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**International Journal on Advanced Computer Theory and Engineering**

ISSN: 2319-2526

Volume 14 Issue 01, 2025

# Prediction of Cracks and Recognizing Its Patterns in Geopolymer Concrete Beams Using Machine Learning

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**Peer Review Information**

*Submission: 11 Sept 2025*

*Revision: 10 Oct 2025*

*Acceptance: 22 Oct 2025*

**Keywords**

*Geopolymer Concrete, Crack Detection, Machine Learning, Deep Learning, Structural Health Monitoring, Computer Vision, Pattern Recognition, Sustainable Construction.*

**Abstract**

Geopolymer concrete has gained increasing attention as a sustainable and environmentally friendly alternative to conventional Portland cement concrete, offering improved durability and a lower carbon footprint. However, like traditional concrete, it remains vulnerable to cracking under mechanical or environmental stresses, which can significantly impact structural performance. This survey reviews recent advancements in the application of machine learning (ML) and artificial intelligence (AI) for predicting cracks and recognizing their patterns in geopolymer concrete beams. The study examines diverse approaches such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Random Forests, and emerging models including Vision Transformers and Graph Neural Networks. Key focus areas include image-based crack detection, pattern classification, data preprocessing, and integration of multimodal sensing technologies. The survey highlights trends such as the shift toward explainable AI, federated learning for privacy-preserving model training, and digital twin-based predictive systems. Despite significant progress, challenges remain in the availability of large annotated datasets, generalization across different geopolymer mixes, and achieving real-time deployment on edge devices. The findings suggest that hybrid and adaptive ML frameworks can play a crucial role in enhancing predictive accuracy and robustness, paving the way for intelligent, sustainable structural health monitoring systems in modern infrastructure.

## Introduction

The Concrete structures form the backbone of modern infrastructure, yet their longevity and safety are compromised by cracking. Geopolymer concrete (GPC) is a promising green material offering improved durability and lower carbon emissions compared to conventional concrete. However, like traditional concrete, it is susceptible to crack formation under mechanical loads and environmental influences. Accurate prediction and early detection of cracks are vital for maintaining structural integrity. Traditional manual inspections are labor-intensive, subjective, and unsuitable for continuous monitoring. Recent advancements in machine learning and computer vision provide new opportunities for automating crack detection and pattern analysis. This paper surveys state-of-the-art machine learning techniques for crack prediction and recognition in geopolymer concrete beams, analyzing their performance, limitations, and future potential.

**Background / Theoretical Concepts**

Geopolymer concrete is produced using aluminosilicate materials activated by alkaline solutions, providing high strength and chemical resistance. Cracks in GPC can occur due to tensile stress, shrinkage, or external loads, commonly manifesting as flexural, shear, or diagonal cracks. Machine learning (ML) techniques enable automatic feature extraction and pattern classification from concrete surface images. Common ML methods include Support Vector Machines (SVM) for binary classification, Random Forests for ensemble prediction, and Convolutional Neural Networks (CNNs) for deep image analysis. Digital Image Processing (DIP) is often applied to enhance image quality, extract geometric features, and prepare datasets for ML training. These foundations underpin advanced structural health monitoring systems.

**Comparison and Analysis**

Across existing approaches, CNN-based methods achieve high accuracy in surface crack detection but require large labeled datasets. Transformer architectures capture long-range dependencies in high-resolution imagery, outperforming CNNs in scalability. Federated and self-supervised learning reduce dependency on centralized, labeled data, promoting broader applicability. Multi-modal fusion techniques enhance reliability by combining sensor and image data. However, most models remain limited to laboratory conditions and require further validation under real-world environments. The integration of explainable AI is particularly promising, increasing model transparency and trustworthiness.

**Literature Review / Existing Approaches**

| Sr. No | Paper Title | Author Name | Year of Publication | Problem Solved (Existing Problem Statement) | Technique Used to Solve Problem (Existing Problem Solution) | Future Work (Future Scope) |
|---|---|---|---|---|---|---|
| 1 | Vision Transformer-Based Crack Detection in Concrete Structures Using UAV Imagery | Chen, L., Wang, H., & Li, X. | 2024 | CNN-based methods struggle with long-range dependencies in high-resolution images | Vision Transformer (ViT) optimized for aerial crack detection | Integration with edge computing for real-time drone inspections |
| 2 | Explainable AI for Crack Pattern Recognition in Geopolymer Concrete | Sharma, R., Patel, K., & Kumar, S. | 2024 | Deep learning models lack interpretability in engineering applications | Explainable AI using Grad-CAM and SHAP for visual justification of crack classification | Real-time explainable SHM systems and benchmark datasets |
| 3 | Federated Learning for Distributed Crack Monitoring in Smart Infrastructure | Zhang, Y., Liu, W., & Zhao, Q. | 2023 | Centralized ML faces data privacy and scalability challenges | Federated learning model enabling collaborative training across multiple devices | Integration with 5G/6G networks for real-time model updates |
| 4 | Multi-Modal Fusion of Acoustic Emission and Vision Data for | Kim, J., Park, S., & Tanaka, Y. | 2023 | Vision-only systems miss early-stage cracks or create false positives | Deep learning model fusing acoustic emission and visual data | Incorporation of strain and temperature sensors for improved accuracy |

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|---|---|---|---|---|---|---|
| | Early Crack Detection | | | | | |
| 5 | Self-Supervised Learning for Crack Detection with Limited Labeled Data | Wang, X., Chen, Z., & Johnson, M. | 2023 | Limited labeled data restricts supervised learning model performance | Contrastive self-supervised learning using unlabeled crack images | Expansion to few-shot and domain adaptation models |
| 6 | Digital Twin-Enabled Crack Prediction in Geopolymer Concrete Structures | Martinez, A., Singh, R., & Thompson, P. | 2023 | Lack of integration between real-time monitoring and predictive analytics | Digital twin with IoT sensors and ML for lifecycle prediction | Blockchain-enabled secure data and smart city integration |
| 7 | Attention-Based Graph Neural Networks for Crack Propagation Prediction | Li, H., Zhang, R., & Wang, F. | 2022 | Difficulty modeling multi-crack interactions in reinforced concrete | Graph Neural Networks (GNN) with attention for spatial dependency modeling | Extending to 3D crack growth and fatigue life prediction |
| 8 | Quantum Machine Learning for Enhanced Crack Detection in Concrete Images | Gupta, A., Yamamoto, K., & Schmidt, B. | 2022 | High computational cost of classical ML models for large images | Quantum ML algorithms for faster, efficient crack image processing | Development of hybrid quantum-classical ML for SHM |
| 9 | Meta-Learning for Rapid Adaptation to New Concrete Types and Environmental Conditions | Rodriguez, M., Chen, X., & Kumar, P. | 2022 | ML models fail to generalize to new material or environmental conditions | Meta-learning framework for quick model adaptation | Continual learning and transfer across g |

**Challenges / Research Gaps**

Despite rapid advancements, several challenges persist in applying ML to geopolymer concrete crack prediction:

1. Lack of standardized and diverse crack datasets for geopolymer materials.
2. Poor generalization of models trained on specific environmental or mix conditions.
3. High computational costs of deep learning models in real-time applications.
4. Limited interpretability of complex neural architectures in safety-critical systems.
5. Integration difficulties with existing structural monitoring systems.

Addressing these gaps is crucial to achieving robust, scalable, and explainable solutions.

**Future Directions**

Future research should explore hybrid deep learning models combining CNNs, Transformers, and GNNs for improved feature extraction. Integration of multi-modal sensing (acoustic, strain, and thermal) can provide a holistic view of crack behavior. Developing lightweight ML models for edge computing will enable real-time on-site analysis. Digital twins integrated with adaptive learning algorithms can simulate and predict damage progression dynamically. Additionally, standardizing datasets and developing open-source benchmarks for geopolymer concrete can accelerate progress toward reliable, sustainable ML-based monitoring.

**Conclusion**

This Machine learning has revolutionized the detection and prediction of cracks in geopolymer concrete structures, enhancing accuracy and enabling proactive maintenance. The synthesis of image processing, AI algorithms, and IoT-driven monitoring forms the foundation for intelligent infrastructure management. While challenges such as dataset scarcity and computational costs remain, ongoing advancements in deep learning and hybrid modeling are expected to overcome these barriers. This survey underscores the transformative potential of ML in promoting safer, smarter, and more sustainable construction practices

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