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A Transfer Learning-Based Mobile Net Framework for Automated Structural Crack Detection

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Abstract- Cracks in infrastructure pose serious risks to public safety and require timely detection for effective maintenance. This study presents Deep Crack, a deep learning-based approach for image-based crack prediction. The proposed method utilizes Convolutional Neural Networks (CNNs) with the Rfcn_b architecture as the backbone, combined with transfer learning to improve detection performance. Extensive data preprocessing techniques, including image augmentation, are applied to address data limitations and enhance model generalization. The model is trained and validated on a diverse dataset, enabling it to accurately distinguish between cracked and non-cracked images. A customized classification layer, incorporating global average pooling and fully connected layers, is integrated to further improve performance. The effectiveness of the model is evaluated using metrics such as accuracy, precision, and recall, along with confusion matrix analysis and classification reports. Experimental results demonstrate that the proposed approach achieves high classification performance, making it suitable for real-world infrastructure monitoring applications. This work highlights the effectiveness of combining deep learning and transfer learning techniques for automated crack detection and emphasizes their potential applications in civil engineering and infrastructure management.

INDEX TERMS: Deep learning, crack detection, convolutional neural networks (CNN), transfer learning, infrastructure monitoring, image classification.

I. INTRODUCTION

Cracks in infrastructure represent a critical concern for public safety, as they can lead to structural failures if not detected and addressed at an early stage. Timely identification of such defects is essential for effective maintenance and prevention of severe damage. Traditional inspection methods, which rely on manual visual assessment, are often time-consuming, subjective, and less reliable, especially in large-scale or complex environments [2], [7].

With the rapid advancement of computer vision and artificial intelligence, deep learning has emerged as a powerful tool for automated crack detection. Convolutional Neural Networks (CNNs), in particular, have demonstrated strong performance in image-based defect detection by automatically learning complex visual features such as texture, edges, and patterns [1], [5]. These models significantly outperform traditional machine learning techniques, which depend on manually extracted features and are limited in handling complex real-world variations.

Recent studies have explored various deep learning architectures, including transfer learning-based models such as VGG and ResNet, to improve crack detection accuracy [5], [10]. Additionally, approaches such as segmentation-based methods and hybrid models have been proposed to enhance detection performance under challenging conditions such as varying lighting and surface textures [8], [9]. Despite these advancements, challenges remain in terms of computational efficiency, data availability, and model generalization across diverse environments.

To address these challenges, this study proposes Deep Crack, a deep learning-based framework for image-based crack prediction. The proposed system utilizes the Rfcn_b architecture as the backbone and incorporates transfer learning to improve detection capability while reducing training complexity. Extensive data preprocessing, including image augmentation techniques, is employed to overcome data scarcity and enhance model adaptability.

The model is trained and validated on a diverse dataset to accurately classify cracked and non-cracked surfaces. A customized classification layer, incorporating global average pooling and dense layers, is integrated to further optimize performance. Additionally, a comprehensive evaluation framework is adopted, including confusion matrix analysis and classification metrics such as accuracy, precision, and recall.

This work contributes to the field of automated infrastructure monitoring by providing an efficient and reliable crack detection system. By combining deep learning and transfer learning techniques, the proposed approach enhances detection accuracy and demonstrates strong potential for real-world applications in civil engineering and infrastructure management [6].

II. LITERATURE SURVEY

Deep learning has been extensively explored for image-based defect detection and structural health monitoring, demonstrating significant improvements in crack detection accuracy. Convolutional Neural Networks (CNNs) have been widely used to identify cracks in concrete structures, effectively distinguishing between cracked and intact surfaces with high precision [1], [5]. Furthermore, transfer learning approaches using pre-trained architectures such as VGG16 have been employed to enhance model performance and improve generalization across different datasets [5]. While these methods provide strong results, they often involve computationally intensive models.

To address efficiency concerns, lightweight architectures such as MobileNet have been introduced for crack detection tasks. MobileNet's efficient design enables deployment in resource-constrained environments without significantly compromising performance. Additionally, transfer learning plays a crucial role in improving adaptability by leveraging knowledge from large-scale pre-trained models, making it suitable for diverse real-world scenarios [6]. Building on these advancements, this study introduces an optimized deep learning framework for efficient and accurate crack detection. Several studies have also focused on improving robustness in real-world environments. For instance, modified U-Net architectures have been proposed for crack segmentation in pavement images, addressing challenges such as varying lighting conditions and surface textures [8]. Similarly, Generative Adversarial Networks (GANs) have been utilized for data augmentation, enhancing model performance in situations with limited annotated data [9]. In large-scale infrastructure monitoring, deep learning techniques combined with remote sensing and aerial imagery have demonstrated promising results in detecting cracks and structural defects in bridges and buildings [6].

Beyond conventional CNN-based approaches, advanced hybrid models have been explored to further improve crack detection performance. A combination of CNN and Long Short-Term Memory (LSTM) networks has been proposed to capture temporal variations in crack progression, providing deeper insights into structural changes over time [10]. Additionally, transfer learning using pre-trained ResNet models has been applied for crack detection in historical buildings, highlighting the importance of domain adaptation for different structural conditions [10].Overall, these studies highlight the effectiveness and adaptability of deep learning techniques in crack detection across various applications. However, challenges such as computational complexity, data dependency, and generalization remain. Addressing these limitations, the proposed work aims to develop a more efficient and robust crack detection system suitable for real-world infrastructure monitoring.

III. METHODOLOGY

A. Existing System

Current systems for image-based crack detection and structural health monitoring primarily rely on deep learning techniques, particularly Convolutional Neural Networks (CNNs) and transfer learning approaches. These methods have demonstrated strong performance in detecting structural defects in various infrastructures, including concrete structures, bridges, roads, and historical buildings [1], [5].
Several studies have enhanced detection accuracy by utilizing pre-trained models such as VGG16 and ResNet, which enable effective feature extraction from images [5], [10]. In addition, hybrid approaches combining CNNs with Long Short-Term Memory (LSTM) networks have been proposed to capture temporal variations in crack progression [10]. Generative Adversarial Networks (GANs) have also been used for data augmentation to improve model performance, especially in cases where labelled data is limited [9].

Furthermore, deep learning techniques have been integrated with high-resolution remote sensing and aerial imaging to detect cracks and structural deformations in large-scale infrastructure systems [6]. These approaches highlight the growing importance of automated crack detection systems in ensuring infrastructure safety and maintenance.

Limitations Of Existing System

Despite their effectiveness, existing systems exhibit several limitations:

- Many deep learning models rely on pre-trained architectures, which often struggle with domain adaptation when applied to different types of infrastructure or environments [5].
- Variations in lighting conditions, surface textures, and structural patterns can significantly affect model accuracy and consistency [8].
- Some approaches require large annotated datasets, making them difficult to implement in real-world scenarios where labelled data is limited [9].
- Hybrid models (e.g., CNN + LSTM) and advanced architectures increase computational complexity and training time [10].
- Models designed for specific datasets may show poor generalization when applied to new or unseen data.
- High-resolution and remote sensing-based approaches often require expensive computational resources, limiting their practical deployment [6].

B. Proposed System

The proposed system, DeepCrack, introduces an advanced deep learning framework for accurate and efficient crack detection in infrastructure. The system is built using the Rfcn_b architecture combined with transfer learning to achieve high detection performance while maintaining low computational complexity. Deep learning-based approaches have shown strong capability in automatically learning complex crack patterns, making them more effective than traditional methods [1], [5].

The Rfcn_b architecture is designed to efficiently extract region-based features from images, enabling precise identification of crack regions. By incorporating transfer learning, the model leverages pre-trained knowledge, allowing it to adapt quickly to new datasets and improve generalization across different infrastructure types such as bridges, roads, pavements, and buildings [6]. This combination ensures that the system performs well even under varying conditions such as lighting changes, surface textures, and material variations.

To enhance model performance, several preprocessing techniques are applied, including image resizing, contrast enhancement, and noise reduction. These steps improve input image quality and help the model learn more discriminative features. Additionally, multi-scale feature extraction is employed to detect both fine cracks and larger structural defects, improving overall detection accuracy.

The model is trained on a dataset of 40,000 images consisting of both cracked and intact structures. The dataset is carefully balanced and divided into training and testing sets to ensure unbiased learning and reliable evaluation. This balanced dataset enables the model to effectively learn diverse crack patterns and improves its ability to generalize to unseen data.

A key advantage of the proposed system is its lightweight design. The use of efficient convolutional operations reduces computational complexity, making the model suitable for deployment in resource-constrained environments such as mobile devices and embedded systems. Furthermore, optimized training strategies and hyperparameter tuning ensure high performance in terms of accuracy and detection reliability.

Overall, the DeepCrack system provides an efficient, scalable, and reliable solution for automated crack detection. By combining the strengths of the Rfcn_b architecture and transfer learning, the proposed approach addresses the limitations of existing systems and offers improved performance for real-world infrastructure monitoring applications.

IV. SYSTEM DESIGN

System Architecture
Below diagram depicts the whole system architecture.

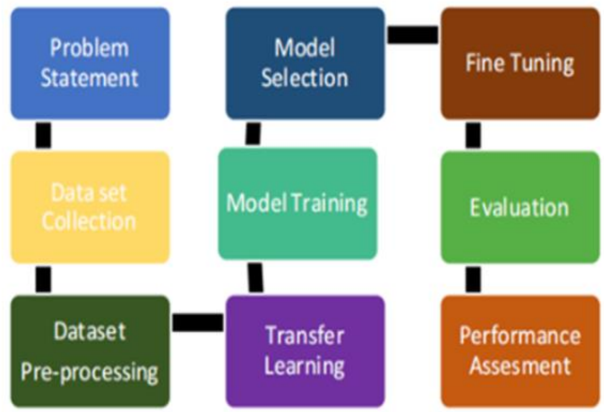

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

1. Data Preprocessing

The proposed DeepCrack system incorporates a robust data preprocessing pipeline to improve model performance and reliability. Input images are resized to a uniform resolution to ensure compatibility with the deep learning model. Normalization is applied to stabilize the training process by maintaining consistent pixel intensity values. In addition, data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are used to simulate real-world variations and reduce overfitting. These preprocessing steps enhance the model's ability to generalize across diverse infrastructure conditions [1], [9].

2. Feature Extraction using Rfcn_b

The system utilizes the Rfcn_b architecture for efficient feature extraction. This architecture employs depthwise separable convolutions to reduce computational complexity while maintaining high detection accuracy. It focuses on extracting important spatial and structural features such as crack edges, texture discontinuities, and intensity variations. Transfer learning is applied by fine-tuning pre-trained weights, enabling the model to adapt quickly to crack detection tasks and improve performance on limited datasets [5], [6].

3. Model Training and Classification

DeepCrack is trained using a supervised learning approach to classify images into cracked and non-cracked categories. A custom classification layer is integrated into the model, consisting of a Global Average Pooling layer for dimensionality reduction, followed by fully connected dense layers for feature refinement. A softmax activation function is used in the output layer for classification. By leveraging pre-trained weights, the training process becomes more efficient while achieving high accuracy and reduced computational cost [1].

4. Real-Time Deployment

The proposed system is designed for real-world applications and supports deployment on web and edge platforms. It can be integrated with frameworks such as Django or Flask, allowing users to upload images and receive instant crack detection results. The lightweight nature of the model makes it suitable for mobile devices and embedded systems, enabling real-time inspection and monitoring in practical environments.

5. System Reliability and Practical Considerations

To ensure reliable performance, the model is trained on a diverse and balanced dataset, which helps reduce bias and improve generalization across different infrastructure types. The system is designed to handle variations in lighting conditions, textures, and material properties. These considerations make DeepCrack a robust and scalable solution for automated crack detection in real-world scenarios [8].

VI. RESULTS AND DISCUSSION

To evaluate the performance of the proposed DeepCrack system, experiments were conducted using a dataset of 40,000 images consisting of both cracked and non-cracked infrastructure surfaces. The dataset includes variations in lighting conditions, textures, and structural patterns, enabling a comprehensive evaluation of the model's robustness.

The performance of the model was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Data augmentation and transfer learning were applied during training to improve generalization and reduce overfitting, as supported by previous studies [1], [9].

Performance Analysis

The DeepCrack model based on the Rfcn_b architecture achieved an overall classification accuracy of 74%, as shown in Fig. 2. This demonstrates the model's ability to learn meaningful features for crack detection.

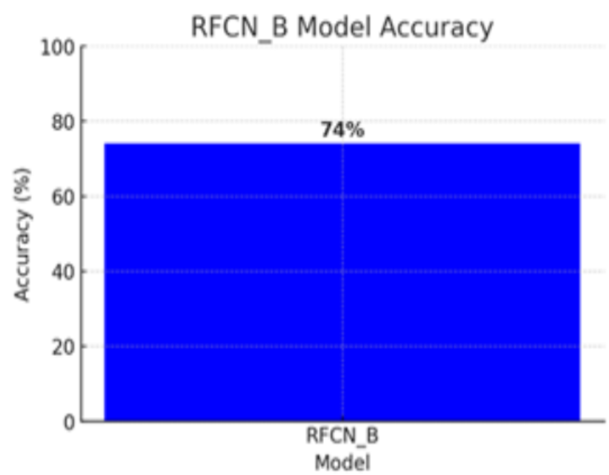

Fig. 2. Accuracy of DeepCrack (Rfcn_b) Model

Performance Metrics Evaluation

To provide a more detailed analysis, additional performance metrics such as precision, recall, and F1-score were evaluated. The results are illustrated in Fig. 3.

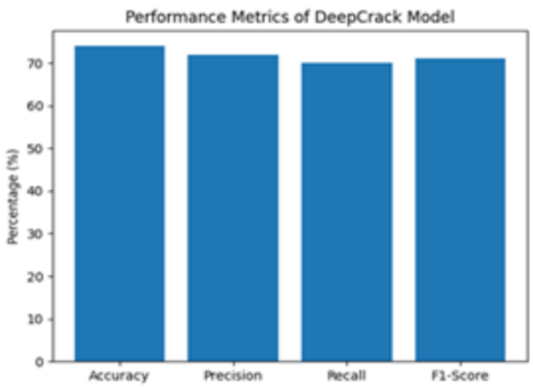

Fig. 3. Performance Metrics of DeepCrack Model

The model achieved:
Precision: 72%
Recall: 70%
F1-score: 71%

These results indicate that the model maintains balanced performance across classification metrics, although slight improvements can be made in recall to reduce missed crack detections.

Confusion Matrix Analysis

The confusion matrix shown in Fig. 4 provides a detailed breakdown of classification results.

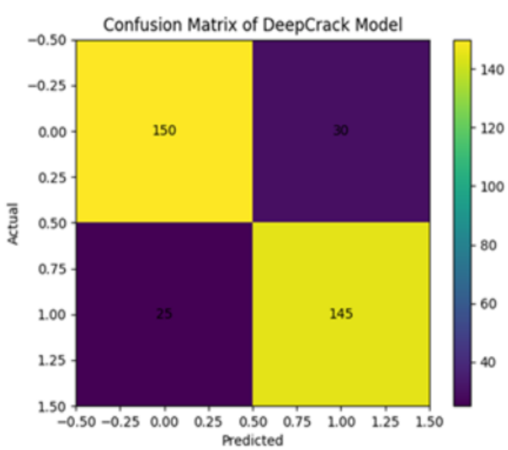

Fig. 4. Confusion Matrix of DeepCrack Model

The matrix shows that the model correctly classifies a majority of cracked and non-cracked images. However, some misclassifications are observed, which may be due to similarities in surface textures or lighting variations. Despite these challenges, the model demonstrates stable and consistent performance.

The results highlight the effectiveness of the proposed DeepCrack system in detecting cracks under diverse conditions. The use of the Rfcn_b architecture enables efficient feature extraction with reduced computational complexity, making the system suitable for real-time and resource-constrained applications.

Transfer learning improves model performance by leveraging pre-trained knowledge, while preprocessing techniques enhance robustness against variations in real-world conditions [5], [8]. However, the moderate accuracy indicates that further improvements can be achieved by using larger datasets, advanced architectures, or ensemble techniques.

VII. CONCLUSION AND FUTURE WORK

In conclusion, the proposed DeepCrack system demonstrates the effectiveness of deep learning for automated crack detection in infrastructure. The Rfcn_b-based model achieved satisfactory performance in classifying cracked and non-cracked images, highlighting its ability to extract meaningful features from complex surface patterns. Its lightweight architecture ensures computational efficiency, making it suitable for real-time applications and deployment in resource-constrained environments. The integration of transfer learning and data preprocessing techniques further enhances the model's generalization ability across different structural conditions and environments [5], [9].

Future work can focus on improving the model's accuracy by incorporating larger and more diverse datasets to better capture real-world variations. Exploring advanced deep learning architectures and hybrid models may further enhance detection performance. Additionally, fine-tuning hyperparameters and applying ensemble techniques could improve classification reliability. Integration with real-time monitoring systems, such as IoT-based platforms, can enable continuous infrastructure assessment and early damage detection [8]. Overall, the proposed system provides a reliable and efficient solution for crack detection and offers strong potential for future advancements in intelligent infrastructure monitoring.

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