Summer Internship Project
Report

Crack Detection and Dimension Measurement using Machine Learning

Submitted by

Mohamed Shanil K K
College of Engineering Munnar

Under the guidance of

Dr A Sudarshan Chakravarthy
Assistant Professor, Department of Computer Science and Engineering,
NIT Calicut

Department of Computer Science and Engineering
National Institute of Technology Calicut

Summer Internship 2023

Abstract

This project focuses on developing a comprehensive solution for crack detection, segmentation, and length and width measurement in concrete structures. The primary objective is to leverage advanced machine learning techniques to automate the identification and analysis of cracks, which play a crucial role in ensuring the structural integrity and safety of concrete infrastructures.

The proposed methodology incorporates the use of the U-Net architecture for crack segmentation. U-Net, a widely recognized deep learning model, has shown remarkable performance in various image segmentation tasks. By training the U-Net model on a dataset of concrete crack images, it can effectively identify and segment cracks within the images, enabling precise localization and accurate measurement.

Following the segmentation process, the project utilizes OpenCV, a powerful computer vision library, for the calculation of crack length and width. By applying appropriate image processing techniques, including thresholding, contour detection, and bounding rectangle estimation, the length and width of the segmented cracks can be accurately determined.

The project's key contributions lie in the automation of the crack detection and analysis process, eliminating the need for manual inspection and measurement. This approach not only enhances the efficiency of crack assessment but also reduces human error and increases the overall accuracy of the measurements.

The project's methodology is implemented and evaluated using a diverse dataset of concrete crack images. The performance of the crack detection, segmentation, and length and width measurement processes is assessed through quantitative evaluation metrics such as F1 score, precision, and recall. The results demonstrate the effectiveness and reliability of the proposed solution.

Overall, this project presents a robust and efficient framework for crack detection, segmentation, and length and width measurement in concrete structures.

Contents

Chapter 1

Introduction

The rapid advancements in technology have opened up new avenues for solving complex real-world problems. In the field of civil engineering, the detection and analysis of concrete cracks play a vital role in assessing the structural integrity of buildings, bridges, and other infrastructure. Traditional manual methods for crack detection and measurement are time-consuming, subjective, and prone to human error. To overcome these limitations, the application of machine learning techniques has gained significant attention.

This internship report documents the experience and outcomes of a project aimed at developing a machine learning model based on the UNet architecture. The primary objective of this project was to create an automated system capable of accurately detecting and segmenting concrete cracks from images, as well as calculating their length and width. The resulting model would offer a more efficient and reliable alternative to the conventional manual approaches used in the field.

Throughout the internship, extensive research and experimentation were conducted to understand the underlying principles of image segmentation and apply them to the specific domain of concrete crack detection. The UNet architecture was chosen due to its proven success in medical imaging tasks, demonstrating potential for adaptation to crack detection in concrete structures.

It has the potential to expedite the inspection and assessment process, improve safety standards, and facilitate proactive maintenance of infrastructure.

Chapter 2

Literature Review

Crack detection and segmentation play a crucial role in the assessment and maintenance of civil infrastructure. Machine learning techniques have shown promising results in automating the crack detection and segmentation process. This literature review provides an overview of research papers that focus on crack detection and segmentation using machine learning.

"Comparison of crack segmentation using digital image correlation measurements and deep learning" [1] compares the performance of crack segmentation using two approaches: threshold method and deep convolutional neural network. The study demonstrates that the deep learning approach achieves higher precision and dice scores compared to the threshold method, preserving the geometry of crack patterns more accurately.

"A review of deep learning methods for pixel-level crack detection" [2] presents a comprehensive survey of deep learning-based pixel-level crack image segmentation methods. The review categorizes the methods into ten topics based on the backbone network architecture and discusses the strengths, limitations, and recent research progress in the field. It also provides insights into publicly accessible datasets, evaluation metrics, and loss functions for pixel-level crack detection.

"Machine Learning for Crack Detection: Review and Model Performance Comparison" [3] offers an overview of machine learning-based crack detection algorithms. The authors review 68 ML-based crack detection methods and conduct a performance evaluation on eight ML-based crack segmentation models. The study identifies the challenges and potential directions for future development, highlighting the effectiveness of deeper backbone networks and skip connections in improving the performance of crack detection models.

"Automatic crack detection on two-dimensional pavement images: An algorithm based on minimal path selection" [4] presents an algorithm for automatic crack detection on pavement images using minimal path selection.

The study focuses on two-dimensional pavement images and demonstrates the effectiveness of the proposed algorithm in crack detection.

"Segnet: A deep convolutional encoder-decoder architecture for image segmentation" [5] introduces SegNet, a deep convolutional encoder-decoder architecture for image segmentation. The study demonstrates the application of SegNet in crack detection and segmentation, highlighting its performance in accurately identifying cracks in images.

"Encoder-decoder network for pixel-level road crack detection in black-box images" [6] presents an encoder-decoder network for pixel-level road crack detection in black-box images. The study focuses on road crack detection and demonstrates the effectiveness of the proposed network architecture.

These are just a selection of research papers on crack detection and segmentation using machine learning. The literature review indicates that deep learning approaches, such as convolutional neural networks and encoder-decoder architectures, have shown promising results in accurately detecting and segmenting cracks in various types of images. The surveyed papers highlight the strengths, limitations, and future research directions in this field, providing valuable insights for further advancements in automated crack detection and segmentation using machine learning techniques.

Chapter 3

Problem Statement

Concrete structures are widely used in various sectors of infrastructure development due to their strength and durability. However, over time, these structures are susceptible to deterioration, particularly the formation of cracks. Concrete crack assessment is a critical task in the field of civil engineering, as it helps identify potential risks and supports timely maintenance and repair actions. Traditional methods of crack detection and measurement are time-consuming, subjective, and often prone to human error.

The existing methods for concrete crack detection and measurement suffer from limitations in terms of accuracy, efficiency, and scalability. Manual inspection methods are not only labor-intensive but also subjective, leading to inconsistencies in crack identification and measurement. Therefore, there is a need to develop an automated solution that utilizes machine learning techniques to detect, segment, and accurately measure the length and width of concrete cracks.

Objective: The primary objective of this internship project is to develop a robust and efficient machine learning model that can effectively detect and segment concrete cracks in images or video footage. The model should also provide accurate measurements of the crack length and width, enabling engineers and inspectors to assess the severity of the cracks and plan appropriate repair strategies. The ultimate goal is to improve the overall efficiency and reliability of concrete crack assessment, ensuring the longevity and safety of concrete structures.

Approach: To achieve the project objective, we will employ state-of-the-art computer vision techniques and machine learning algorithms. The project will involve collecting a diverse dataset of concrete crack images or videos, annotating them with ground truth crack information, and utilizing this labeled data to train and validate the machine learning model. Various image processing techniques, deep learning architectures, and feature extraction methods will be explored to enhance the accuracy and robustness of the model. The performance of the developed model will be evaluated using appropriate metrics.

Expected Outcome: By the end of this internship project, we anticipate the development of a machine learning model capable of accurately detecting, segmenting, and measuring the length and width of concrete cracks. This model will significantly improve the efficiency and reliability of concrete crack assessment, allowing for prompt maintenance and repair actions to ensure the structural integrity of concrete infrastructure. The findings and insights gained from this project will contribute to the field of civil engineering, paving the way for advanced technologies in crack assessment and structural health monitoring.

Chapter 4

Methodology

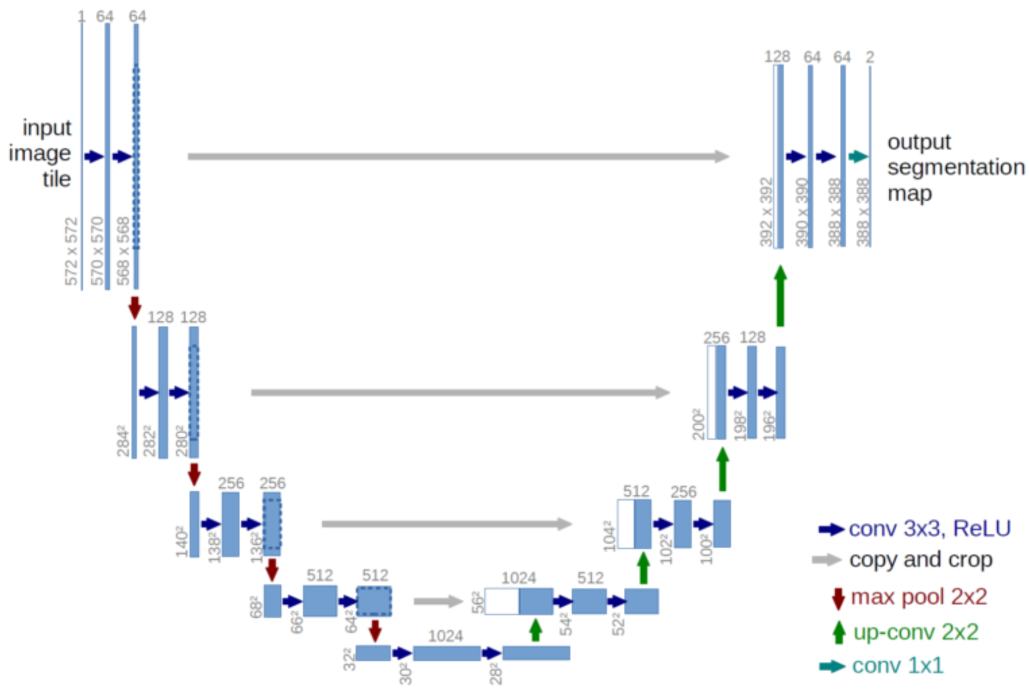
4.1 Dataset

Dataset contains around 11,200 images that are merged from 12 available crack segmentation datasets.All the images are resized to the size of (448, 448). Here 1800 images are used for training,600 images are used for validation and 600 for testing.

4.2 UNet

The UNET architecture is a U-shaped encoder-decoder network, which consists of four encoder blocks and four decoder blocks that are connected by a bridge. The encoder network, also known as the contracting path, reduces the spatial dimensions and increases the number of filters (feature channels) at each encoder block. Conversely, the decoder network increases the spatial dimensions and reduces the number of feature channels.

Encoder The encoder network acts as the feature extractor and learns an abstract representation of the input image through a sequence of the encoder blocks. Each encoder block consists of two 3×3 convolutions, where each convolution is followed by a ReLU (Rectified Linear Unit) activation function. The ReLU activation function introduces non-linearity into the network, which helps in the better generalization of the training data. The output of the ReLU acts as a skip connection for the corresponding decoder block.

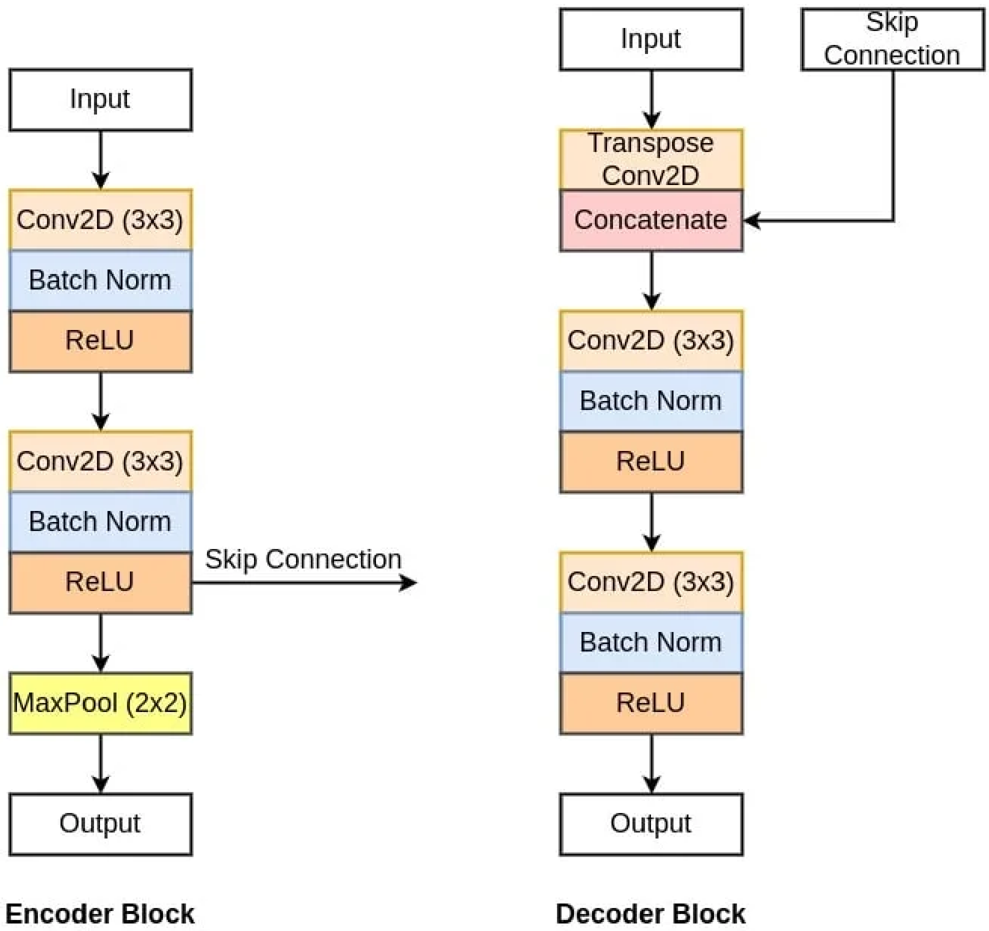


The diagram of UNET Architecture

Next, follows a 2×2 max-pooling, where the spatial dimensions (height and width) of the feature maps are reduced by half. This reduces the computational cost by decreasing the number of trainable parameters.

Skip Connections These skip connections provide additional information that helps the decoder to generate better semantic features. They also act as a shortcut connection that helps in the direct flow of gradients to the earlier layers without degradation. In simple terms, we can say that skip connection helps in better flow of gradient while backpropagation. This helps the network to learn better representation and improve performance.

The block diagram of the encoder and the decoder block of the UNET architecture. The block diagram of the encoder and the decoder block of the UNET architecture. The above figure shows the block diagram of the encoder and decoder block used to build the UNET architecture.



The block diagram of the encoder and the decoder block of the UNET architecture.

Bridge The bridge connects the encoder and the decoder network and completes the flow of information. It consists of two 3×3 convolutions, where each convolution is followed by a ReLU activation function.

Decoder Network The decoder network takes the abstract representation generated by the encoder and generates a semantic segmentation mask. The decoder block starts with a 2×2 transpose convolution, which is then concatenated with the corresponding skip connection feature map from the encoder block. These skip connections provide features from earlier layers that may have been lost due to the depth of the network. After this, two 3×3 convolutions are used, followed by a ReLU activation function

The output of the last decoder passes through a 1×1 convolution with sigmoid activation. The sigmoid activation function gives the segmentation mask representing the pixel-wise classification.

In summary, UNET is a cutting-edge architecture specifically designed for biomedical image segmentation. The architecture comprises of a U-shaped encoder-decoder network that includes four encoder blocks, four decoder blocks, and a bridge that connects the two. The encoder network functions as a feature extractor, extracting abstract representations of the input image. On the other hand, the decoder network utilizes these representations to generate a semantic segmentation mask. Furthermore, the skip connections between the encoder and decoder network provide additional information to the decoder and act as a direct channel for the flow of gradients, thereby enhancing the overall performance of the architecture.

4.3 Proposed Solution

4.3.1 Crack Detection and Segmentation

The provided code implements a U-Net architecture, a popular deep learning model, for the purpose of detecting and segmenting concrete cracks. U-Net is widely used in computer vision tasks, particularly in semantic segmentation, due to its ability to capture detailed information while maintaining spatial context.

The model is built using the TensorFlow and Keras libraries. It consists of an encoder-decoder structure with skip connections to preserve feature information at different scales. Let's break down the key components and functionalities of the model:

1.Convolutional Block: A standard building block that consists of two consecutive convolutional layers followed by batch normalization and ReLU activation. This block is responsible for extracting features from the input.

2.Encoder Block: Takes an input tensor and applies a convolutional block, followed by max pooling, to downsample the spatial dimensions of the features. This process helps capture higher-level representations while reducing computational complexity.

3.Decoder Block: Performs the reverse process of the encoder block. It takes an input tensor, performs transposed convolution (also known as upsampling), and concatenates it with the corresponding skip connection from the encoder block. This allows the model to leverage low-level and high-level features during the upsampling process.

The proposed U-Net model aims to leverage the power of deep learning to automatically detect and segment concrete cracks. By training this model on a diverse dataset of concrete crack images, it has the potential to learn intricate crack patterns and accurately segment cracks from background. This solution can significantly enhance the efficiency and accuracy of concrete crack assessment, enabling engineers and inspectors to take appropriate maintenance and repair actions promptly, thus ensuring the structural integrity and safety of concrete infrastructure.

4.3.2 Length and Width Mesurement

length measurement This solution for calculating the length and width of concrete cracks from segmented images utilizes the OpenCV library to process the segmented mask image and extract relevant measurements. Key processes are:

1. Load and Threshold the Mask Image: Loading the segmented mask image using OpenCV. The image is then thresholded using a binary thresholding technique. This step converts the grayscale image into a binary image, where crack regions are represented by white pixels and the background by black pixels.

2. Find Contours: Identifies contours within the binary image. Contours represent the boundaries of connected regions, in this case, the cracks. It uses the RETR EXTERNAL retrieval mode to retrieve only the outer contours and CHAIN APPROX SIMPLE approximation method to compress the contour representation.

3. Calculate Length and Width: For each contour found, we calculate the length and width of the bounding rectangle.

4. Store Measurements: The length and width of each contour's bounding rectangle are stored in the a list.

5. Select Main Crack Contour: Identifies the main crack contour by selecting the contour with the maximum length from the list. This allows for the identification of the most prominent crack within the image.

6. Retrieve Length and Width of Main Crack: The length and width of the main crack contour are extracted, representing the final measurements for the concrete crack in pixels.

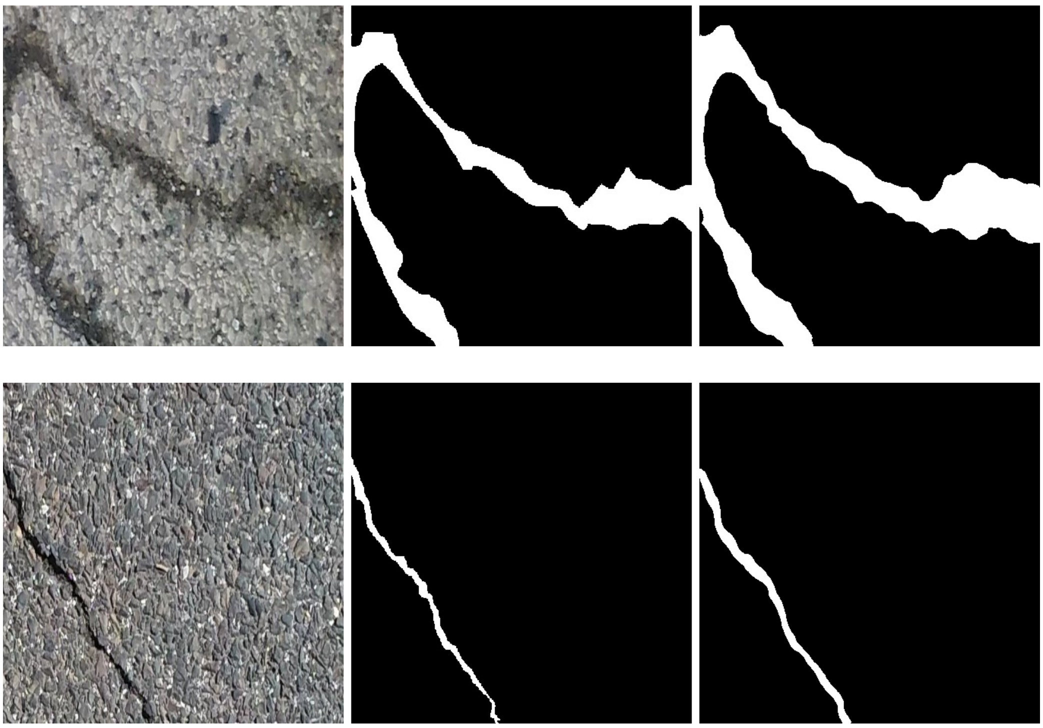
By applying this solution to segmented images, it enables the automated calculation of length and width for concrete cracks. This can streamline the crack assessment process and provide quantitative measurements for further analysis. The findings obtained from this method can assist engineers and inspectors in evaluating crack severity, determining appropriate repair strategies, and monitoring the progression of crack growth over time.

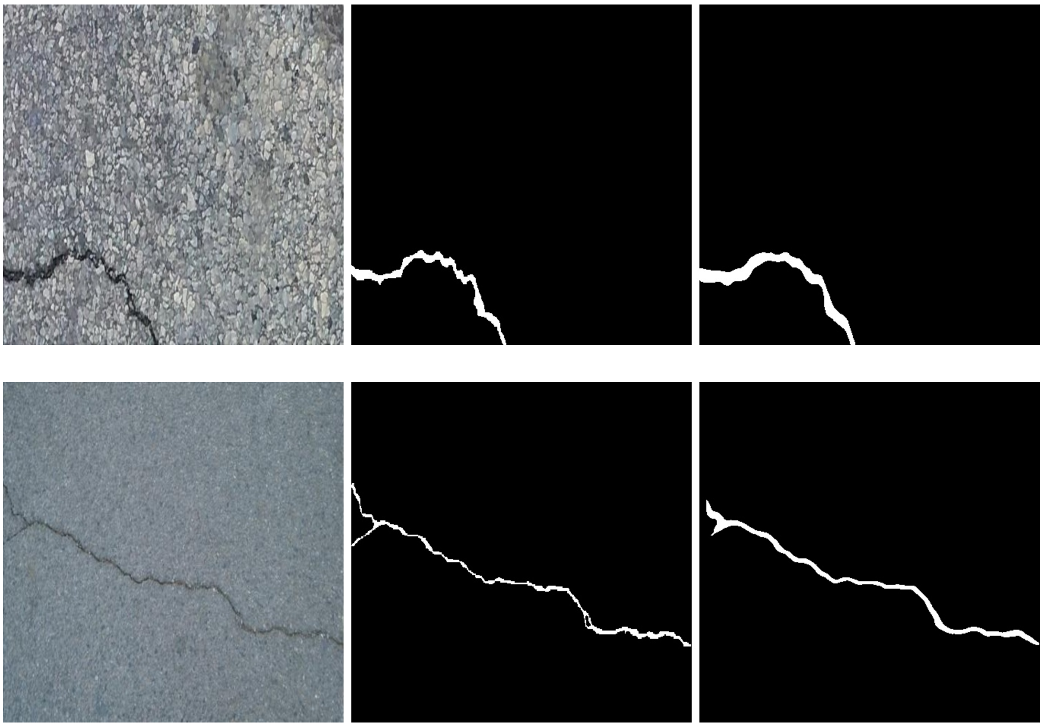
Original length and width in millimeters can be obtained by multiplying the obtained length and width by pixel to millimeter conversion ratio.

Chapter 5

Testing and Evaluation

The trained model, developed for concrete crack detection and segmentation, underwent evaluation on a dataset comprising 600 images. The model was previously trained on a separate set of 1800 images and validated using another 600 images.Conversion ratio of pixel to millimeter used during testing was 0.1. The evaluation process involved calculating various performance metrics, including F1 score, recall, and precision.



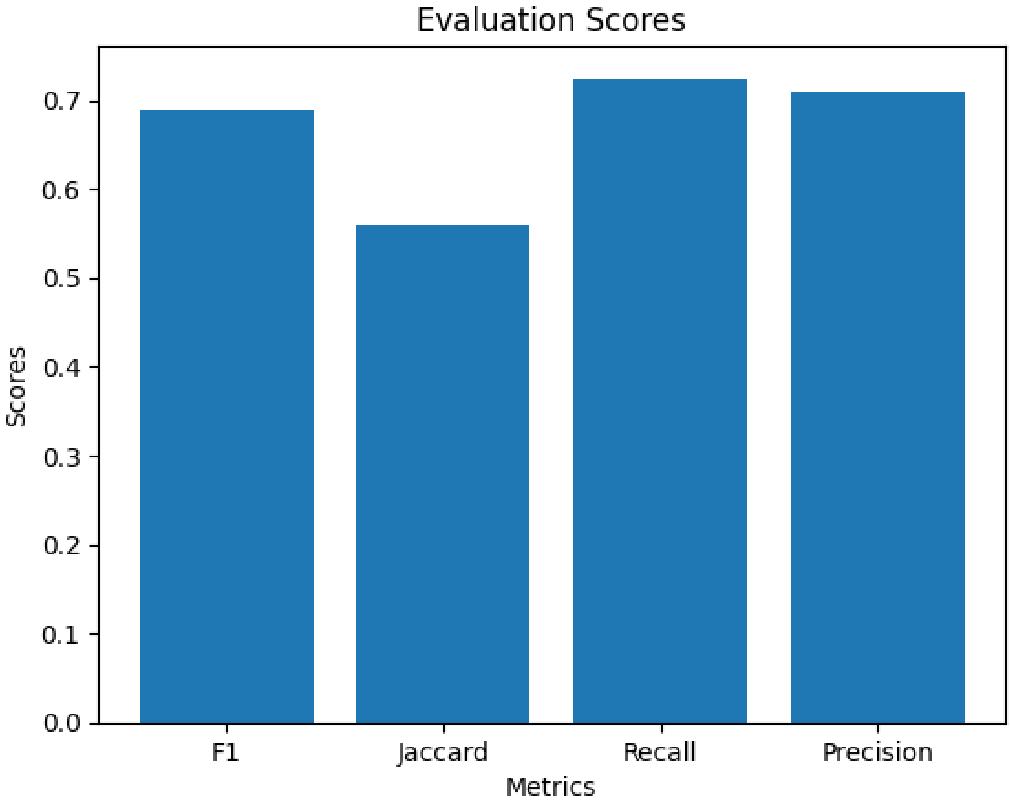


output:P image,original mask, predicted mask

The model achieved an F1 score of 0.68919, indicating a good balance between precision and recall. This metric measures the harmonic mean of precision and recall, providing a comprehensive assessment of the model's overall performance. An F1 score of 1 represents perfect precision and recall, while a score of 0 indicates poor performance. With an F1 score of 0.68919, the model demonstrates reasonable effectiveness in accurately detecting and segmenting concrete cracks.

The recall value of 0.72433 suggests that the model successfully identified a significant proportion of the actual positive instances of cracks in the dataset. Recall, also known as sensitivity or true positive rate, measures the ratio of correctly detected cracks to the total number of actual cracks present. A recall value of 0.72433 indicates that the model has a high ability to capture true positive instances, minimizing the chances of missing actual cracks.

The precision value of 0.70984 signifies the model's accuracy in correctly classifying detected cracks. Precision calculates the ratio of correctly predicted positive instances (cracks) to the total number of instances predicted as positive. A precision value of 0.70984 indicates that the model has a relatively low false positive rate, correctly identifying cracks while minimizing the occurrence of false alarms.



Evaluation Scores

Overall, the evaluation results indicate that the trained model exhibits promising performance in concrete crack detection and segmentation. The achieved F1 score, recall, and precision values demonstrate the model's ability to accurately identify and localize cracks within the evaluated dataset. These findings have practical implications for the field of civil engineering, as the model can assist in efficient crack assessment, maintenance planning, and resource allocation. Length and width prediction of cracks exhibited satisfactory and fairly accurate results.

However, it is important to note that the evaluation is based on a specific dataset, and the model's performance may vary when applied to different datasets or real-world scenarios.Length and width calculation needs further calibration for better accuracy. Further analysis and testing with diverse datasets, including different types of cracks and environmental conditions, would be beneficial to assess the model's robustness and generalizability.

In conclusion, the evaluated model showcases satisfactory performance in detecting and segmenting concrete cracks, as reflected by the obtained F1 score, recall, and precision values. This model holds the potential to support engineers and researchers in automating crack assessment tasks, facilitating efficient infrastructure maintenance.

Chapter 6

Conclusion

In conclusion, the developed model for concrete crack detection and segmentation has shown promising results in accurately identifying and localizing cracks within the evaluated dataset. The achieved F1 score of 0.68919, recall of 0.72433, and precision of 0.70984 demonstrate the model's effectiveness in detecting and segmenting concrete cracks.

The high recall value indicates that the model can successfully capture a significant proportion of actual crack instances, minimizing the chances of missing cracks during the detection process. The precision value demonstrates the model's accuracy in correctly classifying detected cracks, reducing the occurrence of false positive predictions. These findings are crucial for ensuring that cracks are identified and addressed promptly to maintain structural integrity and safety.

The evaluation results highlight the potential practical applications of the model in the field of civil engineering. By automating the crack detection and segmentation process, the model can assist engineers in efficiently assessing infrastructure and planning maintenance activities. It enables the identification of cracks that may not be readily visible to the human eye, facilitating proactive repairs and mitigating potential risks.

However, it is important to acknowledge that the evaluation was conducted on a specific dataset, and the model's performance may vary when applied to different datasets or real-world scenarios. Further validation and testing with diverse datasets, encompassing various crack types and environmental conditions, would provide a more comprehensive assessment of the model's robustness and generalizability.

Continued research and development in this field are necessary to improve the model's performance and address existing challenges. Future efforts should focus on expanding the dataset, refining the model architecture, and exploring additional techniques such as data augmentation and transfer learning to enhance the model's accuracy and adaptability.

Overall, the developed model offers valuable insights into automated concrete crack detection and segmentation. It represents a significant step forward in leveraging machine learning techniques for infrastructure maintenance.

Acknowledgment

I would like to express my deepest gratitude and appreciation to Dr. A. Sudarshan Chakravarthy, for providing me with invaluable guidance and support throughout my internship. Your expertise, encouragement, and mentorship have been instrumental in shaping my understanding of the subject matter and enhancing my professional growth.

I am also grateful to the National Institute of Technology Calicut for granting me the opportunity to undertake this internship. The institute's commitment to excellence in education and research has played a pivotal role in nurturing my passion for the field and providing me with a conducive learning environment.

Lastly, I would like to express my heartfelt appreciation to my family for their unwavering love, encouragement, and support. Their belief in my abilities has been a constant source of motivation, and I am grateful for their presence in my life.

I sincerely thank everyone mentioned above and all those who have contributed to my internship experience in any way. Your support and guidance have been pivotal in shaping my professional development and have made this internship a truly transformative experience.

Mohamed Shanil K K

References

[1] Amir Rezaie, Radhakrishna Achanta, Michele Godio, Katrin Beyer, Comparison of crack segmentation using digital image correlation measurements and deep learning, Construction and Building Materials

[2] Hongxia Li, Weixing Wang, Mengfei Wang, Limin Li, Vivian Vimlund, A review of deep learning methods for pixel-level crack detection, Journal of Traffic and Transportation Engineering

[3] Yung-An Hsieh and Yichang James Tsai, Machine Learning for Crack Detection: Review and Model Performance Comparison,Journal of Computing in Civil Engineering

[4] R. Amhaz, S. Chambon, J. Idier and V. Baltazart, "Automatic Crack Detection on Two-Dimensional Pavement Images: An Algorithm Based on Minimal Path Selection," in IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 10, pp. 2718-2729, Oct. 2016, doi: 10.1109/TITS.2015.2477675.

[5] V. Badrinarayanan, A. Kendall and R. Cipolla, "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 12, pp. 2481-2495, 1 Dec. 2017, doi: 10.1109/TPAMI.2016.2644615.

[6] Bang, S, Park, S, Kim, H, Kim, H. Encoder–decoder network for pixel-level road crack detection in black-box images. Comput Aided Civ Inf. 2019; 34: 713– 727. https://doi.org/10.1111/mice.12440