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Wall Crack Detection using ML

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Abstract: **Structural integrity assessment is crucial for ensuring the safety and longevity of buildings. Manual crack detection methods are often labor-intensive, subjective, and prone to human errors. This paper presents an automated system leveraging deep learning techniques to detect wall cracks from images efficiently. Convolutional Neural Networks (CNNs) are employed for feature extraction and classification. The proposed system demonstrates superior accuracy and efficiency compared to traditional manual and image-processing-based crack detection methods. The study also highlights the robustness of the model under varying lighting and texture conditions.**

Index Terms: **CNN, Deep Learning, Image Processing, Structural Health Monitoring, Wall Crack Detection.**

I. INTRODUCTION

Cracks in walls can compromise the structural integrity of buildings, leading to safety hazards and costly repairs. Traditional crack detection methods rely on manual inspection by experts, which is often time-consuming, expensive, and inconsistent. In recent years, advances in deep learning, particularly Convolutional Neural Networks (CNNs), have provided an effective solution for automating crack detection with high accuracy.

This paper explores the implementation of CNN-based deep learning models for detecting cracks in wall surfaces. The proposed model is trained on a diverse dataset of crack images and evaluated using standard performance metrics. The study aims to develop an efficient and scalable system that can be integrated into real-world applications for structural health monitoring.

II. RELATED WORK

Several studies have explored the use of machine learning and deep learning for automated crack detection:

- Zhang & Hu (2020) proposed a CNN-based model that achieved high accuracy in detecting cracks in concrete structures, demonstrating the potential of deep learning in structural monitoring.
- Kim et al. (2021) extended this approach for real-time crack detection on mobile devices, enabling on-site assessments.
- Li & Wang (2019) explored deep learning models for detecting pavement surface cracks, highlighting the applicability of CNNs across different materials.
- Xu & Yang (2022) implemented CNN-based defect detection techniques for various building structures, further validating the efficiency of deep learning in this domain.
- Patel & Mehta (2021) conducted a comparative analysis of different deep learning models, emphasizing the advantages of CNNs over traditional image processing techniques.
- Huang & Zhang (2020) investigated real-time wall crack detection using edge computing, which enhances the feasibility of deploying deep learning models in practical scenarios.

Despite the advancements, most existing models are designed for specific materials and lack generalization. This study addresses this limitation by developing a model capable of detecting cracks in various wall surfaces under different environmental conditions.

III. METHODOLOGY

A. Data Collection and Preprocessing

The dataset used for training the CNN model consists of publicly available and self-collected images of wall cracks. The images include various textures, lighting conditions, and crack patterns to improve model generalization. Data preprocessing techniques include:

- Image resizing: Standardizing image dimensions for uniformity.

- Data augmentation: Applying transformations such as rotation, flipping, and brightness adjustment to increase dataset diversity.
- Noise reduction: Using image denoising techniques to improve feature extraction.
- Segmentation: Identifying and isolating crack regions using image thresholding techniques.
- Feature normalization: Scaling pixel intensities to a standard range to enhance model learning.

B. Model Development

A Convolutional Neural Network (CNN) architecture is designed for feature extraction and classification. The architecture consists of multiple convolutional layers followed by max-pooling layers to reduce spatial dimensions while preserving important features. The final fully connected layers classify images into crack and non-crack categories. The model is implemented using TensorFlow/Keras and trained on labeled datasets.

- Layer 1: Convolutional layer with 32 filters, kernel size of (3x3), and ReLU activation.
- Layer 2: Max-pooling layer with a pool size of (2x2) to reduce spatial dimensions.
- Layer 3: Second convolutional layer with 64 filters, kernel size of (3x3), followed by max-pooling.
- Layer 4: Fully connected dense layer with 128 neurons.
- Layer 5: Output layer with a sigmoid activation function for binary classification.

C. Performance Evaluation

The trained model is evaluated using the following metrics:

- Accuracy: Measures the overall correctness of predictions.
- Precision: Determines the fraction of true crack detections among all predicted cracks.
- Recall: Assesses the model’s ability to identify all actual cracks.
- F1-score: Balances precision and recall for a comprehensive evaluation.
- ROC Curve Analysis: Measures the tradeoff between true positive and false positive rates.

Additionally, the performance of the CNN model is compared with traditional image-processing techniques such as edge detection and thresholding.

IV. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed CNN model achieves over 90% accuracy in detecting wall cracks. The system outperforms conventional edge detection methods by offering higher robustness against variations in lighting and surface textures.

A. Comparison with Traditional Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Edge Detection	75.4	70.2	72.1	71.1
Thresholding	78.8	74.5	76.3	75.4
Proposed CNN Model	91.5	89.3	90.7	90.0

B. Model Robustness

The CNN model demonstrates excellent performance across different lighting conditions, surface textures, and crack orientations. The integration of data augmentation techniques contributes significantly to the model’s ability to generalize well across diverse datasets.

V. CONCLUSION

This study presents a deep learning-based approach for automated wall crack detection. The proposed CNN model significantly improves detection accuracy and efficiency compared to traditional manual inspection and image-processing methods. The results indicate that deep learning can play a vital role in structural health monitoring by providing reliable and automated crack detection solutions.

Future Work

Future research will focus on:

- Optimizing the model for real-time applications.
- Implementing the system in mobile and edge computing devices.
- Extending the dataset to include more diverse wall surfaces and environmental conditions.
- Exploring transformer-based deep learning architectures for improved feature extraction.
- Integrating IoT sensors for continuous structural monitoring.

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