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STRUCTURAL DAMAGE DETECTION

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Abstract:* Prominent signs of wear and tear, such as cracks and openings on building wall indicate the wear and tear caused by stress over time, and when these defects occur in critical locations, such as load-bearing joints, they can lead to structural failure or collapse. Manually inspecting cracks can take time, and delays in identifying and repairing these cracks can have a significant impact on the structural integrity of infrastructure. To solve this issue we recommend implementing a crack detection method based on a convolutional neural network (CNN). The algorithm is composed of image processing image segmentation and CNN recognition. In the first part of the algorithm, cracks are easily recognized from the background image applying the Otsu's thresholding technique and in the second step segmentation of the image is carried using k means clustering and the existence of cracks is recognized using CNN which is used to determine whether cracks are present or not. The outcomes have demonstrated how well the CNN model distinguished between wall cracks and non- cracks, and the accuracy results are graphically visualized.

Keywords - CNN Recognition, Otsu's Thresholding, Structural Failures, Structural integrity, Image Segmentation.

1. INTRODUCTION

Cracks in building walls are a common occurrence caused by a variety of factors such as concrete erosion caused by chemical contaminants, poor foundation, vibration of the building caused by mild earthquakes, and so on. Thermal movement causes the material to contrast or shrink as the temperature rises and falls. Tree root growth or alteration works to the building all these factors can damage the structural integrity of the building leading to cracks in the wall. Cracks on walls range in size from thin hairline cracks less than 0.1 mm wide to fine cracks up to 1mm wide, mild and severe cracks 5-15 mm wide, and structural damages greater than 25mm wide. Thin and fine cracks generally do not require immediate action, severe cracks do require immediate action else, will result in failure of structural integrity. Manual inspection of building cracks is a time-consuming process that, if delayed, may compromise the structural integrity of the building, putting the occupants at risk. This project focuses on developing a reliable crack detection method based on image processing, image segmentation, and a CNN model to easily identify cracks in building structures so that they can be repaired as soon as possible and keep the building's occupants safe.

2. NEED OF THE STUDY

In today's fast-paced world, where buildings are constructed in a matter of months, less careis taken to ensure structural integrity. Faulty practices such as improper use of construction materials, incorrect assessment of soil bearing capacity, and improper structural design can result in cracks of varying degrees that, if undetected and not repaired on time, may compromise the structural integrity of the building, putting the occupants at risk. Manual crack detection is time consuming, labor intensive, and prone to human error. The detectionof cracks in walls using image processing and the CNN model is helpful in identifying and locating cracks on buildings, allowing for timely repairs and maintenance of the cracks and preventing further damage.

3. LITERATURE REVIEW

1. "Wall Crack Detection Based on Image Processing", Dongna Hu, Tian Tian, Hengxiang Yang, Shibo Xu and Xiujin Wang

In this paper, a novel crack detection method is proposed based on the digital image of building external wall. We strive to record the wall surface condition accurately, and then get the linear characteristics of the image for crack recognition. This paper first does image edge detection, image binary of adaptive threshold and removal of isolated points, obtaining effective linear characteristics. Finally, we distinguish the cracks and the normal lines through the curve fitting and its parameter analysis. The experimental results are satisfactory.

2. "Intelligent Crack Detecting Algorithm on the Concrete Crack Image Using Neural Network",Hyeong-Gyeong Moon and Jung-Hoon Kim.

Safety inspection of concrete structures should be strictly carried out since it is closely related with the structural health and reliability. However, it is difficult to find cracks by a visual check for the extremely large structures. So, the development of crack detecting systems has been a significant issue. Final objective of this research is to develop an automatic crack detection system that can analyze the concrete surface and visualize the cracks efficiently. The algorithm is composed of two parts; image processing and image classification. In the first step, cracks are distinguished from background image easily using the filtering, the improved subtraction method, and the morphological operation. The particular data such as the number of pixel and the ratio of the major axis to minor axis for connected pixels area are also extracted. In the second step, the existence of cracks is identified. Backpropagation neural network is used to automate the image classification. Target data values in the training process were generated by inspector's manual classification. In order to verify the first and second step of the proposed algorithm,the algorithm was tested using real surface images of concrete bridge. Backpropagation neural network was trained using 105 images of concrete structure, and the trained networkwas tested for new 120 new images. The recognition rate of the crack image was 90% and non-crack image was 92%. This method is useful for non-expert inspectors, enabling them to perform crack monitoring tasks effectively.

3. "Cement Pavement Surface Crack Detection Based on Image Processing", Hongwei Leia, Jianlian Cheng b, Qi Xu c

This article introduces the application of image recognition technology in cement pavement crack detection and put forward to method for determining threshold about grayscale stretching. the algorithm is designed about binarization which has a self-adaptive characteristic. After the image is pre-processed, we apply 2D Wavelet and Laplace operator to process the image. According to the characteristic of pixel of grey image,an algorithm designed on binarization for Binary image. The feasibility of this method can be verified the image processed by comparing with the results of three algorithms: Otsu method, iteration method and fixed threshold method.

4. "Structural Damage Detection Based on One-Dimensional Convolutional Neural Network, Zhigang Xue, Chenxu Xu and Dongdong Wen

This paper proposes a structural damage detection method based on one-dimensional convolutional neural network (CNN). The method can automatically extract features from data to detect structural damage. First, a three-layer framework model was designed. Second, the displacement data of eachnode was collected under the environmental excitation. Then, the data was transformed into the interlayer displacement to form a damage dataset. Third, in order to verify the feasibilityof the proposed method, the damage datasets were divided into three categories: single damage dataset, multiple damage dataset, and damage degree dataset. The three types of damage dataset can be classified by the convolutional neural network. The results showedthat the recognition accuracy is above 0.9274. Thereafter, a visualization tool called "t-SNE" was employed to visualize the raw data and the output data of the convolutional neural network. The results showed that the feature extraction ability of CNN is excellent. However, there are many hidden layers in a CNN. The outputs of these hidden layers are invisible. Inthe last section, the outputs of hidden layers are visualized to understand how the convolutional neural networks work.

4. METHODOLOGY

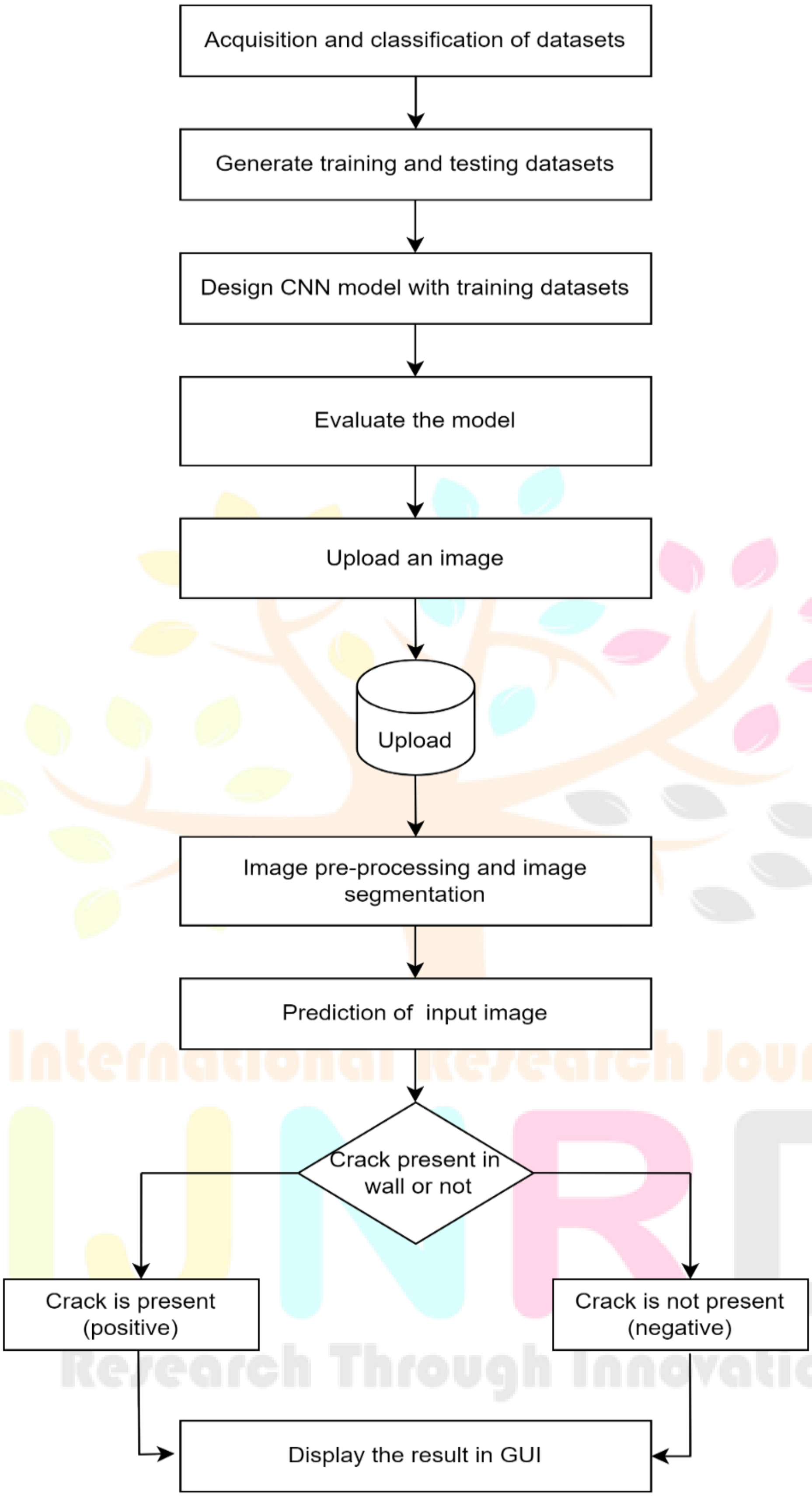

Fig 1. Methodology

4.1 DATA

To train the model, a large dataset containing images of various concrete surfaces from Kaggle is used. The dataset contains two types of images. The positive class represents images of cracked wall surfaces, while the negative class represents images of cracked wall surfaces. Each class has a total of 20000 images.

4.1.1 IMAGE PREPROCESSING, THRESHOLDING

Simple image segmentation is achieved through image thresholding. In this method, a grayscale or full-color image is converted into a binary image. The purpose of this is to separate "object" or foreground pixels from background pixels in order to process the image.

we first convert the resized image from a coloured image to a grayscale image next, we apply a binary threshold to the grayscale image and threshold is determined automatically using Otsu's method.

4.1.2 IMAGE SEGMENTATION

An image segmentation task involves segmenting or partitioning an image into multiple regions in such a way that pixels within the same region have the same properties. Using K-Means clustering, we segment images into groups based on the similar characteristics of the data points within each group. K-Means is a clustering algorithm that groups data points into clusters. It is possible to segment an image using the K-means algorithm by finding subgroups in the image and assigning each pixel to a subgroup.

We first convert the image from BGR to HSV color space this is done because HSV color space separates the color information from the brightness information, making it easier to segment the image based on color. Next, we reshape the image into a 2D array using This is done to prepare the image for k-means clustering, which requires a 2D array as input. we then set the criteria for k-means clustering using. The criteria specifies that the algorithm should terminate either when the specified number of iterations is reached or when the specified accuracy is achieved. The resulting clusters are then used to segment the image into different regions and finally, the segmented image is displayed.

4.1.3 CNN RECOGNITION

In deep learning, CNNs (Convolutional Neural Networks) are commonly used to analyze images and videos. A mathematical operation called convolution is applied to the input images to identify and extract features from the visual data.

We first create two ImageDataGenerator objects, train and test, which are used to generate training and testing data for the model. Next, we create a sequential model using Keras. The model consists of three convolutional blocks, each followed by a max pooling layer. The convolutional layers use a 3x3 kernel to extract features from the input image. The max pooling layers reduce the spatial dimensions of the feature maps by a factor of 2. The dropout layers randomly drop out 20% of the neurons to prevent overfitting. After the convolutional blocks, the feature maps are flattened and passed through two fully connected layers with 64 and 32 neurons, respectively. These layers use the ReLU activation function to introduce non-linearity into the model. Another two dropout layers are added to prevent overfitting. Finally, a softmax output layer with two neurons is added to classify the input image into one of two classes The code then compiles the model using the Adam optimizer and categorical cross-entropy loss. It also includes several metrics to evaluate the model's performance, including precision, recall, specificity at sensitivity 0.5, sensitivity at specificity 0.5, and accuracy. The model is trained using the fit method, with the training and validation data provided by the image generator. The training history is saved to a pickle file, and the trained model is saved to a file using the ModelCheckpoint callback. It creates a ModelCheckpoint object that will monitor the validation accuracy during training and save the best performing model to the specified file path.

5. RESULTS AND DISCUSSION

The input image is preprocessed so that cracks can be easily distinguished from the background image using Otsu's Thresholding Technique.

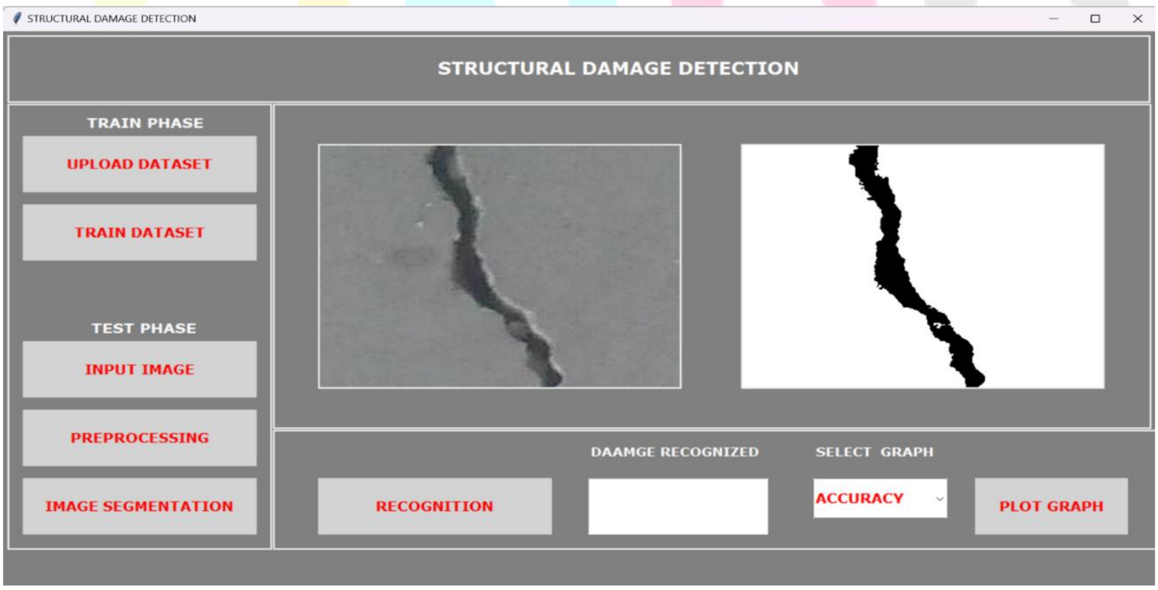

Fig 2. Input Image After Image Preprocessing

Using k-means clustering, image segmentation is performed on the input image to identify the parts of the image that contain cracks.

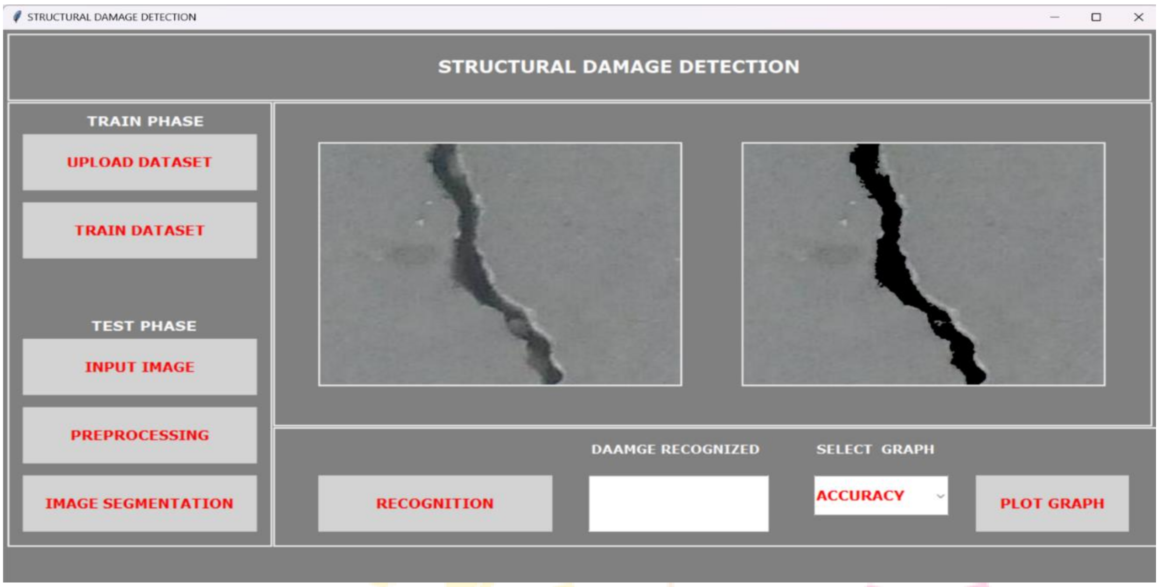

Fig 3. Input image After Image Segmentation

A screenshot of the result page. If the CNN model classifies the input image as positive, it indicates that the wall surface has a crack in it.

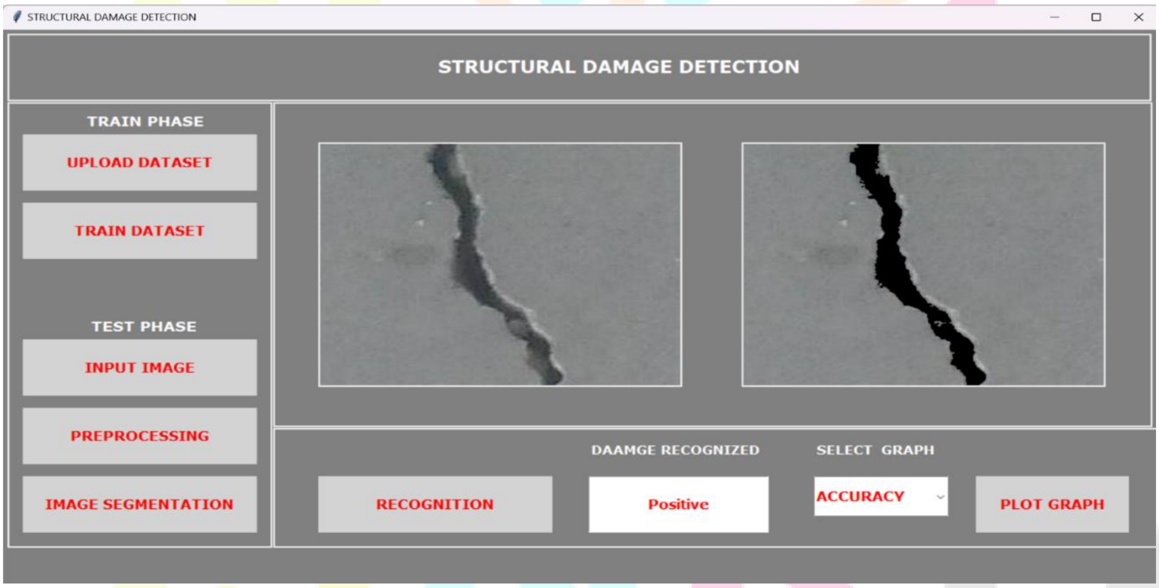

Fig 4. Result Page (Wall surface contains crack)

A snapshot of Result Page. If the CNN model classifies the input image as Negative, it indicates that the wall surface does not have crack in it.

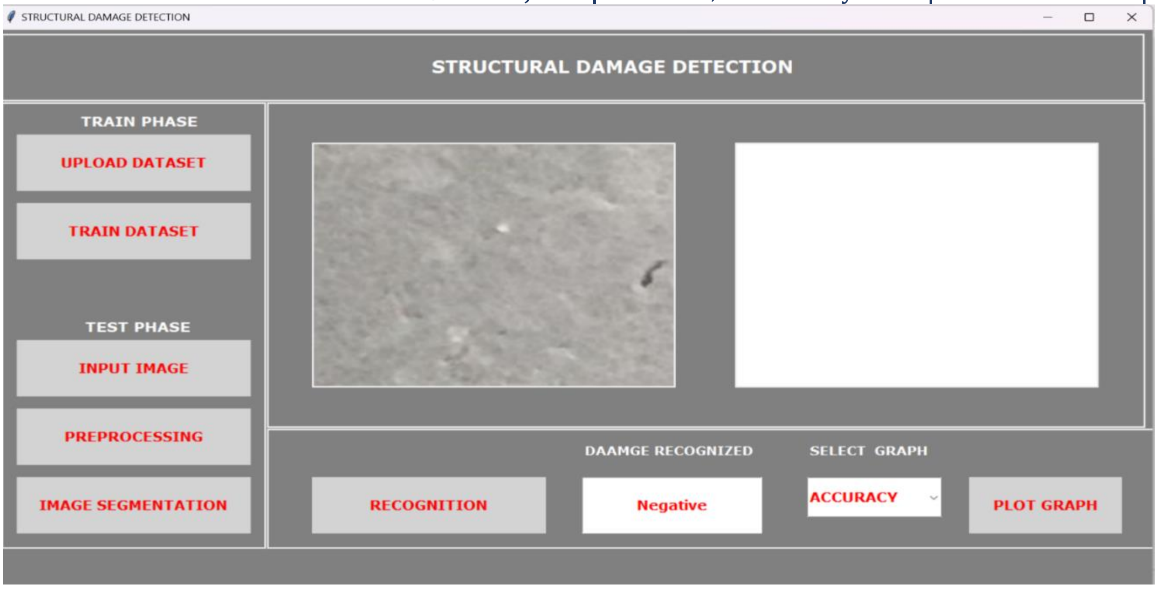

Fig 5. Result page (Wall surface doesn't contain crack)

A snapshot of the graph that displays the model's accuracy as a function of the number of epochs. The graph can help in understanding how the model's accuracy improves throughout the training process. and it also helps to identify the optimal number of epochs for training the model.

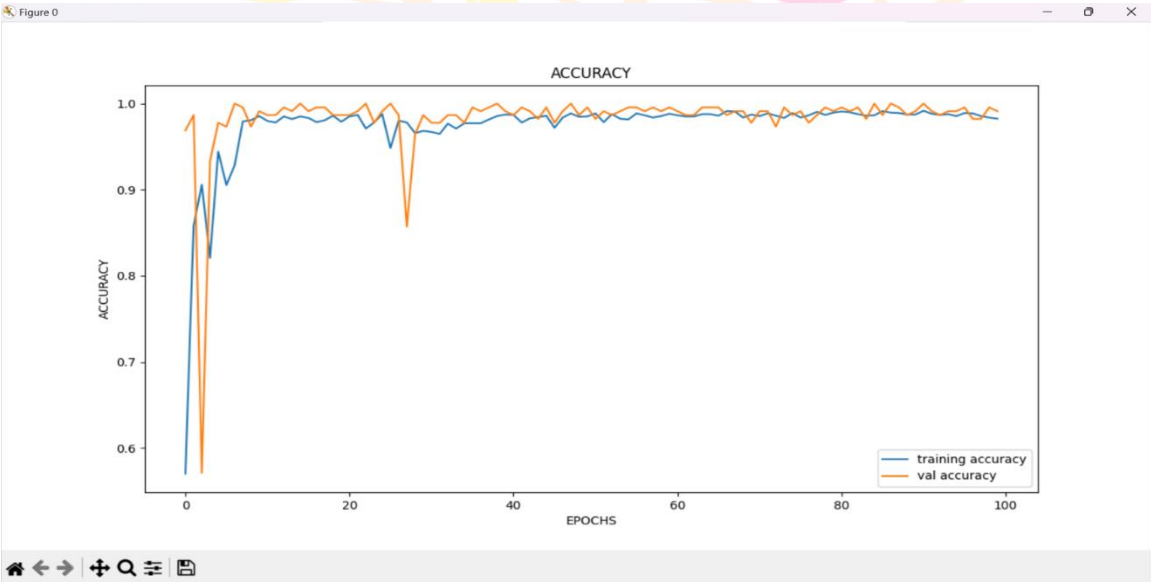

Fig 6. Model Accuracy vs epoch graph

A snapshot of the graph indicating specificity on the y-axis and the number of epochs on the x-axis. Specificity measures the proportion of true negatives that are correctly identified by the model.

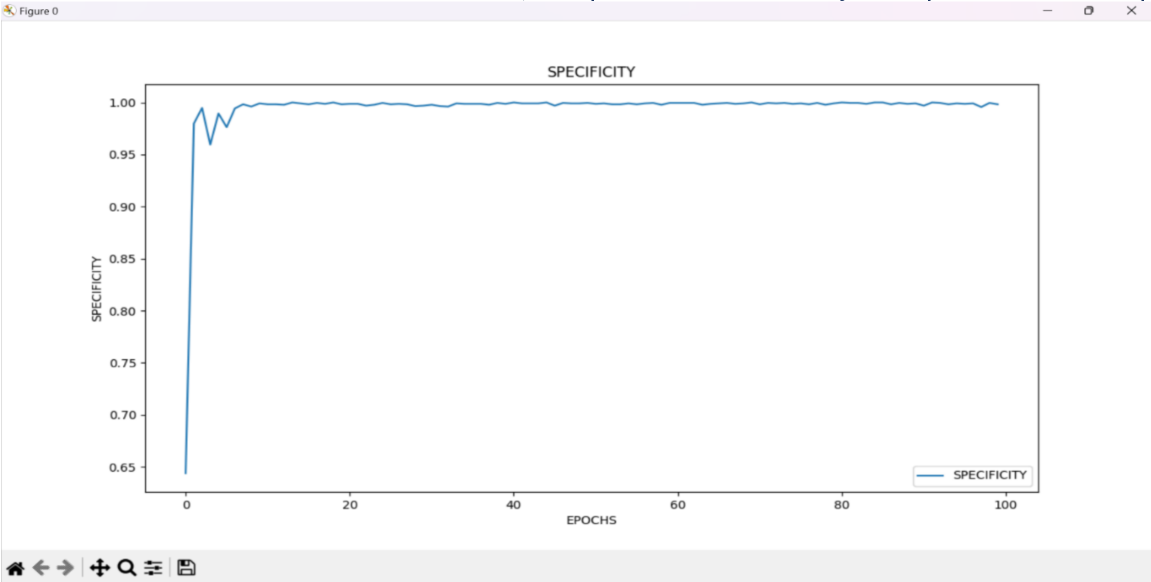

Fig 7. Specificity vs epoch graph

A snapshot of the graph indicating sensitivity on the y-axis and the number of epochs on the x-axis. Sensitivity is a measure of how well a model can detect positive instances.

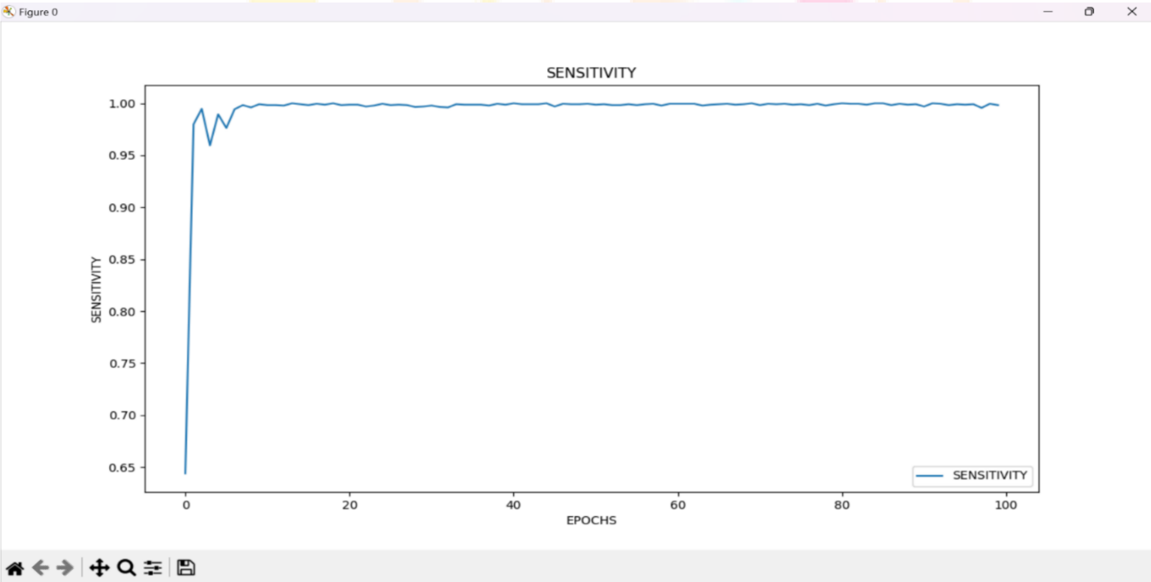

Fig 8. Sensitivity vs epoch graph

A snapshot of graph indicating f1score on the y axis and number of epochs on the x axis. f1 score is an evaluation metric that is used to evaluate the performance of the model The F1 score is defined as the harmonic mean of precision and recall.

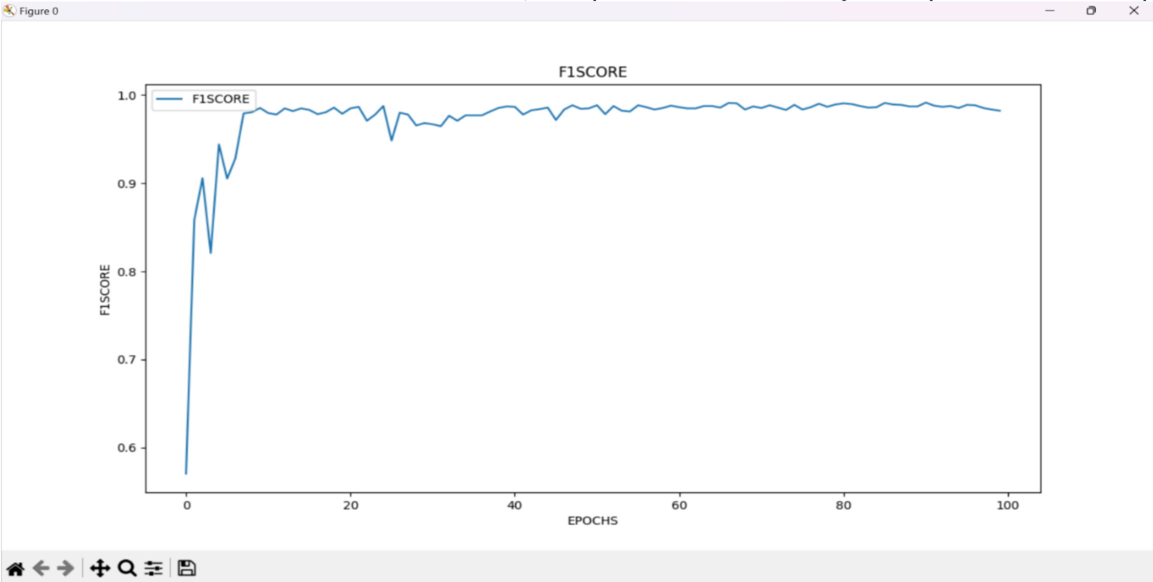

Fig 9. F1score vs epoch graph

6. CONCLUSION

Detecting cracks on wall is a challenging task as a result, deep learning models are utilized, which have a better accuracy rate and are reliable as well as easily scalable. One such model, called Convolutional Neural Networks, has been developed to quickly and accurately predict the presence of cracks on wall surfaces. The proposed model is a user-friendly GUI system that uses image processing techniques to quickly and easily distinguish cracks from background images using Otsu's Thresholding Technique. It also employs image segmentation techniques to identify areas of an image that contain cracks. The CNN model helps in categorizing the image as positive (with a crack) or negative (no crack). The CNN model provided a detection accuracy of --%. Thus, the proposed system is reliable, simple to use and cost-effective, and it can be easily integrated with a real-time system to quickly identify cracks and provide building maintenance personnel with an overview of the wall surfaces that have cracks and need immediate repair.

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