Assessment of the Decay of Monuments Using Deep Learning and CNN

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Abstract. In any culture, the monuments are significant part of the heritage, the witnesses of the history that have been existing upto the current era. Since these monuments are inherited from previous generations, it is essential to preserve them, which can be done by monitoring the monuments. In the proposed method, the deep learning technique of convolutional neural networks [CNN] is used to figure out the reasons that cause the decay of monuments and thereby figuring out the causes that damage them. Using the CNN technique, 20000 images which are resized to 256×256 data set are used to train and test the Convnet, that has 3 layers of 32×3 layers of filters. The proposed work detects the cracks that are present in the monuments, that are caused by various factors including weather and aging. Weather and aging also causes moss and loss of stone. In this work, cracks are identified using CNN with an accuracy of 97.5%, and histogram distribution is used to detect the cracks. In the proposed work, the Keras library is used to create the convolutional neural networks.

Keywords: Crack Detection · Deep Learning Technique · Histogram · Convolutional Neural Network

1 Introduction

Every facet of culture is vital to a nation's development. Every culture embodies the aspirations and principles of a country. India is a country with a wide range of cultural traditions. Every state has its own cultural and ethnic significance. India's monuments offer insights into the country's rich architectural and cultural history. One of the most notable aspects of Indian monuments is their representation of Indian culture.

Structures are usually designed to hold for a particular period of time. It is assumed that structures of Monuments can be up to 100 years. They are also a place for attracting tourists and thus playing a very important role in an economic point of view. Furthermore, due to the frequent visits around the monuments, severe control and maintenance is required to preserve these structures.

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The aging of monuments is becoming a serious issue as the maintenance works keeps on increasing with aging. There are two ways to assess monument deterioration: destructive and non-destructive. Destructive techniques include X-ray diffraction analysis, transmitted light, and scanning electron microscopy. Infrared thermography (IRT), ultrasonic imaging, and digital image processing are techniques that incorporate non-destructive decay [1]. To lower maintenance costs, it would be beneficial to create a radar that uses camera images of monuments that would eventually breaks down concrete and other surfaces, giving us an insight about structural damages. A variety of weathering factors can lead to structural damage to monuments and weathering deterioration comes in three kinds: chemical, physical, and biological.

Rock structures collapse due to molecular structure replacements which have been the consequences of chemical weathering. Biological weathering is the structural deterioration due to plants and animals. Two significant elements that contribute to the monuments' deterioration are moss and cracks. Finding cracks and moss by hand is time-consuming and challenging. Deep learning techniques are hereby used to simplify and reduce the amount of time required to complete the task. The overview and the problem statement are explained in Sect. 1. The literature review has been explained in Sect. 2. The proposed approach along with the existing system has been explained in Sect. 3 and the corresponding results, comparisons, conclusions and future work has been explained in Sects. 4, 5 and 6 respectively.

1.1 Overview

In this paper, various Deep Learning techniques has been studied and analyzed. In order to train a CNN model, images of concrete surfaces or walls of any structures or monuments have been taken from DSLR cameras with a wide range of images.

1.2 Problem Statement

One of the major problems in crack detection is that the time required to find and analyze the cracks present in any structure is too long. As lengthy time is required for the process it is hard to find the decays manually. Also manual analysis may not be accurate. Deep Learning techniques have been implemented to detect decays swiftly and accurately. When it comes to crack detection, cost is another important factor. It is expensive to detect cracks manually. Therefore, we have come up with the solution of detecting crack and moss automatically using python and deep learning. In crack detection methodologies, one of the major concerns is that it can detect only small cracks. For example, using Ultrasonic images it is only possible to detect small cracks. Therefore, there is a need of an alternative solution to detect different types of damages in a single method and to provide even better accuracy and result.

2 Literature Survey

Table 1 presents a literature review of various historical structures with different algorithms. In this review different algorithms are discussed, such as the threshold method, stochastic search, OTSU algorithm, and Convolutional Neural Network.

Table 1. Literature review of historical structures

S.No	Title	Concept	Inference
1	Extending the life span of cultural heritage structures[1]	Uses two level of monitoring (conti-nuous periodic)	Reducing the damage and planning the suitable interventions on time
2	Automatic crack classification and segmentation on masonry surfaces using Convolutional Neural Networks and transfer Learning[2]	Uses DL Algorithm	Accurately detect crack from pixel level masonry surface
3	Application of Internet of Things technology and Convol-utional Neural Network model in bridge crack detection[3]	Uses OTSU algorithm	Improve the efficiency of bridge safety diagnosis and reduced the risk factor.
4	Road crack detection using deep convolutional neural network[4]	Uses novel thresholding method	Less noisy pixel
5	Genetic Algorithm optimization of a Convolutional Neural Network for Autonomous crack Detection[5]	Stochastic search methods	Mimicking Evolutionary processes found in na-ture
6	Crack Identification Via user Feedback, Convolutional Neural Networks and Laser Scanners for Tunnel Infrastructures[6]	The usage of a laser scanner results	Preserves the adverse effects from wrong feature selection
7	Pavement Crack Detection using Convolutional Neural Networks[7]	Using generic Convolutional Neural Networks	Reducing the weights of the Existing CNN network.

3 Existing Method

The existing method uses a standard GA architecture to modify the weights of the CNN to obtain better results. However, the GA won't guarantee the better result, as long as every genetic data available is provided and applied to this method. In addition to this they used numerous input arrays for the CNN architecture [8–12]. They also came with an idea of making use of separate convolutional kernels, which are weight matrices in-order to implement the row and column convolution functioning separately. By using this method, it will reduce the angles of freedom in every layer and simultaneously speed the implementation of layers. Figure 1 illustrates the architecture of CNN, which has multiple neurons in the convolution and intermediate layers [13].

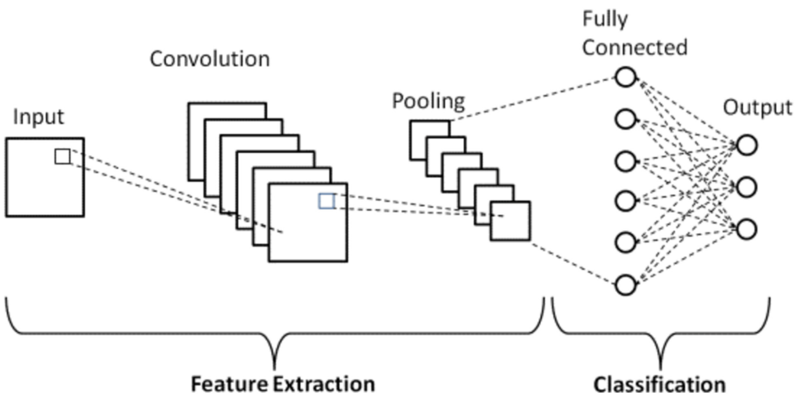

Fig. 1. Architecture of CNN with multiple neurons in the convolution and intermediate layer.

Artificial neural networks (ANNs) are used to train the filters here. The main advantage of this method is to use the natural feature of the images. Therefore, the spatially connected neuron activations are simulating a 2D convolution of the considered images [5, 14–16].

The weights of the CNN are trained with the standard GA process. The standard process undergoes some standard evolution processes such as Population Initialization, Fitness Evaluation, Selection, Crossover, Mutation and Creep. To evaluate the images they are hand- coded with "crack" or "no crack" data. The crack area is noted as black (value - 0), and non-crack as white (value - 255). Ramani et al. developed a deep learning model to classify the decay of monuments [18–21].

3.1 Challenges and Analysis

- The first challenge is to create an CNN network model that has less number of weights associated with it.
- The number of fully connected layers must be in the right amount for the perfect image feature detection.

As we discussed in the previous section CNN is the best architecture for automatic feature detection. However, feature fusion plays an additional role in overall performance to obtain even better results. To solve this problem, we came with a solution to classify patches that has cracks based on training square image patches with ground truth facts. For our basic information, we declared crack and non-crack as positive and negative patches respectively.

3.2 Convolutional Neural Network Architecture

In our Convnet architecture there are convolutional layer, max-polling layer and fully-connected layer. The convolutional network is contemplated as ordered feature extractor, that separates different particular levels of features and considers pixel of crack images into a feature vector.

Each and every, convolutional filter elements are trained from the given data. These filter elements learn from the labeled set of images. To collect features from the adjacent pixels, convnet undergoes max-polling architecture. By using these type of operation, convolutional network learns features which are spatially invariant. Eventually, classification is done using fully connected layers. Due to a common problem for underlying crack or non-crack images, a soft max layer is issued in order to calculate the probability of every input class.

Data Preparation

We used a data set more than 10 thousand images of size 256 $\times$ 256 which was collected using a DSLR camera. Each image is commented by numerous annotators. We manually allocated crack and non-crack images in it. By training the CNN using the said dataset the work done will be much easier and finally to get the region of interest with better accuracy we randomly choose an image from the dataset.

Convolutional Neural Network Training

A random selection method is used to select images from the testing labels and create a dataset of tests, which is then fed into the neural network with the goal of having a difference in the training data set of the images. As the dropout method is also used to minimize the over-fitting of images in there to adaptation on the data in connected layers. In speeding up the process Relu layer is used as the activation function which is proven productive than any other tangent functions. The network is trained using the SGD method along with a batch size of 30 and weight decay 0.0005. With epoch of 25 iterations.

$$\mathbf{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

The true positive rate is number of image sample correctly predicted divided by the total number of samples. It is given by

$$\mathbf{True\ Positive\ Rate} = \frac{TP}{FN + TP} \tag{2}$$

The true negative rate is number of images predicted incorrectly (negative) divided by total images that are actually negative.

$$\textbf{True Negative Rate} = \frac{TN}{TN + FP} \tag{3}$$

Number of images predicted correctly (negative) divide by Total images that are actually negative.

TP stands for "true positive." TN: Average Negative False Positive (FP).

3.3 Basic Design with Diagram

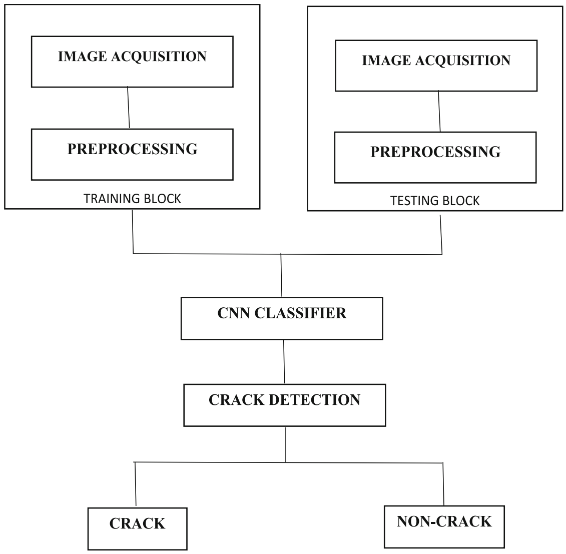

Fig. 2. The proposed architecture for crack detection.

This block diagram depicts the proposed CNN model for detecting the cracks which are present in the monuments. In Fig. 2, the proposed architecture model for crack detection is shown. Using high resolution camera, the images are taken and sent to the proposed model as inputs. These images have been collected from few of the old monuments and have also been collected from other built structures in Tamil Nadu. There are two sections in this model. The first section is training and the second section is the testing which is illustrated in the block diagram given below. In the pre- processing stage, the noise present in the images has been removed and then the images have been resized according to the requirements. The technique of image preprocessing involves noise reduction, and image sizing reduction to 256 by 256 pixels, and the clarity of the image is improved by the contrast enhancement method. After pre-processing, the images are then sent to the CNN model for analyzing and extracting features. A CNN layer consists of 13 convolutional layer, three fully connected and five pooling layer.

The size of the convolutional kernel with 3 × 3 and the pooling layer size is 2 × 2. Each layer uses Relu activation function and the convolution layer contain 32 kernels, each at 256 * 256 pixels. Feature extraction from the images have been done with different types of layers. Finally, in the predicting stage the outcome would be "whether a crack is present or not". Figures 3 and 4 present the image prediction and classification report.

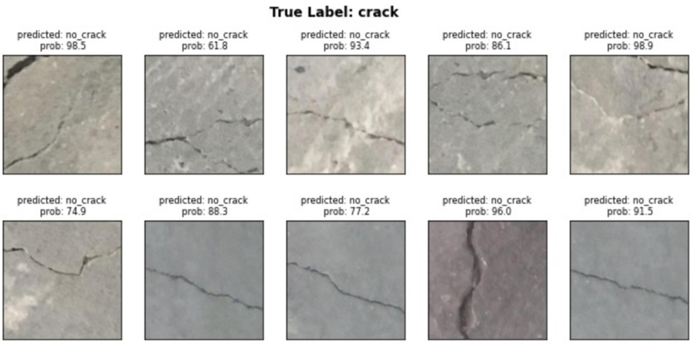

Fig. 3. Prediction of each analyzed images from the CNN model describing crack or no crack

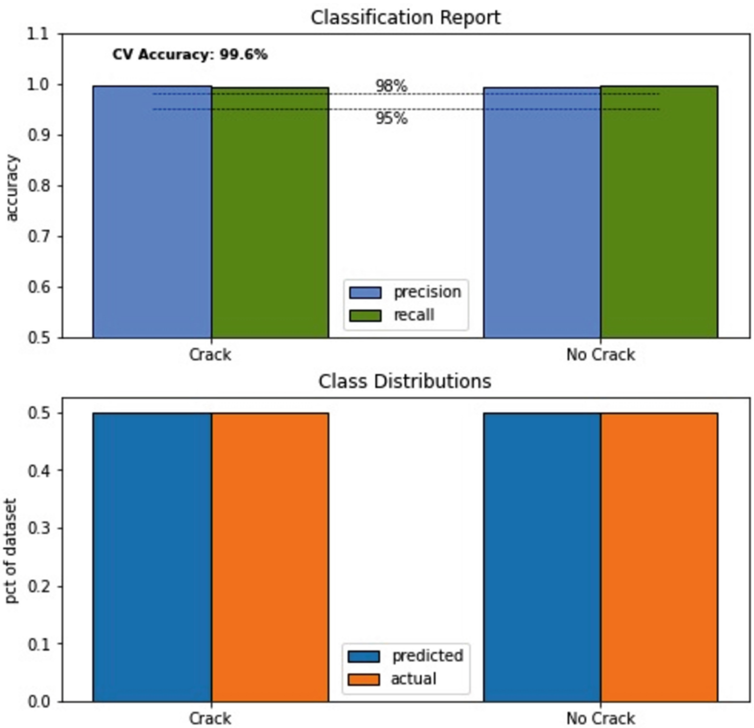

Fig. 4. The classification report of the predicted and actual value

4 Results

The comparison results of different methods, such as SVM, boosting, generic, and convolutional neural networks, with performance metrics are discussed. The histogram of crack images with severity is explained in the assessment section.

4.1 Comparison Table

The precision and accuracy of different classifiers with the proposed method is given in Tables 2 and 3. The proposed method gives better precision than the existing method.

Table 2. Comparison of different classifier with proposed method

SI.NO	METHODS	Precision
1	SVM Method	0.8112
2	Boosting Method	0.736
3	Genetic Method	0.92
4	Conv Net	0.975

Table 3. Accuracy of proposed method with different epochs

EPOCH	ACCURACY	VALUE ACCURACY	VALUE LOSS
1	0.859	0.979	0.058
2	0.985	0.979	0.0759
3	0.986	0.989	0.0345
4	0.9922	0.986	0.058

4.2 Output

Figures 5, 6, 7, 8 9 display the classifier's and predicted crack images, performance metrics for accuracy and loss, the Region of Interest, the calibrated model, and probability threshold model. The histogram distribution of crack images is explained in the assessment section.

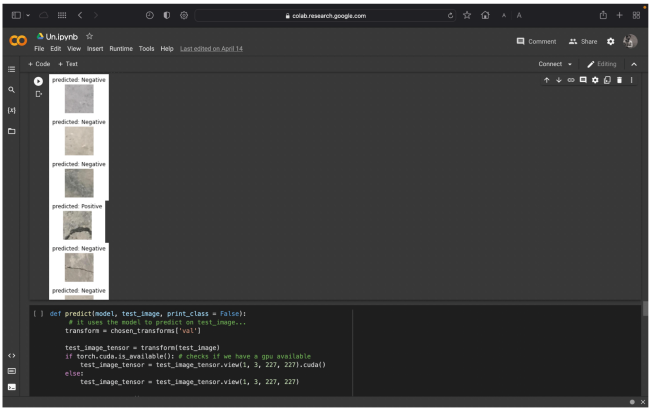

Fig. 5. Classification of Predicted Images

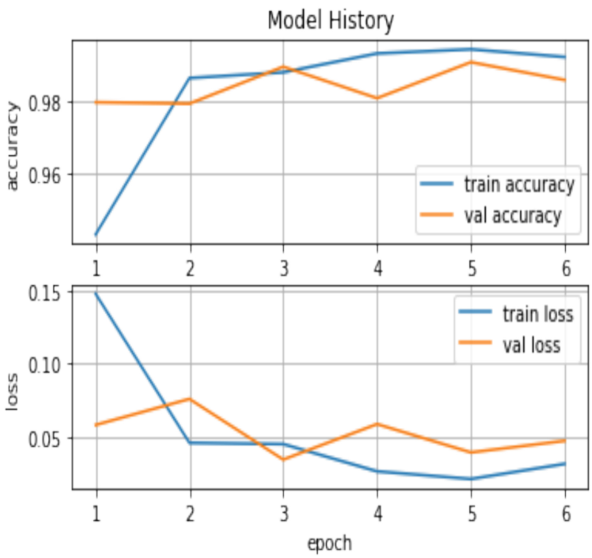

Fig. 6. Model History Graph accuracy & Loss

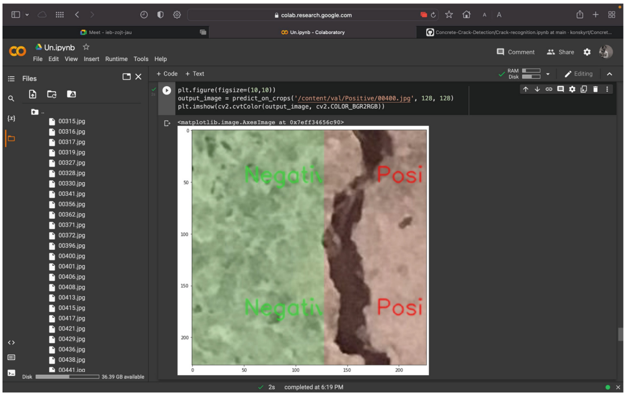

Fig. 7. ROI (Region of Interest)

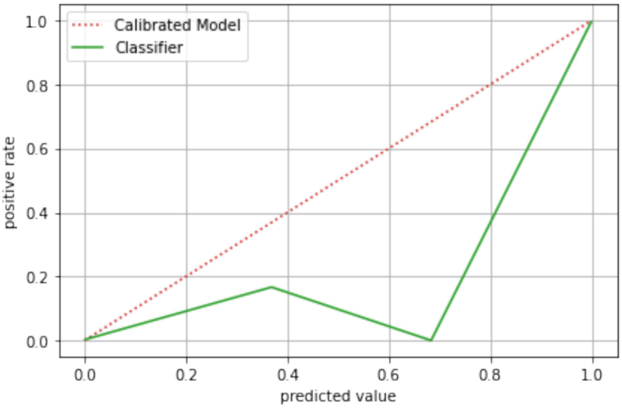

Fig. 8. Calibrated Model Vs Classifier graph

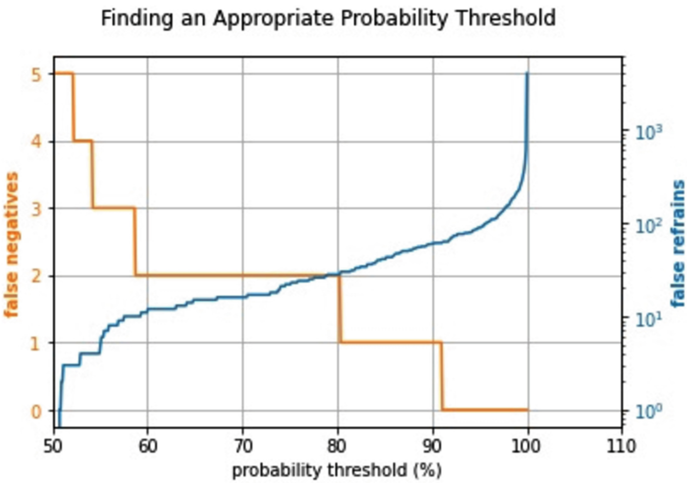

Fig. 9. Probability threshold Graph

4.3 Assessment

The above figure depicts three set of images which are non- crack, moderate crack and severe crack. The original image is at first and then followed by its grey scale image as it helps on making the computational function easier. The crack intensities are highlighted with the contour function here. The histogram mapping of the images which shows peak at center for the non-crack image, a bit of slit dip and then raise in graph towards the left side for moderate crack and full raise on the left side for sever crack has been shown in Fig. 10. Figure 11 displays the input gray color image,while Fig. 12 shows the contour of the crack image.

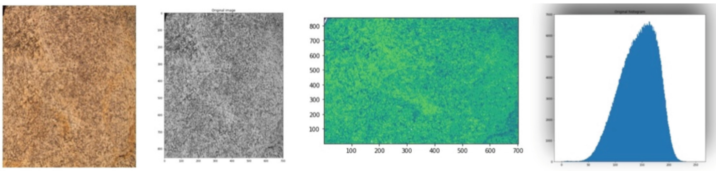

Fig (a) original image (b) Grey Scale image (c)Contour image (d)Histogram

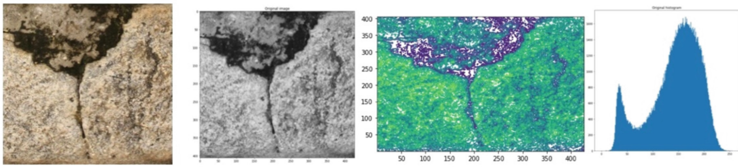

Fig (a) original image (b) Grey Scale image (c)Contour image (d)Histogram

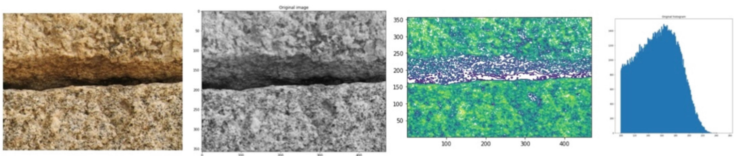

Fig (a) original image (b) Grey Scale image (c)Contour image (d)Histogram

Fig. 10. Histogram distribution of crack images

Table 4 describes the comparison of different crack detection methods with the proposed method using Deep Learning techniques. The different techniques for the detection of cracks such as Convolutional Neural Networks, Supervised approach with CNN was used in all existing method and which produces classification accuracy rate is less than 97% with that of the proposed method.

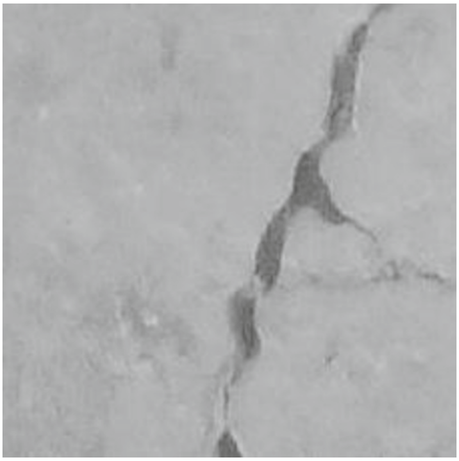

Fig. 11. Input gray color image

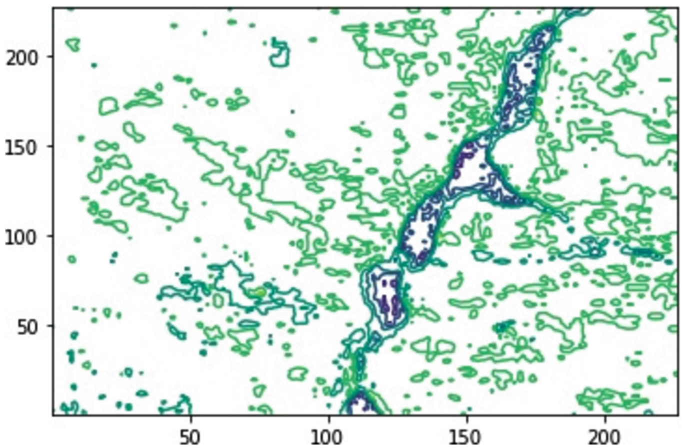

Fig. 12. Highlighting crack using CONTOUR Function

Table 4. Comparison between different crack detection image processing and Deep Learning algorithms

Existing	Techniques used	Accuracy
Krisada Chaiyasarn et al. (2018)	CNN and SVM [21]	85.9%
Manjurul Islam et al. (2019)	DCCN using FCN(Fully Convolutional Neural Networks [22]	92%
Aslam Y et al. (2020)	Supervised approach with CNN [23]	93%
Proposed Method	Proposed CNN	97.5%

5 Conclusion

The demonstrated deep learning technique acts as an automated crack detection on the surfaces of the monuments using the convolutional neural network in which the images have been separated into a separated data set randomly to create the test data and so does eliminating the adaptability and monotonous images. The Convolutional neural network has been created and the cracks has been detected with almost around an accuracy of 97.5% When compared with other methods for crack detection technique having SVM method with 81.2%, Boosting method with 73% and Generic Method 92%. The proposed technique uses the histogram distribution to identify cracks. The most precise approach is the Convnet method.

6 Future Work

A pre-trained CNN model will help in the development of an automatic damage detection model for large and larger structures or monuments (i.e., bridge, buildings, ancient structures etc.) where larger images can be collected using drones, as this equipment can increase the productivity of image capturing process. The developed CNN model will work with large data sets. So, it is expected that the algorithm will be useful for experts in structural analysis team with damage evaluation by increasing efficiency and saving time, cost.

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