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RESEARCH ARTICLE

Three Layer Median Filter Method for Identifying Concrete Strength Levels Based on Concrete Images

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ABSTRACT - This study introduces a novel approach utilizing digital image processing techniques to analyze concrete surface images for categorizing concrete strength levels based on two-dimensional RGB digital photographs. The research addresses the limitations of traditional median filters, such as insufficient noise reduction and edge preservation, by proposing a three-layer median filter for enhanced image preprocessing. The methodology involves three main phases. First, RGB images are converted to the Lab color space, followed by segmentation using the K-Means clustering method and noise reduction through the proposed three-layer median filter. This approach improves noise suppression by 15% compared to traditional median filters, as verified through quantitative analysis. Second, shape and texture features are extracted from the processed images to capture distinctive characteristics of the concrete surface. Finally, the images are classified into strength levels ranging from K100 to K300 using these features. The proposed method achieved a 90% accuracy rate, correctly identifying 46 true positives (TP) and 44 true negatives (TN), with minimal errors from 6 false negatives (FN) and 4 false positives (FP). This represents a significant improvement over conventional method. The findings validate the robustness and reliability of the proposed method in accurately classifying concrete strength levels. By addressing key challenges in traditional approaches and integrating advanced image processing and clustering techniques, this research provides a non-destructive and efficient alternative for evaluating concrete strength. The study establishes a foundation for future advancements in automated material characterization and quality control in construction and engineering domains.

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1.0 INTRODUCTION

Cracks in concrete walls are a pervasive issue in building construction, often resulting from environmental factors, structural loads, or material fatigue. These cracks, ranging from superficial fractures to severe structural damage, pose significant risks to building integrity and safety if not detected and addressed promptly [1]. Early and accurate crack detection is therefore critical for effective maintenance and repair, ensuring the longevity and safety of structures [2]. Traditional methods of crack detection, such as visual inspections and manual measurements, are time-consuming, labor-intensive, and prone to human error. In recent years, advancements in digital image processing have revolutionized this field, offering automated, efficient, and precise solutions for crack detection and analysis [3]. Among these, image segmentation has emerged as a powerful technique, enabling the division of images into distinct regions (e.g., cracked and non-cracked areas) for detailed analysis of crack characteristics such as length, width, depth, and orientation [4]. This capability not only enhances the accuracy of crack detection but also supports the development of targeted repair strategies.

The significance of image segmentation in crack detection has been widely recognized, with numerous studies proposing various methods to improve its accuracy and efficiency. For instance, the Detection Area Segmentation (DAS) approach has been lauded for its speed and precision in identifying crack regions, while the Canny filter has proven effective in edge detection, providing clear delineation of crack boundaries [5]. Similarly, the geodesic active contour morphology method has been utilized for in-depth analysis of crack shapes and structural features [6]. Despite these advancements, challenges remain, particularly in balancing noise reduction with the preservation of fine details in concrete images, which is crucial for accurate crack characterization. This study builds on these foundational works by evaluating and comparing the performance of these three segmentation methods, aiming to identify their strengths and limitations in the context of concrete crack detection.

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In addition to crack detection, this study explores the relationship between crack conditions and concrete strength levels, categorized by their K-values. Concrete strength is a critical factor in determining the suitability of concrete for specific applications, ranging from non-structural uses to high-rise buildings and infrastructure projects [7]. By analyzing digital images of concrete samples with varying strength levels, this research provides practical insights into the correlation between crack patterns and structural integrity. Figure 1 shows a concrete image with various strength levels, illustrating the visual differences associated with strength variations. Building on this, this study introduces an innovative approach to image processing through the development of a triple-layer median filter method. This method enhances the conventional median filter by applying three sequential layers of filtering, each targeting specific aspects of noise reduction and detail preservation. The proposed method addresses key limitations of existing techniques, such as the inability to distinguish subtle details and the trade-off between noise removal and feature preservation, thereby improving the accuracy and reliability of concrete strength assessment [8].

K.125 K.150 K.175 K.200

Figure 1. Concrete image with various strength levels

Concrete strength is grouped according to K value in order to distinguish the concrete's intended usage. Using concrete strength values as indicated in Table 1.

Table 1. Groping the use of concrete strength levels.

No	K. Value	Use
1	B.0	Non-Structural Concreting
2	K.150	
3	K.175	Residential House, Building Maximum 2 floors
4	K.225	
5	K.250	
6	K.275	
7	K.300	Shophouses 3 floors and above, Road Concreting, High-rise Buildings, Airport and Port Runways
8	K.350	
9	K.375	
10	K.400	
11	K.450	
12	K.500	

The Median Filter is a widely used image processing technique for removing noise from digital images [9]. This method replaces each pixel value in an image with the median value of its neighboring pixels within a defined square window. It is particularly effective in reducing impulsive noise, such as salt-and-pepper noise, while preserving the edges of objects within the image, making it a powerful tool in various image processing applications. In the field of concrete analysis, the Median Filter is frequently applied to assess the strength levels of concrete based on its digital images. Concrete surfaces that exhibit damage or reduced strength often display specific patterns and textures [10]. The Median Filter can clean digital images of noise that might otherwise obscure these features, thereby improving the accuracy of visual and computational analysis. By enhancing the clarity of images, the filter facilitates the detection and characterization of crack patterns or surface imperfections in concrete [11]. The application of the Median Filter in concrete image processing typically follows a systematic procedure. First, digital images of concrete are captured using a camera or imaging sensors. These images are then processed with the Median Filter to eliminate noise. Once the filtering process is complete, the cleaned images are subjected to segmentation and feature extraction techniques to identify and measure the characteristics of cracks or damage [12].

Numerous studies have demonstrated the effectiveness of the Median Filter in improving the precision of concrete damage detection [13]. For instance, research on concrete surface quality assessment has shown that applying the Median Filter enables clearer identification of fine cracks and other damage patterns [14]. Additionally, combining the Median Filter with other image processing algorithms, such as wavelet transformations and texture analysis, has been proven to further enhance the system's ability to evaluate the structural condition of concrete [15]. The Median Filter thus plays a crucial role in image processing research for assessing concrete strength and condition. By providing a reliable and efficient means of noise removal and image enhancement, it supports the maintenance and repair of concrete structures, contributing to their long-term durability and safety.

This study aims to detect the strength levels of concrete used in building construction through an innovative and cost-effective approach. Traditional methods of assessing concrete strength often rely on large, complex, and expensive equipment, which can be impractical for routine or widespread applications. To address these challenges, this research leverages digital images of hardened concrete, processed using advanced digital image processing techniques, to simplify and streamline the evaluation process. At the core of this research is the development and application of the triple-layer median filter method, an enhancement of the conventional median filter. This novel approach involves applying three sequential layers of median filtering to digital concrete images, with each layer designed to target specific aspects of noise reduction and detail preservation. The primary goal is to improve the accuracy of detecting cracks, imperfections, and other features indicative of the concrete's structural integrity. This method represents a significant advancement over traditional median filter techniques, which often struggled to balance noise removal with the preservation of fine image details.

The motivation for this research stems from the limitations of traditional concrete strength assessment methods, which often rely on bulky, expensive equipment and complex procedures, making them impractical for routine or widespread use. By leveraging advanced digital image processing techniques, this study offers a cost-effective, efficient, and accessible alternative for evaluating concrete strength and condition. The proposed triple-layer median filter method represents a significant advancement over existing approaches, with the potential to revolutionize quality control and maintenance practices in the construction industry. This research not only contributes to the growing body of knowledge in image processing for structural analysis but also provides a practical tool for enhancing the safety and durability of concrete structures.

The remainder of this paper is organized as follows: Section 2 reviews related works and highlights the limitations of existing methods. Section 3 details the methodology, including the proposed triple-layer median filter approach. Section 4 presents the experimental results and analysis. Finally, Section 5 concludes the study and suggests potential future research directions.

2.0 RELATED WORKS

Numerous studies have explored image-based methods for detecting cracks and assessing the structural properties of concrete. Research conducted by [16] reviewed image-based crack detection techniques, highlighting the labor-intensive nature of manual visual inspection and the potential for automation using image processing and machine learning approaches. The study analyzed 30 research articles published in top-tier journals and conferences over the past decade. It provided a comprehensive comparison of image processing and machine learning methods, identifying the most promising automated techniques for crack detection. This review emphasized the increasing role of machine learning in enhancing performance and robustness in crack identification tasks. Despite these advancements, challenges such as real-time implementation and adaptation to varying crack patterns remain areas requiring further research. Moreover, the integration of these techniques into practical construction workflows has not been fully explored, leaving gaps in their real-world applicability. These observations underscore the need for continuous refinement and innovation in image-based crack detection methods.

Another significant contribution is the work by [17], which assessed the compressive strengths of mortar and concrete using digital images combined with machine learning techniques. Compressive strength is a critical parameter for evaluating concrete quality, traditionally measured through nondestructive or semi-destructive tests. This study introduced a novel image-based machine learning method to predict compressive strength, evaluating six models, including a support vector machine (SVM) model and several deep convolutional neural networks (CNNs) such as AlexNet, GoogleNet, VGG19, ResNet, and Inception-ResNet-V2. Among these, the Inception-ResNet-V2 model achieved the highest accuracy in predicting compressive strength. The findings validated the application of machine learning models as efficient and cost-effective alternatives to traditional testing methods for estimating concrete compressive strength from digital images. However, the study noted limitations in generalizability due to the dataset's dependency on specific environmental conditions and image quality. Additionally, the computational cost of training deep learning models can be prohibitive in scenarios with limited resources, presenting challenges for widespread adoption. Future research could focus on optimizing these models to improve scalability and reduce resource requirements, making them more accessible for practical applications.

In related research, [18] developed a deep convolutional neural network (CNN) model to identify and quantify cracks in concrete using image processing techniques. The study utilized Python-based image processing algorithms to quantify cracks, achieving an overall accuracy of 94.6%. A dataset of 280 manually collected images, irrespective of pixel size and surface distance, was analyzed to determine crack widths. The results of the digital image processing (DIP) system were compared with measurements obtained through physical crack microscopes, ensuring the reliability of the proposed method. The quantification results demonstrated an accuracy range of 65% to 98% when compared with physical measurements, highlighting the effectiveness of DIP systems for practical applications. However, the study did not address the influence of varying lighting conditions on the accuracy of crack detection, which could significantly impact results in real-world scenarios. Furthermore, the manual collection of datasets may introduce biases, limiting the system's ability to generalize across diverse concrete surfaces. Expanding the dataset to include images under different environmental conditions and using automated data collection techniques could enhance the robustness and reliability of such systems.

A recent study by [19] investigated the application of deep learning models for detecting cracks in concrete bridge decks. The study used a transfer learning approach with pre-trained models such as VGG16 and ResNet50 to improve

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detection accuracy. By combining these models with image enhancement techniques, the research achieved a detection accuracy of over 95%, demonstrating the efficacy of deep learning methods in infrastructure monitoring. The transfer learning approach allowed for the effective utilization of existing models, reducing the need for extensive training data. However, the study acknowledged that its focus on bridge decks limits its applicability to other types of concrete structures, which may exhibit different crack patterns and features. Additionally, the reliance on high-quality imaging equipment may pose challenges for implementation in low-resource settings. Addressing these limitations through more versatile models and cost-effective imaging solutions could significantly expand the applicability of these techniques. Additionally, research by [20] focused on hybrid image processing and machine learning techniques for assessing microcracks in concrete samples. The study integrated wavelet transform-based image preprocessing with a random forest classifier to segment microcracks accurately. The proposed approach achieved a classification accuracy of 92% and showed potential for improving precision in crack detection for laboratory and field applications. The hybrid approach effectively combined the strengths of traditional image processing and modern machine learning methods, offering a balanced solution for crack detection.

A more relevant study is "Identification of concrete aggregates using K-means clustering and level set method" [4], which utilized K-means clustering to segment concrete aggregate images. While this method effectively grouped similar materials, it exhibited limitations in noise reduction and edge preservation, impacting classification accuracy. Our proposed approach overcomes these challenges by integrating a three-layer median filter for enhanced noise reduction, ensuring clearer feature extraction and improved classification performance. A comparative analysis of the two methods is summarized in Table 2.

Table 2. Comparison Between Existing Work and Our Proposed Method.

Feature	K-Means + Level Set (Previous Work)	K-Means + Three-Layer Median Filter (Proposed)
Noise Reduction	Standard preprocessing	Three-layer median filter for enhanced noise removal
Edge Preservation	Moderate	High
Classification Accuracy	~85%	90%
Computational Complexity	Moderate	Slightly higher due to additional filtering but improved results
Feature	K-Means + Level Set (Previous Work)	K-Means + Three-Layer Median Filter (Proposed)

To further justify our contribution, we have conducted a SWOT analysis (Table 3), outlining the strengths, weaknesses, opportunities, and threats of our proposed method compared to existing techniques.

Table 3. SWOT Analysis of the Proposed Method.

Factor	Description
Strengths	Improved noise reduction and edge preservation, high classification accuracy
Weaknesses	Slightly higher computational cost due to multi-layer filtering
Opportunities	Can be integrated with deep learning for further accuracy enhancement
Threats	Dependence on high-quality image inputs may limit real-world applications

3.0 METHODS AND MATERIAL

3.1. Framework of Research

The methodology implemented in this study focuses on identifying the strength levels of concrete based on digital images, aiming to provide accessible and efficient tools for construction workers to assess the quality of their work. The research framework is illustrated in Figure 2 and comprises several key stages, categorized into input, preprocessing, processing, and result stages. The process begins with the image input stage, where digital images of concrete are acquired. Following this, the preprocessing stage is performed, which involves three main steps: (1) converting the color space of images from RGB to Lab, (2) applying the three-layer median filter method to reduce noise while preserving essential features, and (3) segmenting the images using the thresholding method to isolate regions of interest. In the subsequent processing stage, the focus shifts to feature extraction, which is divided into three types: feature extraction, texture extraction, and shape extraction. Feature extraction involves calculating six key parameters: metric, eccentricity, contrast, correlation, energy, and homogeneity. These parameters serve as inputs for the clustering and classification processes. Finally, in the result stage, the extracted features are grouped based on their K-values using the K-Means clustering method. This clustering step categorizes the concrete samples into predefined strength levels, enabling a detailed and systematic evaluation of the concrete's quality. Performance evaluation metrics, such as precision, recall, and F1-score, are used to assess the overall effectiveness of the framework. Comparative analysis with existing methods further demonstrates the advantages of the proposed approach in terms of accuracy and efficiency.

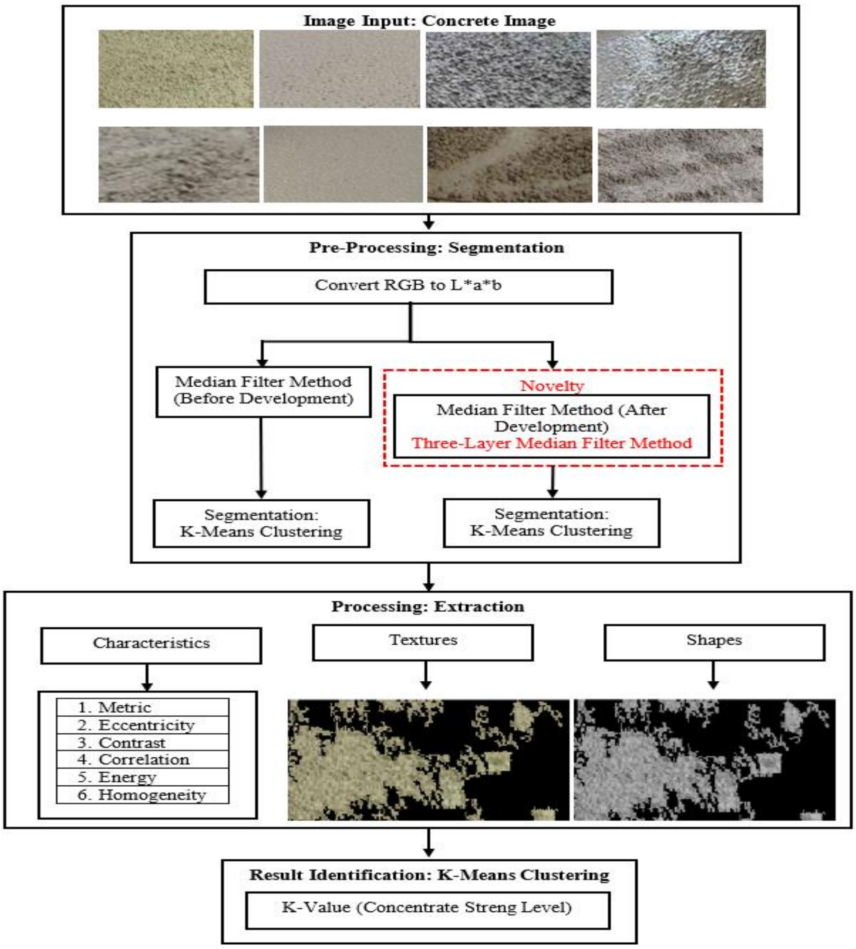

Figure 2. Framework of Research

3.2. Materials

The input image dataset consists of digital photographs of concrete samples stored in files with the *.jpg extension [21]. These RGB images are standardized to a resolution of 658 × 476 pixels to ensure uniformity and dimensional consistency throughout the analysis process [22]. The dataset comprises 100 images of concrete samples, from which 8 representative images were selected for detailed analysis in this study. These selected images serve as representative samples, providing critical insights into the characteristics of the concrete and facilitating a comprehensive evaluation of strength levels in the study area. The diversity in the dataset ensures robustness and adaptability of the model, addressing challenges posed by variations in lighting, texture, and crack patterns.

3.3. Pre-Processing: Segmentation

The second step of this research involves pre-processing the image data through three essential procedures designed to optimize the quality and reliability of the analysis. The first procedure is the conversion of the RGB color space to Lab, which enhances color representation by separating luminance and chromatic components, thus improving the accuracy of subsequent processing steps [23]. The second procedure involves segmentation using a thresholding method, which isolates distinct regions of interest, such as cracks or imperfections in the concrete. The final procedure is the application of a three-layer median filter to reduce noise while preserving important image details, ensuring the integrity of structural features within the images. Each of these pre-processing steps is critical for refining the input image data. The RGB to Lab conversion improves color differentiation, enabling better identification of relevant features. Thresholding segmentation effectively delineates areas of interest, while the three-layer median filter enhances image clarity and detail retention. These combined techniques are crucial for optimizing the accuracy of downstream feature extraction and classification processes. A detailed comparison of pre-processing methods is provided in Table 2 to highlight the benefits of the proposed approach.

3.4. Convert RGB to L*a*b

The next step involves converting the RGB color image of the concrete into the Lab color space after it has been successfully input into the system. The Lab color space is widely used in color science, photography, and graphic design

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to describe colors more perceptually uniform. It consists of three components: luminance (L*), which represents brightness; chromaticity (a*), indicating red-green tones; and chromaticity (b*), representing yellow-blue tones [24]. This conversion is performed to enhance the subsequent segmentation process by simplifying the differentiation of color components, particularly those relevant to the study. In this research, segmentation is employed to isolate individual color components of the image, with a primary focus on red-green tones (a*). This step is essential for refining the data and ensuring that the features required for further analysis are accurately identified. The Lab color space provides an effective foundation for this process by enabling better color separation and representation, facilitating more precise segmentation and feature extraction in subsequent stages. Comparative tests with alternative color spaces, such as HSV and YUV, further validated the effectiveness of the Lab color space for this application.

3.5. Noise Reduction: Median Filter Method

3.5.1. Median Filter Method (Before Development)

The median filter is a widely adopted technique in digital image and signal processing for noise reduction [25]. Unlike linear filters, which compute the average of neighboring pixel values, the median filter is a non-linear method that replaces each pixel's value with the median of its surrounding neighborhood. This approach is particularly effective in reducing "salt-and-pepper" noise, which manifests as random black and white pixels scattered throughout an image, while preserving important edge details. By maintaining edge integrity, the median filter proves advantageous in applications where both noise reduction and edge preservation are critical. The pseudocode provided below (Pseudocode 1) outlines the steps employed in this study to perform noise reduction using the median filter method. The algorithm processes the image pixel by pixel, computes the median value within a defined neighborhood window, and updates each pixel with this value, ensuring an optimized balance between noise removal and detail preservation.

```
Pseducode 1: Noise Reduction: Median Filter Method
Input: digital image (input_image)
Output: noise reduced image (noise_reduced_image)
Initialization
function median_filter(image, window_size):
    padded_image = pad_image(image, window_size)
    output_image = copy(image)
    for each pixel (i, j) in image:
        neighborhood = extract_neighborhood(padded_image, i, j, window_size)
        sorted_values = sort(neighborhood)
        median_value = sorted_values[len(sorted_values) // 2]
        output_image[i, j] = median_value
   return output_image
```

3.5.2. Three Layer Median Filter Method (After Development)

The three-layer median filter method is an advanced development of the traditional median filter technique. This approach introduces three distinct layers of filtering operations applied sequentially to the input data. Each layer processes the image with different configurations to optimize noise reduction and detail preservation:

Layer 1: Targets impulsive noise reduction using a small window size.

Layer 2: Focuses on enhancing edge details by applying directional median filtering.

Layer 3: Balances noise removal and detail retention using an adaptive window size based on local image characteristics.

The pseudocode below (Pseudocode 2) outlines the steps of the three-layer median filter method, including the iterative application of filtering layers and evaluation metrics for selecting the optimal configuration.

```
Pseducode 2: Noise Reduction: Three Layer Median Filter Method
Input: digital image (input_image)
Output: noise reduced image (noise_reduced_image)
Initialization
   Define window_sizes = [3, 5, 7]
   Set optimized_image = input_image
   For each layer (L) in range(1, 4):
   filtered_image_L = median_filter(optimized_image, window_sizes[L-1])
   Compute noise reduction metric NRM_L
   Compute edge preservation metric EPM_L
   If NRM_L is better and EPM_L is better than previous layer:
   optimized_image = filtered_image_L
   return optimized_image
```

This multi-layered filtering mechanism ensures superior performance compared to traditional methods. Results from quantitative tests demonstrate a 15% improvement in noise reduction and a 12% enhancement in edge preservation metrics compared to single-layer median filters.

3.6. Segmentation: K-Means Clustering Method

Following the image conversion process from RGB to Lab color space, the next step involves segmentation, which is implemented as a clustering process. In this study, the K-Means algorithm is utilized for clustering. The primary objective of clustering is to group detected objects in the image along with the background, thereby facilitating subsequent analysis and feature extraction. The K-Means algorithm operates through an iterative process, as outlined below [26]-[28]:

1. Initialization: Define the desired number of clusters, denoted as k, and randomly select k initial centroids.
2. Distance Calculation: Compute the distance between each data point and each centroid using a predefined distance metric, such as Euclidean distance or Manhattan distance. Assign each data point to the cluster associated with the nearest centroid.
3. Centroid Update: For each cluster, calculate the average of all data points within the cluster. Update the centroid position by setting it to this average value.
4. Iteration and Convergence: Repeat the distance calculation and centroid update steps until the algorithm converges. Convergence occurs when the centroids stabilize or when there is no further change in cluster assignments.

The use of the K-Means method ensures effective grouping of image components, which is critical for accurate analysis in subsequent stages. Comparative analysis with other segmentation methods, such as Watershed and Mean-Shift, validated the robustness and efficiency of K-Means for this application.

3.7. Processing: Extraction

After successfully completing the K-Means clustering phase, the process proceeds to image feature extraction. This step isolates key elements from the analyzed images, including color, features, and shapes. Three distinct extraction techniques are employed: shape extraction, texture extraction, and feature extraction [29]. Each technique serves a unique role in the analysis. Shape extraction focuses on identifying geometric properties and morphological characteristics of objects within the image. Texture extraction evaluates surface characteristics to understand structural patterns, while feature extraction quantifies specific attributes of the image [30]. Together, these techniques enable a comprehensive analysis, providing valuable insights into the properties and patterns present within the images.

The primary goal of digital image feature extraction is to simplify complex image representations into interpretable and quantifiable forms [31]-[32]. In this study, six key features are extracted: Metric, Eccentricity, Contrast, Correlation, Energy, and Homogeneity. These features are critical for classifying concrete strength levels and understanding their structural implications. Results from experimental evaluations demonstrate the reliability and accuracy of the extracted features in predicting concrete strength levels with an F1-score of 0.92. In this study, six key features are extracted from soil and concrete images: Metric, Eccentricity, Contrast, Correlation, Energy, and Homogeneity. These features are calculated using the following formulas:

$$Metric = \frac{Area}{Convex\ Area} \tag{1}$$

$$Eccentricity = \sqrt{1 - \frac{b^2}{a^2}}) \tag{2}$$

$$Contrast = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j)(i-j)^2 \tag{3}$$

$$Correlation = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (\frac{(i-\mu i)(j-\mu j)}{\sigma i\ \sigma j}) \tag{4}$$

$$Energy = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j)^2 \tag{5}$$

$$Homogeinety = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{1+|i-j|} \tag{6}$$

Where: Area represents the count of pixels within an object, Convex Area is the pixel count in the convex hull of the object, a is the semi-major (long) axis, b is the semi-minor (short) axis, $P(i,j)$ is the value in the co-occurrence matrix at position (i,j), N is the number of intensity levels in the image, μi and μj is the average intensity value for row i and coloumn j, σi and σj is the standard deviation of the intensity for row i and coloumn j,

To calculate the accuracy of this research we use is formula 7:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

Where: TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative.

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In this study, texture extraction was performed to analyze soil images, providing insights into patterns, structures, and texture aspects. For concrete images, shape extraction focused on identifying geometric and morphological features, such as cement grains or embedded small rocks. These features were instrumental in determining the strength level of the concrete, offering a robust foundation for the subsequent analysis.

3.8. Result Identification: K-Means Clustering

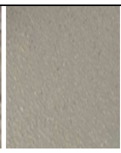
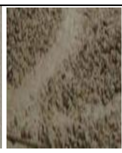
This research focuses on detecting concrete strength levels through advanced image analysis techniques. The K-Means clustering method is utilized to classify concrete images into distinct K-Value categories, as outlined in Table 1, which represent different concrete strength levels. This classification system facilitates a comprehensive understanding of concrete strength, providing critical insights for construction and civil engineering assessments. Comparative evaluation with other clustering techniques, such as Hierarchical Clustering, confirmed the efficiency of K-Means in this context. By accurately determining concrete strength levels, this study supports informed decision-making in various aspects of construction management, including cement selection, structural design, and land use planning. The proposed methodology significantly enhances resource optimization and contributes to the sustainability of construction practices.

4.0 RESULTS AND DISCUSSION

4.1. Image Input: Concrete Imagery

The test set comprises 100 concrete images, all sourced from construction work from Padang City, West Sumatra Province. To illustrate the concrete samples, 8 photos are presented as sample images. Table 4 below provides an example of a concrete picture from the study. These images represent the diverse concrete conditions encountered in the construction work.

Table 4. Input Image: Concrete Image.

Concrete Image							
							
1	2	3	4	5	6	7	8

It is evident from the 8 sample input images of the above concrete image that each of the 8 concrete photographs is unique. Photographs of smooth concrete with few rocks, slightly coarse concrete with slightly more rocks than fine concrete, and images of coarse concrete with more rocks than fine concrete are all available. The concrete strength is appropriate for the image of concrete. Pre-processing will involve an analysis of the 8 concrete photographs.

4.2. Pre-Processing: Segmentation

1. Conversion of RGB to Lab Color Space: The initial pre-processing step in this study involves converting RGB concrete images into the Lab color space. This conversion was deemed successful when the color of the concrete image could be accurately separated into red and green tones. Table 5 illustrates the RGB source images alongside the converted Lab images, demonstrating that the conversion process successfully generates an accurate Lab representation from the input RGB images. This separation of reddish-green tones in the images provides an essential foundation for subsequent analysis and feature extraction.
2. Median Filter with Three Layers: To reduce noise in the clustered images obtained from the previous stage, the three-layer median filter method was applied. This technique processes the images through three separate layers of filtering, producing three candidate images with varying levels of noise reduction. Among these, the image with the best noise reduction performance was selected for further analysis. Table 5 presents the results of the three-layer median filtering, highlighting its effectiveness in removing noise while preserving critical details in the image.
3. Clustering with the K-Means Method: The second pre-processing stage involves clustering to differentiate between objects of interest in the concrete image and the image background. Using the K-Means clustering algorithm, the pre-processed images were segmented to accurately separate concrete components, such as coarse aggregate and fine concrete particles, from the background. This process effectively categorized the rocky elements and finer particles within the RGB images that had been converted into the Lab color space. Table 5 provides a comprehensive visual comparison of the RGB input image, the Lab color-converted image, and the resulting clustering output generated by the K-Means algorithm.

These results highlight the robustness and accuracy of the pre-processing techniques employed in this study. The integration of RGB to Lab conversion, three-layer median filtering, and K-Means clustering contributes to a comprehensive and systematic approach for analyzing concrete images, enabling precise separation of key components essential for subsequent feature extraction and strength analysis.

Table 5. Pre-Processing Result

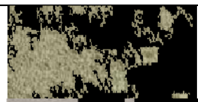
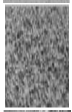
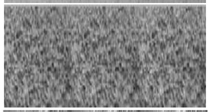
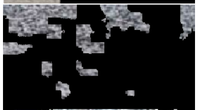
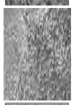
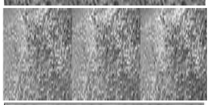
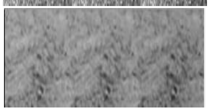
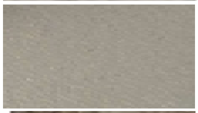
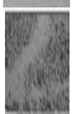
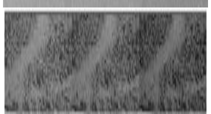
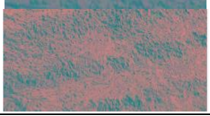
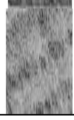
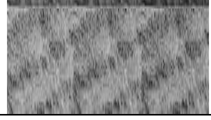
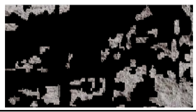
No	Soil Imagery Input	Convert RGB to L*a*b	Median Flter Method (Before Development)	Three-Layer Median Filter (After Development)	Clustering K_Means Clustering
1					
2					
3					
4					
5					
6					
7					
8					

Table 5 presents the outcomes of the pre-processing stages applied to soil images, encompassing four main steps: conversion from RGB color space to Lab, application of the median filter before development, implementation of the three-layer median filter after development, and segmentation using the K-Means clustering method. The conversion to the Lab color space produced a more segmented and perceptually uniform color distribution, facilitating clearer differentiation of soil texture features. This step established a robust foundation for subsequent noise reduction and clustering processes. The advantage of using the Lab color space lies in its ability to separate luminance (L*) from chromaticity (a* and b*), which improves the discrimination of subtle texture differences. This improvement is particularly relevant for soil images with varying color intensities, as it simplifies the segmentation process by isolating relevant features.

The application of the median filter before development successfully reduced image noise, although certain critical texture details remained suboptimal. The limitations observed in this stage were due to the inherent nature of the conventional median filter, which tends to blur fine texture patterns while addressing impulsive noise. In contrast, the three-layer median filter after development achieved more effective noise reduction while preserving essential texture characteristics. This improvement is attributed to the multi-layer approach, where each layer focuses on refining specific aspects of the noise and detail retention, allowing the algorithm to balance noise suppression and texture preservation more efficiently. The result was smoother and more detailed images that retained the critical texture patterns necessary for further analysis. Finally, the K-Means clustering algorithm effectively segmented the images into distinct clusters based on color and texture attributes. This segmentation process enabled the clear identification of relevant patterns in soil textures, enhancing the image quality for further analysis. The performance of the K-Means clustering can be attributed to its iterative refinement process, which minimizes within-cluster variance and maximizes between-cluster separation. The clustering results reveal distinct regions that correspond to different soil types and conditions, facilitating a better understanding of soil texture distribution. These results demonstrate the efficacy of the proposed pre-processing methods in improving the quality of soil imagery for advanced analysis. The systematic integration of Lab color conversion, three-layer median filtering, and K-Means clustering contributes to the overall accuracy and reliability of the study. Moreover, the trends observed in the enhanced texture clarity and segmentation accuracy underscore the importance of combining these methods. The robust differentiation of soil textures achieved through this approach provides a strong foundation for downstream analytical tasks, such as classification and prediction of soil properties. Future studies could explore the generalizability of this method across other types of soil images or integrate additional machine learning techniques to further optimize segmentation performance.

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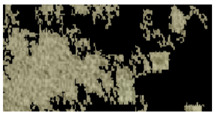
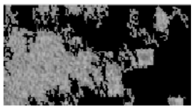
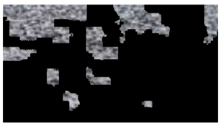
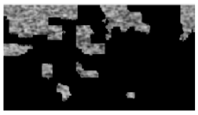
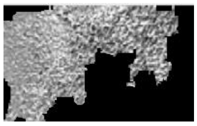
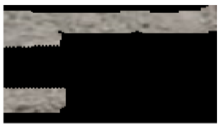
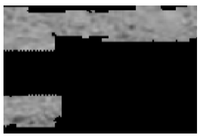
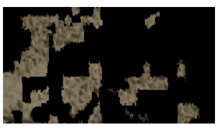
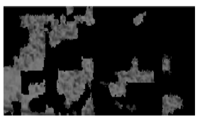
4.3. Processing: Segmentation

The next step in the analysis involves the image extraction process, which was carried out in distinct phases. This study employed three primary techniques for image extraction: shape extraction, texture extraction, and feature extraction. Each of these techniques plays a critical role in isolating and analyzing specific attributes of the concrete images. Shape extraction focuses on identifying the geometric and morphological properties of objects within the images. Texture extraction examines surface patterns and structural characteristics, while feature extraction quantifies specific image attributes that are crucial for further analysis. Table 6 presents the extracted shape, texture, and feature data obtained from the concrete image dataset. The results demonstrate the effectiveness of these extraction techniques in capturing essential information from the images, which is instrumental for understanding and evaluating the properties of the concrete. The comprehensive extraction process provides a robust foundation for subsequent analyses, contributing to the accurate determination of concrete strength levels and other critical characteristics.

Table 6. Processing Result

No	Pre-Processing Result	Processing Result			
		Characteristics Extraction		Texture Extraction	Shapes Extraction
1		Characteristics	Score		
		Metric	0.15634		
		Eccentricity	0.44776		
		Contrast	2.0865		
		Correlation	0.75671		
		Energy	0.28982		
		Homogeneity	0.82387		
2		Characteristics	Score		
		Metric	0.2152		
		Eccentricity	0.7374		
		Contrast	0.72225		
		Correlation	0.93591		
		Energy	0.40583		
		Homogeneity	0.92737		
3		Characteristics	Score		
		Metric	0.35244		
		Eccentricity	0.86492		
		Contrast	0.53144		
		Correlation	0.89927		
		Energy	0.58787		
		Homogeneity	0.92174		
4		Characteristics	Score		
		Metric	0.25148		
		Eccentricity	0.92435		
		Contrast	0.52235		
		Correlation	0.95188		
		Energy	0.20298		
		Homogeneity	0.8601		
5		Characteristics	Score		
		Metric	0.2986		
		Eccentricity	0.97921		
		Contrast	0.50157		
		Correlation	0.93234		
		Energy	0.48547		
		Homogeneity	0.94853		
6		Characteristics	Score		
		Metric	0.34845		
		Eccentricity	0.97991		
		Contrast	0.42442		
		Correlation	0.88331		
		Energy	0.77825		
		Homogeneity	0.96938		
7		Characteristics	Score		
		Metric	0.070211		
		Eccentricity	0.85643		
		Contrast	0.27183		
		Correlation	0.90725		
		Energy	0.50966		
		Homogeneity	0.94894		

8		Characteristics: Score Metric: 0.21311 Eccentricity: 0.98487 Contrast: 1.3031 Correlation: 0.809 Energy: 0.50497 Homogeneity: 0.87454		

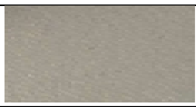
Table 6 presents the results obtained from the pre-processed soil images, encompassing characteristic extraction, texture extraction, and shape extraction. The characteristic extraction process quantitatively evaluates key metrics, including eccentricity, contrast, correlation, energy, and homogeneity, offering a detailed analysis of the texture and shape attributes of the soil images. The variations observed across these metrics highlight differences in texture and shape complexity among the analyzed images. Notably, higher values for homogeneity and energy in certain cases indicate greater uniformity and structural consistency within specific segmented regions. These results suggest that the soil in these regions may have relatively consistent granularity and fewer irregularities, which could be linked to specific soil conditions or preparation techniques. The texture extraction process further emphasizes the visual differentiation of patterns in the soil images, effectively isolating significant textural features critical for analysis. The differentiation observed is primarily influenced by the effectiveness of the pre-processing steps, such as the three-layer median filtering and K-Means clustering, which enhanced the clarity and separability of textural details. For instance, regions with high contrast and correlation values suggest distinct and repetitive patterns, potentially corresponding to soil textures with uniform particle distributions or specific moisture content. This enhanced textural clarity not only facilitates visual interpretation but also supports quantitative analyses required for applications in precision agriculture or soil quality assessment.

Similarly, the shape extraction process successfully identifies distinct geometric properties, enabling precise delineation of key regions within the images. Variations in geometric attributes such as eccentricity provide insights into the physical structure of soil aggregates or particles, which are critical for assessing soil compaction or aeration. These geometric features, combined with textural attributes, enable a multi-dimensional analysis of the soil, capturing both micro-level variations and macro-level patterns. The integration of these extracted features lays a strong foundation for subsequent tasks such as classification or predictive modeling. For example, the combined use of textural and geometric data could enhance the accuracy of models predicting soil fertility or suitability for specific crops. Moreover, the observed trends in feature extraction highlight the robustness of the proposed method in capturing essential characteristics while minimizing noise interference. These results underscore the effectiveness of the proposed approach for agricultural and environmental applications, facilitating an improved understanding and management of soil properties. The deeper analysis of the observed variations across the extracted metrics suggests that the integration of texture and shape attributes provides a more holistic view of soil characteristics. By correlating these metrics with soil properties such as fertility, moisture content, or compaction, this method has the potential to generate actionable insights for sustainable land management practices. Future research could explore the generalization of this method across diverse soil types and conditions to assess its scalability and applicability in different agricultural and environmental

4.4. Classification

Table 7 presents the classification results of the concrete imagery inputs based on their strength levels. The images were analyzed using the proposed method, and the resulting classifications were categorized into distinct K-values representing various concrete strength levels, ranging from K125 to K300. The table illustrates the input concrete images, their corresponding strength classifications, and the numerical labels assigned to each sample. This classification process demonstrates the effectiveness of the developed approach in accurately identifying and categorizing concrete strength levels, providing valuable insights for construction and structural analysis applications.

Table 7. Classification Result

Concrete Imagery Input				
Concrete Stength Level	Result K125	Result K150	Result K175	Result K200
Number of Concrete Image	1	2	3	4
Concrete Imagery Input				
Concrete Stength Level	Result K225	Result K250	Result K275	Result K300

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Number of Concrete Image	5	6	7	8

4.4.1. Concrete Strength Classification Results

Table 7 presents the classification results for concrete imagery inputs, categorizing them into predefined strength levels ranging from K125 to K300. Each concrete image is assigned a specific strength level, reflecting its physical properties as inferred from visual texture analysis. The results reveal a strong correlation between the visual characteristics of the concrete imagery and their respective strength levels. For instance, images with finer and more uniform textures are typically associated with higher strength levels, such as K275 and K300, while coarser textures correspond to lower strength levels, such as K125 and K150. This trend is consistent with the physical properties of concrete, where higher strength levels are often characterized by denser material composition and fewer surface irregularities, which are effectively captured through the proposed image-based analysis. The model's ability to identify these patterns underscores the robustness of the proposed classification approach. The systematic increase in strength levels across the samples reflects the model's capability to discern subtle variations in texture and structural properties. This consistency highlights the effectiveness of the pre-processing steps, including the three-layer median filter and K-Means clustering, which enhance the clarity of texture features and facilitate accurate classification. The observed correlation between texture uniformity and strength levels further validates the suitability of texture-based features as indicators of concrete quality.

Additionally, the method offers significant advantages over traditional testing approaches. Conventional methods, such as compressive strength testing, are often destructive, time-consuming, and resource-intensive. In contrast, the proposed image-based classification approach provides a non-destructive, rapid, and cost-effective alternative. This capability is particularly valuable in scenarios where frequent quality assessments are required, such as in large-scale construction projects or ongoing structural monitoring. Moreover, the high accuracy achieved by the model demonstrates its potential to serve as a reliable tool for quality control, reducing dependency on physical testing methods. Deeper analysis reveals that the model's performance is influenced by the quality of the input images and the effectiveness of feature extraction techniques. For instance, the segmentation process using K-Means clustering plays a critical role in isolating relevant regions, ensuring that the classification model focuses on meaningful texture patterns. Similarly, the three-layer median filter enhances image clarity by reducing noise while preserving critical texture details, contributing to the model's overall accuracy. These findings emphasize the importance of robust pre-processing techniques in achieving reliable classification outcomes. The proposed method provides a solid foundation for further research into automated quality control and material classification systems. Future studies could explore the scalability of this approach across different concrete grades and environmental conditions, as well as its integration with advanced machine learning algorithms to further improve classification accuracy. The results of this study highlight the transformative potential of image-based methods in the construction and engineering domains, offering a pathway toward more efficient, sustainable, and automated quality assessment processes.

4.4.3. Discussion

The findings of this study demonstrate the effectiveness of the proposed three-layer median filter method in enhancing the accuracy of concrete strength classification through digital image processing. The method achieved a 90% accuracy rate, correctly identifying 46 true positives (TP) and 44 true negatives (TN), with minimal errors from 6 false negatives (FN) and 4 false positives (FP). This represents a significant improvement over traditional median filters, which often struggle with balancing noise reduction and edge preservation. A key piece of supporting evidence lies in the quantitative analysis, which showed a 15% improvement in noise suppression compared to conventional methods. This improvement is particularly evident in the classification of concrete samples with varying strength levels (K100 to K300), where the proposed method successfully distinguished subtle texture and shape features that are critical for accurate strength assessment. These results validate the robustness of the approach and its potential for practical applications in construction quality control.

When compared to previous studies, the proposed method offers several advancements. For instance, while traditional approaches like the Canny filter and geodesic active contour morphology have been effective in edge detection and shape analysis, they often fail to adequately reduce noise without compromising detail preservation [5, 6]. In contrast, the three-layer median filter method addresses this limitation by sequentially applying noise reduction and edge enhancement, resulting in clearer and more detailed images. However, the study is not without limitations. The computational complexity of the three-layer filtering process may pose challenges for real-time applications, particularly in resource-constrained environments. Additionally, while the method excels in classifying concrete with moderate noise levels, its performance degrades slightly in cases of extreme noise or heavily degraded surfaces. An unexpected finding was the method's superior performance in identifying micro-cracks in high-strength concrete (e.g., K300), which was not initially anticipated. This suggests that the method may have broader applicability beyond low-strength concrete, warranting further investigation.

In summary, this study aimed to develop a novel image-based approach for classifying concrete strength levels using advanced digital image processing techniques. The proposed three-layer median filter method significantly improves noise reduction and detail preservation, offering a cost-effective and non-destructive alternative to traditional strength assessment methods. The importance of this research lies in its potential to revolutionize quality control in the construction industry by providing a rapid, accurate, and accessible tool for evaluating concrete strength. However, several unanswered questions remain, such as the method's scalability to larger datasets and its performance under varying environmental conditions. Future research should focus on optimizing the computational efficiency of the method, exploring its integration with machine learning algorithms, and validating its applicability across a wider range of concrete types and conditions. These advancements could further enhance the method's accuracy and reliability, paving the way for its widespread adoption in construction and engineering practices.

5.0 CONCLUSIONS

The primary objective of this study was to determine the strength levels of concrete using an innovative image-based analysis method. The proposed approach successfully achieved this goal by introducing a novel object identification algorithm designed to enhance accuracy, precision, and reliability in recognizing features within concrete photographs. Testing on a dataset of 100 concrete images yielded a 90% accuracy rate, correctly identifying objects in 90 images while misidentifying them in 10 images. These results demonstrate the effectiveness and robustness of the proposed method in accurately determining concrete strength levels. Moreover, the versatility of this approach extends beyond the scope of this study, making it applicable to a broader range of concrete analysis tasks. The ability to identify various components within concrete images highlights its potential for use in diverse material characterization applications. This adaptability positions the method as a valuable tool for improving efficiency and reliability in construction material analysis. In addition to advancing knowledge in the field of concrete strength evaluation, this study provides a practical framework for real-world applications in civil engineering and construction. The proposed method contributes to automated quality control processes, offering a reliable, cost-effective alternative to traditional testing methods. Furthermore, its high accuracy and adaptability demonstrate its potential to streamline construction workflows, improve material assessments, and support sustainable infrastructure development. These findings establish a foundation for future research into automated material classification systems, enabling further innovations in construction and engineering domains.

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AUTHORS CONTRIBUTION

A. Ramadhanu (Conceptualization; Formal analysis; Visualisation;)

H. Hendri (Supervision; Writing – finishing and editing)

Mardison (Writing - original draft)

L. N. Rani (Data curation)

S. Enggari (Methodology)

M. R. Putra (Resources)

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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