Detection of Historical Building Crack Using CDNet Model

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Keywords: Cracks, Building Crack, Deep Learning, CDNet, Detection SDG.

Abstract: It is crucial to address the cracks in ancient monuments to preserve and safeguard them in alignment with the sustainable development goals (SDG). Thus, a new deep learning-based innovative CNN model, CDNet, is proposed for crack detection, which overcomes the challenges of manual detection. Our model was trained and evaluated using the Historical Crack Dataset. It achieved outstanding results, with 99% accuracy, 98.99% precision, and 99.01% recall. These results beat the performance of both the VGG16 and ResNet-50 models. The CDNet model can be subsequently deployed to the cloud for real-time applications.

1 INTRODUCTION

The protection and preservation of the cultural heritage of ancient monuments is one of the issues that must be addressed by the upcoming generations. Cracks that result in the loss of historical heritage and grandeur and the risk to the lives of living beings are a consequence of the numerous threats that these ancient structures face from environmental changes and human practices. Cracks are significant defects in building infrastructure that can have a significant economic impact and pose a safety risk if left unattended. Consequently, it is essential to evaluate the crack's profundity to ascertain the most suitable restoration method and forestall significant damage (Laxman, Tabassum, et al. , 2023). Crack detection has been conducted manually in the past, a process that is labor-intensive, time-consuming, and less precise (Xu, Tang, et al. , 2023).

Due to these constraints, there is a need for the development of more effective and precise techniques to identify and evaluate cracks in building structures.

In past years, there has been substantial growth in the utilization of deep learning methods for the identification of cracks in civil structures, including buildings, bridges, dams, and roads. These advancements have prompted the development of a novel deep-learning model that can be used to detect cracks or potential damage to buildings. This model is capable of analyzing images of structures, identifying existing cracks, and predicting potential future damage.

We introduce a novel model, CDNet, that is specifically designed for the verification of cracks in building structures. The CDNet model extracts spatial features from a dataset that comprises images of cracks in buildings. 80% of the dataset is utilized to train the model, while the rest 20% is reserved for evaluating its performance. The F1 score, precision, accuracy, and recall of the model are assessed while testing it on unseen data.

In this paper, the working of the CDNet model is discussed. In Section II, various works done by researchers are examined. Further, the proposed model CDNet is discussed in section III. The subsequent section IV of the paper focuses on the results of the method's implementation. Finally, the paper concluded with a summary, which was followed by references to the numerous works.

2 RELATED WORK

In this part, a detailed review is presented of the crack detection methods. Tran et al. (Tran, Nguyen, et al. , 2023) created a deep-learning model called U-Net to

Mittal, P., Sharma, B., Kumar, K. S. and Mohameed, H.
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DOI: 10.5220/0013621200004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 3*, pages 438-443
ISBN: 978-989-758-763-4

detect cracks on the bridge deck. The model demonstrates exceptional performance, with an accuracy rate of 92.38 percent. Popli et al. (Popli, Kansal, et al. , 2023) Suggested the use of a robotic model called Xception to detect cracks in roads. The newly proposed model achieves an accuracy of 90%.

Tabernik et al. (Tabernik, Šuc, et al. , 2023) proposed a novel paradigm, SegDecNet++, to streamline quality control during building and maintenance processes. The proposed model obtained a dice score of 81%. Pham et al. (Pham, Ha, et al. , 2023) concluded the research using Ostu Method to detect ground cracks along with their length and width and the accuracy recorded was 86.7% to 99.9%. Yadav et al. (Yadav, Sharma, et al. , 2024) suggested a new Convolutional Neural Network based model, HCTNet to identify cracks in roads ensuring sustainable road safety. The model achieved the F1 score of 97.20%.

Sun et al. (Sun, Yang, et al. , 2021) suggested conducting research utilizing the DeepLabV3+ model to accurately identify cracks and bugholes on the surface of the concrete. The model attained an impressive outcome, with a mean average precision of 95.58%.

Lin et al. (Lin, Li, et al. , 2023) suggested a model, DeepCrackAt based on the encoder-decoder network for crack segmentation and recorded an accuracy of 97.41%. Karimi et al. (Karimi, Mishra, et al. , 2024) proposed the implementation of a YOLO (You Only Look Only) deep learning model to diagnose damage in tiles. The CDNet model attained an accuracy rate of 72%.

Katsigiannis et al. (Katsigiannis, Seyedzadeh, et al. , 2023) suggested a deep learning-based model, MobileNetV2 to diagnose the cracks in brickwork masonry and achieved the F1 score of 100%. Yadav et al. (Yadav, Prasad, et al. , 2024) proposed the CCTNet to improve the precision of crack detection in structures. The model recorded a precision of 99.33% for the proposed dataset. Tasci et al. (Tasci, Acharya, et al. , 2023) developed a new architecture inception and concatenation residual (InCR) to identify damaged buildings. The model outperforms other models by showing an accuracy of 99.82%.

Reis et al. (Reis, Turk, et al. , 2024) created a combination model of ResNet152 +SVM to recognize the cracks in roads after the earthquake. The hybrid model had the highest level of success, with accuracy values of 98.68%. Zheng et al. (Zheng, Lei, et al. , 2020) suggested three deep learning models out of which RFCN (Richer Fully Convolutional Network) showed the best results for identifying the fractures in buildings with a recorded accuracy as 91%. Akgul et al. (Akgül, 2023) introduced a novel fusion model called Mobile-DenseNet for accurately recognizing cracks that appear on the surface of the concrete. The fusion model achieved a success percentage of 99.87%.

Roy et al. (Roy, Kukreja, et al. , 2023) developed a hybrid model of a deep CNN to detect the intensity of defects in painting in heritage buildings. The hybrid model resulted in an accuracy of 84.23%. Joshi et al. (Joshi, Singh, et al. , 2022) created a deep-learning model to identify surface cracks or defects in various structures. The model achieved an average precision of 93.445% in its predictions. ABDELLAOUI et al. (ABDELLAOUI, Errousso, et al. , 2024) concluded the study by considering the VGG-based learning model as the most superior for detecting cracks in the pavement as the model records an accuracy of 86.5%.

3 ARCHITECTURE OF THE MODEL

There are several issues with the earlier models that used deep learning methods that need to be fixed. Based on the previously employed ResNext and VGG16 models, a new model is built in order to optimize the performance of the crack detecting model through deep learning. This study developed a CDNet (Crack Detection network) sequential model for diagnosing building cracks. In this model, 5 convolution blocks. The sizes of the convolutional layers, conv1, conv2, conv3, conv4, and conv5, are 16, 32, 64, 128, and 256, respectively. The model consists of four different stages as shown in Figure 1.

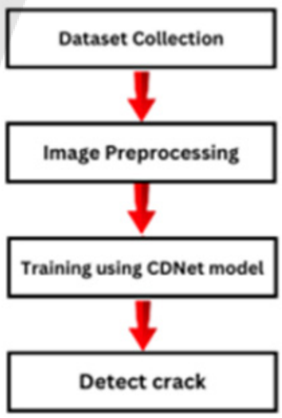


Figure 1: Stages During Crack Detection

3.1 Working of the CDNet model

A 2D convolutional layer processes an input image or feature map by applying several filters, extracting local features that are useful for tasks including image recognition, classification, and segmentation. The CDNet contain 5 convolution layer. The convolution layers have 16, 32,64,128, and 256 filter. Furthermore, each convolution layer is followed by ReLU activation and a maxpooling layer.

In the CDNet each filter detects specific features such as edges, corners, or textures. Each convolution layer is followed by ReLu activation functions and a max-pooling layer. To decrease computational load and the risk of overfitting, the max-pooling layer shrinks the feature maps in spatial dimensions while keeping the most crucial information. The network can learn more complicated functions because of the Relu layer's non-linearity. The Relu Layer applies the Relu function to every input element. Equation 1 is the mathematical formula for Relu Function.

$$f(x) = max(0,x) \tag{1}$$

After every convolutional block, a channel attention block (CAB) is also included as shown in

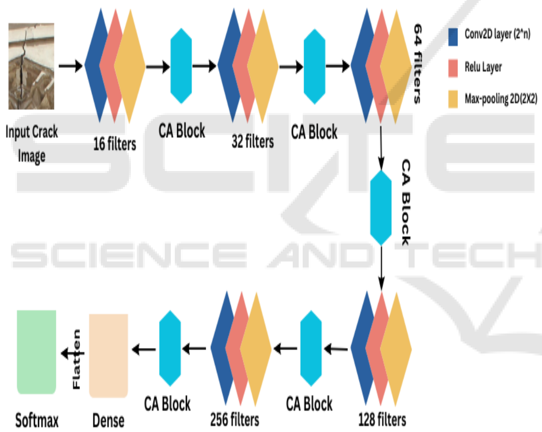


Figure 2. Structure of CDNet model to detect cracks

Channel Attention is a mechanism that allows a neural network to dynamically focus on the most informative channels of feature maps. It helps the model to weigh the importance of each channel and suppress less useful ones. It operates by first compressing spatial dimensions into channel-wise summaries using global pooling. These summaries are processed via thick layers to create channel-specific attention weights, which are then used to scale the relevance of each channel. Channels with higher weights are emphasized, while less relevant ones are suppressed. This mechanism improves feature learning and computational efficiency by ensuring that the network focuses on the most informative channels, leading to better model performance.

The experimental setting of the CDNet method is shown in Table I.

Table 1: Observations

Crack Images	3896
Batch size	8
Epochs	50
Channels	5
Training	80%
Validation and Testing	20%

4 RESULTS

This section discussed the proposed model CDNet's dataset description and quantitative results.

4.1 Dataset

The Historical Building Crack2019 collection comprises approximately 3886 meticulously curated images of cracked areas of antiquated structures. The dataset contains approximately 45 photographs of a medieval mosque (Masjid) of Egypt. There are 758 photographs of fractured surfaces and 3,138 photographs of non-cracked surfaces in the collection. The digital camera was used to capture the images, which had a resolution of 5184 × 3456 pixels. Some of the sample crack images are displayed in Figure 3. Also, by utilizing the rotational invariance, the size of the dataset has been expanded, and additional data was added through the use of the ImageGenerator method found in the Keras package. The crack image was subjected to augmentation techniques such as rotating clockwise, rotating anticlockwise, horizontal flip, and vertical flip.

(a) (b)

Figure 3. Sample crack images

4.2 Experimental Setting

Before testing with the CDNet model, the photos were scaled to 300 by 300 pixels. The model was then trained with batch size of 8. The initial learning rate was set at 0.001 to improve the performance. We let the model train and alter its values for 50 epochs.

Parameters that are evaluated to check the performance are F1 score, Accuracy, Recall, Precision, and Sensitivity from the confusion matrix. These parameters are computed by indicators like TP, TN, FP, and FN. With these data, the necessary metrics can be computed as follows:

$$Accuracy = (TN + TP)/(TN + TP + FN + FP) \tag{2}$$

$$Precision = TP/(TP + FP) \tag{3}$$

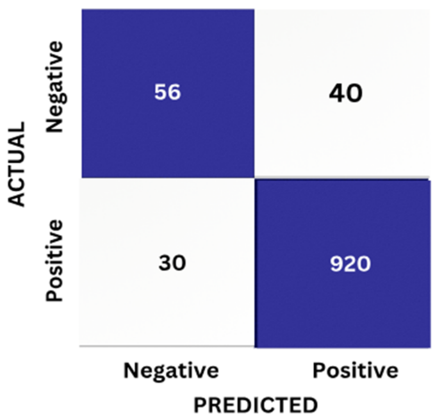
$$Recall = TP/(FP + TN) \tag{4}$$

$$F1\ score = (2 * Recall * Precision)/(Precision + Recall) \tag{5}$$

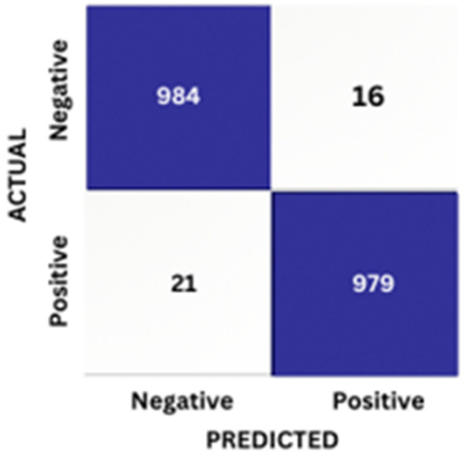
Kappa is utilized to verify the performance of a classification model, such as a CNN, by comparing the predicted labels to the actual labels. Kappa = 1 indicates a perfect match and a negative value indicates no match or worst agreement.

4.3 Performance evaluation on the Building Crack dataset

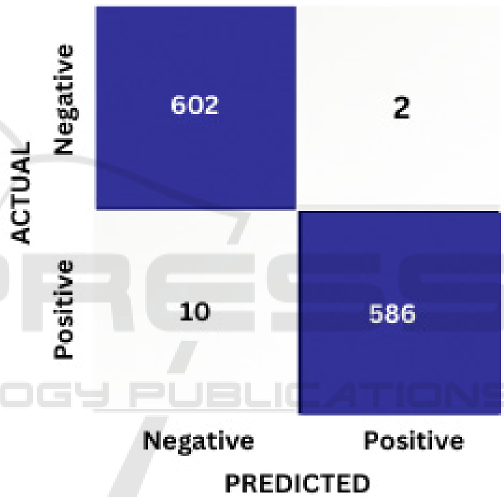
The Building Crack collection consists of 758 pictures illustrating surfaces with cracks and 3138 images exhibiting surfaces without cracks. First input image is resized to 300x300x3 pixels. After that, images are fed to the ResNet-50, VGG16, and CDNet models for training. We utilized batch sizes of 64 over 50 epochs for training of models. In addition, training process was expedited by using the Adam optimizer, with a starting learning rate of 0.001. After training, confusion matrices were created for each model and may be seen in Figure 4.



(a)



(b)



(c)

Figure 4: Confusion matrix (a) VGG16 (b) ResNet-50 and (c) proposed CDNet model

From the confusion matrices, Kappa, accuracy, F1 score, recall, and precision can be calculated using the formulas described in section B and shown in Table 2.

Table 2: Performance metric on Building Crack dataset

	VGG16	ResNet-50	CDNet
Precision	95.24%	96.15%	98.99%
F1 score	94.53%	95.70%	98.99%
Recall	93.85%	95.27%	99.01%
Accuracy	93.52%	95.43%	99%
Kappa	0.90	0.93	0.98

4.4 Training and Validation Loss

Valuable insights into the model's learning progress are provided by training and validation losses. The model is enhancing its ability to learn from the training data is indicated by a decrease in loss over time. Overfitting can be detected by comparing these losses: it is characterized by a decrease in the training loss and an increase in the validation loss, which suggests that the model is memorizing the training data rather than learning to generalize from it. The training (TR) and validation (VL) contours for the proposed technique are depicted in Figure 5, which utilizes the Historical Building Crack2019 dataset.

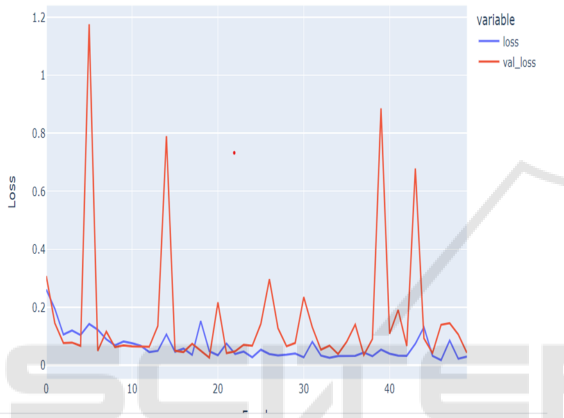


Figure 5: Training and Validation Loss over time

4.5 ROC plot

One often used statistic to evaluate building crack performance is the receiver operating characteristic (ROC). Taking the true positive rate (TPR) on the y-axis and the false positive rate (FPR) at the x-axis at several threshold values generates the ROC curve. The area under the curve (AUC) measure shows the likelihood that a positive value selected would rank better than a random negative instance picked. Figure 6 shows the comparison of ResNet-50, VGG16, and the CDNet model in which VGG16 has an AUC of 0.95, ResNet-50 has 0.96 AUC and CDNet boasts the highest AUC of 0.99.

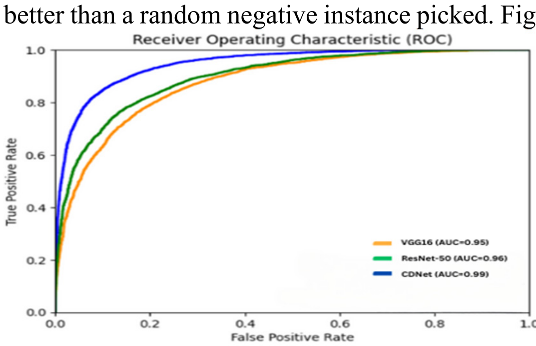


Figure 6. Roc-based comparisons of the VGG16, ResNet-50 and CDNet model

5 CONCLUSIONS

By leveraging deep learning techniques, the CDNet model offers a powerful tool for the preservation and maintenance of historical buildings. Its application can significantly enhance our ability to identify and repair cracks, ultimately collaborating with the preservation of cultural heritage. The proposed CDNet model shows an accuracy of 99% and a precision value of 98.99% which is higher than the previously used VGG16 and ResNet-50 models for which accuracy of 93.52% and 95.43% were recorded respectively. Also, the area under the curve for the CDNet model i.e. 0.99 is greater than the VGG16 and ResNet-50 models. Despite showing high accuracy, the model has a high computational cost. So, the CDNet model needs to be further modified to achieve low computational cost. Future work will emphasized on further modifying the model and enlarging the dataset to include a broader range of structures and crack types, ensuring even greater accuracy and reliability in real-world applications.

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