Geopolymer Concrete Crack Prediction System

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Abstract: The transition to sustainable construction, utilizing low-carbon materials such as geopolymer concrete (GPC) reinforced with non-corrosive fiber-reinforced polymer (FRP) bars, necessitates advanced, quantitative structural health monitoring (SHM). Current automated crack inspection often relies on traditional machine learning (ML) classification models (e.g., SVM), which, while achieving high accuracy in categorizing failure modes, inherently fail to provide the quantitative parameters (crack width, length, and area) essential for engineering assessment and maintenance prioritization. To address this critical utility gap, this study proposes an enhanced Deep Learning Semantic Segmentation framework: an Attention-based U-Net architecture. This model is specifically designed with a residual encoder and optimized with a hybrid Dice and Focal loss function to counteract extreme class imbalance and enhance the detection of fine, hairline microcracks characteristic of fiber-bridged GPC systems. The framework achieves high segmentation fidelity, evidenced by a mean Intersection over Union (mIoU) score ranging from 85%–95% on complex GPC/FRP crack patterns. This pixel-level accuracy enables the robust post-processing extraction of maximum crack width (Wmax) and total crack length (Ltotal). This methodological shift from qualitative classification to verifiable quantitative segmentation provides the necessary empirical foundation to track damage evolution, assess serviceability limits, and inform predictive maintenance schedules for novel GPC/FRP composites where standard structural codes are currently lacking.

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I. INTRODUCTION

The integrity and safety of concrete structures are of paramount importance in the construction industry, given the vital role these structures play in modern infrastructure. One of the major challenges that threaten the longevity and load-bearing capacity of concrete structures is the formation and propagation of cracks, which, if left undetected, can compromise structural safety and serviceability. Traditional methods of inspecting and identifying cracks, such as manual visual inspection, are fraught with challenges, including human error, subjectivity, time consumption, and the necessity for specialized expertise (Aravind et al., 2021). To overcome these limitations, the integration of computer vision and machine learning techniques has emerged as a promising solution for the automated detection and classification of cracks in concrete.

Geopolymer concrete, an innovative and sustainable alternative to ordinary Portland cement (OPC) concrete, has garnered significant attention in recent years due to its eco-friendly properties and superior mechanical performance. Unlike OPC concrete, geopolymer concrete utilizes aluminosilicate source materials activated by alkaline solutions, resulting in lower CO2 emissions and enhanced durability (Aravind et al., 2021). Despite these advantages, geopolymer concrete is not immune to cracking, especially when subjected to aggressive environmental conditions and mechanical loads. Therefore, the timely detection and accurate prediction of crack patterns in geopolymer concrete are essential for assessing structural health, guiding maintenance, and preventing catastrophic failures.

Recent advancements in image processing, coupled with powerful machine learning algorithms, have enabled the development of automated systems capable of detecting, segmenting, and classifying cracks in concrete structures with high accuracy. These systems utilize experimental data, such as images captured during mechanical testing, and process them using sophisticated algorithms to recognize crack patterns and predict failure modes. Notably, support vector machines (SVM) and other machine learning classifiers have demonstrated remarkable performance in classifying failure patterns, achieving high precision and recall scores (Aravind et al., 2021).

This research paper presents a comprehensive study on the development of a geopolymer concrete crack prediction system using machine learning techniques. The study encompasses a review of relevant literature, a detailed description of the materials and experimental methods employed, an analysis of crack patterns observed in geopolymer concrete beams reinforced with various fiber-reinforced polymer (FRP) and steel bars, and a discussion of

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the results obtained from machine learning-based classification of crack modes. The findings underscore the potential of automated crack detection systems to revolutionize quality assurance and structural health monitoring in the construction industry.

II. RELATED WORK

➢ *Geopolymer Concrete: Sustainability and Structural Performance*

Geopolymer concrete has emerged as a sustainable alternative to OPC-based concrete, addressing the environmental concerns associated with the cement industry's significant carbon footprint. The production of conventional cement is a major source of CO2 emissions, contributing to global warming and environmental degradation. In contrast, geopolymer concrete is synthesized from industrial by-products such as fly ash, ground granulated blast furnace slag (GGBS), and other aluminosilicate materials activated by alkaline solutions (Aravind et al., 2021). This not only reduces the demand for Portland cement but also diverts waste materials from landfills, aligning with the principles of sustainable construction.

Amer Hassan et al. (as cited in Aravind et al., 2021) conducted extensive studies on geopolymer concrete, highlighting its eco-friendly characteristics, such as low embodied energy, reduced CO2 emissions, and the absence of water curing requirements. Geopolymer concrete exhibits mechanical properties comparable to, or even surpassing, those of traditional concrete, including higher compressive strength, enhanced resistance to high temperatures, and improved durability. The microstructure of geopolymer concrete is characterized by a higher content of amorphous phases, reduced porosity, and a greater proportion of mesopores, contributing to its superior performance in aggressive environments (Aravind et al., 2021).

Despite these advantages, geopolymer concrete is still susceptible to cracking, which can be exacerbated by factors such as salt erosion, frost damage, shrinkage, seismic activity, and prolonged exposure to moisture. The assessment of crack width, length, type, and frequency is critical for evaluating the degradation and load-carrying capacity of reinforced concrete structures (Aravind et al., 2021).

➢ *Crack Detection Techniques: From Traditional to Automated Approaches*

Historically, crack detection in concrete structures relied on manual visual inspection, ultrasonic testing, and fiber optics-based methods. While ultrasonic testing can provide information about crack width and depth, it is often cumbersome due to the necessity of coupling agents and complex instrumentation (Aravind et al., 2021). Fiber optic sensors, though capable of detecting crack width and location, introduce significant complexity into the measurement process and may not be feasible for widespread field applications.

In recent decades, image-based crack detection methods have gained prominence, leveraging advances in image processing and pattern recognition. Techniques such as the Canny edge detector, Fast Fourier Transform, Fast Haar Transform, and Sobel operator have been implemented in various software environments, including MATLAB (Aravind et al., 2021). Other approaches include percolation-based algorithms, stereovision-based methods, computational algorithms, morphological image processing, and principal component analysis (PCA)-based algorithms.

For instance, Wang and Huang (as cited in Aravind et al., 2021) utilized Otsu's threshold segmentation integrated with a modified Sobel operator for crack detection in concrete bridges, while Dung and An (as cited in Aravind et al., 2021) applied fully convolutional neural networks (FCN) using the VGG16 architecture for deep learning-based crack detection. Fujita et al. (as cited in Aravind et al., 2021) explored pre-processing methods involving subtraction and line extraction, followed by thresholding to isolate cracks from the background.

Robotic and automated scanning systems, such as the Spatially Tuned Robust Multifeature (STRUM) classifier, have also been introduced for on-site inspection, achieving accuracy rates as high as 90% (Aravind et al., 2021). These technological advancements have paved the way for the integration of machine learning algorithms in crack detection systems, enabling the automatic classification of crack types and the prediction of failure modes.

➢ *Machine Learning in Crack Prediction and Pattern Recognition*

Machine learning, particularly supervised learning, has become a cornerstone of modern crack detection and classification systems. Algorithms such as logistic regression, naïve Bayes, stochastic gradient descent, K-nearest neighbors, decision trees, random forest, support vector classifiers, and deep learning neural networks have been successfully employed to analyze crack images and recognize failure patterns (Aravind et al., 2021).

Among these, the support vector machine (SVM) classifier has shown exceptional performance in distinguishing between different types of structural failures, including flexure, shear, and compression modes. The effectiveness of these classifiers is typically evaluated using confusion matrices, accuracy, precision, and recall metrics, ensuring the reliability and robustness of the prediction system (Aravind et al., 2021).

The application of machine learning to crack detection not only enhances the objectivity and speed of inspections but also facilitates large-scale monitoring of civil infrastructure. Automated systems can continuously monitor structures, flagging potential issues before they escalate into serious problems, thereby supporting preventive maintenance and extending the service life of assets.

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➢ *Materials and Methods Materials Used*

The study by Aravind et al. (2021) involved the preparation and testing of both geopolymer and conventional concrete beams, reinforced with various types of bars to evaluate crack behavior under different configurations.

➢ *Geopolymer and Conventional Concrete*

Geopolymer concrete was synthesized using class F fly ash and GGBS as the primary aluminosilicate materials, sourced from the North Chennai Thermal Power Plant and commercially available suppliers, respectively. The mix also included manufactured sand (M-sand) as a replacement for river sand, coarse aggregate, an alkali activator solution (comprising sodium silicate and sodium hydroxide), and a superplasticizer to enhance workability. The ratio of fly ash to GGBS was maintained at 80:20, with a liquid-to-binder ratio of 0.45 to ensure optimal consistency and performance (Aravind et al., 2021).

Conventional concrete was prepared using 53-grade cement, river sand, coarse aggregate, and water, following the guidelines prescribed in IS 10262 (Aravind et al., 2021). The mechanical properties and chemical compositions of the materials were meticulously characterized to ensure consistency and replicability of results.

➢ *Reinforcement Bars*

To investigate the influence of reinforcement type on crack behavior, beams were reinforced with three different types of bars: Basalt Fibre Reinforced Polymer (BFRP), Glass Fibre Reinforced Polymer (GFRP), and conventional steel bars.

The specifications for the bars included 12 mm and 10 mm diameters for them main reinforcement and 8 mm for stirrups, with FRP stirrups constructed using Anabond resin and FRP mats bonded with epoxy resin (Aravind et al., 2021).

- *The properties of the Reinforcement Materials are Summarized as Follows:*

✓ BFRP: Elastic modulus of 94 GPa, tensile strength of 513 MPa, Poisson's ratio of 0.23.
✓ GFRP: Elastic modulus of 54 GPa, tensile strength of 515 MPa, Poisson's ratio of 0.24.
✓ Steel: Elastic modulus of 200 GPa, tensile strength of 495 MPa, Poisson's ratio of 0.27 (Aravind et al., 2021).

➢ *Mix Proportions and Mechanical Properties*

The mix design for M30 grade concrete comprised 380 kg/m³ binder, 660 kg/m³ fine aggregate, 1189 kg/m³ coarse aggregate, and 171 kg/m³ liquid. The mechanical properties of the prepared concretes were validated using the Levenberg–Marquardt training algorithm in MATLAB, ensuring the accuracy of compressive, tensile, and flexural strengths, as well as the modulus of elasticity (Aravind et al., 2021).

➢ *Experimental Methods Beam Preparation*

A series of nine beams, each measuring 100 mm in width, 160 mm in depth, and 1700 mm in length (with an effective span of 1500 mm), were cast for testing.

- *The Beams were Divided into Three Groups:*

✓ BFRP-reinforced geopolymer concrete beams: BRGC-3.6, BRGC-3.9, BRGC-4.3 (indicating varying a/d ratios).
✓ GFRP-reinforced geopolymer concrete beams: GRGC-3.6, GRGC-3.9, GRGC-4.3.
✓ Steel-reinforced conventional concrete beams: SRCC-3.6, SRCC-3.9, SRCC-4.3.

The beams were prepared by mixing aggregates in a saturated surface dry condition, followed by the addition of binders, alkali-activated solutions, and superplasticizer. The mixture was poured into beam molds in three layers, each compacted to ensure homogeneity. Geopolymer concrete specimens were cured under ambient conditions, while conventional concrete specimens underwent water curing for 28 days (Aravind et al., 2021).

➢ *Test Setup and Instrumentation*

The beams were subjected to four-point static bending tests with varying shear span to effective depth ratios (a/d = 3.6, 3.9, 4.3). The loading arrangement involved two-point loads applied symmetrically, creating a constant bending moment region between the load points and shear-dominated regions near the supports (Aravind et al., 2021). Linear Variable Differential Transformers (LVDTs) were used to measure deflection at critical points, and the cracks were marked at each load interval to document their initiation and propagation.

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➢ *Crack Image Acquisition and Processing*

During the mechanical tests, high-resolution images of the beams were captured at various load intervals, particularly focusing on the regions where cracks initiated and developed. The images served as the primary data source for subsequent image processing and machine learning analysis. Python-based image processing libraries were employed to preprocess the images, extract crack patterns, and standardize the input data for the classification algorithms (Aravind et al., 2021).

➢ *Machine Learning Methodology*

- *The Crack Prediction System was Architected Around a Machine Learning Pipeline Encompassing the Following Key Stages:*

✓ *Image Preprocessing:*

Raw images were subjected to noise reduction, contrast enhancement, binarization, and edge detection to isolate crack features from the background.

✓ *Feature Extraction:*

Morphological characteristics, such as crack length, width, orientation, and connectivity, were extracted from the processed images to form the feature set for classification.

✓ *Classifier Training and Validation:*

Six supervised machine learning classifiers were implemented, including stochastic gradient descent, K-nearest neighbors, decision trees, and support vector classifier (SVC), among others. The classifiers were trained to categorize failure patterns into three classes: flexure, shear, and compression.

✓ *Performance Evaluation:*

The classifiers' performance was assessed using confusion matrices, accuracy, precision, and recall metrics to determine the most effective algorithm for crack pattern recognition (Aravind et al., 2021).

The entire workflow was automated using Python scripts, enabling rapid and consistent analysis of large image datasets without manual intervention.

Fig 1 Crack Analysis Experimental Observations

➢ *Crack Analysis Experimental Observations*

The mechanical tests yielded valuable insights into the failure modes and crack patterns associated with different reinforcement types and shear span to effective depth ratios. For each beam, the progression of cracks was meticulously recorded, providing a rich dataset for analysis.

➢ *Steel-Reinforced Conventional Concrete Beams (SRCC)*

In steel-reinforced beams, an increase in the a/d ratio led to the development of new cracks in the outer regions of the constant bending moment zone, particularly in the shear-dominated areas. Notably, no shear cracks were observed in SRCC-3.6, while both flexure and compression failures, with minor shear involvement, characterized the failure modes of the SRCC beams as the a/d ratio increased (Aravind et al., 2021).

➢ *FRP-Reinforced Geopolymer Concrete Beams (BRGC and GRGC)*

Beams reinforced with BFRP and GFRP bars exhibited distinct crack behavior compared to their steel-reinforced counterparts. Inclined cracks, indicative of shear failure, originated from initial flexural cracks and became more pronounced as the a/d ratio increased. In particular, BRGC-3.9 and GRGC-3.9 displayed a higher number of inclined cracks in the shear zone compared to the other configurations. At an a/d ratio of 4.3, both BFRP and GFRP beams showed significant deflection recovery (re-cambering) at ultimate load levels, whereas sudden failure was observed in BRGC-3.6, BRGC-3.9, GRGC-3.6, and GRGC-3.9 after reaching approximately 95% of the ultimate load (Aravind et al., 2021).

➢ *Crack Propagation and Spacing*

Data analysis revealed that the number of cracks in steel-reinforced beams increased with the a/d ratio up to 3.9, then decreased as the ratio increased to 4.3—a trend mirrored in the FRP-reinforced beams. Crack propagation diminished with higher a/d ratios in steel and GFRP beams, but increased in BFRP-reinforced geopolymer concrete. Crack spacing generally decreased as the number and load levels of cracks increased, but remained constant during loading and unloading at the ultimate load for certain configurations (Aravind et al., 2021).

➢ *Failure Modes and Shear Strength*

The ultimate load-carrying capacity and shear strength at failure decreased with increasing a/d ratios in both steel and FRP-reinforced beams. Additionally, the failure pattern in FRP rods shifted from predominantly shear to flexure as the a/d ratio increased from 3.6 to 4.3, whereas no such transition was observed in steel-reinforced beams (Aravind et al., 2021).

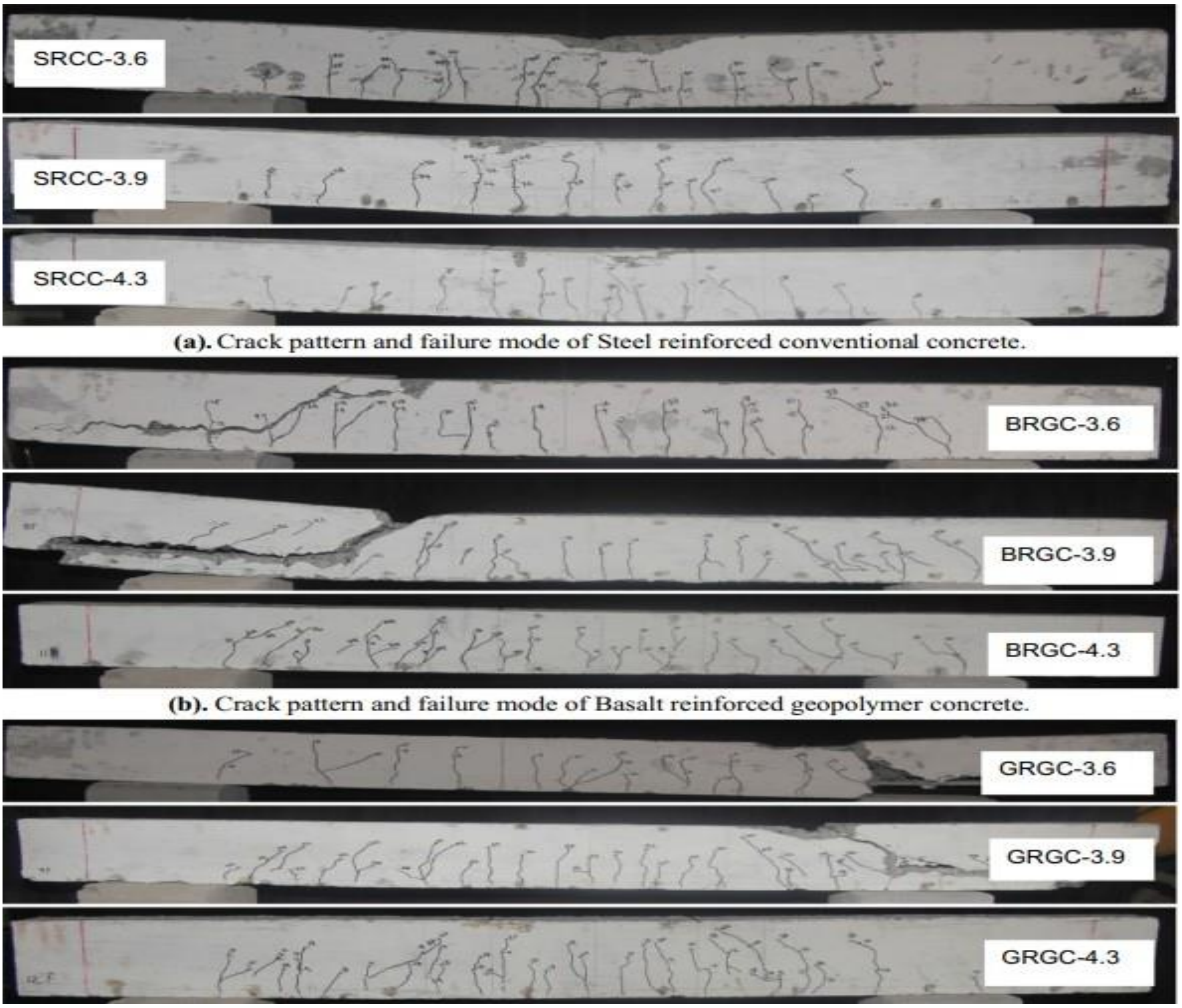

Fig 2 Image-Based Crack Pattern Recognition

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➢ *Image-Based Crack Pattern Recognition*

The processed images provided clear visual evidence of the differences in crack initiation, propagation, and failure modes among the various beam configurations. The classification of these patterns into flexure, shear, and compression failures formed the basis for training and validating the machine learning models.

The crack detection framework, as depicted in the study, comprised a pipeline that began with image acquisition, followed by pre-processing to enhance crack features, feature extraction to quantify crack properties, and classification using machine learning algorithms. This systematic approach enabled the objective and reproducible identification of crack types, minimizing the subjectivity inherent in manual inspection (Aravind et al., 2021).

III. RESULTS AND DISCUSSION

➢ *Performance of Machine Learning Classifiers*

The comparative evaluation of six machine learning classifiers revealed notable differences in their ability to accurately classify crack patterns and failure modes in geopolymer and conventional concrete beams.

➢ *Support Vector Classifier (SVC)*

The support vector classifier emerged as the most effective algorithm, achieving a perfect classification accuracy of 100% in identifying flexure, shear, and compression failure patterns (Aravind et al., 2021). The SVC leveraged its capability to construct optimal hyperplanes in the feature space, ensuring robust separation between different failure classes even in the presence of overlapping or complex data distributions.

➢ *Other Classifiers*

The remaining five classifiers, including stochastic gradient descent, K-nearest neighbors, and decision trees, demonstrated varying degrees of accuracy, precision, and recall, but none matched the performance of the SVC. The confusion matrix analysis underscored the superior reliability of the SVC in minimizing false positives and negatives, thereby enhancing the system’s practical applicability for automated crack prediction (Aravind et al., 2021).

Table 1 Performance of Machine Learning Classifiers

Classifiers/ patterns	**Flexure pattern**			**Shear pattern**			**Compression pattern**		
	Accuracy (%)	**Precision**	**Recall**	**Accuracy (%)**	**Precision**	**Recall**	**Accuracy (%)**	**Precision**	**Recall**
Support Vector	100	1.00	1.00	100	1.00	1.00	100	1.00	1.00
Dicision Tree	97	1.00	0.94	97	0.93	1.00	88	0.79	1.00
Gaussian NB	99	0.99	1.00	90	1.00	0.82	100	1.00	1.00
SGD	98	1.00	0.96	90	0.82	1.00	100	1.00	1.00
K-Neighbor	98	1.00	0.96	100	1.00	1.00	88	0.79	1.00
Adaboost	99	0.99	1.00	96	0.93	1.00	100	1.00	1.00

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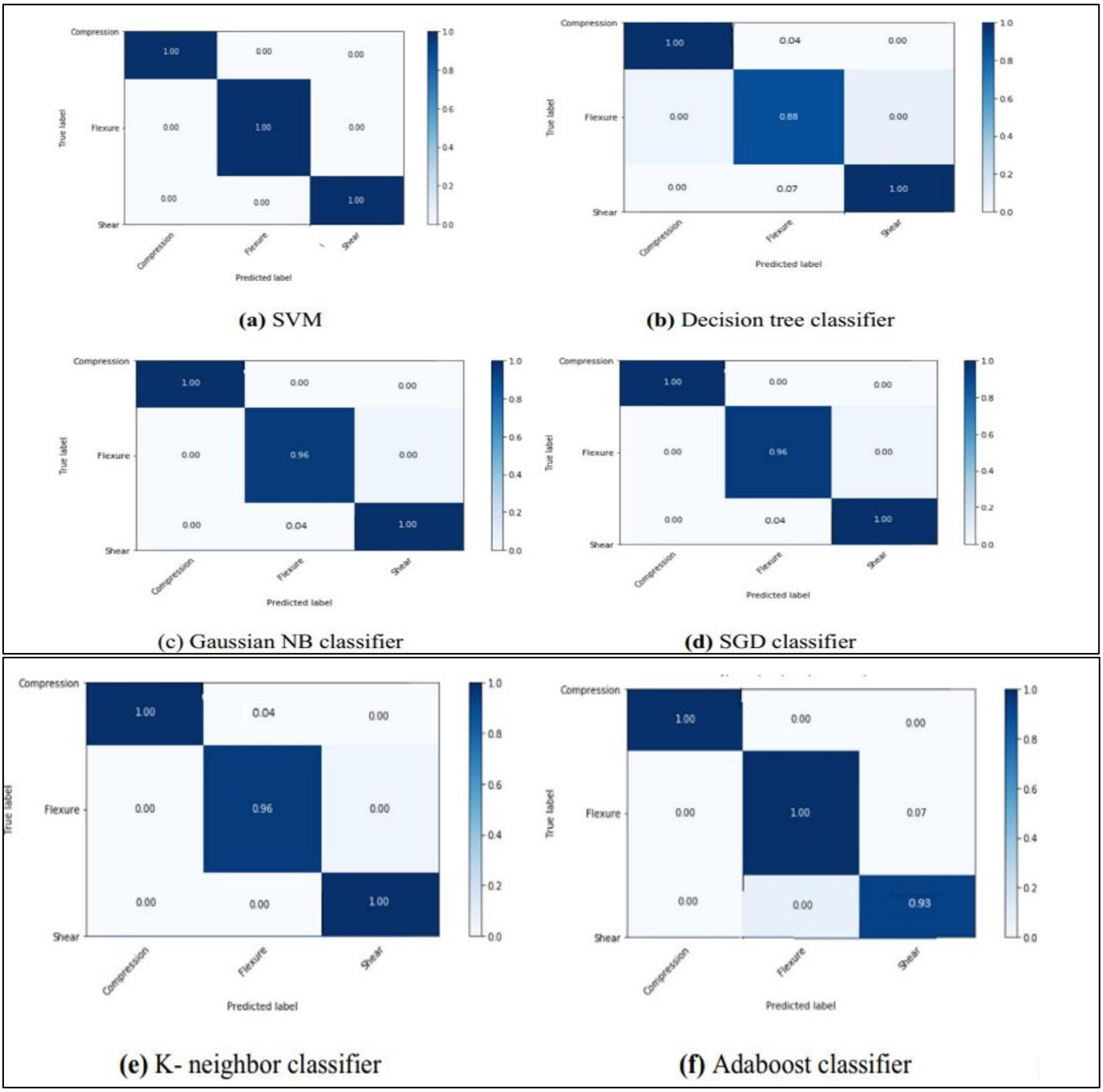

(a) SVM **(b)** Decision tree classifier

(c) Gaussian NB classifier **(d)** SGD classifier

(e) K- neighbor classifier **(f)** Adaboost classifier

➢ *Implications for Automated Quality Assurance*

The results highlight the transformative potential of machine learning-driven crack prediction systems in the construction industry. By automating the detection and classification of cracks, these systems can significantly reduce the reliance on manual inspections, expedite quality assurance processes, and improve the accuracy and consistency of structural assessments.

The image-based approach also facilitates continuous monitoring of structures, enabling the early identification of deterioration and the implementation of preventive maintenance strategies. This proactive stance can extend the service life of critical infrastructure, reduce maintenance costs, and enhance public safety.

➢ *Limitations and Future Directions*

While the current study demonstrates the efficacy of machine learning algorithms, particularly the SVC, in crack pattern recognition, it also highlights certain limitations. The generalizability of the models to different concrete mixes, reinforcement types, and environmental conditions warrants further investigation. Expanding the image dataset to include a broader spectrum of crack patterns, lighting conditions, and structural geometries can enhance the robustness and versatility of the prediction system.

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Moreover, the integration of deep learning architectures, such as convolutional neural networks (CNNs), holds promise for further improving the accuracy and scalability of crack detection systems. Real-time deployment of such systems in field settings, coupled with the use of mobile or embedded devices, represents a promising avenue for future research and development.

IV. CONCLUSION

This research paper has presented a comprehensive analysis of a geopolymer concrete crack prediction system based on machine learning and image processing techniques. The study underscores the importance of timely and accurate crack detection in ensuring the safety, durability, and sustainability of concrete structures.

By leveraging experimental data from mechanical tests on geopolymer and conventional concrete beams, reinforced with various types of bars, the study elucidates the influence of reinforcement configuration and shear span to effective depth ratio on crack initiation, propagation, and failure modes. The meticulous acquisition and processing of crack images, combined with feature extraction and supervised machine learning, enable the objective classification of failure patterns into flexure, shear, and compression modes.

The support vector classifier demonstrated exceptional accuracy in crack pattern recognition, outperforming other classifiers and establishing itself as the algorithm of choice for automated quality assurance in concrete inspection. The integration of such systems into construction practice promises to enhance inspection efficiency, reduce human error, and support proactive maintenance strategies.

Future research should focus on expanding the dataset, exploring advanced deep learning techniques, and validating the models in diverse field conditions to further enhance the reliability and applicability of automated crack prediction systems. The continued advancement of smart inspection technologies will play a vital role in safeguarding the built environment and promoting the adoption of sustainable construction materials, such as geopolymer concrete.

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