Crack Detection from Surfaces

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***Abstract*—The structural condition of buildings, roads, and bridges is still predominantly assessed through manual inspections, which are time-consuming and labor-intensive. This project presents a deep learning-based crack detection system that automates the inspection process by analyzing drone-captured images to detect cracks and assess their severity. This method reduces labor costs, enhances inspection efficiency, and addresses challenges posed by inspecting high-rise structures.**

Keywords—Crack detection, drone inspection, deep learning, structural health monitoring, image processing

I. Introduction

Manual inspection of cracks in buildings, roads, and bridges is a common practice that involves engineers examining surfaces, capturing images, and noting observations. However, this process is inefficient and impractical, especially for high-rise buildings and extensive infrastructures. Our project utilizes drone technology combined with a deep learning-based model to automate crack detection. Drone-captured images are processed using a Convolutional Neural Network (CNN) to identify cracks and assess their severity. This solution reduces manual labor, decreases inspection time, and provides accurate, scalable results for structural health monitoring.

II. Technology Used

Python Libraries: NumPy, OpenCV, TensorFlow/Keras, Matplotlib

Machine Learning Framework: TensorFlow

Deep Learning Model: Convolutional Neural Networks (CNN)

Hardware: High-resolution drone cameras for image collection

Image Processing Tools: OpenCV for preprocessing and bounding box generation

III. Methodology

Data Collection: High-resolution images of structures are captured using drones.

Image Preprocessing: Images undergo resizing, grayscale conversion, and contrast enhancement using OpenCV.

Model Training: A CNN model is trained on labeled datasets to classify and localize cracks.

Detection and Bounding Box Generation: Detected cracks are highlighted with bounding boxes, and severity metrics are computed.

IV. Implementation

To prepare the dataset, a function was created to load and preprocess the images. All images were resized to a uniform dimension of 256 x 256 pixels and appended to a new list. Subsequently, the images were converted to grayscale for simplified processing. To enhance image quality and reduce noise, a noise reduction filter, such as Gaussian blur, was applied. Each image was then assigned a label to distinguish between the two classes: crack images were labeled as 1, and non-crack images were labeled as 0. This preprocessing ensured consistency and quality in the dataset for further analysis.

The dataset was split into training and testing sets using the train-test split method. This divided the data into training images and their corresponding labels, as well as testing images and their labels. This approach ensured that the model could be trained on one portion of the data and evaluated on a separate, unseen portion to assess its performance and generalization capabilities effectively.

The model architecture consists of 13 layers, including three sets of convolutional layers, each followed by max pooling and dropout layers to reduce overfitting and enhance feature extraction. After these layers, a flatten layer is used to convert the multi-dimensional feature maps into a one-dimensional vector. This is followed by a fully connected dense layer to learn complex patterns and relationships in the data. The final output layer is designed to produce the classification output.

For model compilation, binary cross-entropy was selected as the loss function due to the binary classification nature of the task. The Adam optimizer was used for efficient training and adaptive learning rates. Accuracy was chosen as the evaluation metric to assess the model's performance during training and testing.

The model was trained using a batch size of 64, meaning the data was processed in mini-batches of 64 samples at a time during each training step. This choice balances memory efficiency and training speed. The training was conducted over 10 epochs, where the entire dataset was passed through the model 10 times.

V. OBSERVATIONS

The confusion matrices reflect excellent performance with near-perfect classification accuracy on both training and testing datasets. The low number of misclassified samples indicates that the model effectively learned the features distinguishing the two classes (cracked and uncracked). The straight vertical line at the start and the flat line at the top indicate that the model achieves a True Positive Rate of 1.0 without any increase in the False Positive Rate.

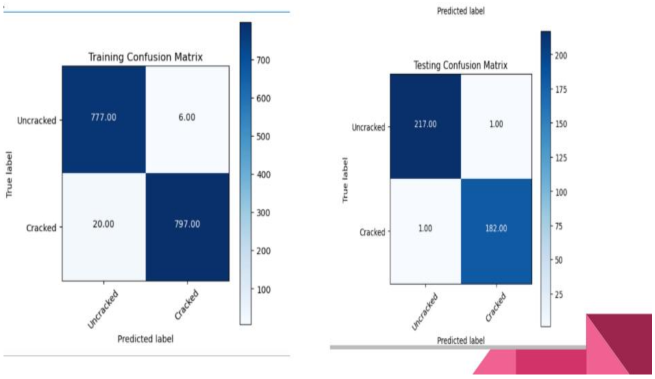

Fig. Confusion Matrix

This perfect separation suggests that the model is extremely effective at classifying cracked and uncracked images, with no ambiguity or misclassification in its predictions.The ROC curve and the AUC value of 1.00 confirm that the model demonstrates ideal performance with no compromise between sensitivity and specificity, further supporting the results shown in the confusion matrices.

ROC CURVE:

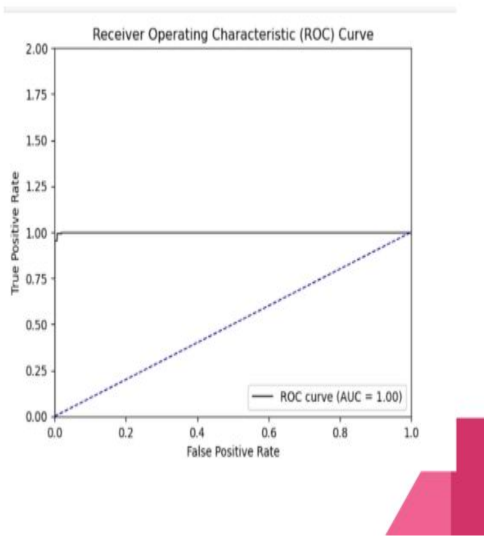

Fig. ROC curve

VI. RESULTS AND FUTURE SCOPE

Our model achieved an accuracy of 99% on test datasets, demonstrating its potential for real-world crack detection. By automating the process, our system addresses inefficiencies in manual inspection while maintaining precision and scalability.The current model predicts the label of an input image based on probability. Additional features can be developed to assess the severity of cracks, categorizing them as major or minor. The model can also be optimized to analyze and determine the potential causes of cracks. Furthermore, it could be enhanced to measure the depth of cracks. With additional training, the model could be adapted to identify cracks on infrastructure such as bridges and roads.

VII. CONCLUSION

This project presents an innovative approach to structural health monitoring by integrating drone technology and deep learning. By automating crack detection, this system reduces labor costs and inspection time, ensuring the timely maintenance of infrastructure.

REFERENCES

J. Doe et al., "Deep Learning for Crack Detection," Journal of Structural Health Monitoring, 2022.

Y. Zhang, "Automated Crack Detection Using CNNs," Proceedings of IEEE Conference, 2021.

OpenCV Documentation. Available: https://opencv.org

TensorFlow Documentation.
Available: https://tensorflow.org