CRACK LEVELCLASSIFICATION AND SEGMENTATION USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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ABSTRACT

It uses the Unity Neural Encoding Tool (U-Net) and LeNet-5 to present a novel approach to crack-level classification using Artificial Intelligence techniques. For safety reasons, the primary goal of this study is to locate cracks in a variety of structures, including walls, bridges, and infrastructure. A substantial dataset of 10,000 images was used for this project, of which 8,000 were designated for training and 2,000 for testing. With the help of state-of-the-art deep learning and image processing techniques, the model can classify six distinct types of cracks. They are Normal crack, Deep crack, Gap crack, Riss crack, Wall care crack, and No crack. Using cutting-edge architectures makes it easier to improve upon current practices. In addition to improving safety and maintenance procedures in the civil engineering and construction industries, this research advances the field of quality monitoring by providing a trustworthy method for locating and categorizing cracks.

I. INTRODUCTION

It addresses the urgent need for accurate and efficient detection of structural flaws in roads, bridges, and buildings, and represents a critical intersection of technology and infrastructure maintenance [1]. These initiatives are essential for maintaining public safety, increasing the longevity of civil structures, and reducing the need for expensive repairs and potential catastrophes brought on by unseen fissures[2]. Recent years have seen a revolution in the field of crack analysis and detection with the integration of cutting-edge technologies like deep learning, machine learning, and computer vision. Computer vision, especially convolutional Neural Networks, improves detection over manual methods, even in tough photo conditions[3]. In this project, the prominent methods include Convolutional Neural Networks (CNNs), U-Net, and LeNet, which provide strong capabilities in crack segmentation and classification[4]. Manual inspections are slow. Vision-based techniques like Fully Convolutional Neural Networks (FCNN) offer accurate crack detection. Challenges remain in achieving consistent performance with models likeUnity Neural Encoding Tool[5]. This introduces a Dual-encoder Network fusing Transformer and CNN for crack segmentation(DTrC-Net), blending transformers, and convolutional neural network for accurate crack segmentation. It employs parallel coding branches, feature fusion, and weighted loss optimization for high precision[6]. By precisely identifying cracks of various sizes and kinds, these models can analyze photos of infrastructure surfaces and offer important information about the structural integrity of the asset[7]. This study introduces a highly supervised approach with multi-scale class activation mapping for improved segmentation[8]. Furthermore, the performance and resilience of crack detection systems are further improved by the application of ensemble methods, transfer learning, and data augmentation[9].

II. LITERATURE SURVEY

Yang et al.[10] Attention U-Net(MST-Net) is a new method for accurately detecting road fractures. It tackles class imbalances and complex backgrounds using multiscale input and attention mechanisms. Zhang et al. [11]With features like deep supervision and aggregation, it outperforms other models in fracture detection accuracy. Mirbod et al. [12] This research provides a unique machine vision and Artificial Neural Network (ANN) based technique for concrete fracture identification. This method requires less hardware and simplifies the code, with an accuracy of 84.88% when compared to CNNs. Zhang et al. [13] approach, which makes use of the Utah State University dataset, has potential for use in structural health monitoring in practical settings. Canchila et al. [14] study examine current developments in deep learning for crack segmentation and assess how well they work with various kinds of images. Lau et al. [15] To analyze nine CNN architectures and establish the best performance and insights for further research, present the dataset, which consists of several picture kinds.

III. PROPOSED METHODOLOGY

Thorough data collection is necessary to create reliable and accurate models, which will progress the field of crack-level classification and segmentation. The images in the dataset contain a wide variety of crack types, including deep cracks, gap cracks, Riss cracks, Wall care cracks, and no cracks. This covers fissures found in various surfaces, including walls, concrete, and pavement. The dataset contains exact details about the shapes and locations of cracks. In addition, the model incorporates information from multiple sources, including different types of infrastructure, to improve its capacity for generalization. Optimizing the input data for further analysis during the pre-processing stage requires a strong rescaling strategy to be implemented. Along with improving the model's performance, this pre-processing stage also makes the subsequent crack classification and segmentation processes much more dependable and interpretable.

Structural Health Evaluation using Regression Analysis(SHERA), is important for evaluating structural integrity through the examination of various parameters. SHERA is an important tool for assessing the size and severity of cracks in crack-level classification, allowing for more accurate classification according to the severity levels of the cracks. Shera also helps in crack segmentation by precisely defining crack patterns, which leads to better segmentation outcomes.

On the other hand, detailed images of cracks at different scales depend heavily on the zoom range, which denotes the range of magnification levels used to capture structural data. Processes include preprocessing, careful data collection, and the use of specialized models like U-Net for segmentation and LeNet for classification.

To assess these models' generalizability, extensive testing is conducted on fresh datasets. For segmentation, U-Net is the better choice because it can capture fine details in complicated crack patterns, whereas LeNet excels at classification tasks. Metrics for evaluating the performance of the model that are specific to classification and segmentation are used, such as pixel-wise accuracy, recall, accuracy, precision, and Intersection over Union (IoU). Using binary cross-entropy loss function and backpropagation, model parameters are optimized during training to measure the difference between ground truth and predicted pixel values.

Data augmentation methods like rotation, flipping, and scaling are used to improve robustness and generalization. During testing, LeNet analyzes datasets or new images that contain potentially cracked structures that are different from its training set to test its generalization abilities. LeNet applies its trained architecture to a forward pass on the input data to produce classification outputs that express class probabilities or predicted labels for every image.

The model's classification accuracy is then thoroughly assessed through a quantitative evaluation that makes use of metrics unique to classification, including accuracy, precision, and F1 score. LeNet's accuracy in crack-level classification for structural health monitoring applications is improved by this rigorous testing process, which allows for iterative refinement and optimization.

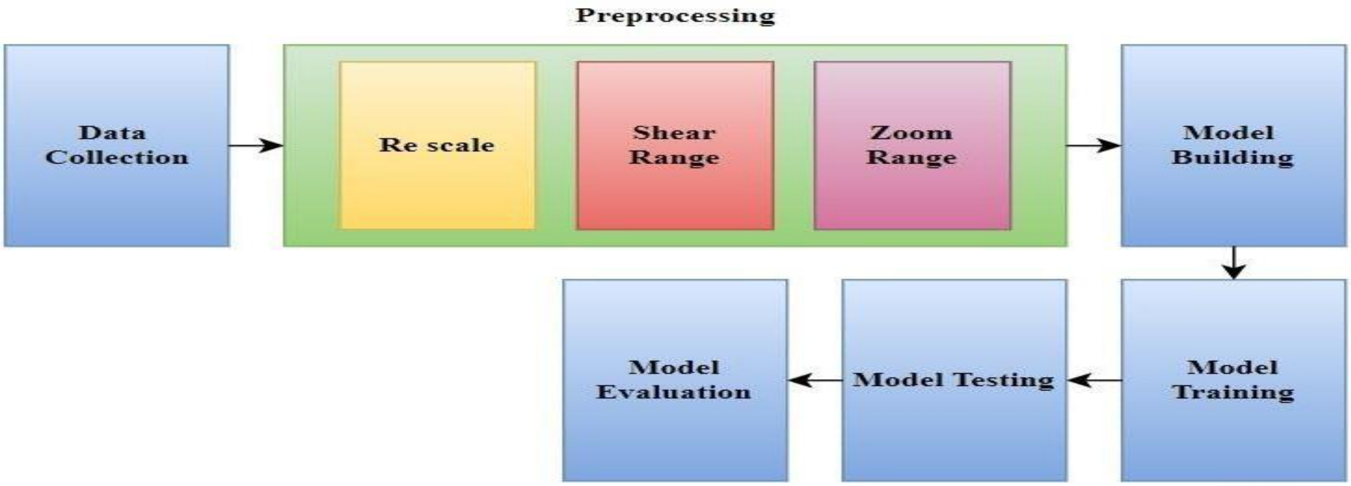

Figure 1. Block Diagram for crack level classification

After applying a forward pass to the input data, the U-Net creates segmentation masks at the pixel level that draw attention to areas that have been identified as cracks. The U-Net, which is well known for capturing minute details, is excellent at accurately segmenting complex crack patterns. Visual inspection of the segmentation outputs helps identify possible errors or inaccuracies by ensuring that they match expectations.

IV. PERFORMANCE EVALUATION

Table 1 displays the accuracy of a crack detection system. The accuracy is shown as 100 percent, meaning it's very reliable. For all types of cracks, the accuracy is above 93%, which is quite high.

Among them, Gap Cracks have the highest precision at 97.5%, while RISS Cracks have the lowest at 93.67%. It's worth noting that the effectiveness of any automatic crack detection system may differ based on the particular conditions in which it's employed.

Table 1. Accuracy of different models

S.No	Crack Type	Accuracy (%)
1	Crack	96.33
2	Deep Crack	94.97
3	Gap Crack	97.5
4	Riss Crack	93.67
5	Wall care Crack	95.27
6	No Crack	100

- Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
- Precision = $\frac{TP}{TP+FP}$
- Recall = $\frac{TP}{TP+FN}$
- F1= $\frac{2*\text{Precision}*\text{Recall}}{\text{Precision} + \text{Recall}}$
- IoU = $\frac{TP}{TP+FP+FN}$

where the definitions of TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative.

The graph provided shows the performance of a machine-learning model over multiple training cycles, or epochs. In machine learning, a crucial aspect is the use of a loss function, which measures the difference between the model's predictions and the actual data. The goal during training is to minimize this loss function to improve the model's accuracy. On the graph, the Y-axis represents the model's loss, with lower values indicating better performance. The X-axis represents the number of training epochs, showing how many times the model has been exposed to the dataset. The decreasing trend in the graph suggests that the model's performance is improving over time, as indicated by the reduction in loss. Machine learning's iterative training process is responsible for the model's performance improvement, which is indicated by the trend of the loss function decreasing over training epochs.

The model's predictions may be wildly inaccurate in the beginning, during the early epochs, leading to a comparatively high loss value. This is to be expected given that the model lacks a clear understanding of the underlying patterns in the data and begins with random weights and biases.

Based on the feedback given by the loss function, the model gradually modifies its parameters (weights and biases) as training goes on. The model adjusts its parameters to minimize the difference between its predictions and the actual data using methods like gradient descent and backpropagation.

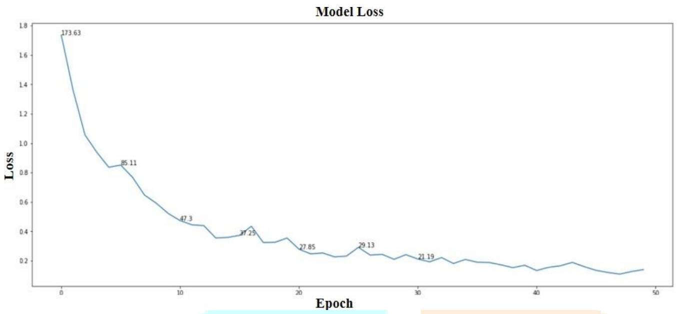

Figure 2. Loss Vs EpochsPerfomance Evaluation

The Y-axis shows the model's accuracy, with 1.0 being perfect accuracy and the Y-axis's range is between 0 and 1. The X-axis likely represents the number of times the model has been trained on a dataset.The text labels on the Y-axis are missing some decimal places, but it appears the accuracy starts low and increases over time. This suggests that the model is learning and improving its performance as it is trained on more data.

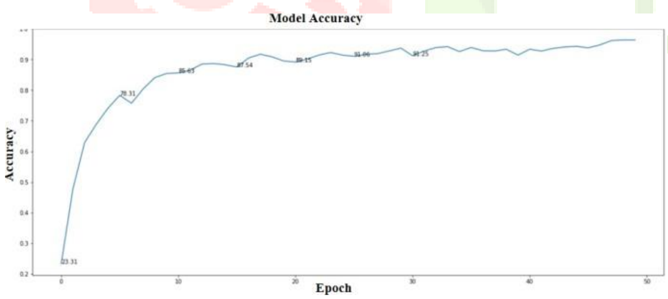

Figure 3 Accuracy Vs EpochsPerfomace Evaluation

With a range of 0 to roughly 50, the x-axis is designated as an "Epoch". Accuracy is represented by the Y-axis, and values fall between roughly 0.3 and just under 1.0. The accuracy approaches 0.9 at about epoch 10. After that, the accuracy varies a little but stays near the 0.9 threshold. The accuracy of the model increases dramatically in the first few epochs and then stabilizes at 0.9, as the graph illustrates.

Table 2 Accuracy and loss table

S. No	Epoch	Accuracy	Loss
1	1	29.78	173.63
2	5	70.02	83.60
3	10	82.30	52.18
4	20	88.67	35.43
5	30	93.53	24.11
6	40	95.24	16.92
7	50	96.75	19.97

Table 3 LeNet Architecture

Layer Type	Parameters/Configuration
Input Image	Dimensions: 28x28, 1 Channel
Convolutional Layer	Kernal Size: 5x5, Padding: 28x28x6
Max Pooling Layer	Pool Size: 2x2
Convolutional Layer	Kernal Size: 5x5, Padding: 10x10x16
Max Pooling Layer	Pool Size: 2x2
Flatten Layer	-
Fully Connected Layer (Dense)	Units: 120
Fully Connected Layer (Dense)	Units: 84
Fully Connected Layer (Dense)	Units:10
Output	1 of 10 Classes

Features extraction and classification tasks would be the main uses of the LeNet architecture in a crack-level classification and segmentation project. A Convolutional Neural Network (CNN) called LeNet was first created to recognize handwritten digits. It is composed of fully connected layers that are followed by layers with convolutional and pooling operations. This project would use the LeNet architecture to analyze crack images, with convolutional layers being used to extract unique features at different scales and then classify the cracks according to their type or severity. LeNet's layers could also be adjusted to predict pixel-by-pixel classifications, which would enable it to distinguish cracks from the background of images and be used for segmentation. For an accurate assessment and subsequent action, this segmentation capability helps to precisely identify the extent and boundaries of cracks within an image.

In existing work, there are differences in methods and results among the four papers reference paper 1 has a dataset of 1431 samples, and reference paper 1 used the MST NET approach to detect three cracks with an accuracy of 94.9%. In contrast, reference paper 2 used an ANN to detect one crack out of a much bigger dataset of 56,000 samples with an accuracy of 84.88%. Using a CNN, reference paper 3 also found three cracks from a dataset of 6000 samples, but at a lesser accuracy of 89.81%. In this study, we provide a novel approach that employs both U-Net and L-Net architectures to successfully identify six cracks from a dataset of 10,000 samples, with the greatest accuracy of 95.34%.

In existing work, there are differences in methods and results amongst the four papers we compared that dealt with crack detection. Using a dataset of 1431 samples, reference paper 1 used the MST NET approach to detect three cracks with an accuracy of 94.9%. In contrast, reference paper 2 used an ANN to detect one crack out of a much bigger dataset of 56,000 samples with an accuracy of 84.88%. Using a CNN, reference paper 3 also found three cracks from a dataset of 6000 samples, but at a lesser accuracy of 89.81%. In this study, we provide a novel approach that employs both U-Net and L-Net architectures to successfully identify six cracks from a dataset of 10,000 samples, with the greatest accuracy of 95.34%. It is clear from this comparative analysis that our suggested methodology performs better than current methods in both

Table 4 Comparison Table of Proposed Work with Existing Work

Values	Reference Paper 1[9]	Reference Paper 2 [10]	Reference Paper 3 [11]	Proposed Paper
No of Cracks	3	1	3	6
Data Set Size	1431	56,000	6000	10,000
Accuracy	94.9	84.88	89.81	95.34
Used Method	MST NET	ANN	CNN	U-Net, L-Net

V. CONCLUSION

Furthermore, the results show promising accuracy rates for different types of cracks. With accuracy levels surpassing 93% across the board and peaking at 97.5% for Gap Cracks, the system demonstrates its effectiveness in identifying and categorizing cracks accurately.

By creating interactive AI solutions that incorporate human feedback and allow inspectors to amend and validate AI-generated results for increased accuracy and reliability, researchers can improve the efficacy of crack detection systems. Furthermore, researching edge computing solutions makes it possible to directly install AI models on edge devices, enabling real-time processing and resolving privacy issues. Proactive maintenance tactics are further enabled by the integration of AI-powered crack detection systems into long-term monitoring and maintenance programs for infrastructure assets, which ultimately extend the life of critical infrastructure.

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