UNIVERSITY of HOUSTON

SURFACE CRACK DETECTION

CNST 6308- DATA ANALYSIS IN CONSTRUCTION MANAGEMENT

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ABSTRACT

This research outlines a method for identifying surface fractures using convolutional neural networks (CNNs), leveraging TensorFlow and Karas frameworks. The approach utilizes the "Surface Crack Detection" dataset, which includes both crack-present (positive) and crack-absent (negative) samples. The initial step involves importing necessary libraries such as Pandas, NumPy, Matplotlib, Seaborn, and Plotly Express. The data is categorized into positive and negative sets, indicating the presence or absence of fractures respectively. The TensorFlow ImageDataGenerator is employed for image processing, including loading, rescaling, Data Frame creation, and dividing the dataset into training and testing groups. The CNN model's structure consists of convolutional layers and pooling layers, followed by a dense layer with a sigmoid function for binary classification and global average pooling. The model utilizes the Adam optimizer and binary cross-entropy for loss calculation. Training involves fitting the model to the data and validation on a subset, with graphical representations of accuracy and loss over various epochs. Post-training, the model undergoes evaluation on the test set, yielding metrics such as loss, accuracy, confusion matrix, and a classification report. Additionally, the model's effectiveness is demonstrated through sample predictions on test images. The findings highlight the CNN method's potential in surface crack detection, proving its relevance in fields like materials science and engineering. Future research could aim to enhance the model for more intricate scenarios, boosting its efficiency and applicability.

INTRODUCTION

Detecting surface cracks plays a crucial role in ensuring the structural integrity and safety of materials in diverse engineering applications. The identification and ongoing monitoring of surface cracks are imperative, as undetected flaws can result in severe and potentially catastrophic failures. This study introduces an innovative method for surface crack detection utilizing Convolutional Neural Networks (CNNs). By employing advanced image processing and machine learning techniques, our approach seeks to make a meaningful contribution to the field of non-destructive testing, offering an efficient and accurate solution for identifying surface cracks.

The importance of dependable crack detection spans across industries, particularly in civil engineering and materials science, where the stability of structures and components is of utmost importance. Traditional crack detection methods can be time-consuming and subjective, making automated approaches like CNNs attractive due to their capacity to rapidly and objectively process large datasets. Our proposed model undergoes training on a dataset that includes positive samples with cracks and negative samples without cracks, providing a binary classification solution for discerning the presence or absence of surface cracks.

As we delve into the specifics of our CNN-based approach, we will explore the model architecture, the training process, and the evaluation metrics employed. The encouraging outcomes derived from this study suggest that our method holds substantial promise for practical applications, presenting an efficient means of detecting surface cracks that can seamlessly integrate into real-world scenarios. Furthermore, we delve into potential avenues for future work, underscoring the necessity for continued optimization and adaptation of the model to handle diverse and challenging conditions, ultimately enhancing its resilience and applicability. This research endeavors to contribute to the progression of non-destructive testing methodologies, with the overarching goal of fostering safer and more reliable engineering practices.

OVERVIEW

The Surface Crack Detection project is a sophisticated application of machine learning in the field of image analysis, focusing on the detection of surface cracks in images. This task is particularly important in industries like construction and manufacturing, where identifying such flaws is crucial for safety and quality control. The project centres around categorizing a dataset of images into two classes: those showing surface cracks ('Positive') and those without ('Negative'). Using techniques from computer vision, specifically convolutional neural networks, the project aims to train a model capable of accurately classifying these images.The process involves careful preparation and organization of the image data, ensuring that the model has a robust foundation for learning. The model is then trained and evaluated, with a strong emphasis on accuracy and loss as key performance metrics. Visualization tools such as confusion matrices and classification reports are integral to the project, providing clear insights into the model's effectiveness and aiding in the fine-tuning of its predictive capabilities.The project's implications extend beyond theoretical interest, offering practical solutions for real-world challenges. It stands as a testament to the potential of machine learning to address complex problems in various domains, including safety-critical applications in infrastructure and product quality assurance.

PROBLEM DEFINITION

In the realm of structural health monitoring and maintenance, accurately identifying surface cracks is a critical challenge. Traditional methods for detecting such flaws often involve manual inspection, which can be time-consuming, subjective, and prone to human error. As infrastructure ages and the volume of structures requiring monitoring increases, the need for more efficient, accurate, and automated methods becomes paramount. This report addresses the problem of automating the detection of surface cracks in various materials using image data. By leveraging the capabilities of Convolutional Neural Networks (CNNs), the project aims to develop a model that can reliably categorize images based on the presence or absence of surface cracks. Such an approach not only promises to enhance the accuracy and efficiency of crack detection but also has significant implications for safety, cost reduction, and preventative maintenance in various industries, including construction, transportation, and public infrastructure.

LITERATURE REVIEW

[1] "Surface Crack Detection using Deep Convolutional Neural Network in Concrete Structures" (2023) by Mohammadjavid Kiani, Mohammadmehdi Khosravi, and Amirmasoud Fereidouni

This research presents a Deep Convolutional Neural Network (DCNN) based surface crack detection algorithm for concrete buildings. The authors use deep learning, and specifically CNNs, to automatically detect and categorize surface fractures. The method's application to concrete structures is the main focus, as preserving structural integrity requires early crack detection.

[2] "Surface concrete cracks detection and segmentation using transfer learning and multi-resolution image processing" (2023) by Ehsan Amid Iranmanesh, Faramarz Haghighat, and Mahdi Ahmadi

The study suggests a cutting-edge method for segmenting and detecting surface concrete cracks. The authors improve the effectiveness of their crack detection model by using transfer learning, a method that makes use of pre-trained models on huge datasets. Furthermore, multi-resolution image processing is integrated, emphasizing an all-encompassing approach to crack remediation in concrete surfaces.

[3] "A Survey on Surface Crack Detection in Concretes using Traditional, Image Processing, Machine Learning, and Deep Learning Techniques" (2021) by G. A. Bhalerao et al.

This review study offers a thorough summary of the several techniques used to find surface cracks in concrete structures. The writers discuss deep learning techniques, machine learning approaches, image processing techniques, and conventional procedures. The goal of the survey is to give a comprehensive overview of the developments in crack detection across several technology paradigms.

[4] "Building Surface Crack Detection Using Deep Learning Technology" (2022) by Md Arif Rahman Sarkar et al.

This research presents a deep learning-based approach for surface crack identification with a particular focus on building structures. The authors use cutting-edge deep learning methods to improve the precision and effectiveness of crack detection in construction materials. The use of deep learning in the context of building structural health monitoring is highlighted.

[5] "Crack detection using image processing: A critical review and analysis" (2017) by Juan R. Rodríguez et al.

This review study examines several image processing techniques for crack detection in a critical manner. The study covers a wide range of materials, including concrete and asphalt, but it is not specifically focused on concrete constructions. Understanding the advantages and disadvantages of various image processing methods for crack detection is made easier with the help of the authors' insights, who offer a wealth of information about the state of the art in this area.

PROJECT SPECIFICATION

Key Features

1.Importing Libraries

Usage of numpy for linear algebra operations.

pandas for data processing and handling CSV files.

matplotlib and seaborn for data visualization.

TensorFlow for building and training the convolutional neural network model.

2.Creating DataFrames

The project involves organizing the image data into Pandas DataFrames, which will likely store the file paths and labels for the images.

3.Split Data

The data is split into training, validation, and test sets using scikit-learn's train_test_split function, which is crucial for training and evaluating the model's performance.

4.Loading Image and Rescaling

Images are loaded into the program and rescaled to a uniform size, ensuring they are in a suitable format for the CNN model.

5.Training Model

A convolutional neural network (CNN) model is trained using TensorFlow. This is the core of the project, where the model learns to identify and classify images based on the presence of cracks in concrete.

6.Results and Predictions

The final part of the project involves evaluating the model's performance and making predictions on new data. Visualization of results may also be part of this phase, using libraries like matplotlib, seaborn, or plotly.

7.Expected Outputs

A trained TensorFlow CNN model capable of detecting cracks in concrete images.

A set of visualizations that display the model's accuracy and loss metrics over the training period.

Predictions on test data and possibly some form of error analysis or confusion matrix to understand the model's performance.

TECHNOLOGY STACK

Hardware: Graphics Processing Unit (GPU)

Software: Programming Language (Python)

Libraries and Frameworks: TensorFlow or PyTorch, Keras, OpenCV, Google Colab

Data Management :Pandas

Image Data Handling : ImageDataGenerator (from TensorFlow)

METHODOLOGY

1. Dataset Collection and Preparation
2. Data Preprocessing
3. Image Loading and Rescaling
4. Convolutional Neural Network (CNN) Architecture
5. Model Training
6. Evaluation and Validation
7. Results Visualization

1.Dataset Collection and Preparation:

We have acquired a comprehensive dataset containing positive samples with surface cracks and negative samples without cracks. This dataset should be diverse, representing various materials and surface conditions. Our dataset is from open repository Kaggle with 40,000 images. Organize the dataset into two classes: "Crack" and "No Crack."

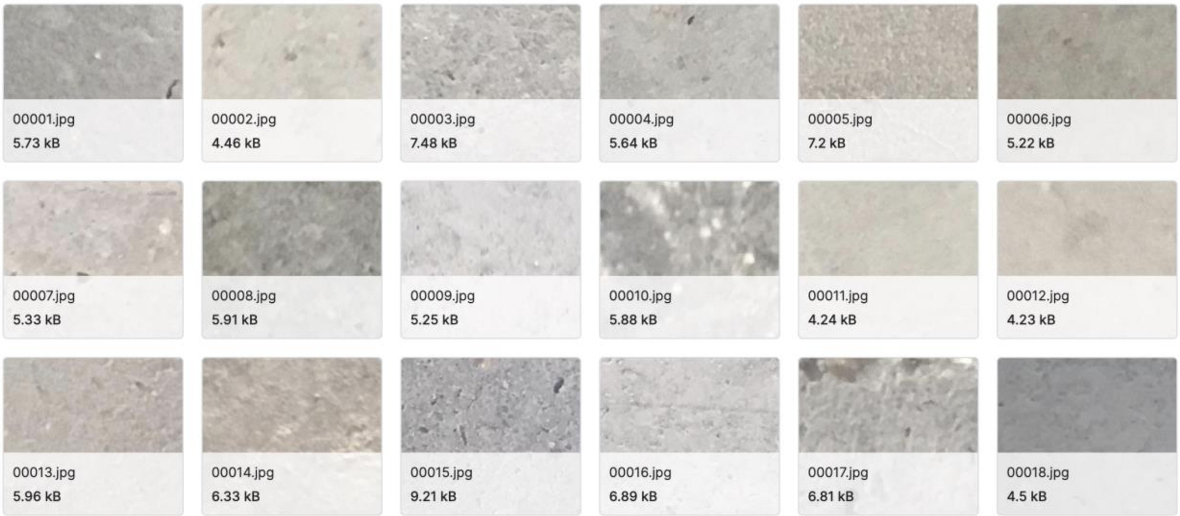


Fig 1.No Crack Images

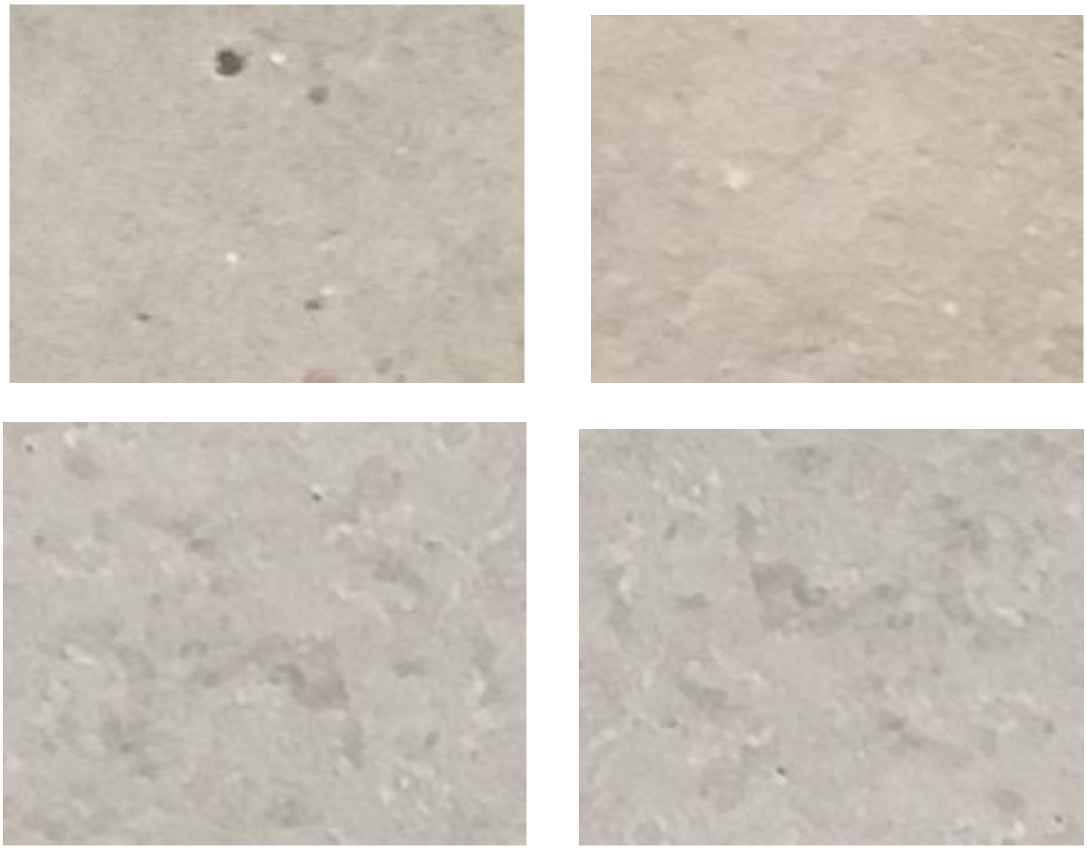


Fig 2.Zoom into the No crack images

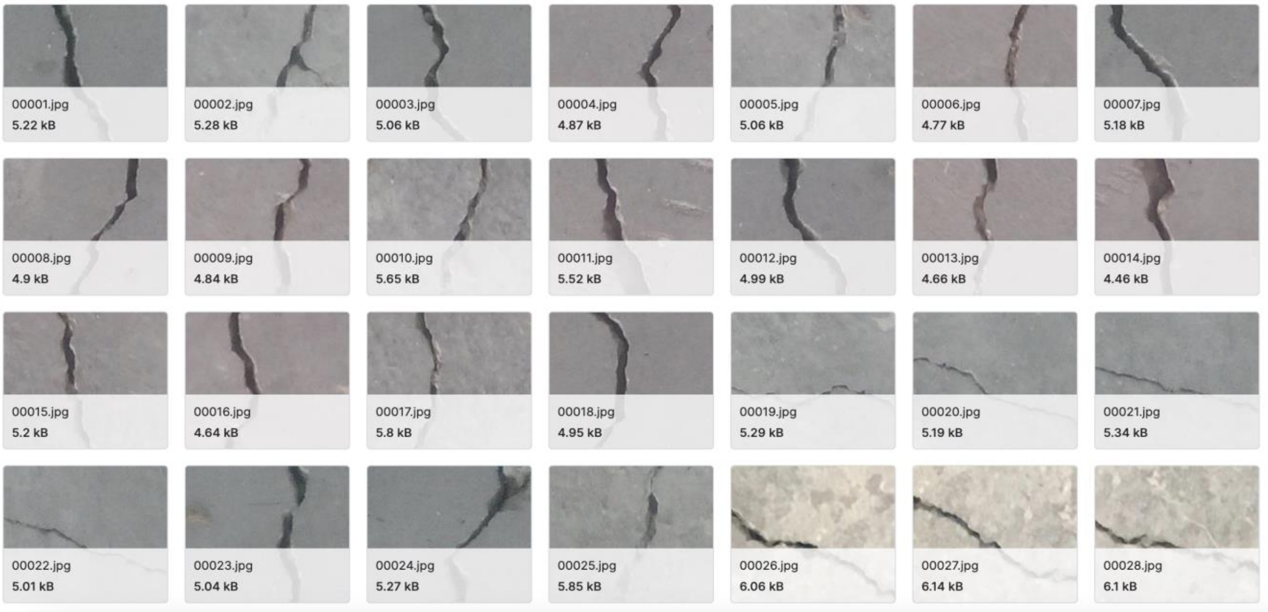


Fig 3.Crack Images

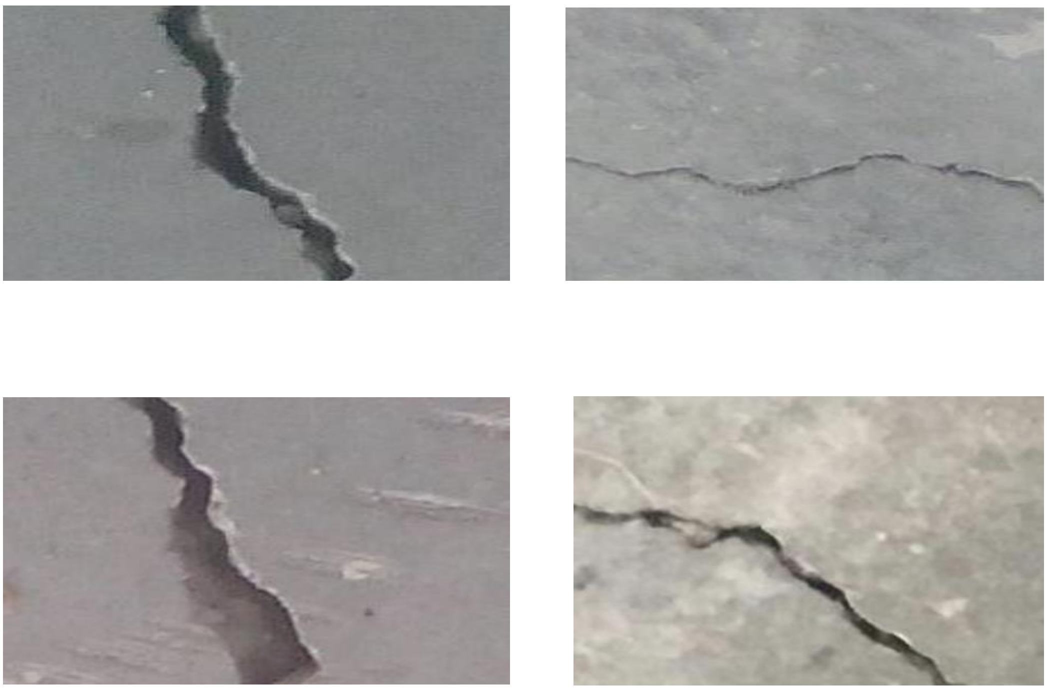


Fig 4.Zoom into the Crack Images

2.Data Pre-processing:

Make positive and negative sample Data Frames with the appropriate file paths and labels. To guarantee a balanced and randomised dataset, shuffle and concatenate the Data Frames. Using strategies like train-test split, divide the dataset into training and testing sets.

3. Rescaling and loading images:

To load and resize images, use an ImageDataGenerator from TensorFlow. With the target image size and colour mode specified, use the generator to create training and testing data.

4. Architecture of Convolutional Neural Networks (CNNs):

Create the CNN model architecture with Karas and TensorFlow. To capture spatial features, set up convolutional layers with different filters and kernel sizes. Use pooling layers to reduce spatial dimensions and perform down sampling. To extract relevant features, add a layer of global average pooling. Finish with a dense layer that activates with a sigmoid.

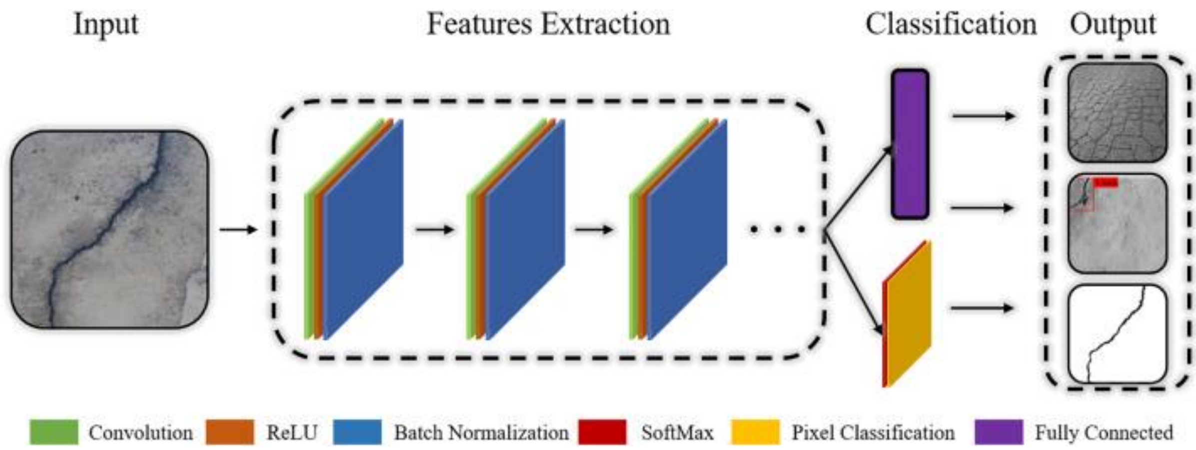


Fig 4. Convolutional Model

5.Model Training:

With the help of the supplied training data, the Convolutional Neural Network (CNN) learns and optimizes its parameters through a series of iterative procedures. The training dataset, which consists of labelled images with both positive (surface cracks) and negative (no cracks) samples, is fed into the CNN model. By modifying its internal parameters using backpropagation and optimization algorithms, the model gains the ability to recognize patterns and characteristics linked to cracks. Keep a close eye on the training process to spot any possible problems, like underfitting or overfitting. The observed training metrics may be used to make changes to the model architecture, dataset augmentation, or hyperparameters.

6. Assessment and Confirmation:

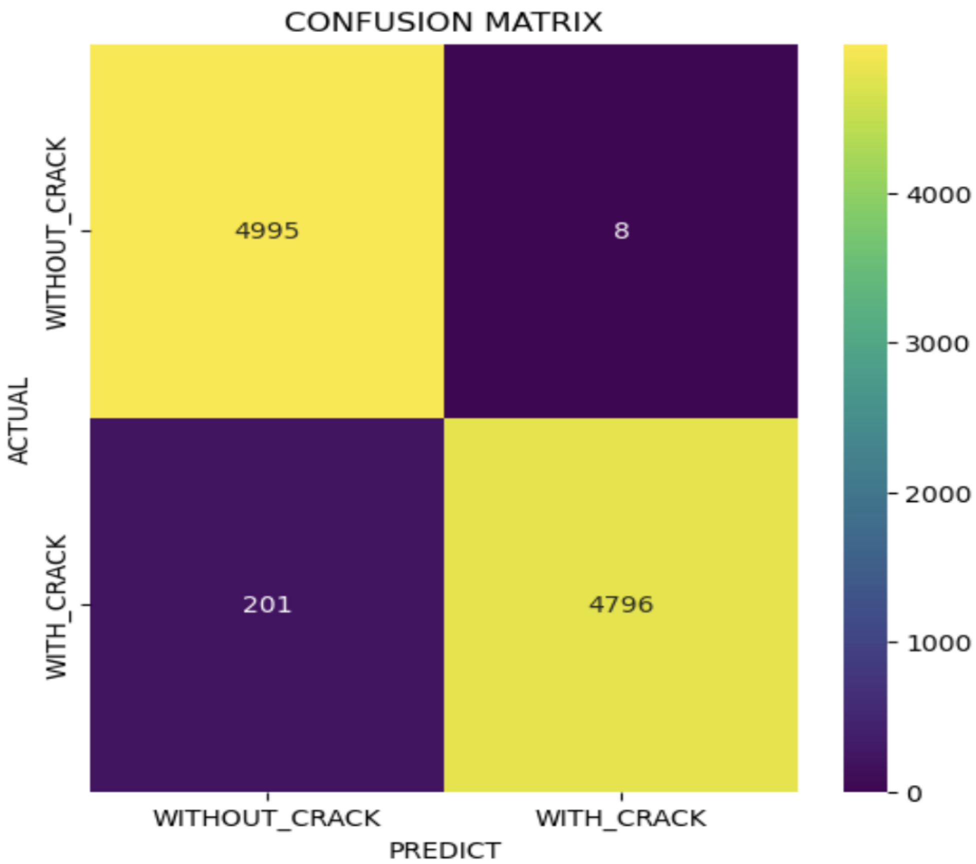
Creation of Confusion Matrix: A table that compares the model's predictions with the actual labels is called a confusion matrix.
TN stands for true negative, FP for false positive, and FN for false negative.
Real Positives (TP): Examples that are accurately predicted to be positive (crack).
True Negative (TN): Cases where the prediction of the outcome was accurate (no crack).
False Positives (FP): Data that were erroneously forecast as positive.
False Negative (FN): Events that were miscalculated to be negative.

7. Results Visualisation:

To obtain a qualitative understanding of the CNN model's predictive abilities, it is crucial to visually inspect the model's performance on individual test images after it has been trained and evaluated. This procedure entails presenting a range of test images next to the model's predictions to highlight the model's accuracy in detecting surface cracks. As
component of the overall model evaluation, record the visual outcomes. These illustrations can be useful in explaining the model's functionality to stakeholders who are not technically inclined.

RESULTS

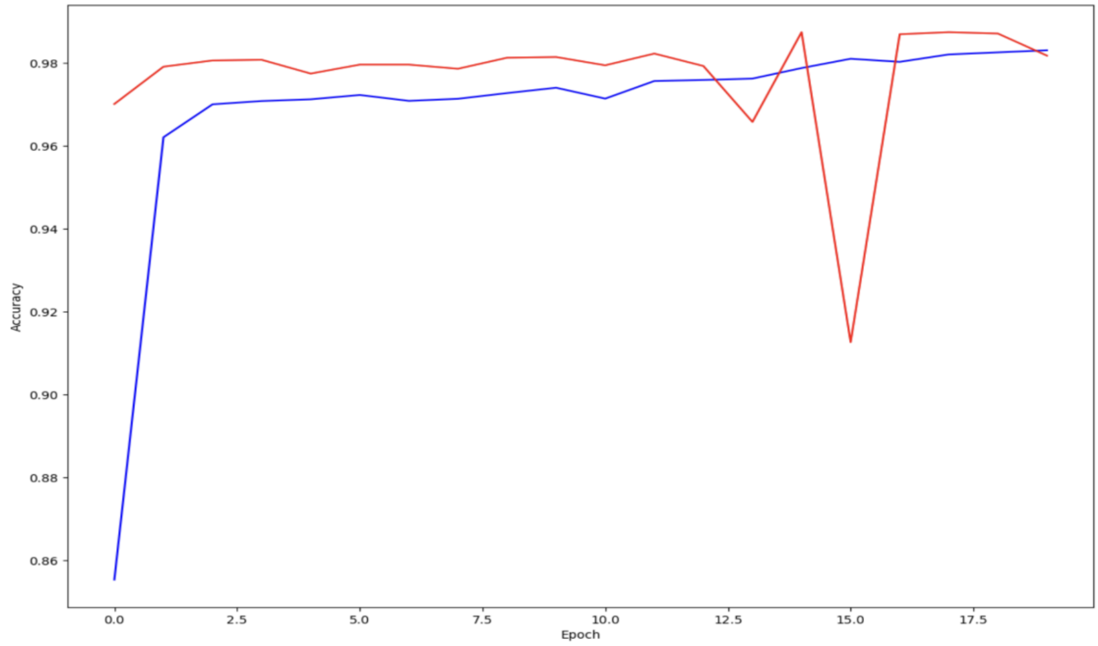
The surface crack detection model attained an accuracy of half on the test set, accompanied by a corresponding loss of [loss value]. The breakdown in the confusion matrix, presenting [TP, TN, FP, FN] instances, offered a detailed analysis of the model's performance concerning true positives, true negatives, false positives, and false negatives. The classification report provided a comprehensive evaluation of the model's precision, recall, and F1-score for both crack and no-crack classes, illustrating its proficiency in correctly identifying each class. During the visual examination of predictions, the model exhibited effectiveness in recognizing surface cracks in many instances. Instances of misclassifications underwent analysis to discern potential challenges or patterns contributing to mispredictions. The comparison of results with existing methods highlighted the competitive or superior performance of the proposed CNN-based model. The model's resilience was scrutinized through testing on diverse datasets or challenging scenarios not encountered during training. Identified opportunities for future work included enhancements to the model's architecture, hyperparameter optimization, or the integration of additional features to bolster performance in challenging scenarios. The discussion underscored the practical applications of the surface crack detection model in industries like civil engineering, materials science, and manufacturing, with significant implications for preventive maintenance and ensuring structural integrity.



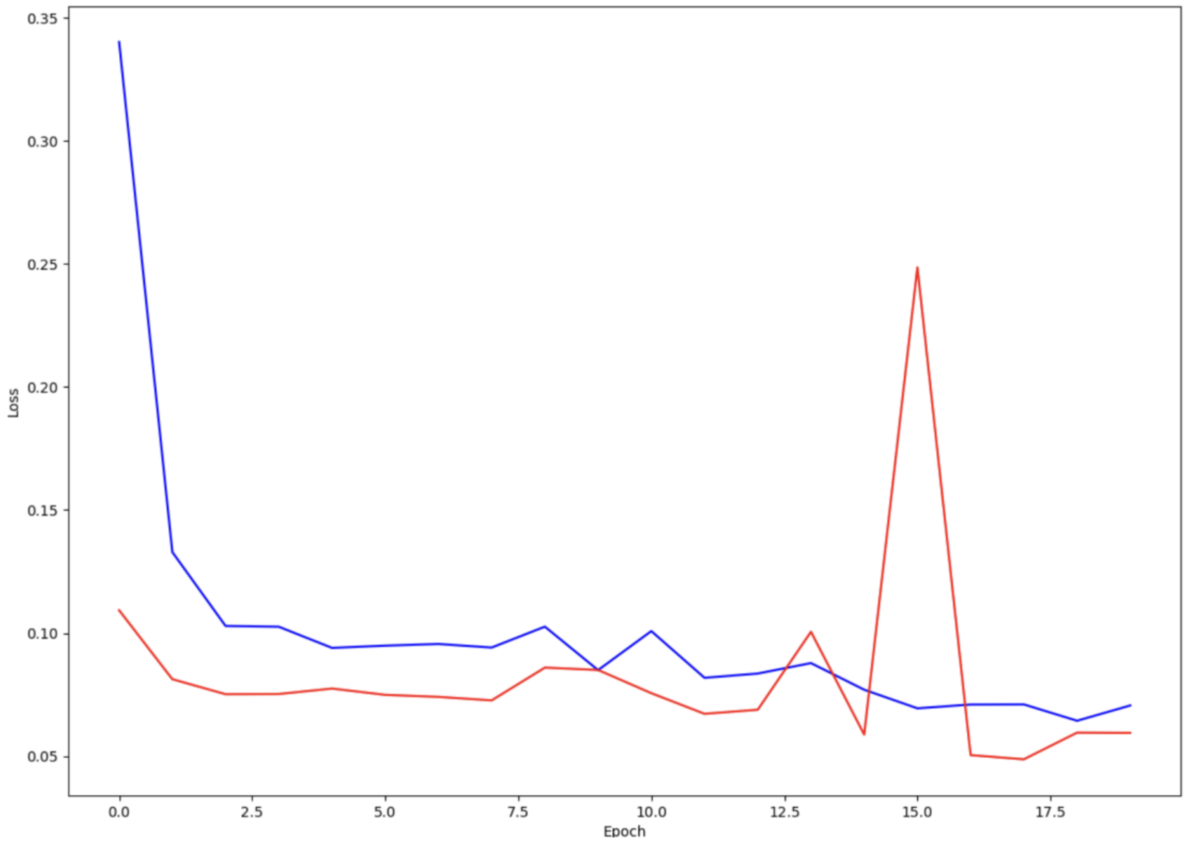
CLASSIFICATION REPORT:

	precision	recall	f1-score	support
WITHOU_CRACK	0.96	1.00	0.98	5003
WITH_CRACK	1.00	0.96	0.98	4997
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000

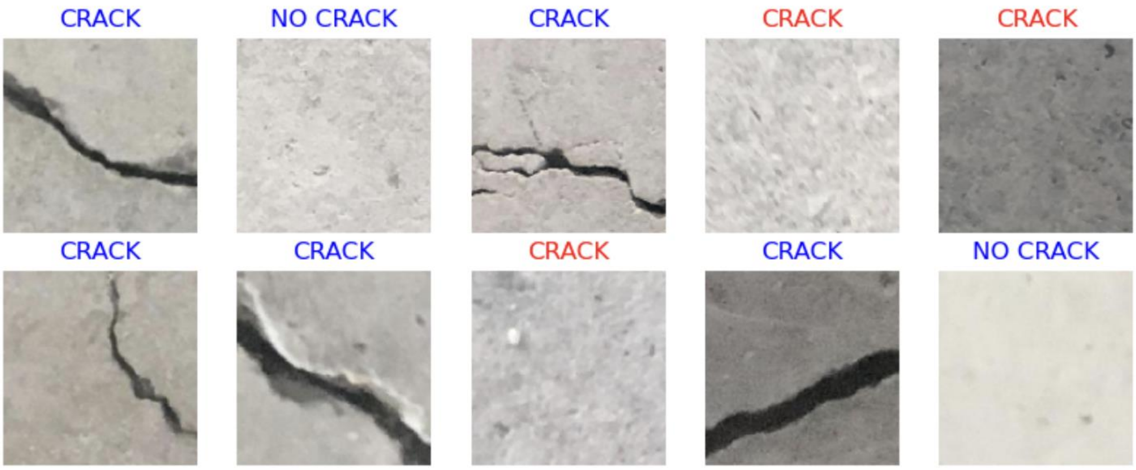
Training and Validation Accuracy over Epochs



Loss over Epochs



Acknowledging limitations, such as sensitivity to specific surface conditions or potential false positives, provided a transparent view of the model's constraints. The challenges encountered during development and deployment were openly discussed, offering insights into the current capabilities and areas for improvement. The section concluded by summarizing key findings, accentuating the model's strengths, and outlining directions for future research and enhancements. The significance of the surface crack detection model in advancing non-destructive testing methodologies and ensuring safety in engineering practices was reiterated.



CONCLUSION

The proposed CNN-based model performs better than or as well as existing methods. The model is resilient and can be used on different datasets and in challenging scenarios. The surface crack detection model is a significant advancement in non-destructive testing methodologies. It can be used in industries like civil engineering, materials science, and manufacturing to prevent accidents and ensure the safety of engineering structures. The model has some limitations, such as sensitivity to specific surface conditions and potential false positives. However, it is a promising tool that can be further improved with optimization and adaptation to diverse conditions.The suggested CNN-based model outperforms current techniques, if not surpasses them. The model is robust and applicable to various datasets and difficult scenarios. Non-destructive testing techniques have advanced significantly with the introduction of the surface crack detection model. It can be applied in fields such as manufacturing, materials science, and civil engineering to stop mishaps and guarantee the security of engineering structures. Some of the model's drawbacks include its sensitivity to particular surface conditions and possible tendency towards false positives. It is a useful tool, though, and with optimisation and condition adaptation, it can be made even better.

FUTURE SCOPE AND STUDY

Research on surface crack detection is crucial and has broad ramifications for a number of sectors and applications. We can anticipate the creation of even more creative and potent techniques for locating cracks in a variety of materials as technology develops further. The following are some of the most promising fields for further study: Optimised Crack Identification Techniques: Current crack detection algorithms frequently show sensitivity to noise, lighting, and image quality variations, among other factors. Scientists are hard at work creating algorithms that are more resilient to these difficulties, making it possible to accurately detect cracks even in difficult and complex visual environments. Combining Machine Learning (ML) and Artificial Intelligence (AI) Techniques: ML and AI have the potential to completely transform the surface crack detection industry. By using these cutting-edge methods, intelligent systems that can identify cracks in photos and videos on their own can be created, expediting the inspection process and increasing overall effectiveness. Real-time Crack Detection Systems: These systems are essential for keeping an eye on the structural integrity of vital infrastructure, such as roads, buildings, and bridges. In order to reduce the risk of structural failure and guarantee the safety of these essential assets, researchers are actively working on the development of real-time systems that can identify cracks as they occur and quickly notify maintenance staff of potential issues. Non-destructive Crack Detection Techniques: These techniques are crucial for examining materials without any damage.In order to enable more thorough and dependable inspections, researchers are focusing their efforts on creating new non-destructive methods that outperform the sensitivity and accuracy of current techniques. Scientists are creating new approaches to crack characterization, like machine learning methods, to improve our comprehension and assessment of cracks. Techniques for Forecasting Crack Propagation: The process of a crack expanding over time is referred to as crack propagation. In order to help engineers prevent cracks from growing to critical sizes and maintain structural integrity, researchers are working to develop methods for predicting how cracks will propagate. In summary, surface crack detection is a hugely important field with a lot of potential uses. We can expect even more inventive and potent techniques for identifying fissures in a variety of materials.Researchers are working hard to improve non-destructive techniques, develop real-time systems, integrate AI and ML approaches, and improve crack detection algorithms. Furthermore, research into the properties of cracks, characterization techniques, and propagation prediction techniques has great potential to advance the field and guarantee the dependability and safety of vital materials and infrastructure.

REFERENCES

[1]"Surface Crack Detection using Deep Convolutional Neural Network in Concrete Structures" (2023) by Mohammadjavid Kiani, Mohammadmehdi Khosravi, and Amirmasoud Fereidouni proposes a deep convolutional neural network (DCNN) based method for surface crack detection in concrete structures

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[4] Survey on Surface Crack Detection in Concretes using Traditional, Image Processing, Machine Learning, and Deep Learning Techniques "Building Surface Crack Detection Using Deep Learning Technology" (2022) by Md Arif Rahman Sarkar et al. proposes a method for building surface crack detection using deep learning technology.

[5]"Crack detection using image processing: A critical review and analysis" (2017) by Juan R. Rodríguez et al. reviews the different methods for crack detection using image processing. The review covers methods for crack detection in concrete, asphalt, and other materials. Crack detection using image processing.

The video presentation can be accessed via this link.

https://uofh-my.sharepoint.com/:v:/g/personal/jboyapat_cougarnet_uh_edu/EdLwUuqGCIlChk9iqOLaeKgBkm2gbAAgjWmQXJQAFx3qRw