RESEARCH ARTICLE

International Journal of Civil, Environmental and Agricultural Engineering

DOI: 10.34256/ijceae2412

Image processing and Machine learning in Concrete Cube Crack detection

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Received: 18-03-2024, Revised: 10-05-2024, Accepted: 18-05-2024, Published: 25-05-2024

Abstract: Concrete cube testing plays a crucial role in various aspects of modern construction. The structural performance of concrete cubes under direct compressive stress can result in failure through concrete cube breakout. Failure modes related to concrete can be classified into two types: acceptable and non-acceptable, with further classification into various modes. However, most of the time 80% to 90% of the cubes are inaccurately selected, leading to lower strength and sustainability of concrete. Moreover, the excessive usage of cement required due to these inaccuracies contributes to global warming and increases costs. To address these issues, this research aims to develop an industry 4.0 solution for the construction and civil engineering fields. The proposed solution will be reliable, efficient, and based on image processing techniques. Convolutional Neural Networks (CNN) is used to detect and analyze cracks in concrete cubes. By examining the crack patterns, the damage area can be determined. By leveraging industry 4.0 technologies and advanced analysis techniques, this research aims to revolutionize the way concrete cube testing is conducted. The proposed solution will provide a reliable and efficient method for evaluating concrete cube quality, mitigating the negative impacts associated with inaccurate cube selection, and improving the performance and environmental sustainability of concrete in construction applications.

Keywords: Concrete, Cube, Image Processing, CNN, Crack Detection

1. Introduction

Concrete is prepared with the help of fine and coarse aggregates which are bonded together with the help of liquid cement and the mixture hardens as time elapses. The compressive strength testing is done on the concrete cubes after 3 days, 7 days and 28 days. In this the load is applied on the minimum three cubes in the range of 0 to 14 newton per sq. mm cube per minute. The compressive strength of cube is calculated by dividing the load applied to the face area of the cube. Once the cube has reached the failure the shape of the cube altered. And depending upon the pattern of the cracks and the damage pattern the cube is classified as satisfactory or non-satisfactory failure mode. If the cracks are evenly distributed among all the exposed face, then it is considered as satisfactory failure mode and if the cracks occurred unevenly, T- pattern cracks, diagonal cracks then it leads to unsatisfactory failure mode. If the concrete is classified wrongly then the concrete structures are prone to cracks, if the cracks are ignored then it will be dangerous for the structure we build and the size of the crack is increased or widened and there is possibility of salt penetration inside the cracks and the impact of this is there will be leakage in the structure or the structure may collapse. The impact of this is that when cracks are developed and propagate, they tend to cause the total loading area will be decreases which in turn increases stress and subsequently the concrete or the structure will lead to failure.

We first understand why concrete cracks. Concrete requires water to achieve strength, but the quantity should not be more, In the residential construction process a large amount of water is added to prepare the concrete on the actual site. Due to this the strength of the concrete deteriorated. The ratio of Water Cement should be in between 0.45 to 0.60 for the better concrete material, if this ratio is not maintained then there will be a chance of degradation of concrete surfaces which will lead to cracks on the concrete surface.

It is important to analyze the pattern of the cracks well in advance which will secure the integrity of a concrete structure. In the current infrastructure field crack detection is done manually and this manual crack detection method requires experts and trained people. But this method is not dependable, and it is prone to error, and it involves the cost also. The larger cracks are visible through human eyes, but the smaller cracks are difficult to measure.

Advancement of technology is reshaping many fields which are based on qualitative parameters. Computerized automation overcomes the dependency on human parameters, and we can achieve an elevated level of accuracy at affordable expense. Vision based technology is now emerging in the construction field that will minimize the loss and failure in the construction sites.

Cracks are classified into two type's active cracks and non-active cracks. In the active cracks the direction, width and depth of the cracks varies over period and the non-active cracks remain same. Examples of active cracks are longitudinal cracks, cross way cracks, miscellaneous cracks, crocodile cracks and reflection cracks. The non-active cracks are noticeably short in length and width, and they cure over time.

In the automated process there is a requirement to analyze the crack in terms of its length, width, and depth through which the severity of the crack can be estimated. These measures are used to classify the failure modes of the concrete structure and the soundness of the infrastructure.

Some of the methods used for crack testing are laser and infrared techniques. Thermal and radiographic techniques were also used to assess the cracks. But recently image processing and machine learning techniques are widely used to detect the crack present on concrete surfaces. In concrete structure maintenance, Crack detection plays especially vital role and it directly associated with the safety and robustness of the concrete structure.

But recently there is increasing use of image processing techniques based on machine learning to identify and analyze the crack on the concrete structure. Researchers explored concrete crack detection based on identifying the crack, its length, and width and depth measurement. The researchers have used thresholding, edge detection, preprocessing image processing techniques and convolutional neural network (CNN) to search and analyze the cracks in the concrete structure. Nowadays, the ultrasonic sensors are inserted at the center of the concrete which will detect the internal cracks in the structure and send the information of the internal cracks in concrete structure of the buildings which cannot be visible with bare eyes. The ultrasonic sensor can be fixed inside the concrete structure which can monitor the internal crack.

2. Literature Review

The length of crack measured theoretically was compared through Finite Element method modeling and practical experimentation [1]. Along with that the identification of the crack and depth calculation is done using ultrasonic pulse velocity in cracked concrete structures. This can be an effective tool to preserve the strength and durability of the structure. It is reported that ultrasonic sensor is used inside the concrete structure which will detect the internal cracks of the concrete [2]. Further the GSM and GPS module is used which will send the information related to the crack severity to the alerting authority along with the location information of the crack. This will help to prevent disaster. A CNN through modifying the Alex Net is remarkable CNN for image classification [3]. The author has captured the1455 images from the real concrete surface by a mobile device which is used to initially train the network then validating the network, and finally assess the CNN architecture. The results show that the proposed methodology detects cracks more efficiently without interference of noise. The crack detection by deep learning based on CNN is used to improve the CNN classification. The images were preprocessed by doing grayscale thresholding then it is used for training the CNN model [4]. A novel deep learning method built upon a convolutional neural network (CNN) combined with Agent-based modeling for crack detection and damage characterization in ultra-high-performance concrete (UHPC) is reported [5]. In this paper the CNN architecture is developed by four primary layers and four secondary layers associated with the gradient descent algorithm. Investigation of crack zone is based on percolation theory. The accuracy of crack identification is measured by loss functions, and the reliability of these numerical methods was independently improved by a Java-based graphics program.

There are various noises present on concrete structures which are due to uneven lightening, shadowing, flaws, dark spots, and dents in the concrete images. Due to these noises, it is exceedingly difficult to detect the cracks in automatic crack detection [6]. Subtraction pre-processing is done with the low passed image is done to remove the uneven illuminated condition and shading which occurs in image. Line filter based on the Hessian matrix is used to emphasize line structures associated with cracks. Thresholding is also one of the pre-processing which is used to extract cracks from background [6].

Classification of 40,000 images as cracked and non-cracked are reported which is used as an input to the system to detect the cracks. Here it is found that the CNN approach gives better accuracy than RNN [7].

Investigation on the extraction error suggests a solution to the difficulty of identification of crack while processing [8]. Here the author used the OTSU algorithm to detect and separate the crack and fill the cracked part based on the direction of the crack growth and the grayscale mutation of the crack. Three stages of image processing pipeline are proposed to obtain crack detection and its characteristics [9]. In the first and second stages, two- dimensional convolutional neural networks are used for crack image detection. In the third stage, crack thinning is done and applied the algorithm to track the crack to analyze length and width of crack in the image. The results showed superior performance of crack detection and its measurement. Image augmentation technique is also reported which will identify the cracks in presence of shadow [10].

3. Image Processing Techniques

In the automated crack detection technique image processing plays a particularly vital role. In the image processing methodology, the four basic stages (Figure 1) are important.

i) image acquisition ii) image preprocessing iii) Crack detection iv) Parameter estimation

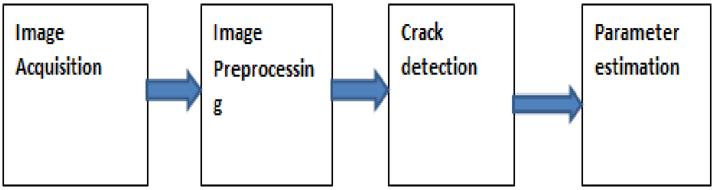

Figure 1. Image processing

Image capturing sensors are used to capture the images from the concrete surface. The high-resolution imaging system will do scaling and converting the RGB image to gray scale image.

The image contains various noises while capturing. The surface of concrete structure is very noisy. There are various unwanted signals such as uneven lighting conditions, shadowing, faults, blurring, and dents occur in the concrete images. So various preprocessing techniques are used such as subtraction preprocessing and line filters are used. Other preprocessing techniques are used such as median filtering, smoothing, and sharpening which will enhance the crack features. There are various crack detection techniques used like Sobel, canny edge detectors, histogram method, thresholding. After crack identification the parameters of the crack can be estimated like crack length is measured with the help of percolation theory, the direction of crack is measured by region growing. The accuracy of the image processing technique is studied in detail. Most of the researchers focus on the thresholding and feature extraction. But these methods give large extraction error and difficulty in identification. In image processing thinning algorithm is implemented to make the width of crack by one pixel size in terms of binary image either 1 or 0. Then tracking algorithms like region growing can be used to track and calculate the length of the crack. For that, any random pixel is chosen in the binary image as an initial starting point for crack length tracking. Then the algorithm identifies neighborhood pixels that are analogous or matching pixel or not. If they are homogeneous then adding that pixel in the group and expanding the area by grouping the pixels with the same neighborhood criteria. The process of collecting the homogeneous pixel can be performed in four direction or eight directions. The eight-direction tracking gives better tracking results. The output of the above neighborhood principle used in the crack tracking algorithm is the sequence of crack pixel.

To find the length of the crack the pixel in a line is summed and it depends on the distribution pattern of the pixels. The crack width is calculated by the profiling algorithm [9]. Using morphological processing the geometric features are used to detect the cracks in noisy environments. In Morphological Image Processing the original image, if it is affected by noise can be restored by using techniques like Dilation, Erosion, Opening and Closing operations.

4. Machine Learning

Machine learning is a subfield of artificial intelligence that focuses on developing algorithms and models that enable computers to learn and make predictions or decisions without explicit programming. It involves the use of statistical techniques to enable computers to automatically identify patterns, extract meaningful insights from data, and improve their performance over time. In machine learning, algorithms are trained on a large amount of data, which serves as examples or input-output pairs. The algorithms analyze the data, identify patterns, and learn from them to make predictions or take actions when presented with new, unseen data.

The core idea behind machine learning is to create models that can generalize from the training data and make accurate predictions or decisions on new, unseen data. This ability to generalize is what distinguishes machine learning from traditional rule-based programming. Machine learning algorithms can adapt and improve their performance by continuously refining their models based on feedback and new data. There are several types of machines learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training models with labelled data, where the desired output is known. Unsupervised learning deals with unlabeled data, and the algorithms discover patterns or structures within the data. A schematic diagram is given in Figure 2, illustrating the processes.

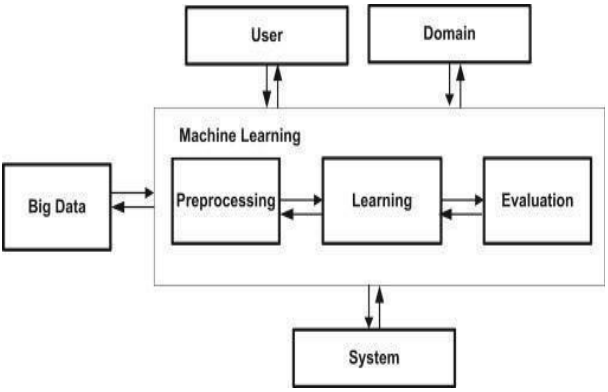

Figure 2. Machine Learning

Reinforcement learning involves training agents to interact with an environment and learn from the feedback received. Machine learning has wide- ranging applications in various fields, including image and speech recognition, natural language processing, recommendation systems, fraud detection, predictive maintenance, and autonomous vehicles. Its ability to analyze and learn from large volumes of data has revolutionized industries and contributed to significant advancements in technology.

In summary, machine learning is a branch of artificial intelligence that focuses on enabling computers to train themselves from large data, identify the similarity pattern, and make predictions or decisions without explicit programming. It has become a dominant tool for solving complex problems and has numerous applications across various domains.

A neural network is a computer simulation inspired by the structure and functioning of biological neural networks, such as the human brain. It is a key component of machine learning and artificial intelligence systems. Neural networks (Figure 3) consist of interconnected nodes, called neurons or artificial neurons, which are organized in layers. Each neuron receives inputs, processes them, and produces an output based on a specific mathematical function. The outputs of one layer of neurons serve as inputs to the next layer, allowing information to flow through the network. The connections between neurons are associated with weights that determine the strength and influence of each connection. The process of training a neural network involves adjusting these weights based on the input data and desired outputs so that the network can learn to make accurate predictions or decisions. This training is typically done through a technique called backpropagation, which involves propagating errors backward through the network and updating the weights accordingly.

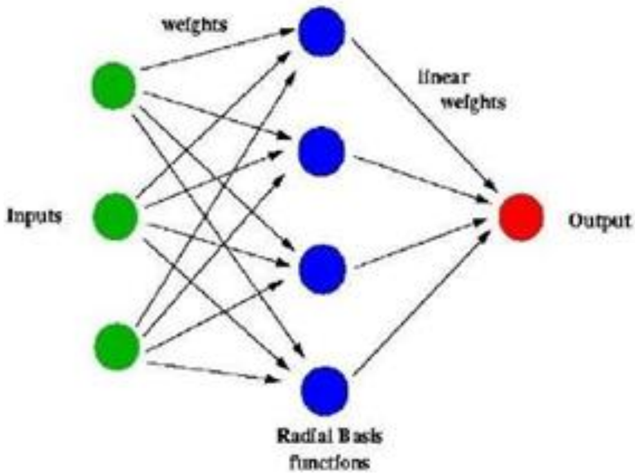

Figure 3. Neural Network

Neural networks are capable of learning and extracting complex patterns and relationships from data. They can handle tasks such as classification, regression, pattern recognition, and sequence generation. The architecture of a neural network, including the number of layers and neurons, can vary depending on the specific problem and data characteristics. Deep learning is a subset of neural networks that consists of multiple hidden layers, allowing for even more complex representations and higher levels of abstraction.

5. Methodology

5.1 Dataset

The concrete cube crack images dataset for classification was successfully imported into a Google Collab notebook using the Kaggle API command. This convenient method allowed for seamless retrieval of the dataset directly from Kaggle's servers, eliminating the need for manual downloading and uploading of files.

The dataset itself consists of a substantial collection of 40,000 concrete crack images, each with dimensions of 227 x 227 pixels. These images are divided into two classes: positive and negative. The positive class contains 20,000 images depicting concrete cracks, while the negative class includes another 20,000 images without any cracks. The availability of such a large and balanced dataset is highly beneficial for training and evaluating machine learning models for concrete crack classification tasks. With an equal distribution of positive and negative samples, the dataset enables the development of robust models that can accurately differentiate between cracked and non- cracked concrete images. Utilizing this dataset, researchers, and practitioners in the field of computer vision and image classification can explore various approaches for automatically detecting and classifying concrete cracks. The high-resolution images provide ample detail for capturing intricate crack patterns and their characteristics.

5.2 System implementation

The concrete crack image classification is implemented using Python in a Google Collab Notebook. The primary library utilized for this task is TensorFlow's Keras, which serves as an open-source Python interface for artificial neural networks. Keras, in turn, acts as a high-level API for the TensorFlow library, facilitating the development of neural network models. In addition to Keras, several commonly used libraries were employed, including NumPy for numerical computations, pandas for data manipulation, matplotlib for data visualization, and split folders for splitting the dataset into training, validation, and testing sets. The process flow is given in Figure 4.

We are developing a ML model for classification of compression break out patterns of concrete cube using the Convolutional Neural Network (a.k.a ConvNet or CNN) which is a type of artificial neural network using the open source TensorFlow framework by Google.

The dataset used for the initial training purpose is from Kagal dataset which consists of cracked and non-cracked images. Initially the model would be trained and cross validated.

Consequently, another annotated image dataset would be used for the testing phase after which the confusion matrix would be plotted which would give the results of testing. If the test results are satisfactory then the model would be ready for deployment or else retraining would be required. The proposed model gives better performance if the training database images of positive and negative cracks are increased.

6. Results & Discussion

For the binary image classification task, a convolutional neural network (CNN) is implemented. The CNN architecture consists of four main layers, with two Conv2D layers followed by Batch Normalization and Maxpooling2D layers. Subsequently, two Dense layers are included. The total number of parameters in the CNN model amounted to 15,764,929, of which 15,764,737 were trainable, while 192 were non-trainable. To compile the CNN model, the Adam optimizer is used, and binary cross-entropy is selected as the loss function. The model is trained on the training dataset and validated using the validation dataset over the course of ten epochs. Following the training phase, the model achieved an impressive accuracy of 98.65% when evaluated on the test dataset.

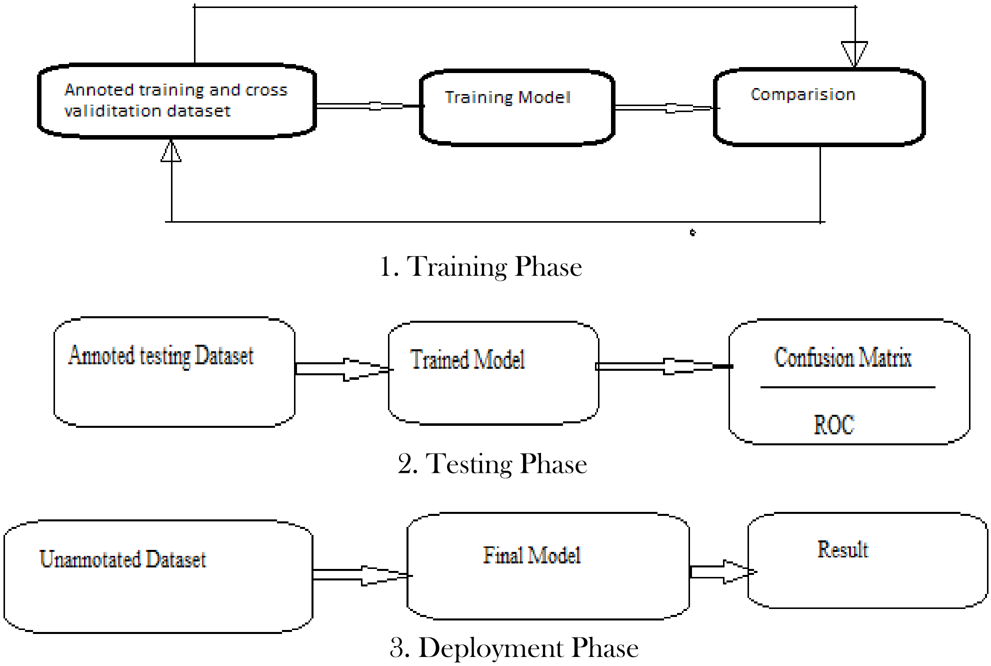

Figure 4. Block diagram of process

By leveraging the power of the TensorFlow Keras library and implementing a well-designed CNN architecture, the code successfully achieved the accurate classification of concrete crack images. This has significant implications for the field of civil engineering and infrastructure maintenance, as it provides a reliable and efficient approach for automating the identification of concrete cracks, aiding in timely detection and maintenance efforts. To create a user-friendly interface for our concrete crack image classification model, we incorporated Gradio, an open- source Python library. This interface serves to demonstrate the functionality and capabilities of our ML model in a user-friendly manner. By leveraging Gradio, we provided a seamless and intuitive platform for users to input concrete crack images and receive instant predictions.

7. Conclusion

Concrete cube crack detection with image processing and machine leaning has emerged as a powerful and efficient approach in recent years. By leveraging the capabilities of deep learning algorithms, it has become possible to automatically detect cracks in concrete structures with high accuracy and speed. By training on extensive collections of annotated images, these networks can learn to recognize several types of cracks, including those that are subtle or challenging to detect by the human eye alone. This technology holds enormous potential for applications in civil engineering, infrastructure management, and construction industries, contributing to improved safety, durability, and cost- effectiveness in maintaining concrete structures. However, it is important to note that while neural networks have demonstrated promising results, the performance of the system heavily relies on the quality and diversity of the training dataset. Adequate representation of crack types, variations in lighting conditions, and different concrete surfaces is essential for achieving robust and reliable detection. Additionally, ongoing research is necessary to continuously improve the accuracy and efficiency of neural network models, as well as to address challenges related to generalization, interpretability, and deployment in real-world scenarios.

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Funding: No funding was received for conducting this study.

Conflict of interest: The Author's have no conflicts of interest to declare that they are relevant to the content of this article.