Crack Detection using Deep Learning

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***Abstract*— Concrete cracks are one of the primary signs of a structure that would cause major harm to the entire infrastructure. The conventional method of addressing cracks is manual inspection. We discovered during the survey that there are numerous existing technologies, including approaches based on computer vision and image processing. There are several techniques for locating fractures on different surfaces utilizing manual inputs. Different factors influenced the performance of traditional models, which provided results with variable degrees of accuracy. Because there are many different strategies that can be used to produce a good crack detection output, the performance and efficiency were influenced by the environment. Using a Convolutional Neural Network, we have constructed a deep learning model for fracture classification and segmentation. Convolution, activation, and pooling layers make up the foundation of convolutional neural networks. These layers enhance the performance and generalization of neural networks by extracting picture information, introducing nonlinearity, and reducing feature dimensionality. The observed model's accuracy was between 97 and 98 percent. This model can be used to keep track of the condition of the concrete surfaces of bridges, tunnels, and other public transportation infrastructure.**

Keywords*— *Crack detection, Deep Learning, Image Processing, Convolutional Neural Networks, Edge detection, Image Segmentation, Feature Extraction.

Introduction

Finding surface cracks is crucial for maintaining infrastructure like roads and buildings. Using any of the processing approaches, crack detection is the process of locating cracks in structures. Early identification enables the implementation of preventative steps to stop potential failure and damage [1]. The conventional method required a lot of time and labor. By using a range of contemporary cameras to record crack images, it is possible to get beyond the lack of manual inspection and complete successful maintenance. The issue of fracture identification has recently been solved by modern technology, although it is not particularly precise because cracks can differ from structure to structure and be different on different surfaces. Accurately recognizing various types of cracks is also difficult because of the intricacy of crack topologies and noise in collected crack pictures. Pavement crack detection using image processing is now both affordable and effective [2][3].

In practice, approaches for hand-crafted feature extraction from sub-windows based on intensity thresholding, edge detection, and other image processing techniques are frequently used [4].Although the efficiency of these systems in detecting pavement surfaces has been established, there is still room for development, particularly in the classification of different pavement fracture kinds. However, both computer vision and non-computer vision techniques have difficulties recovering fracture characteristics from pavement with shadows and complicated background pavement, as well as extracting cracks using low-level image cues [5].

Convolutional Neural Networks (CNN), a prominent tool of the artificial intelligence branch of Deep Learning (DL), have demonstrated their effectiveness in object detection.

In contrast to conventional machine learning techniques, deep learning (DL) offers end-to-end classifiers that internally learn characteristics and can recognise objects automatically. The recent advancement of graphics processing units (GPU), which allows for extremely quick computations, together with this characteristic of DL algorithms have increased their use in a variety of sectors. In the instance of crack detection from images, the user need only supply various photos as input, and any detected cracks in these photos are returned as output without the need for any operator involvement [6]. Mendeley's Concrete Crack Images for is the source of the information in our model. Our deep learning model has a classification accuracy of between 97 and 98 percent.

I. LITERATURE REVIEW

Crack detection is identified and segmented based on a variety of characteristics because it is an intriguing issue with numerous challenging parameters. There are different ways to find cracks. There are several techniques that use manual inputs to find fractures in a variety of surfaces.

Image processing methods using cameras.

This section provides a summary of the processing methods used to identify cracks in engineering structures using camera images. Many of the publications that were reviewed here used camera input.

The information regarding the fracture is gathered through pre-processing, image segmentation, and feature extraction. Following the smoothing of the acceptable input image, the Threshold method of segmentation was applied. The size and perimeter of the roundness index are determined for picture justification. The presence of the crack in the image is then assessed in comparison [7]. Many commercial camera-based image processing methods simply require pre-processing, however some methods focus on the integration algorithm, which is where feature extraction is doneThe faults are represented quantitatively in a model that was created. The fracture quantification and detection, neural network, and 3-D visualization models, respectively, make up the integration model [8].

A stitching algorithm for images was created. For the retrieval of the crack segments, that has been utilized, which uses a feature-based registration and skeletonization technique. The evaluation of the crack quantification model served as the sole foundation for the width and length-based crack detection. An integrated model that combined fracture length and change detection with 3D crack pattern visualization and neural network prediction of crack depth was developed [1].

Image Processing Methods

Preprocessing is a phase used in image processing techniques to reduce noise and improve crack characteristics. To identify cracks, it uses threshold segmentation. The morphological approach method finds fracture formations by evaluating curvature and using mathematical morphology. The neighbourhood pixels are used to estimate the size of the crack in the percolation-based approach to identify whether a focus pixel is a part of it. While the automatic route-finder algorithm calculates the length and width of the cracks in the practical technique, the endpoints of the crack are manually identified. As the initial stage in enhancing the crack detection algorithm's performance, all IP approaches preprocess photos. There has been a lot of research done on these IP approaches' accuracy [1].

The majority of studies concentrate on non-intrusive techniques like feature extraction and thresholding. The lack of uniformity in particular IP techniques has been highlighted, nevertheless. Thresholding, for instance, has relied on extremely basic techniques like a fixed 0.5 or halving the maximum image brightness; this differs with more sophisticated techniques like Otsu and Niblack [9].

Edge detection

Concrete cracks are one of the primary signs of a structure that would cause major harm to the entire infrastructure. The conventional method of addressing cracks is manual inspection. Manual procedures omit the quantitative and qualitative analysis. Experiments with automatic fracture identification utilizing image processing techniques yield reliable results. In more recent publications, a wide variety of image-processing approaches have been tested. For the purpose of identifying concrete cracks, a thorough analysis of several edge detection methods is done. Prewitt, Sobel, Gaussian, Roberts, Canny, and Laplacian edge detector performance is discussed [18].

A break in the intensity field of the greyscale is referred to as an ideal edge. In order to discover image cracks more quickly and effectively within a big picture dataset, edge detection refers to the employment of filters in an image processing algorithm to detect or enhance the cracks in an image. Matrix representations of images are used in mathematics [20].

A discontinuity in the intensity level is referred to as an edge. Methods for crack identification use filters in the spatial or frequency domain to locate edges. These techniques outperform manual examination in terms of reliability. The following stages are generally followed by all edge detector-based fracture detection techniques:

- Smoothing
- Enhancement
- Detection
- Binarization

Types of Edge detector algorithm:

- Sobel Edge Detector
- Canny Edge Detector
- Prewitt
- Robert
- Laplacian of Gaussian (LOG)
- Fast Fourier Transform (FFT)

This suggests that visual assessment of concrete structures by people is a more time- and money-intensive task. Concrete structure cracks are automatically detected, reducing the need for human intervention. This study examines various edge detection techniques' analyses of concrete crack detection. We investigate two frequency domain-based edge detector approaches and four spatial domain-based edge detector methods. The outcomes from the edge detection techniques were fairly satisfactory. It should be expanded using deep learning techniques in order to achieve higher performance in conventional edge detection techniques [18].

Traditional ML methods:

Crack evaluation has always been done manually using human field surveys. These manual survey methods, however, have low repeatability and reproducibility, require a lot of time and labour, and put surveyors in danger. Additionally, due to subjectivity of the raters, the data collected may differ. There have been significant research efforts to develop automated crack survey methods to address the drawbacks of manual surveys. Data collection, crack detection, and crack diagnosis make up the automatic crack evaluation.

The crack detection method receives two- or three-dimensional (2D or 3D) input data from data capture. Crack detection is the process of identifying cracks in the 2D and/or 3D data provided by automated data capture, with the least amount of human participation. Crack diagnosis requires key inputs from crack detection, including classification data like type, severity, and extent that are critical for planning maintenance. Through the management process, crack diagnosis can be utilized to choose the best time and intensity of therapy [11].

Before training the models, traditional ML techniques use a predetermined feature extraction stage. Support vector machines (SVM), artificial neural networks (ANN), random forests, clustering, Bayesian probability, and naive Bayes fusion are the most popular conventional ML techniques. Both crack identification and image processing with the best parameters have been accomplished using conventional ML algorithms. These are also frequently employed for the extraction of predetermined features. They are unable to handle massive datasets, though. Traditional ML techniques have a drawback in that they are unable to learn more complicated features and cannot handle the complex data included in photos, such as backdrop pavement with varying lighting [9].

Predefined feature extraction requires image-processing procedures, and diverse features have been applied in various research projects, including statistical values of images, vertical and horizontal projections of feature maps, and characteristics of specified crack objects. The primary issue with conventional ML approaches is that they only use superficial learning strategies. Those approaches can't handle the complicated information in the photos without learning higher-level features. For instance, lighting and the environment have a significant impact on the background of photos of pavement.

II. METHODOLOGY

In our approach, crack segmentation is formulated as a binary image labelling problem, where "Positive" and "Negative" stand for, respectively, "crack" and "non-crack." If there is a crack in the output image, deep learning will be used to further segment it. A task like this necessitates both high-level features and low-level clues. Convolution, activation, and pooling layers make up the foundation of convolutional neural networks (CNNs). These layers enhance the performance and generalization of neural networks by extracting picture information, introducing nonlinearity, and reducing feature dimensionality.

Layers used in convolution, activation, and pooling are the foundation of CNNs. These layers enhance the performance and generalisation of neural networks by extracting picture information, introducing nonlinearity, and reducing feature dimensionality. Convolution layers in CNNs are used mostly for feature extraction, which also maintains the spatial relationship between pixels in the source pictures. The output of the convolution kernel or filter is computed by sliding the image by pixels, performing element-wise multiplication, and adding the pixels. The feature map is the name of the output matrix. A collection of 2D arrays of weights is what makes up a convolution kernel or filter in deep learning. Each 2D array of weights is used to generate additional channels by applying it to all of the input channels from the preceding layer.

While feature maps of higher layers include more semantic meaning and less location information, lower convolution layers primarily extract structural elements and location information from an image. An error backpropagation technique can be used to learn and improve the convolution kernels with weights during training. A CNN is one of the several kinds of artificial neural networks that are used for different applications and data sources. It is also a sort of network architecture for deep learning algorithms and is specifically utilised for tasks like image recognition and pixel data processing. An activation function is used to provide nonlinearity to neural networks after the convolution process. Rectified Linear Units are frequently used activation functions.

CNN Architecture:

There are two main parts to a CNN architecture

- Feature extraction is a procedure that uses a convolution tool to separate and identify the distinct characteristics of an image for study.
- There are numerous pairs of convolutional or pooling layers in the feature extraction network.
- a fully connected layer that makes use of the convolutional process's output and determines the class of the image using the features that were previously extracted.
- This CNN feature extraction model seeks to minimize the quantity of features in a dataset. It generates new features that condense an initial set of features' existing features. The number of CNN layers is numerous, as seen in Figure 1.

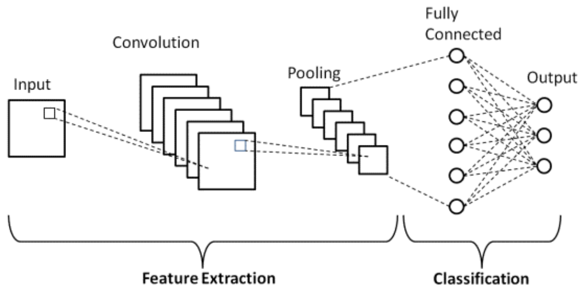

Figure-1: CNN Architecture

[Source: Binary Image classifier CNN using TensorFlow - Medium.com]

An overview of how to use a CNN to find cracks is shown in Figure 2 below. The dataset for concrete cracks, modelling, and testing the trained CNN classifier are the three processes. Many raw photos of the concrete surface are obtained in order to train this model. The gathered raw images are reduced in size by cropping, and the reduced images are then manually differentiated into photographs with and without cracks. The training set and validation set are then arbitrarily chosen from the dataset and loaded into a CNN for training and validation, respectively. A CNN classifier is created through training that can distinguish between images with and without cracks. Cracks in photos can be distinguished from others using the trained CNN classifier.

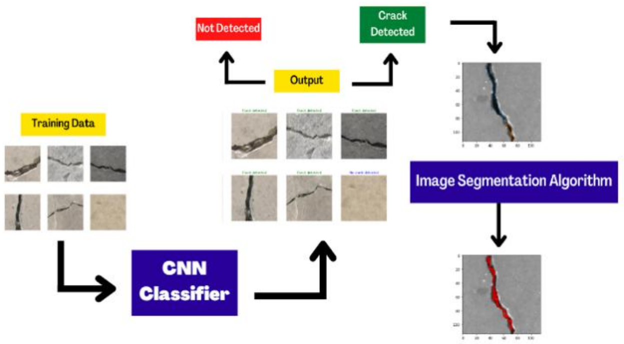

Figure-2: Model Workflow

Model Training

- The number of epochs can be increased to improve accuracy.
- Here, learning pace is equally crucial. Training at various learning speeds can lead to better results. However, this significantly lengthens the training period.
- If a low learning rate is chosen, training moves more slowly; if a high learning rate is chosen, training moves faster but accuracy suffers.

Classification Report

- The function for creating classification reports generates a text report with the key classification metrics.
- The ratio of true positives to the total of true and false positives is the definition of precision for each class..
- Recall is determined for each class as the proportion of true positives to the total of true positives and false negatives.
- Since F1 scores incorporate precision and recall into their computation, they are less accurate than accuracy measures.

III. DATA COLLECTION & PLATFORMS USED

Tools / Platform	Description
Miniconda	A free basic installer for conda is called miniconda. It is a stripped-down, bootstrapped version of Anaconda that just contains conda, Python, and the packages they require, as well as a select few other important packages like pip, zlib, and a few more..
CUDA	NVIDIA's CUDA is a general-purpose parallel computing platform and programming model that accelerates deep learning and other compute-intensive apps by taking advantage of the parallel processing power of GPUs.
Google Colab	Google Research produces Google Colaboratory, sometimes known as "Colab." Colab is particularly useful for machine learning, data analysis, and education because it enables anyone to write and run arbitrary Python code through the browser.
Jupyter	The first web application for producing and sharing computational documents was called a Jupyter Notebook. It provides a straightforward, efficient, document-focused experience.
Command Prompt	For the operating systems OS/2, eComStation, ArcaOS, Microsoft Windows, and ReactOS, it serves as the default command-line interpreter.
VSCode	On your desktop, Visual Studio Code is a quick yet effective source code editor that runs on Windows, macOS, and Linux.

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IV. DATASET

CLASSIFICATION IMAGES OF CONCRETE CRACK

Images of diverse concrete surfaces, both with and without cracks, can be found in the datasets. For image classification, the picture data are split into two categories: negative (without crack) and positive (with crack). Totaling 40000 photos with 227 × 227 pixels and RGB channels, each class comprises 20,000 images. 458 high-resolution photos are used to create the dataset (4032x3024 pixel). High levels of variance were discovered in high resolution photos [19].

V. DESIGN, IMPLEMENTATION AND MODELLING

Step-1: Setting the Dataframe

Images that have cracks are kept in a category called "POSITIVE," whereas those without cracks are kept in "NEGATIVE."

Step-2: Training Period

We have a fully convolutional model that has been trained and fed the aforementioned dataset.

We installed the prerequisites, imported the required libraries, and handled the project's dependencies to ensure proper implementation. The dataset including images with and without cracks is initially input to the model. The initial dataset was split into 60 percent Training data and 40 percent Testing data, with the epochs set at 10. The model successfully classifies the Test pictures into two groups when each epoch is complete: "Crack Detected" and "No Crack Detected."

Figure-3: [Images are classified into 'Crack Detected' and 'No Crack Detected']

Step-3: Model Summary

Using Keras, a neural network is created in this stage. ReLu and sigmoid activation functions were used for these layers because they produce more accurate results for the project at hand.

Image Segmentation

The model has been trained and can now label the new photos. We'll be dealing with photos that have cracks in them. Any image can be used as an input to the model.

Figure-4: [Initial Image as an input]

For this, the images with cracks are saved into a folder called positive. The model will now be transmitted with an image that includes a crack. An appropriate size change will be made to this image. Red dots, also known as scatter marks in the matrix, will be used to label the whole image after adjustments. In the next step, the red dots are reduced so that the features, Crack marks are covered with red dots. Finally, this marked part will be colored red.

The final output generated is an image that is classified into a crack label with crack highlights.

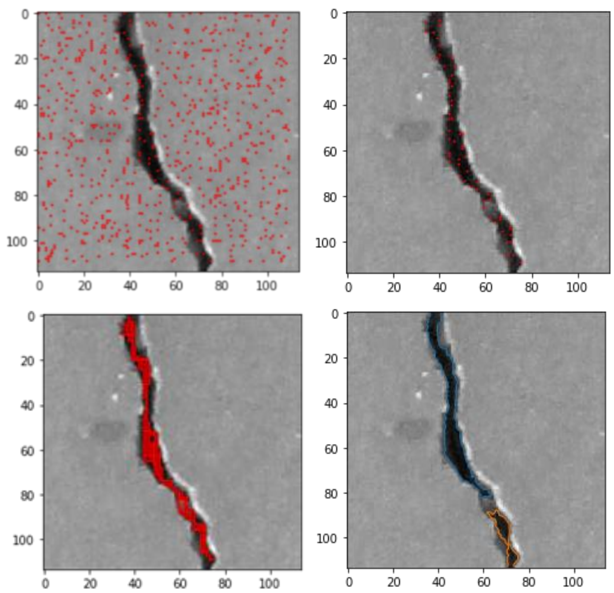

Figure-5: [Image with crack highlights in red]

Image Processing technique:

a model that applies multiple image processing methods, including grayscale image conversion, hue scale, and other methods. These methods are employed to draw attention to the entire image and extract the features. The next stage is to use a clever edge detection method after image processing. The multi-stage technique Canny Edge Detection determines the Edge Gradient from the images to mark the outlines.

$$Edge\_Gradient\ (G) = \sqrt{G_x^2 + G_y^2}$$

This method had a problem with photos that were noisy, overexposed to light, and blurry. The following is a list of the results that the image processing techniques produced.

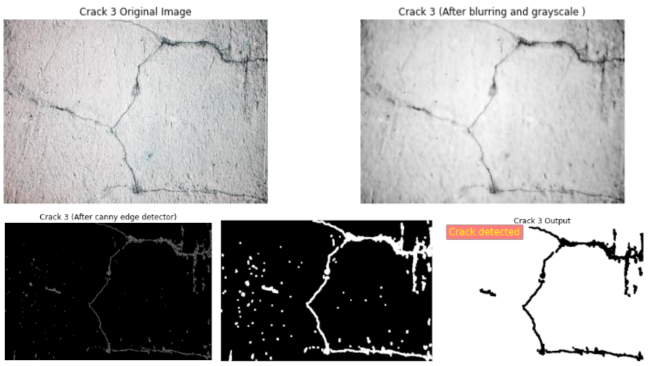

Figure-6: [Image with image processing technique]

VI. RESULTS

In the testing phase, we used an image that contains a crack. Example-

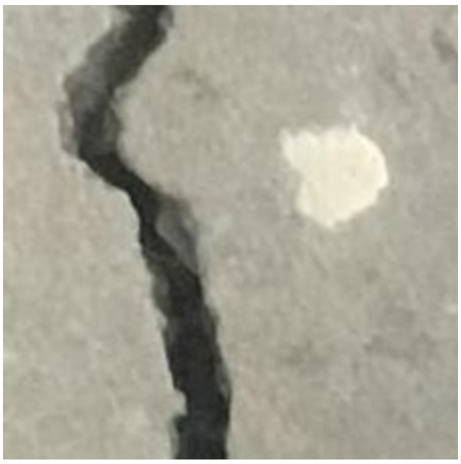

Figure-7: [Initial Image for testing]

The model will categorise this image as having been cracked when it enters the first stage. This image is now utilised in the following stage, where the image's crack will be highlighted and indicated in red. Any image can be provided to the model as an input. This image has a label indicating whether it is cracked or not. The model that will mark the crack is now given the image.

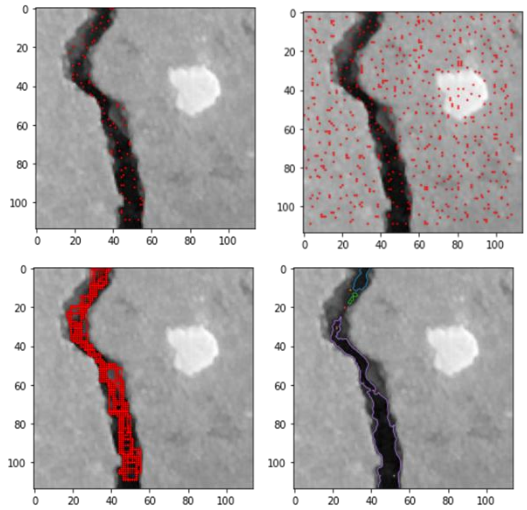

Figure-8: [Image with crack highlights in red]

Confusion Matrix

The figure below mentions the confusion matrix produced using 10 epochs. The actual positive and negative numbers are highest. The mistake rate is significantly reduced. After being used as an input by the model, the testing starting image is accurately classified as having a Crack.

The number of images that actually had no cracks and the anticipated value were both correctly characterized, hence the algorithm was able to estimate True Values accurately for 1206 images.

However, 1147 of the photos genuinely had crack and were accurately classified.

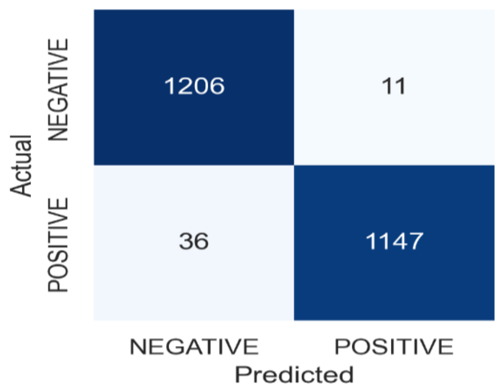

Figure-9: [Confusion Matrix]

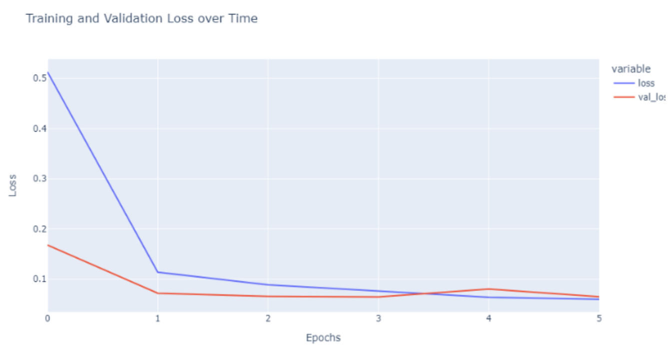

Figure-10: [Training and Validation Loss over Time]

Classification Report

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Classification Report:
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              precision    recall  f1-score   support

    NEGATIVE       0.97      0.99      0.98      1217
    POSITIVE       0.99      0.97      0.98      1183

    accuracy                           0.98      2400
   macro avg       0.98      0.98      0.98      2400
weighted avg       0.98      0.98      0.98      2400
```

Figure-11: [Classification Report]

The model's accuracy was between 97 and 98 percent, and it can recognize photos with cracks. The generated f1-score is 98 percent. This indicates that the model is prepared to assess additional photos.

VII. CONCLUSION

The classification of photos into "Crack detected" and "Crack not Detected" is successful. A random image provided as input is reliably and precisely labelled. The model correctly classified the image labels with an accuracy of 97–98%. Further processing is applied to the cracked images, and the cracks are segmented. Cracks are first designated with a red color before being accentuated. The output is a picture with a segmented crack as its final form. A multi-class algorithm called Edge detection is implemented as part of a similar strategy for image pre-processing in order to identify the image's cracks. When compared to image processing methods, deep learning algorithms do better in segmenting images. Image processing methods, blur, noise, and lighting conditions all have downsides. To classify a crack and then separate the crack from the image, a deep learning model learns how to label various sorts of images.

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