	precision	recall	f1-score	support
NEGATIVE	0.96	0.99	0.98	917
POSITIVE	0.99	0.95	0.97	883
accuracy			0.97	1800
macro avg	0.98	0.97	0.97	1800
weighted avg	0.98	0.97	0.97	1800

Figure: Confusion Matrix of CNN model

VIII. Conclusion

In this study, we tried to explore the opportunity to detect the surface crack with the help of deep learning methods. This project shows how easy it has become to build real-world applications using deep learning and open-source data. The benefit of the project is that users such as surveyors will be able to record cracks at a rapid rate as they would not need to manually record the conditions. The reason why that benefit is important is that users such as surveyors are required to write a report on a building which is a long process, but if surface crack detection was used they would be able to quickly take pictures of the building, send the classification results to themselves and go back to the office to elaborate on the classification made by the application for their report. This would improve the workflow of surveyors.

To conduct this research, we looked into some previously completed studies on the same topic. After gathering initial knowledge, we collected our dataset from Kaggle which was made publicly available on Kaggle. In this project, we use 40,000 photos of the dataset, and the number of cracks and non-crack images is set to equal. The data set consists of 20,000 images of concrete structures with cracks and 20,000 images without cracks. The dataset is generated from 458 high-resolution images (4032x3024 pixels). Each image in the data set is a 227 x 227 pixels RGB image. Once the data pre-processing was completed we applied different models including DNN, CNN, Logistic Regression, etc. on them.

After the evaluation, it is found that both of these models score perfectly on this dataset where multiple layers with the Leaky relu function in the Deep neural network the accuracy is 82.64%, CNN with 98.33%, logistic regression with 87.56%. The study in this paper proves that a CNN is especially powerful in image classification as it can automatically learn certain features from a large number of images. The research approach of this paper can also be adopted in other types of damage detection such as the scaling of the concrete surface, corruption, peeling paint of steel and concrete, and more.

In future studies, more images with more types of concrete damages under various conditions will be provided and added to the existing database to increase the adaptation and robustness of the proposed method, and comparative studies will also be performed.

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