

Article

Integrating Image Processing and Machine Learning for the Non-Destructive Assessment of RC Beams Damage

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Abstract: Non-destructive testing (NDT) is a crucial method for detecting damages in concrete structures. Structural damage can lead to functional changes, necessitating a range of damage detection techniques. Non-destructive methods enable the pinpointing of the location of the damage without causing harm to the structure, thus saving both time and money. Damaged structures exhibit alterations in their static and dynamic properties, primarily stemming from a reduction in stiffness. Monitoring these changes allows for the determination of the failure location and severity, facilitating timely repairs and reinforcement before further deterioration occurs. A systematic approach to damage detection and assessment is pivotal for fortifying structures and preventing structural collapse, which can result in both financial and human losses. In this study, we employ image processing to categorize damaged beams based on their crack growth and propagation patterns. We also utilize support vector machine (SVM) and k-nearest neighbor (KNN) methods to detect the type, location, and extent of failures in reinforced concrete beams. To provide context and relevance for the laboratory specimens, we will compare our findings to the results from controlled experiments in a controlled laboratory setting.

Keywords: image processing; reinforced concrete beam; crack propagation; damage detection; non-destructive testing; machine learning; support vector machine; k-nearest neighbor



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1. Introduction

Today, commonly employed displacement and strain measurement instruments, including the linear variable differential transformer (LVDT), as well as mechanical and electrical strain gauges, are associated with a number of inherent limitations. These limitations encompass high costs, incompatibility with various environmental conditions, the need for physical contact during equipment installation, time-intensive setup procedures, and the inability to capture all the displacement fields and strain measurements of the target structural components [1]. In recent decades, there has been a notable surge in research dedicated to structural health monitoring (SHM), due to the increased demand for the continuous surveillance of critical structures. Efforts to enhance concrete quality through

the use of additives have been instrumental in mitigating potential damage [2]. The timely detection of structural damage or failures holds paramount significance as it can prevent subsequent catastrophic harm to a building or infrastructure. Structural health monitoring encompasses the process of identifying and detecting such issues in engineering structures. Accordingly, any alteration in the material or geometric properties of a structural system that negatively impacts its performance is classified as damage.

Recent years have seen numerous research endeavors dedicated to improving the accuracy and reliability of SHM methods. Many researchers have actively engaged in developing structural damage assessment methodologies, with several studies delving into the intricacies of RC beam damage [3]. In this regard, the occurrence of concrete cracking is recognized as a significant concern [4,5]. Barad and Sharma [6] introduced an effective method for determining both the depth and location of cracks. This method involves manipulating the natural frequency of the structure and modeling the crack using a torsional spring, allowing for precise crack assessment. Nasery et al. [7] proposed an approach for automated damage detection in concrete-encased composite column-beam connections using model updating techniques. Their findings demonstrated that their proposed method identified the location and severity of the damage. Salehi et al. [8] introduced a new element formulation, the gradient inelastic (GI) force-based (FB) element formulation, for assessing the damage and collapse capacity of reinforced concrete structures. Their findings showed that the GI-FB element formulation predicted the damage to RC columns and frames. Malipatil and Itti [9] delved into the stress intensity factor (SIF) and damage index of reinforced concrete beams by employing numerical and analytical approaches. They examined the impact of crack width and reinforcement cover on the SIF and damage index of RC beams. Their findings revealed that the SIF and damage index increased with escalating crack width, and decreased with increasing reinforcement cover. Md Nor et al. [10] investigated the prognosis of damage intensity for reinforced concrete beams under cyclic loading. Their findings revealed that the damage intensity increased with increasing load cycles and load amplitude. Nor et al. [11] emphasized the importance of determining the acoustic emission (AE) trend for reinforced concrete beam fatigue damage. They conducted experimental tests on RC beams subjected to fatigue loading and monitored the AE signals emitted during the tests, and concluded that determining the AE trend is essential for developing reliable fatigue damage assessment methods for RC structures. Ai et al. [12] conducted a numerical simulation to investigate the feasibility of using embedded piezoelectric transducers (PZTs) for corrosion damage identification in reinforced concrete beams. They developed a three-dimensional Finite Element (FE) model of a full-scale RC beam and simulated the response of PZTs embedded in different locations within the beam under various corrosion scenarios. Gong et al. [13] introduced an equivalent quantization method to assess the corrosion damage to reinforcement cages in concrete beams subjected to island and reef environments.

Meslemani and Koyankin [14] proposed a method for restoring reinforced concrete beams that have sustained localized damage due to combat impacts. They developed a two-stage repair process involving the removal of the damaged concrete and the replacement of the damaged section with a prefabricated concrete segment. Le and Thammarak [15] investigated the feasibility of employing the modal strain approach for damage detection in reinforced concrete beams. They conducted experimental tests on RC beams subjected to various damage scenarios and analyzed the modal strain data to identify the damage locations and severity. Their findings revealed the potential of the proposed model as a non-destructive testing method for structural health monitoring. Yu et al. [16] conducted an experimental study to investigate the fatigue damage behavior of continuous steel-concrete composite (CSCC) beams using acoustic emission monitoring. They subjected CSCC beams to cyclic loading and monitored the AE signals emitted during the tests. They analyzed the AE data to identify the AE trend, which reflects the damage state of the CSCC beam. Liang et al. [17] investigated the fatigue damage behavior of concrete beam specimens under varying amplitude loads. Their findings demonstrated that the numerical model predicted

the fatigue damage behavior of the concrete beam specimens under varying amplitude loads. Parente et al. [18] developed a fiber beam element for modeling prestressed concrete structures that considers the nonlinear material behavior, time-dependent effects, and a force-based approach. The element uses concrete, steel reinforcement, and prestressing cable fiber discretizations to model the cross-section. Damage and plasticity models are used to model concrete, and plasticity models are used to model steel.

Digital image correlation (DIC) stands as an image processing-based technique for measuring displacements, and has found extensive applications across various research domains. Belletti et al. [19] reported on the corrosion effects on the failure modes, shear capacity, and ductility of full-scale prestressed concrete (PC) beams without transverse reinforcement. That paper described the four-point bending tests performed after a visual inspection of the corrosion damage, and also presented the strains measured using DIC. Funari and Verre [20] investigated the effectiveness of steel-reinforced grout in shear strengthening beams, revealing that continuous two-layered SRG strips increased the load-bearing capacity, with DIC proving effective for assessing the shear crack distribution during testing. Pan et al. [21] employed DIC to investigate the propagation speed and spreading direction of multiple dynamic cracks in steel fiber-reinforced cement-based composites, revealing unprecedented high speeds of crack propagation.

The DIC method has primarily been employed to ascertain the concrete elasticity modulus and to explore fracture mechanics, enabling the precise calculation of concrete strain. While the DIC technique is currently employed for measuring the displacement and strain fields, it is important to note that achieving accurate calculations of strain fields can present challenges in certain cases [22]. There are also algorithms for the detection of damages through the utilization of digital image pre-processing techniques [23]. In the realm of non-destructive investigations, there is a notable emphasis on image-based crack detection. However, challenges can arise when using image-based damage detection due to the presence of random, irregular, or noisy elements in the images, such as spots or fluctuations in the lighting [24].

Machine learning (ML) techniques have been considered in recent years for the detection of damage in RC beams. The ML models, for example, support vector machines (SVMs), have emerged as a powerful tool in various scientific domains, offering robust and efficient solutions for tasks such as classification, regression, and anomaly detection. In numerous studies, support vector machine (SVM) has proven to be a highly effective method for classifying damage detection techniques [25–27]. The analysis of crack characteristics was performed by Shan et al. [28] utilizing the SVM and k-nearest neighbor (KNN) algorithms. Subsequently, a classification algorithm was trained to determine the specific damage modes exhibited by columns. There has also been a growing effort to reduce the reliance on extensive laboratory work by applying SVM modeling techniques. Both linear and nonlinear models have been harnessed to forecast new concrete properties and determine its compressive strength, thereby streamlining the research process and minimizing the need for extensive laboratory experimentation [29]. Yang and Huang [30] proposed a novel damage identification method for prestressed concrete beam bridges utilizing convolutional neural networks (CNNs). Their method involves extracting damage features from the flexibility curvature data and employing a CNN to classify the bridge damage status. Nariman et al. [31] developed surrogate models to predict the damage responses of reinforced concrete beams subjected to explosive charges. They developed surrogate models using artificial neural networks to approximate the complex relationship between the explosive charge parameters and the damage responses. Guo et al. [32] proposed a machine learning-driven approach to evaluate and optimize compression-yielded fiber-reinforced polymer (FRP)-reinforced concrete beams with T sections. Pathak et al. [33] introduced an artificial neural network model for predicting the fracture energy of concrete notched beams. They utilized a database of experimental results and numerical simulations to train the ANN model. The proposed ANN model offers a tool for estimating the fracture energy of concrete structures, which is crucial for designing safe and durable structures.

2. Research Significance

Reinforced concrete beams are integral components of civil engineering structures, and any damage to or malfunction of these beams could lead to severe consequences. Numerous studies have been conducted to enhance the accuracy and reliability of SHM methods, including the use of digital image correlation for displacement measurement and crack detection. However, challenges persist in accurately calculating the strain fields, and various techniques have been proposed to address this issue. This research introduces a technique for damage detection using digital image pre-processing, which is of particular relevance for non-destructive investigations. This study also explores the application of support vector machine and k-nearest neighbor methods to classify different damage modes in concrete structures. Additionally, the use of SVM for modeling the properties of low-volume fly ash self-compacting concrete is highlighted, providing valuable insights into predicting new concrete properties and compressive strength. Given the prevalence of concrete cracking in high-strength concrete structures, the application of SVM for classifying damage detection methods is a noteworthy contribution. This research offers insights and methodologies that contribute to the ongoing efforts in the field of SHM and damage detection, specifically focusing on the challenges of and solutions for concrete structures, making it a valuable addition to the existing body of knowledge.

3. Preparation for the Imaging Procedure

High-quality cameras are employed to capture the crucial moments throughout the testing process, ensuring the reliability of the results from the subsequent image processing of the reinforced concrete beams. Specifically, only images of acceptable quality are selectively collected during the loading of the beam, as illustrated in Figures 1 and 2. A series of continuous image frames is documented at each stage of the experiment, offering a comprehensive view of the beam response to the applied loads. Figure 3 provides a glimpse into several loading frames for the SBDCM15-3 specimen, showcasing the meticulous documentation of the entire process, from the initiation of loading to the eventual failure of the specimen. This meticulous recording of images serves as the foundational step in the non-destructive testing process, allowing for the detailed analysis and validation of the beam structural behavior under varying conditions.



Figure 1. Recording of vertical changes in concrete beams.



Figure 2. Depicting cracks to be subjected to image processing following beam failure.



Figure 3. Image captured.

3.1. Specimen Nomenclature

The constructed beams in this study are classified into two main categories based on their failure modes, including the beams exhibiting concrete failure and those displaying rebar failure. Rebar failures entail deliberate corrosion measures, involving the reduction in rebar diameter by half (7 mm), and a 2.5 cm length corrosion located at the one-third span of the bottom rebar. This corrosion process differs between the specimens, with the SBDRS specimens experiencing symmetrical corrosion on both sides, and the SBDRA specimens and concrete failure specimens undergoing asymmetrical corrosion on one side. In addition, the introduction of polystyrenes with varying widths and heights contributes to the creation of well-defined failures. These failures are designated using specific nomenclature: “M” signifies failure at the mid-span, “O” denotes failure at the one-third span of the beam, and “S” (typically found at the beginning of some specimens) represents an FRP-strengthened specimen.

3.2. Image Processing Steps

Machine learning is a field that leverages various algorithms for data-driven decision making [34–36]. ML methods offer the ability to harness and analyze vast datasets, enabling more accurate and nuanced predictions for complex problems [37–42], like seismic responses near active fault zones, enhancing the understanding of and preparedness for such critical scenarios. When dealing with structures near fault lines, the seismic response can be significantly different [43]. The utilization of KNN and SVM, along with other machine learning methods, can help engineers account for these distinctive characteristics and the potential for severe damage. Among these, the KNN method is a straightforward instance-based learning approach, capable of both classification and regression. In contrast, SVMs are powerful classifiers that aim to maximize the margin between different classes through the use of hyperplanes, making them versatile for linear and non-linear classification tasks [44]. These techniques showcase the diversity and utility of machine learning for solving a wide range of problems, from simple and intuitive methods like KNN, to more advanced approaches like SVM that handle complex decision boundaries.

The image processing techniques of KNN and SVM play a pivotal role in this study. Initially, specific images are identified, and as the loading process ensues, the developed cracks are highlighted in red. To facilitate categorization and assessment, the beams are classified into 16 categories based on their failure types and performance criteria. Throughout the loading process (e.g., Figure 4), sixteen images are captured from each

beam and input into the image processing tool in MATLAB software version 2019a. Figure 5 illustrates the processing of the image cracks while taking into account their growth. These models use the detected cracks to classify the beams into their respective categories. Subsequently, one image is selected from each folder, and the program automatically processes all the images within the folder. It is important to note that the time it takes for the program to read certain folders varies based on the image size and the number of cracks present. As the program sequentially processes all the images, it classifies them based on the detected cracks from the beginning to the end of the loading process.

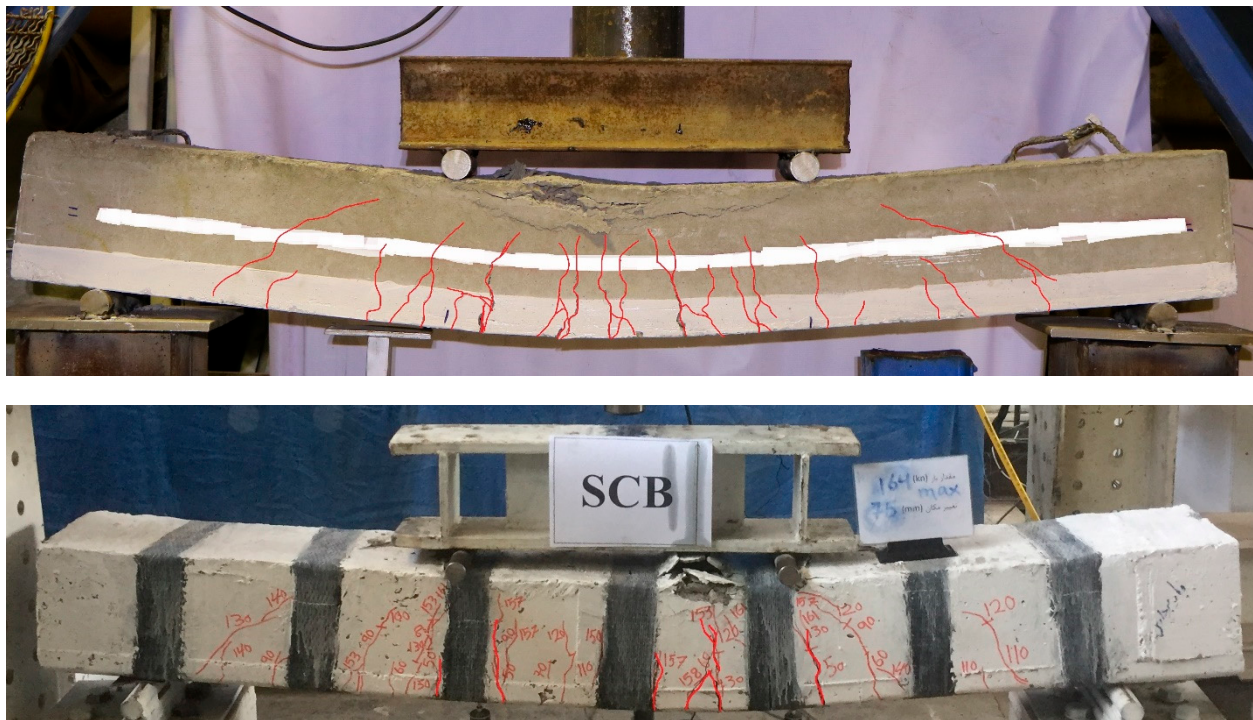


Figure 4. Beam cracks.

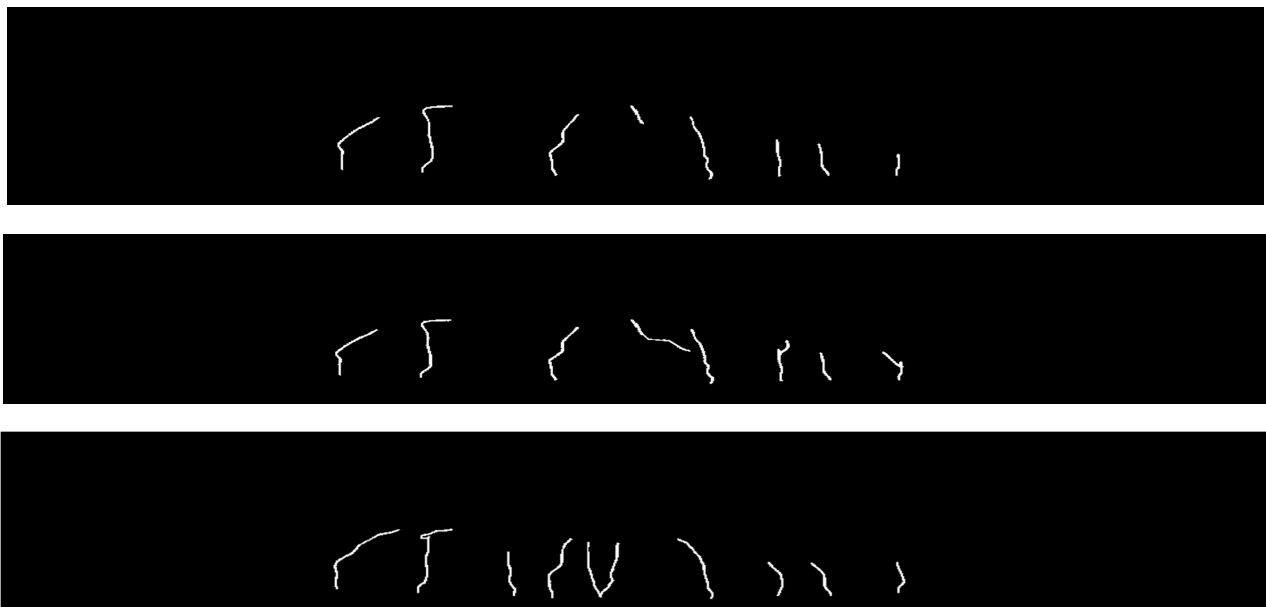


Figure 5. Cont.



Figure 5. Cont.

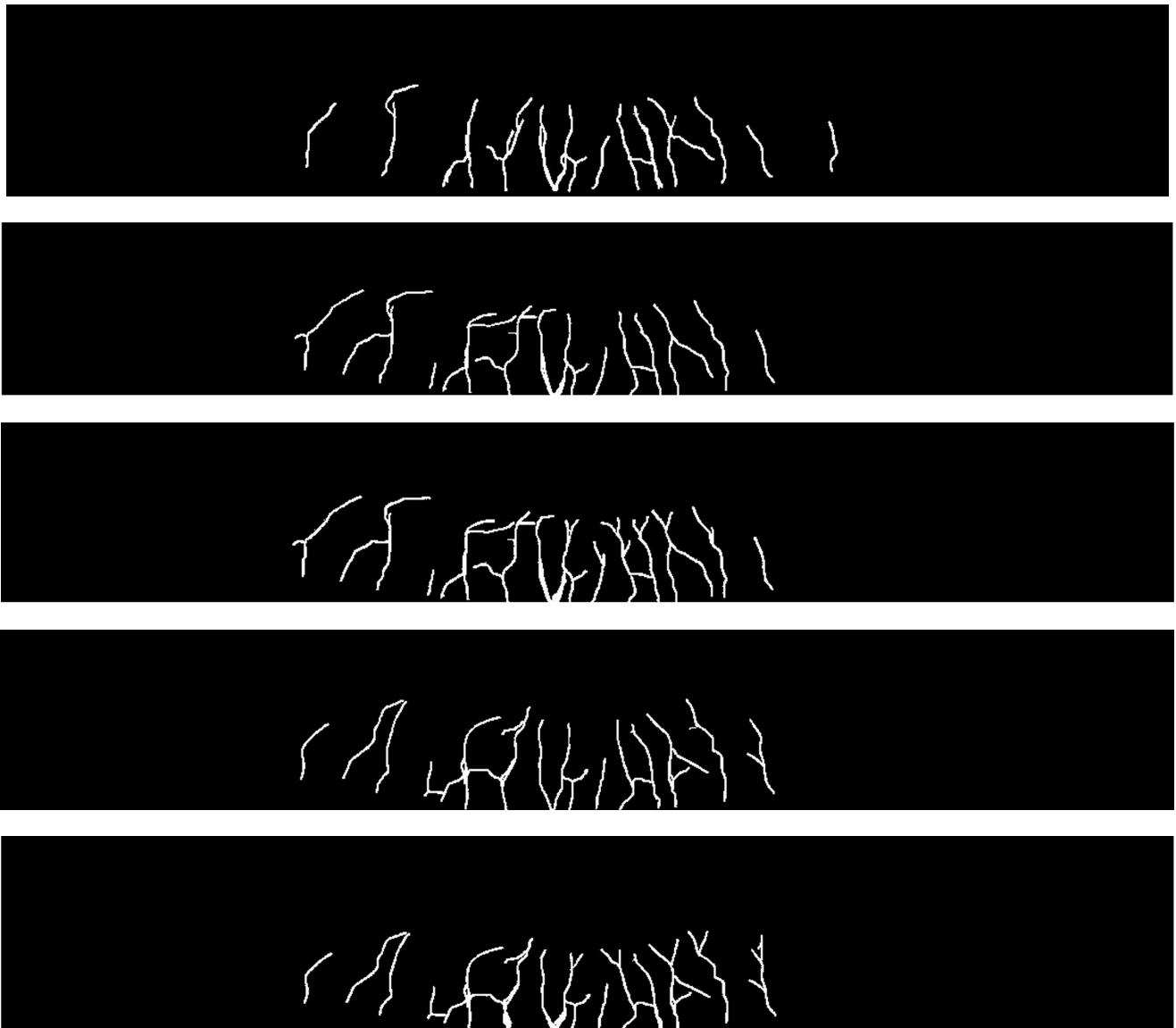


Figure 5. Processing of cracks in images with consideration of their growth and the loading conditions applied.

3.2.1. KNN Algorithm Steps

The data processing methodology constitutes a comprehensive sequence of pivotal stages. Initially, the data undergo the crucial phases of downloading and meticulous preparation, setting the foundation for the subsequent analysis. Following this preparatory stage, the determination of the optimal number of nearest neighbors, symbolized as ‘K,’ emerges as the pivotal parameter, wielding significant influence over the precision and efficacy of the ensuing calculations. Upon establishing the value of ‘K,’ a meticulous series of computations is undertaken for each primary data point within the scope of consideration. This computational sequence involves the precise measurement of distances between the focal data point and all the primary data points, forming a web of interconnected relationships. The outcome of these calculations is then systematically compiled, taking into account both the sample spacing and index information, resulting in a coherent set.

This compiled set, embodying the distances (specimen) calculated, undergoes a process of refinement through sorting, with a meticulous arrangement in ascending order based on the calculated distances. From this meticulously ordered set, a critical selection is made, wherein the K points are judiciously chosen from the subset exhibiting the small-

est distances. This strategic selection encapsulates the essence of identifying the nearest neighbors, a pivotal aspect of the data analysis journey. The culminating phase of this intricate methodology involves the generation of the output, a step that exhibits variability contingent upon the selected mode or classification mode. This final output serves as the tangible manifestation of the data analysis process, encapsulating the insights, patterns, or classifications derived from the meticulous computations and selection processes undertaken throughout the preceding stages. In essence, the data processing methodology unfolds as a strategic and systematic journey, navigating through the intricacies of distance measurements, sorting, and selection, to distill meaningful and actionable outcomes.

3.2.2. SVM Algorithm Steps

The SVM algorithm stands as a prominent pattern recognition tool employed for pattern recognition and object classification tasks. In the traditional SVM framework, it is defined based on a single-tag training set, denoted by X , where the decision function is expressed as Equation (1):

$$f(x) = w^T X_i + b = 0 \quad (1)$$

where T represents the i th training image with d properties, $X_i = (x_{i1}, \dots, x_{id})$, and w is a d -dimensional vector, while b remains a constant. The primary objective of SVM is to maximize the margin between the positive and negative support vectors, while minimizing the overall risk. The binary problem is solved by adopting a Lagrangian approach, yielding a solution represented by (w, b) , which is then used for classifying a given test image x' . The predictions for tag labels are made through Equation (2):

$$h(x') = \text{sign}(f(x')) \quad (2)$$

Following this, depending on the selected method (SVM or KNN) within the classification tool in the MATLAB software, the program identifies the nearest beam with a similar crack size and growth characteristics compared to the test beam. This process results in two distinct responses as follows:

- The beam is close and similar to the test beam; accordingly, the type of failure is estimated.
- The position of the beam is pass or fail.

During the intricate process of generating and validating the program responses, the models are seamlessly integrated into the program structure, operating within three distinct categories that meticulously facilitate a thorough comparative analysis of the outcomes. These categories can be delineated as follows.

- Category 1: Beam Inclusion and Matching

In this initial category, the program incorporates 15 out of the 16 beams, utilizing the remaining beam as the reference for matching, thereby totaling 15 beams. This rigorous inclusion and matching process lays the foundation for assessing the model's proficiency in accurately aligning with the reference beam.

- Category 2: Model Variation with FRP Strengthening

The second category introduces a nuanced exploration by incorporating eight models, both with and without fiber-reinforced polymer strengthening. Correspondingly, this category presents a set of eight distinct beams, aligning with the models under scrutiny. The inclusion of FRP-strengthened and non-strengthened beams results in a total of eight beams, providing a comprehensive platform for evaluating the program's response across varied structural conditions.

- Category 3: Training Dataset Inclusion

In the third category, the program is strategically exposed to seven out of the eight beams from each group, encompassing both the FRP-strengthened and non-strengthened beams for training purposes. The remaining beam in this category serves as the benchmark

for matching, culminating in a total of seven beams. This deliberate selection of training data aims to enhance the program's learning capabilities and evaluate its performance in accurately matching beams against the established reference.

These meticulously designed categories collectively form a systematic framework for evaluating the program's performance in matching beams, thereby offering a robust and comprehensive validation of the responses generated. This structured approach ensures a nuanced exploration of the various scenarios, contributing to the program's adaptability and reliability in diverse conditions.

4. Results of the Categories

Each of the three categories ultimately yields unique image processing characteristics. The first category encompasses all the beams, with and without FRP strengthening, offering a diverse range of beams for validation. The second category provides insights into the program's precision and the variations in results when considering the utilization or absence of composite materials. The third category assesses the program's accuracy for beams within a specific category, and this can be measured with regard to a particular beam type and its features. In Table 1, the symbols and models used for categorization are detailed, providing a clear reference for understanding the classification and properties of the beams employed in the program's evaluation and validation.

Table 1. Image processing results with KNN and SVM (first group).

Beam Code	15 Beams		8 Beams		7 Beams	
	KNN	SVM	KNN	SVM	KNN	SVM
CB	SBD CO (15-3)	BDC M (15-3)	SBD CO (15-3)	SBC	BDC M (10-3)	BDC M (10-3)
SCB	SBD CM (10-0.5) (15-1)	SBD CM (10-0.5) (15-1)	BDC M (10-3)	BDC M (15-1)	SBD CM (10-0.5) (15-1)	SBD CM (10-0.5) (15-1)
BDCM (10-3)	BDC M (15-1)	BDC M (15-1)	SBD CM (10-3)	SBD CM (15-1)	BDC M (15-1)	BDC M (15-1)
SBD CM (10-3)	SBD CM (15-1)	SBD CM (15-3)	BDC O (10-3)	BDC M (15-3)	SBD CM (15-1)	BDC M (15-1)
BDCM (15-1)	BDR S	BDC M (10-3)	SBD CM (10-3)	SBD CM (10-3)	BDR S	BDC M (15-3)
SBD CM (15-1)	SBD CM (15-3)	SBD CM (10-0.5) (15-1)	BDC M (10-3)	BDC M (15-1)	SBD CM (15-3)	SBD CM (10-0.5) (15-1)
BDC O (15-3)	BDC M (10-0.5) (15-1)	SBD RA	SBD RA	SBD CM (15-1)	BDC M (10-0.5) (15-1)	BDC M (10-0.5) (15-1)
SBD CO (15-3)	SBC	SBD CM (10-0.5) (15-1)	BDC M (10-0.5) (15-1)	BDC O (15-3)	SBC	SBD CM (15-1)

4.1. Results for CB and SCB Beams

Expanding our perspective to encompass the various image processing modes, a notable uniformity in outcomes became apparent. Irrespective of the specific processing method employed, the results remained nearly identical. However, a more nuanced scrutiny of the two prominent methods, SVM and KNN, revealed a discernible discrepancy in their performance. The SVM approach exhibited a closer alignment with the anticipated response, distinguishing itself from the KNN method. This discrepancy implies that the SVM model more accurately mirrored the expected behavior, underscoring its efficacy in this particular context.

The numerical model for the RC beam of CB type was meticulously constructed using Ansys® Academic Research Mechanical, Release 2021 R2 software, as depicted in Figure 6. This sophisticated representation serves as a pivotal tool for comprehending the structural intricacies and failure mechanisms inherent in CB beams. Furthermore, Figure 7 provides a visual insight into the image processing techniques employed to analyze cracks in the CB beams. The intricate details captured through image processing offer a

comprehensive understanding of the crack patterns, contributing valuable insights into the structural integrity of the CB beams under examination. Figure 8 extends this exploration by illustrating the application of image processing to the detection and analysis of cracks in the CB beams. This visual representation serves as a testament to the effectiveness of the employed image processing techniques, showcasing their capability to discern and analyze the intricate details associated with crack formation and propagation. The meticulous examination of compliance modes, coupled with the nuanced analysis of image processing methods, has provided a rich reservoir of insights into the behavior of CB beams under various conditions. The combination of experimental observations, numerical modeling, and image processing techniques has facilitated a holistic understanding of the structural performance and failure mechanisms of the Cantilever-Bracket beams.

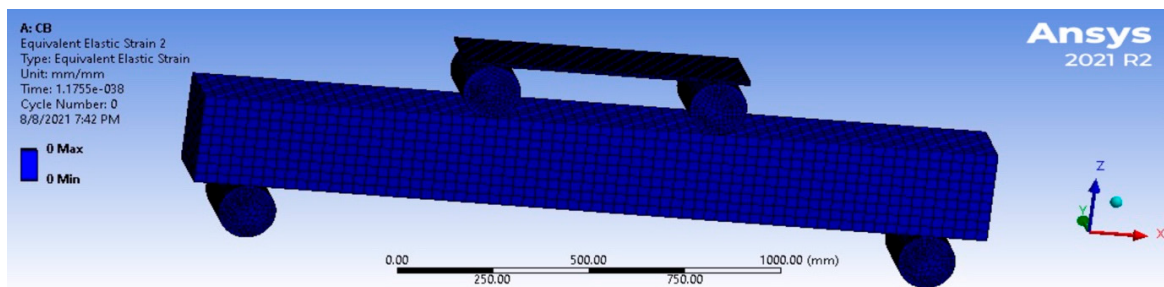


Figure 6. The reinforced concrete beam (CB).



Figure 7. Image processing of cracks in CB beams.

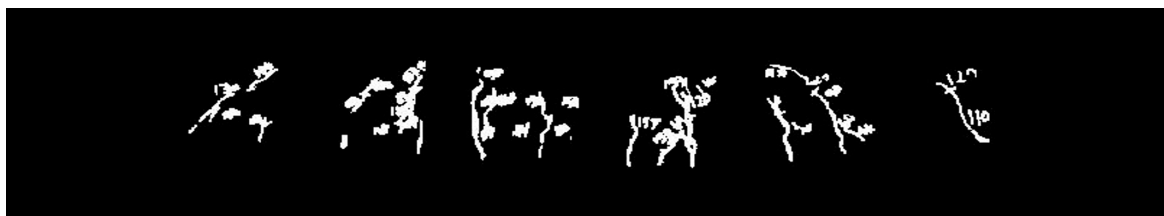


Figure 8. Image processing of cracks in SCB beams.

4.2. Results for BDCM (10-3) and SBDCM (10-3) Beams

In a broader context, the comparison of the various image processing modes revealed a remarkable consistency in results, with the notable exception of the eight-specimen scenario where BDCO was matched in only one case. Despite this anomaly, the overall trend showcases nearly identical outcomes across the different image processing modes, reaffirming the robustness of the methods employed in capturing the structural nuances. Delving into a comparative analysis of the two primary methods, the SVM approach once again demonstrated a closer alignment, with the expected response in contrast to the KNN method. This distinction underscores the superior predictive capacity of the SVM model for encapsulating the structural behavior under scrutiny. The nuanced differences between these methods contribute to a refined understanding of their respective strengths and limitations in the context of this study.

Figure 9 serves as a visual representation of the image processing techniques applied to cracks in the BDCM (10-3) beams, offering detailed insights into the intricate patterns of crack formation and propagation. This visual depiction enhances the comprehensibility

of the image processing methodology employed, facilitating a deeper understanding of the structural response to various loading conditions. Furthermore, Figure 10 extends this exploration by illustrating the image processing techniques specifically tailored for cracks in the SBDCM (10-3) beams. This visual representation provides a focused examination of the cracks in this particular specimen, contributing to a more granular understanding of the failure mechanisms within the SBDCM context. The analysis of the compliance modes and image processing methods has unraveled valuable insights into the structural behavior of the SBDCM beams. The elevated compliance observed in the SBDCM (10-0.5) (15-1) specimen, coupled with the nuanced comparisons between the image processing modes and methods, deepens our understanding of the intricate interplay between the failure patterns and structural responses for the studied scenarios.



Figure 9. Image processing for cracks in BDCM (10-3) beams.



Figure 10. Image processing for cracks in SBDCM (10-3) beams.

4.3. Results for BDCM (15-1) and SBDCM (15-1) Beams

A comprehensive overview of all the modes underscores a consistent alignment with the SBDCM specimens, with nearly identical results observed across the various image processing modes. This robustness of the outcomes emphasizes the reliability of the methodologies employed, providing a solid foundation for understanding the structural behavior and failure mechanisms. Intriguingly, in both the 7- and 15-specimen scenarios, the KNN method appears to emulate the BDRS similarity mode, a phenomenon possibly linked to the clustering of cracks in a specific region of the beam devoid of FRP. This observation introduces a layer of complexity into the interpretation of the results, highlighting the sensitivity of image processing methods to localized conditions and material characteristics. A pivotal revelation emerges in the comparative analysis of the two primary methods, with the SVM approach exhibiting a closer correspondence to the expected response than the KNN method. This observation underscores the efficacy of the SVM model for capturing and predicting structural behavior, offering valuable insights for future applications and refinements of analysis methodologies (see Figures 11 and 12).



Figure 11. Image processing for cracks in SBDCM (15-1) beams.



Figure 12. Image processing for cracks in BDCM (15-1) beams.

To complement the visual exploration, Figure 13 provides a schematic representation of the BDCM (15-1) beam. This visualization serves as a powerful tool for unraveling the structural design and features of the beam, offering a deeper understanding of the physical characteristics that contribute to its response under various loading conditions. The meticulous examination of compliance, crack propagation, and image processing methods has yielded a nuanced understanding of the structural behavior of the SBDCM specimens. The interplay between FRP presence, crack patterns, and methodological nuances contributes to a rich tapestry of insights, laying the groundwork for advancements in structural analysis and design considerations.

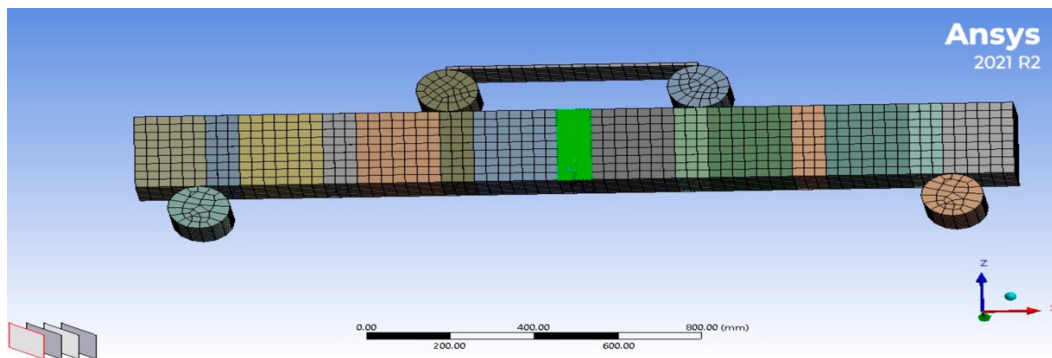


Figure 13. Schematic representation of the BDCM (15-1) beam.

4.4. Results for BDCO (15-3) and SBDCO (15-3) Beams

Intriguingly, all the cases demonstrate compliance with BDCM and SBDCM, highlighting the consistent nature of the results across the different image processing modes. The remaining image processing modes exhibit nearly identical outcomes, underscoring the robustness of the methodologies employed for capturing structural nuances. In the context of the scenario involving 15 specimens, the accuracy of the response is notably higher. This was attributed to the presence of a beam experiencing both concrete and rebar failure, leading to the accumulation of cracks. Both the KNN and SVM methods exhibit similar response accuracies, as depicted in Table 2, positioning them in close alignment with the expected outcomes. This concordance reaffirms their reliability for predicting structural behavior under varied conditions (see Figures 14 and 15).

To enhance the conceptual understanding, Figure 16 provides a numerical schematic representation of the BDCO (15-3) beam. This visualization serves as a valuable tool for unraveling the structural intricacies and design features, offering insights into the factors influencing the beam response to the loading conditions. The amalgamation of compliance analysis, crack propagation observation, and image processing methodologies has unveiled a nuanced understanding of the structural behavior of the examined specimens. The consistent compliance with the BDCM and SBDCM, coupled with the unique insights derived from the FRP reinforcement and failure patterns, contributes to a comprehensive understanding of the structural dynamics and will inform future considerations about design and analysis.



Figure 14. Image processing for cracks in BDCO (15-3) beams.

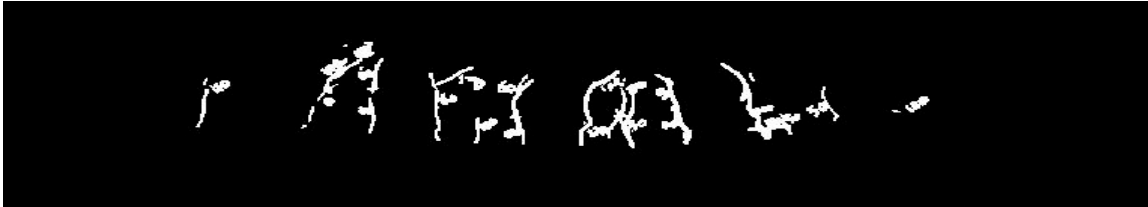


Figure 15. Image processing for cracks in SBDCO (15-3) beams.

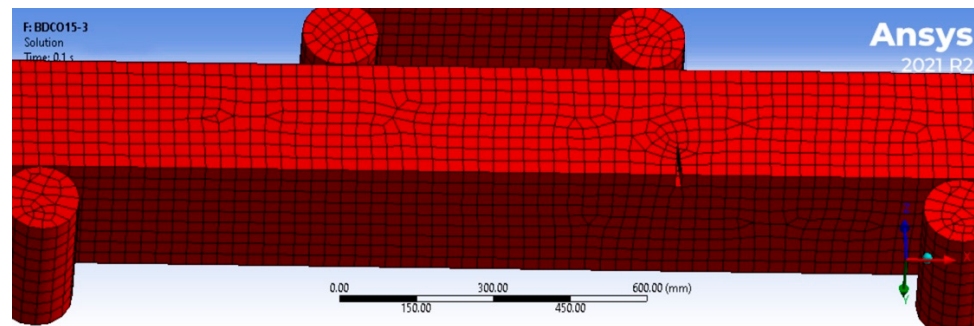


Figure 16. Schematic representation of the BDCO (15-3) beam.

Table 2. Results of image processing utilizing KNN and SVM (second group).

Beam Code	15 Beams		8 Beams		7 Beams	
	KNN	SVM	KNN	SVM	KNN	SVM
BDCM (15-3)	BDRA	BDCM (15-1)	SBDCM (15-1)	SBC	BDCM (10-0.5) (15-1)	BDCM (10-0.5) (15-1)
SBDCM (15-3)	SBDCM (15-1)	SBDCM (10-3)	BDCM (15-3)	BDCM (15-1)	SBC	SBDCM (15-1)
BDCM (10-0.5) (15-1)	SBDRRA	SBC	SBDRRA	SBDCM (10-3)	SBDCM (15-3)	SBDCM (15-1)
SBDCM (10-0.5) (15-1)	SBDCM (15-3)	SBDCM (15-1)	BDCM (15-3)	BDCM (15-1)	BDCM (15-3)	BDCM (15-3)
BDRA	BDCM (15-3)	SBDCM (10-0.5) (15-1)	SBDRRA	SBC	BDCM (15-3)	BDRS
SBDRRA	BDCM (15-3)	SBDCO (15-3)	BDRA	BDCM (10-3)	BDCO (15-3)	SBDCM (10-0.5) (15-1)
BDRS	BDCM (15-1)	BDCO (15-3)	SBDCM (10-3)	SBDRS	BDCM (15-1)	BDCO (15-3)
SBDRS	SBDCM (10-0.5) (15-1)	BDCM (15-1)	BDCM (10-3)	BDRA	SBDCM (10-0.5) (15-1)	SBDCM (10-3)

4.5. Results for BDCM (15-3) and SBDCM (15-3) Beams

The images extracted from the image processing, as depicted in Figures 17 and 18, are subjected to evaluation across three different modes. In the cases under examination, the SBDCM (15-1) specimen stands out as the most compliant. An analysis of the processed images indicates that the specimen reinforced with FRP exhibits variations in crack length, characterized by both decreases and increases. In contrast, the FRP-free specimen, because

of a mid-span failure (in the center) measuring 15.3 cm, primarily exhibits the formation of cracks within the same area. In both instances, regardless of the presence of FRP reinforcement, cracking initiates at the center and subsequently experiences growth as a consequence of the applied force.



Figure 17. Image processing for cracks in BDCM (15-3) beams.

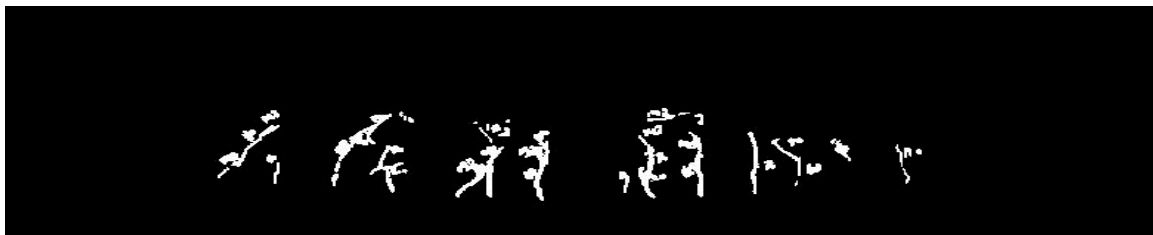


Figure 18. Image processing for cracks in SBDCM (15-3) beams.

The images extracted through the image processing, illustrated in Figures 17 and 18, undergo comprehensive evaluation across three distinct modes. Notably, within the scope of the examined cases, the SBDCM (15-1) specimen emerges as particularly noteworthy for its exceptional compliance. A meticulous analysis of the processed images unveils the distinctive characteristics of the behavior of the specimen reinforced with FRP. This particular specimen exhibits variations in crack length, showcasing a dynamic interplay of both decreases and increases in crack dimensions. Conversely, its FRP-free counterpart, experiencing a mid-span failure at the center measuring 15.3 cm, predominantly displays the formation of cracks within the same spatial confines. Regardless of the presence or absence of FRP reinforcement, the initiation of cracking consistently takes place at the center and subsequently undergoes growth in response to the applied force. This observation not only highlights the unique response of the SBDCM (15-1) specimen, but also underscores the influence of FRP reinforcement on crack evolution. The dynamic nature of the crack length variations in the FRP-reinforced specimen adds a layer of complexity to the understanding of failure mechanisms, providing valuable insights into the material's behavior under loading conditions. The examination of the SBDCM (15-1) specimen through image processing reveals distinctive compliance characteristics and nuanced crack evolution patterns, contributing to a deeper understanding of the structural response in the presence of FRP reinforcement. These findings hold implications for the design and analysis of structures, particularly those incorporating FRP components, and add valuable dimensions to the ongoing exploration of material behavior and failure mechanisms.

Broadly speaking, a consistent trend emerges across all the cases, with each demonstrating compliance with SBDCM (15-1) and SBDCM (15-3). The uniformity in outcomes underscores the reliability of these specific compliance modes, showcasing their effectiveness for capturing the structural nuances inherent in the specimens under examination. Notably, the remaining image processing modes contribute to nearly identical results, reinforcing the robustness of the analytical methodologies applied. In the context of the scenario involving 15 specimens, a notable increase in the response accuracy is observed. This heightened accuracy can be attributed to the central damage experienced by the beam in this specific scenario. The presence of central damage introduces a critical factor that significantly influences the response accuracy, offering a more comprehensive understanding of the structural behavior under diverse conditions. Comparatively assessing the

performance of the KNN and SVM methods, optimal responses are achieved in distinct scenarios. The KNN method excels in the 8-specimen scenario, while the SVM method delivers superior results in the 15-specimen scenario. This nuanced observation positions SVM as a more comprehensive and adaptable approach, especially in scenarios with a larger dataset, as exemplified by the 15-specimen case. The wealth of information available in this scenario allows SVM to leverage a broader set of data points, contributing to its enhanced predictive capacity.

To complement the analytical insights, Figure 19 provides a numerical schematic representation of the BDCM (15-3) beam. This visualization serves as a powerful tool for elucidating the structural design and features of the beam, offering detailed insights into the factors that govern its response under diverse loading conditions. The overarching compliance with the SBDCM modes, coupled with the nuanced performance of the KNN and SVM methods, highlight the intricacies of the structural behavior under different scenarios. The heightened response accuracy for the 15-specimen case underscores the significance of central damage in influencing outcomes. The numerical schematic representation further enhances our understanding, providing a visual roadmap to unravel the complexities of the BDCM (15-3) beam's structural dynamics. These findings contribute valuable insights into the broader exploration of image processing and numerical modeling in structural analysis and design.

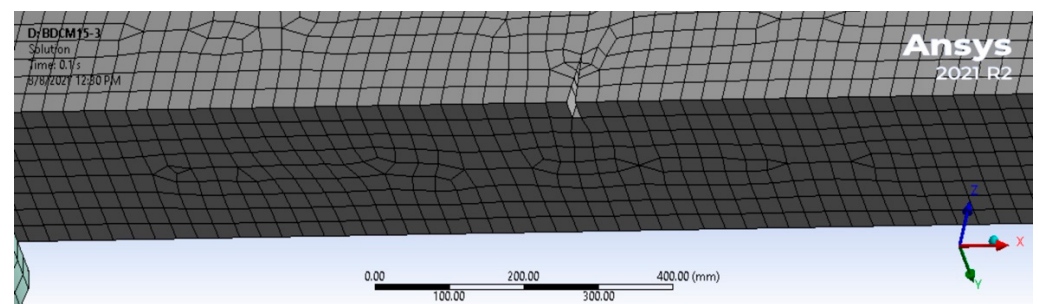


Figure 19. Schematic representation of the BDCM (15-3) beam.

4.6. Results for BDCM (10-0.5) (15-1) and SBDCM (10-0.5) (15-1) Beams

The scrutiny of the images derived from the image processing, delineated in Figures 20 and 21, involves a meticulous assessment under three distinct modes. Within the ambit of this investigation, the SBDCM (15-1) and SBDCM (15-3) specimens emerge as standouts, exhibiting the highest compliance. A closer inspection of the processed images unveils the distinctive behaviors of the specimen reinforced with FRP. Notably, this specimen undergoes direct crack growth without branching, shedding light on the specific influence of FRP reinforcement on crack propagation. In stark contrast, its FRP-free counterpart, experiencing both mid-span and one-third span failures, has most of the cracks concentrated in the corresponding areas. Irrespective of FRP reinforcement, the initiation of cracking consistently occurs at the center and one-third span, followed by their growth due to the applied force. All the examined cases demonstrate compliance with SBDCM (15-1), SBDCM (15-3), and BDCM (15-3), with the other image processing modes yielding nearly identical results. This uniformity in the outcomes is particularly due to the presence of beam damage at the center, emphasizing the critical role of damage location in shaping structural responses.

Aligning with the image processing methodology, the SBDCM specimen (10-0.5) (15-1) stands out for producing the most similar response, further validating the reliability of the chosen mode for capturing structural nuances. In the comparative analysis of the SVM and KNN methods, the SVM method emerges as the superior performer, delivering the most accurate response in this specific context. This observation underscores the versatility and robustness of the SVM model for extracting meaningful insights from the processed images. To augment the conceptual understanding, Figure 22 provides a

numerical schematic representation of the BDCM (10-0.5) (15-1) beam. This visualization serves as a valuable tool for unraveling the structural intricacies and design features, offering insights into the factors influencing the beam's response to loading conditions, especially in scenarios involving complex failure modes. The comprehensive assessment of compliance, crack propagation, and image processing methods provides a nuanced understanding of the structural behavior of the examined specimens. The influence of FRP reinforcement, coupled with the consistent compliance observed for the various modes, contributes valuable insights into the ongoing exploration of material behavior and failure mechanisms. These findings hold implications for the design and analysis of structures, particularly those incorporating FRP components, and contribute to the broader field of structural engineering research.



Figure 20. Image processing for cracks in BDCM (10-0.5) (15-1) beams.

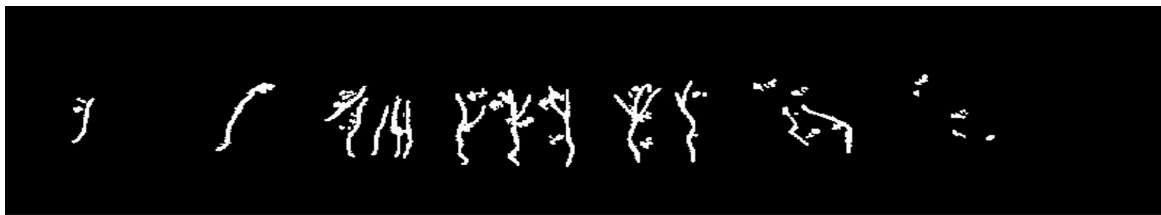


Figure 21. Image processing for cracks in SBDCM (10-0.5) (15-1) beams.

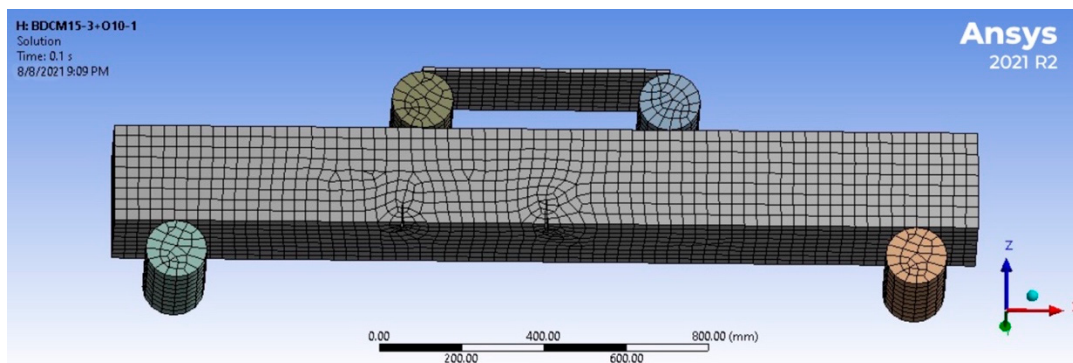


Figure 22. Schematic representation of the BDCM (10-0.5) (15-1) beam.

4.7. Results for BDRA and SBDRA Beams

The scrutinized images obtained from the image processing, as illustrated in Figures 23 and 24, undergo a thorough evaluation through three distinct modes. Notably, within the cases under examination, the specimen experiencing a one-third span failure emerges as the epitome of compliance. In the comprehensive scenario involving 15 specimens, the SVM processing stands out for its efficacy at effectively detecting the one-third span failure. This particular observation underscores the discriminative power of SVM for capturing nuanced structural responses, especially in scenarios with complex failure modes. A detailed analysis of the processed images unravels intricate details about the specimen reinforced with FRP. This specimen exhibits crack growth, a phenomenon attributed to

the presence of the FRP reinforcement. While cracks also manifest in other regions of the beam, they are less pronounced, predominantly due to a higher applied load. The degree of crack opening, intricately reflected in the line width of the formed cracks in the processed images, provides valuable insights into the varying degrees of structural damage and the impact of FRP reinforcement on crack propagation. Conversely, in the FRP-free counterpart, substantial cracks are concentrated in the same area, indicative of a one-third span failure. Regardless of the presence or absence of FRP reinforcement, the consistent initiation of cracking at the one-third span is a key observation, followed by its further growth in response to the imposed force. This consistent pattern underscores the reproducibility of failure mechanisms and the influence of specific failure modes on structural behavior. The meticulous assessment of images through diverse processing modes reveals a rich tapestry of compliance nuances. The effectiveness of SVM processing for detecting the one-third span failure in the 15-specimen scenario adds a layer of sophistication to the analysis. The differential crack patterns observed in the FRP-reinforced and FRP-free specimens contribute to a deeper understanding of the interplay between the material composition, applied load, and crack propagation. These insights hold significance for refining structural design considerations and advancing the understanding of failure mechanisms in complex scenarios.



Figure 23. Image processing for cracks in BDRA beams.



Figure 24. Image processing for cracks in SBDRA beams.

In all the examined cases, there is consistent compliance with SBDCA (15-3) and SBDCA (10-0.5) (15-1), emphasizing the reliability of these specific compliance modes. Notably, the remaining image processing modes contribute to nearly identical results, highlighting the robustness of the methodologies employed. In the specific scenario involving eight specimens, a marked increase in response accuracy is observed. This heightened accuracy is attributed to the presence of a one-third span failure in the beam, a critical factor that significantly influences the structural response. In this context, the KNN method emerges as the superior performer, delivering the most accurate response when compared to the SVM method. The differential performance of these methods underscores the sensitivity of image processing outcomes to the specific conditions and failure modes present in the structural elements.

To complement the analytical insights, Figure 25 presents a schematic representation of the SBDRA beam with rebar failure. This visual representation serves as a valuable tool for unraveling the structural intricacies and design features of the beam, offering insights into the factors that govern its response under various loading conditions. The inclusion of rebar failure introduces a unique dimension to the structural analysis, further enriching the understanding of failure mechanisms in complex scenarios. The observed compliance with

specific modes, coupled with the nuanced performance of the image processing methods, contributes to a comprehensive understanding of the structural behavior. The heightened response accuracy in the presence of a one-third span failure highlights the critical influence of localized damage on the outcomes. The schematic representation of the SBDRA beam adds a visual layer to the exploration of rebar failure, offering valuable insights for future considerations into the design and analysis of structures with intricate failure modes.

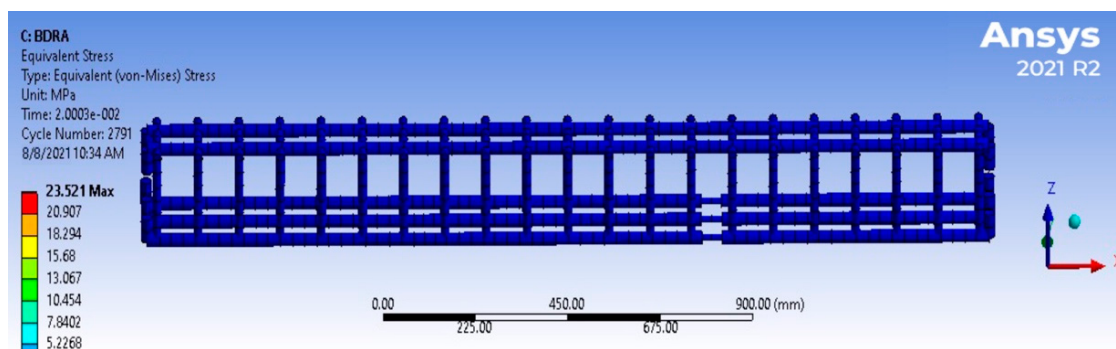


Figure 25. Schematic representation of the SBDRA beam with rebar failure.

4.8. Results for BDRS and SBDRS Beams

Figures 26 and 27 present a visual exploration of the images derived from the image processing, inviting scrutiny across three distinct modes. A notable highlight within the considered cases is the specimen showcasing a one-third span failure, exhibiting the pinnacle of compliance. Remarkably, the eight-specimen scenario stands out for achieving the highest level of compliance, underscoring the significance of this localized failure mode. Within the 15-specimen scenario, the effectiveness of SVM processing for detecting the one-third span failure becomes evident. This nuanced capability of SVM adds a layer of sophistication to the analysis, particularly in scenarios with complex failure modes. A detailed analysis of the processed images offers valuable insights into the behavior of the specimen reinforced with FRP. This specimen undergoes crack growth, with the extent of crack formation in other sections of the beam being notably less pronounced. The diminished prominence of cracks in these areas can be attributed to the higher applied load. The degree of crack opening, represented by the line width in the processed images, serves as a quantitative measure of the structural response, enriching the understanding of the impact of FRP reinforcement on crack propagation. Conversely, in its FRP-free counterpart experiencing a one-third span failure, significant cracks are concentrated in the same area. The consistent observation of crack initiation at the one-third span, followed by further growth due to the imposed force, highlights the reproducibility of failure mechanisms and their sensitivity to the presence or absence of FRP reinforcement. Across all the cases, compliance with BDCM (15-1) is consistently demonstrated, with the other image processing modes yielding nearly identical results. The heightened response accuracy observed for the eight-specimen scenario, primarily attributed to the presence of a one-third span failure, adds a critical dimension to the analysis. In this context, the SVM method outperforms the KNN method, emphasizing its adaptability for capturing nuanced structural responses.

Figure 28 provides a schematic representation of the SBDRA beam with rebar failure, offering a visual insight into the structural intricacies and design features. The inclusion of rebar failure introduces an additional layer of complexity, contributing to a deeper understanding of the failure mechanisms in structures with intricate failure modes. The amalgamation of compliance analysis, crack propagation observation, and image processing methodologies contributes to a comprehensive understanding of the structural behavior of the examined specimens. The nuanced performance of SVM for detecting specific failure

modes and the visual representation of the SBDRA beam further enrich the exploration of material behavior and failure mechanisms in diverse scenarios.

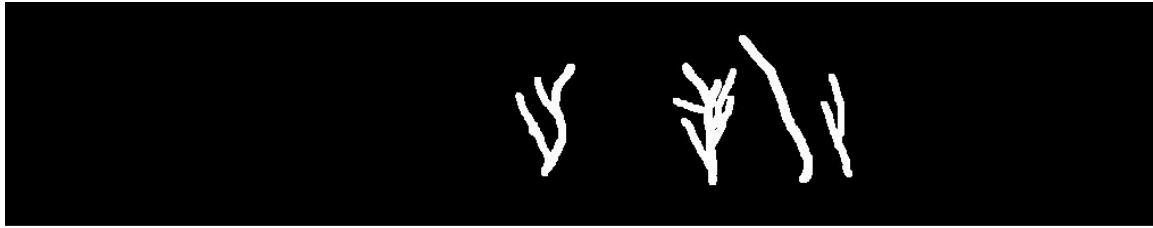


Figure 26. Image processing for cracks in SBDRA beams.



Figure 27. Image processing for cracks in BDRS beams.

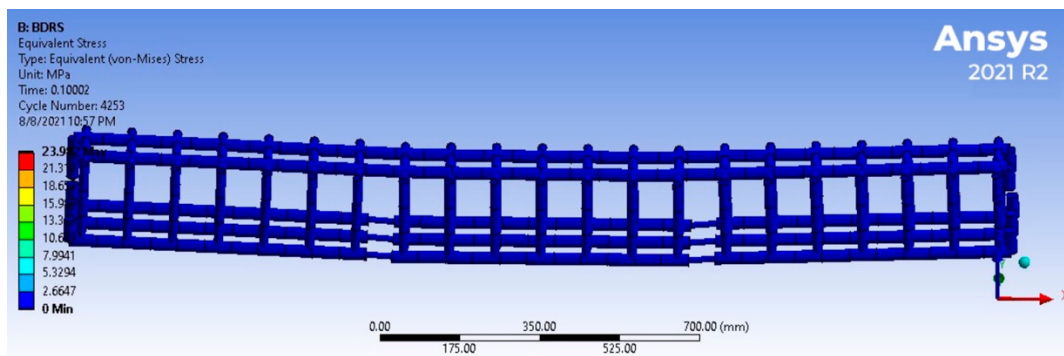


Figure 28. Schematic representation of the SBDRA beam with rebar failure.

5. The Results of the Failure Index of Reinforced Concrete Beams

The failure index serves as a crucial indicator for tracking the evolving failure behaviors of nonlinear structures. Within the realm of structural characteristics, a wide array of indices have been put forth in the literature, encompassing factors like tension, displacement, elastic stress, energy dissipation, stiffness, and dynamic properties. These indices can be categorized into two main groups: cumulative and non-cumulative. Cumulative indices gauge the extent to which failure is contingent on the load range and the number of load cycles. The ultimate failure index is derived by amalgamating these cumulative indices in the context of cyclic loading. In contrast, non-cumulative indices are assessed in conjunction with mechanical parameters, such as displacement, rotation, and curvature. In the literature, there are damage indices that have been established based on the maximum displacement experienced during the loading cycle. The initial index highlights the linear accumulation of failure. First, the parameter β_{ω} is calculated using Equation (3):

$$\beta_{\omega} = c \sum_i \frac{\delta_i}{\delta_f} \quad (3)$$

where:

$$C = 0.1;$$

δ_i : The maximum displacement of the cycle;

Δ_y : The displacement at steel yielding;

δ_f : The displacement of failure time in uniform loading.

The values for extreme cases, where $f(1) = 1$ and $f(0) = 0$, can be determined using Equation (4):

$$D = \frac{e^{n\beta\omega} - 1}{e^n - 1} \quad (4)$$

The second index is computed by summing the plastic displacement ratios for $n = 1$ at the reinforced nodes and $n = -1$ for other states, as defined using Equation (5):

$$D = \sum \left(\frac{\Delta\delta}{\Delta\delta_f} \right)^{1.77} \quad (5)$$

where:

$\Delta\delta_+$: A positive increase in plastic displacement;

$\Delta\delta_f$: 10%.

The categorization of the structural response to varying levels of displacement is determined by the failure threshold range, as follows: When the failure index falls within the range of 0 to 0.1, no structural breakdown occurs at that specific point of displacement. For failure indices within the range of 0.1 to 0.25, the response is characterized as a low level of failure. In the event that the failure index is within the range of 0.25 to 0.4, it signifies a state of moderate failure at that particular displacement point. For failure indices ranging from 0.4 to 0.8, the response is classified as a severe failure. When the failure index reaches the range of 0.8 to 1, it indicates a condition of structural collapse. This categorization of failure thresholds provides insights into the progressive deterioration and response of the structure under different levels of displacement. The sample index is depicted as linear curves, indicating an assumed linear progression of failure. The failure threshold is illustrated in Figure 29.

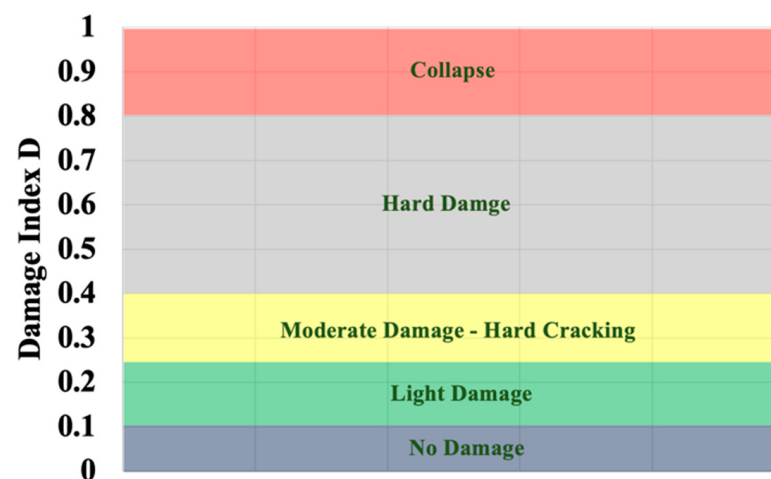


Figure 29. The range of the failure threshold based on the failure index D.

Figures 30 and 31 depict the failure index plotted for all the samples. In this context, a lower ascending slope indicates that the beam is less damaged and exhibits greater deflection tolerance, resulting in a lower failure index. Consequently, the CB and SBDCM (10-3) specimens display the lowest failure index graph slope, while the BDRA and SBDRS specimens exhibit the highest failure index graph slope, signifying the most severe form of failure among the existing failure modes. Furthermore, the failure index slope varies across the other specimens featuring distinct types and sizes of failure.

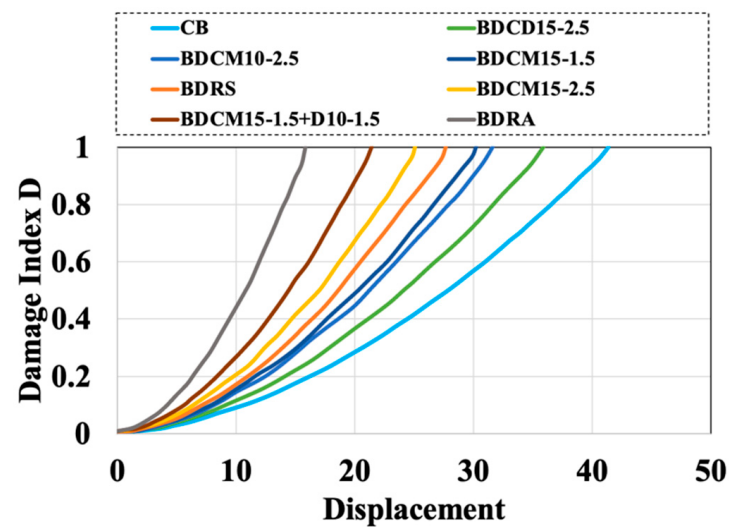


Figure 30. Diagram of the failure index of beams without FRP tested in terms of vertical displacement.

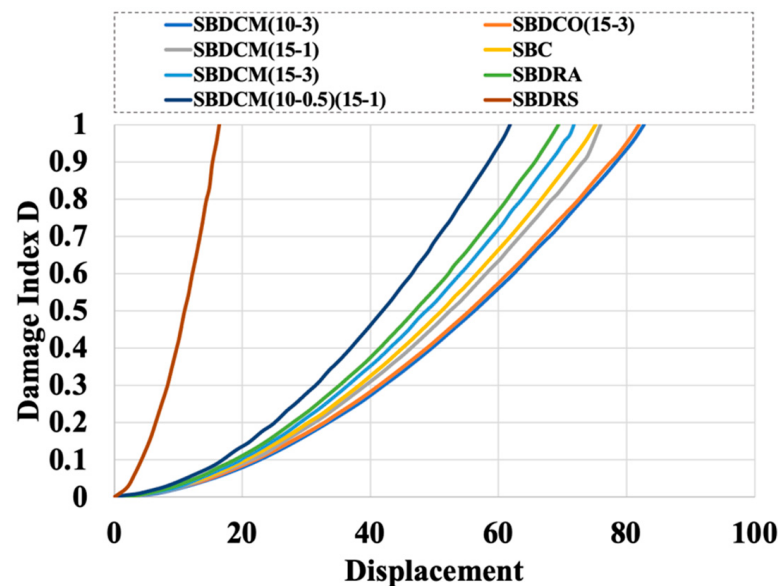


Figure 31. Diagram of the failure index of beams with FRP tested in terms of vertical displacement.

6. Conclusions

The analysis of RC beams involves the utilization of image processing techniques, specifically KNN and SVM. By highlighting the cracks formed on the beams in red, the images are fed into the developed MATLAB software for training. The accuracy of the software is tested for three defined categories:

- In the first category, the software is trained with 15 beams, and one remaining beam is used for damage detection.
- The second category involves eight beams from each category and an opposite category for damage detection.
- The third category assigns seven beams from each category for training, with one remaining beam compared to its category.

It is noteworthy that SVM yields considerably more accurate results compared to KNN, making the responses in the first category significantly more acceptable. The analysis of the images depicting the growth of RC beam cracks reveals that the cracks exhibit high continuity at the location of the beam failure, extending vertically towards the top of the beam. In cases of concrete failure, crack branching is predominantly higher in the images.

Additionally, the use of FRP reduces the continuity of the cracks. Increasing the number of specimens in the training categories results in improved accuracy in identifying the location and type of failure. The analysis underscores the importance of the imaging quality in conjunction with the two methods. It is worth mentioning that the SVM method demonstrates superior performance, particularly in normal and medium-quality imaging scenarios.

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