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A Six-Layer Framework for RCC Crack Analysis: Engineering Judgment Meets Machine Learning

Parameswaran Easwaran, Rajkiran Singh
Mangalayatan University, India

Abstract: This study presents a comprehensive, field-based diagnostic model for analysing cracks in reinforced cement concrete (RCC) structures, based on empirical observations across forty buildings in Tamil Nadu and Karnataka. Despite adherence to structural design codes, these structures continue to exhibit cracking due to a convergence of causes such as material shrinkage, poor detailing, substandard construction practices, and environmental stressors. Conventional diagnostic approaches, which rely heavily on permissible crack width thresholds, often neglect crucial indicators like orientation, spatial distribution, and progression behaviour. To overcome these diagnostic limitations, this study introduces a six-level analytical framework that integrates descriptive statistics, frequency pattern analysis, chi-square and correlation testing, risk profiling, and machine learning-based decision tree classification. Results demonstrate that crack orientation and structural location are significantly correlated with risk levels (χ^2 = 109.32 and 134.37, $p < 0.001$). The findings also reveal a weak inverse relationship between crack width and length ($r = -0.13$), which questions the assumption that wider or longer cracks necessarily indicate greater severity. Crack widths ranged from 0.4 mm to 20 mm (mean = 3.51 mm), and lengths ranged from 23 cm to 1000 cm (mean = 148.6 cm), covering a wide range of structural responses. High-risk cracks— defined as those exceeding 5 mm in width or 500 cm in length—were typically found in slabs and retaining walls, suggesting vulnerability to moisture ingress and flexural stresses. The predictive model achieved 75% accuracy and 100% precision in classifying high-risk cracks, highlighting the potential for integrating data-driven tools into structural diagnostics. This work presents more than just an improvement in inspection methodology; it represents a paradigm shift in understanding cracks as structural indicators rather than superficial defects. The study urges the revision of design codes like IS 456:2000 and ACI 224R-01 to accommodate multifactorial diagnostic criteria and recommends training for engineers in statistical and predictive diagnostic skills. The framework proposed here also lays the groundwork for further integration with sensor-based monitoring systems and geotechnical calibration models, particularly in the context of climate variability and rapid urban development.

Keywords: Reinforced Cement Concrete (RCC); Structural cracks; Crack diagnostics; Field-based assessment; Empirical study; Tamil Nadu; Karnataka; Crack orientation; Crack width; Crack length; Risk profiling; Descriptive statistics; Chi-square analysis; Pearson correlation; Decision tree classification; Predictive modelling; Structural health monitoring; Design code revision; Machine learning in civil engineering; Urban infrastructure; Climate variability.

I. INTRODUCTION

Cracks in reinforced cement concrete (RCC) structures are often misinterpreted as mere cosmetic issues. However, such visible fissures frequently indicate deeper structural or procedural failures. These may be triggered by a range of factors, including thermal expansion, shrinkage, poor construction practices, inadequate detailing, and prolonged exposure to environmental fluctuations (Mehta & Monteiro, 2014; Neville, 2011). Although RCC is lauded for its strength and versatility, its actual behaviour under real-world conditions often deviates from ideal assumptions. Design codes such as IS 456:2000 (Bureau of Indian Standards, 2007) and ACI 224R-01 (American Concrete Institute, 2018) provide permissible crack width guidelines based primarily on aesthetic and durability parameters. These guidelines, however, are based on controlled design environments and often fail to capture the variability encountered in the field—especially in regions with diverse climate and inconsistent workmanship. In the absence of structured diagnostic tools, engineers and site supervisors typically rely on visual judgment and prior experience. This leads to inconsistencies in classification, delayed mitigation, and inefficient resource allocation (Kabir, 2012; Rao & Jain, 2017). Additionally, important clues such as the orientation and spatial position of cracks remain underutilized in standard assessment protocols, despite their critical role in understanding stress distribution and structural vulnerability (Neville & Brooks, 2010).

This study introduces a diagnostic model that is grounded in empirical observation and statistical reasoning. Based on data from forty RCC buildings across Tamil Nadu and Karnataka, it examines how parameters such as crack width, length, orientation, location, and type correlate with structural risk.

The model proposes a six-stage analytical method that bridges observational practice with predictive precision, aiming to enhance the diagnostic literacy of civil engineers. Instead of treating cracks as surface defects to be patched, this research advocates interpreting them as structural narratives that reveal insights into material fatigue, construction quality, and environmental exposure. By integrating analytical tools with on-ground engineering judgment, the study aims to support a shift toward safer, more responsive, and context-sensitive infrastructure management.

II. METHODOLOGY

The study adopts a cross-sectional, field-based research design grounded in empirical observation and analytical modelling. A purposive sample of forty RCC buildings from urban and semi-urban locations in Tamil Nadu and Karnataka was selected based on the presence of visible, measurable cracks. Data were gathered using a structured field documentation tool designed for this study, which recorded crack characteristics such as width (in millimeters), length (in centimeters), orientation (vertical, horizontal, diagonal), location (beam, slab, lintel, column, wall), and classification (structural or non-structural).

Six interlinked analytical techniques were employed. First, descriptive statistics were used to understand central tendencies and variations in crack dimensions (Mehta & Monteiro, 2014). Second, frequency distribution analysis revealed dominant occurrence patterns across structural components (Neville & Brooks, 2010). Third, chi-square cross-tabulations were conducted to test associations between crack type and both orientation and location (Kabir, 2012). Fourth, Pearson correlation was calculated to assess the relationship between crack width and length (Patil & Kale, 2018). Fifth, empirical risk profiling was developed using severity thresholds based on structural standards (BS EN 1504-3, 2005; Thiruvengadam et al., 2015). Sixth, supervised classification using decision tree models was conducted to predict high-risk cracks, drawing on dimensional and spatial variables (Zhao, He, & Zhang, 2020). Data accuracy was ensured through triangulation by experienced structural engineers and corroborated with photographic and GPS-tagged evidence.

Ethical standards were maintained through the anonymization of building identities and informed consent from property owners, following non-invasive assessment protocols (Creswell & Plano Clark, 2011). This methodology ensures scientific rigor, reproducibility, and practical relevance for RCC crack diagnostics.

III. RESULTS AND DISCUSSION

The field data collected from forty RCC structures revealed considerable heterogeneity in crack characteristics. Widths ranged from 0.4 mm to 20 mm (mean = 3.51 mm), while lengths varied from 23 cm to 1000 cm (mean = 148.6 cm). This wide variation highlighted that not all cracks are structurally equivalent; some serve as early warnings of serious structural compromise, while others may be superficial. Structural cracks constituted 35% of the total, with the highest concentration found in brick masonry walls (22.5%), lintels (15%), and slabs (12.5%).

These areas are typically subject to stress concentration, poor detailing, and inadequate reinforcement anchorage, which make them vulnerable to both flexural and shear forces.

The presence of diagonal or horizontal cracks in these zones was consistent with known stress redistribution patterns (Neville, 2011). Chi-square tests revealed statistically significant associations between crack type and both location ($\chi^2 = 109.32$, $p < 0.001$) and orientation ($\chi^2 = 134.37$, $p < 0.001$), reinforcing the importance of positional and directional attributes in structural diagnosis. Diagonal cracks Above lintels, for example, often indicated shear-related failures or suboptimal load transfer. mechanisms—insights not discernible through width analysis alone (Kabir, 2012; Rao & Jain, 2017). Pearson correlation analysis between width and length yielded $r = –0.13$, indicating a weak inverse relationship. This finding disrupts the assumption that larger cracks are automatically more dangerous. Instead, different crack types—caused by shrinkage, flexure, settlement, or thermal expansion—behave differently and demand nuanced interpretation (Patil & Kale, 2018).

The classification system categorized 15% of all observed cracks as high-risk, primarily due to exceeding width (>5 mm) or length (>500 cm) thresholds. These were predominantly found in slabs and retaining walls, where the interplay of moisture, dead load, and dynamic stress is greatest. Moderate-risk cracks made up 35% and low-risk ones 50%, enabling an efficient triage system for prioritizing repair (BS EN 1504-3, 2005; Thiruvengadam et al., 2015). The supervised decision tree model, trained on crack dimensional and spatial features, achieved 75% accuracy and 100% precision in identifying high-risk cracks. Its key decision criteria— such as crack width above 8 mm and location in beam-lintel junctions—aligned with empirical observations and validate the tool's utility for field engineers (Zhao, He, & Zhang, 2020). Taken together, the results affirm the limitations of visual-width-based inspection models and promote a multi-variable, analytical approach to crack diagnosis.

By leveraging pattern recognition, spatial analysis, and predictive modelling, the study advances a diagnostic methodology that is both more accurate and more attuned to real-world variability.

IV. CONCLUSION AND RECOMMENDATIONS

This study has demonstrated that cracks in RCC structures are not merely aesthetic blemishes but meaningful indicators of deeper structural or procedural deficiencies. The field data collected from forty RCC buildings across Tamil Nadu and Karnataka reveal that spatial location and orientation of cracks often provide more consistent indicators of structural vulnerability than crack width alone. The weak correlation between width and length further supports the necessity for multifactorial diagnostic frameworks. The six-layered analytical model, integrating descriptive statistics, spatial pattern analysis, association testing, empirical risk profiling, and supervised classification, has shown robust predictive capability. The success of the decision tree classifier—with 75% accuracy and 100% precision in identifying high-risk cracks—validates the integration of machine learning into civil diagnostic workflows. This study recommends that national codes such as IS 456:2000 and international standards like ACI 224R-01 be revised to account for orientation and location-based criteria and not rely solely on width thresholds. Furthermore, it advocates for the creation of standardized diagnostic protocols—including photographic documentation, orientation tagging, and digital geolocation—to ensure consistency in assessments across varied field conditions. Training modules for field engineers and supervisors should incorporate diagnostic reasoning based on empirical data, statistical tools, and predictive algorithms. The findings also suggest the integration of these diagnostic models with real-time monitoring systems, including sensor-based and geotechnical inputs, for long-term infrastructure health management. Ultimately, this research provides a replicable and scalable framework for early detection, classification, and risk-based prioritization of cracks in RCC structures. By bridging intuitive field judgment with analytical precision, it contributes to a more resilient, responsive, and contextually informed civil engineering practice.

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