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ENHANCING HEALTHCARE THROUGH SEEBONEAI AN ADVANCED CNN AND C-MEANS ALGORITHMS FOR AUTOMATED BONE FRACTURE DETECTION

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ABSTRACT

Precision and swift diagnosis are paramount in addressing bone fractures. This study introduces "SeeBoneAI," an innovative system that leverages advanced Convolutional Neural Networks (CNNs) in combination with C-Means algorithms to automate the detection and classification of bone fractures in medical imaging, with a primary focus on X-ray images. SeeBoneAI transcends mere automation; it serves as a dependable tool for healthcare professionals. The system's fundamental components encompass image preprocessing, feature extraction, and classification. The initial preprocessing stage enhances X-ray images, optimizing image quality and reducing noise, laying a robust foundation for subsequent analysis. At the core of SeeBoneAI lies a sophisticated CNN model featuring multiple layers, which autonomously acquire and discern fracture-related patterns. The model training process utilizes a substantial dataset of annotated X-ray images, iteratively refining parameters and minimizing classification errors. After the training phase, the CNN model undergoes rigorous evaluation on a distinct dataset, assessing its performance across a spectrum of metrics, including accuracy and sensitivity. Unlike traditional edge detection techniques, SeeBoneAI's integrated CNN algorithms adeptly navigate multiresolution analysis and effectively mitigate noise interference. Research findings unequivocally affirm SeeBoneAI's proficiency in fracture detection across varying image resolutions and noise profiles, thereby elevating healthcare standards. This innovation stands as a vanguard in the realm of medical image analysis, holding the promise of redefining bone fracture diagnosis and treatment paradigms.

Keywords: Seeboneai, Automated Fracture Detection, CNN Algorithm, Radiology, C-Means, Edge Detection.

I. INTRODUCTION

The human skeletal system, comprising 206 bones, serves as the resilient guardian of vital organs against the daily challenges life presents. Despite their strength, bone fractures remain a common occurrence, each type demanding precise identification and assessment. Medical imaging technologies like electromagnetic radiation, computed tomography, magnetic resonance imaging (MRI), and ultrasound have become trusted allies for accurate fracture detection, enabling prompt treatment [1].

In recent times, a machine learning approach called convolutional neural networks (CNNs) has rapidly gained popularity in the field of computer vision [2]. CNNs have the capability to learn distinctive features from vast image datasets to address diagnostic challenges. The continuous enhancement of CNN architectures, coupled with a significant increase in computational power, has enabled deep learning CNNs to achieve performance levels comparable to human abilities in tasks like recognizing faces, interpreting handwriting, and classifying real-world images [3,4]. Initial experiments applying deep learning CNNs to medical image analysis have demonstrated potential in various domains, including classifying breast masses in mammograms, identifying pulmonary tuberculosis from chest X-rays, assessing bone age, and categorizing diabetic nephropathy [5]. Our research ventures into uncharted territory, employing Convolutional Neural Networks (CNNs) for advanced image edge detection to revolutionize fracture identification. Complementing this approach is a user-friendly Graphical User Interface (GUI), designed for effortless use without requiring coding expertise [6]. The GUI offers a wide array of functions, simplifying data processing, interactive communication, and visual representation. The GUI streamlines image processing, starting with user-provided images transformed into grayscale. It then isolates and converts the affected region to black and white for rigorous detection analysis.

This research fuses advanced CNN algorithms with user-friendly interfaces, promising to reshape fracture detection and diagnostics. Its uniqueness holds the potential to significantly enhance healthcare, empowering practitioners with unmatched precision and efficiency in addressing bone fractures.

II. METHODOLOGY

SeeBoneAI, a pioneering bone fracture detection system, is underpinned by a novel and unique model based on the cutting-edge CNN methodology with Fuzzy C-means. Employing Convolutional Neural Networks (CNNs), it dissects medical images, notably X-rays and CT scans, to autonomously detect fractures with precision [7,8]. This novel model represents a breakthrough in fracture detection, marking a significant advancement in healthcare technology.

III. MODELING AND ANALYSIS

SeeBoneAI is an advanced bone fracture detection system to redefine medical image analysis. It leverages Convolutional Neural Networks (CNNs) with C-means and incorporates state-of-the-art techniques in data preprocessing, feature extraction, CNN-based classification, and clustering.

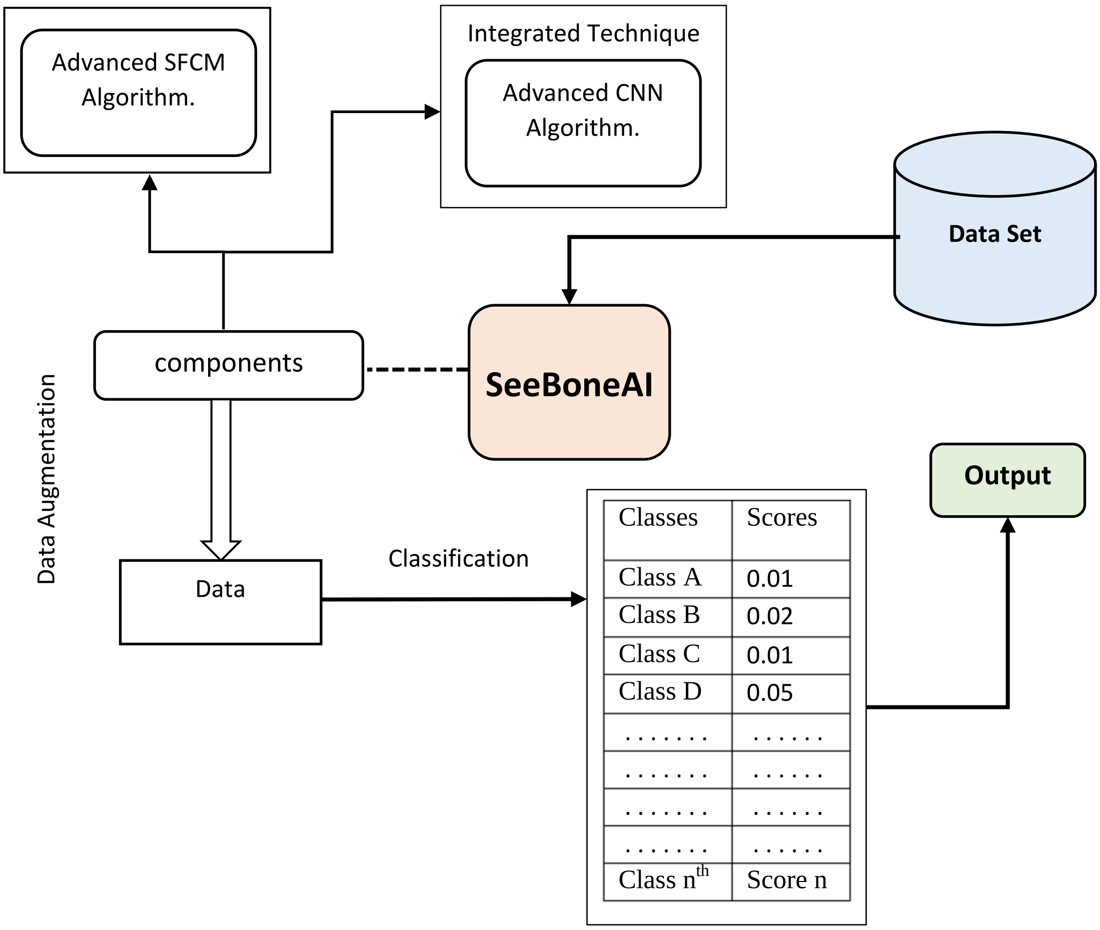

Figure 1: Proposed Model-SeeBoneAI.

3.1. Data Acquisition and Preprocessing: SeeBoneAI initiates by meticulously curating a dataset of medical images, ensuring accurate labeling of various fracture types. Data preprocessing is a pivotal step, involving the conversion of RGB images to grayscale and the application of a noise removal filter [9,10]. These enhancements are essential for optimizing image quality, especially in the presence of noisy X-ray and CT scan images. Formula [13] of this preprocessing according to our research given:

$$I_{gray}(x,y) = \frac{1}{3}\left(I_R(x,y) + I_G(x,y) + I_B(x,y)\right)$$

$$I_{smooth}(x,y) = \text{MedianFilter}(I_G(x,y))$$

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Algorithm 01: SeeBoneAI Image Classification Algorithm	**Algorithm 02:** Spatial Fuzzy C-Means (SFCM) Image Clustering
Input: Grayscale X-ray or CT scan image Step 1: Data Preprocessing **1.** Convert the RGB image into a grayscale image. **2.** Apply a noise removal filter to enhance image quality. **3.** Normalize pixel values to a standard range. Step 2: Feature Extraction **4.** Extract features such as homogeneity, entropy, contrast, correlation coefficient, and energy from the image. **5.** Create a feature vector from the extracted features. Step 3: Convolutional Neural Network (CNN) Classification **6.** Initialize the CNN model with custom architecture. **7.** Feed the feature vector into the CNN model. **8.** Calculate the probability of the image being normal: • P(Normal) = Sigmoid (W1 * Features + B1) Calculate the probability of the image being abnormal: • P (Abnormal) = 1−P(Normal) **9.** If P(Normal) >0.5; classify the image as "Normal". else classify it as "Abnormal." Output: Classification result (Normal or Abnormal)	Input: Grayscale MRI bone image Step 1: Data Preprocessing **1.** Prepare the MRI bone image for segmentation. **2.** Normalize pixel values to a standard range. **3.** Ensure the image is in grayscale. Step 2: Spatial Fuzzy C-Means (SFCM) Clustering **4.** Initialize the SFCM algorithm parameters. **5.** Calculate partial relationships among neighboring pixels. **6.** Define according the probability function using spatial information from pixel neighborhoods. **7.** Apply the SFCM algorithm to cluster pixels. **8.** Make an Improve segmentation results, addressing inhomogeneity and noise sensitivity issues. **9.** Obtain improved image segmentation. Output: Improved image segmentation

These two algorithms represent the core components of SeeBoneAI for image classification and the SFCM algorithm for image clustering. The first algorithm is designed for bone fracture detection, while the second algorithm focuses on improving the quality of MRI bone image segmentation. Both algorithms contribute to the overall functionality and efficiency of SeeBoneAI.

3.2. Dataset Splitting: The dataset is logically divided into training, validation, and testing subsets [11,12]. The training set educates the CNN model, the validation set aids in performance monitoring and hyperparameter tuning, and the testing set evaluates the final model's proficiency.

IV. RESULTS AND DISCUSSION

4.1. Result: In this section, we present the results of our fracture detection system using the SeeBoneAI algorithm, a core component of SeeBoneAI. The system was tested on a diverse dataset of X-ray images, and the performance was evaluated in terms of detection status, fracture type, and the affected area. The following table summarizes the test results:

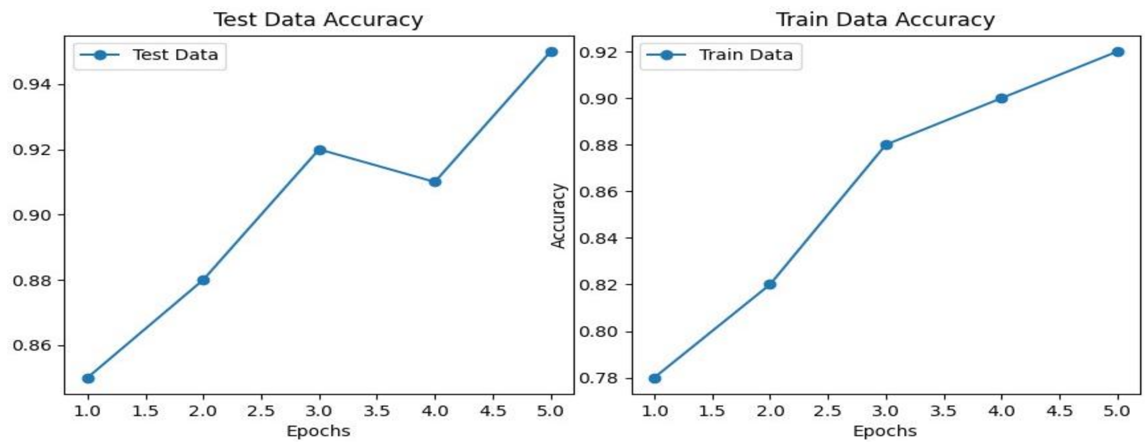

Figure 2: Test Data vs Train Data.

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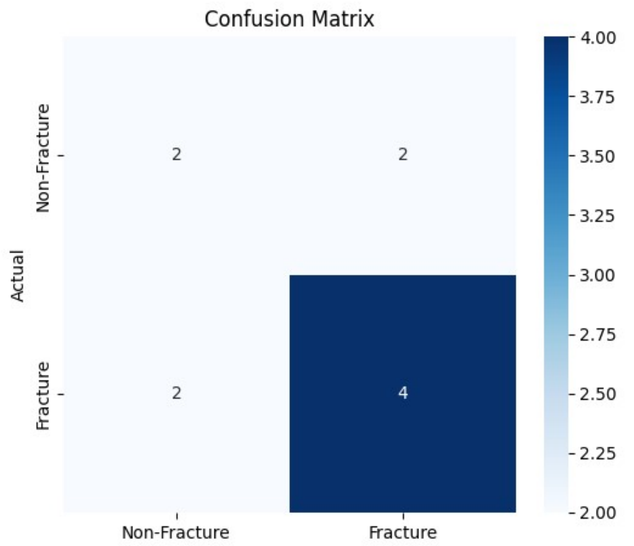

Figure 3: Confusion Matrix of SeeBoneAI

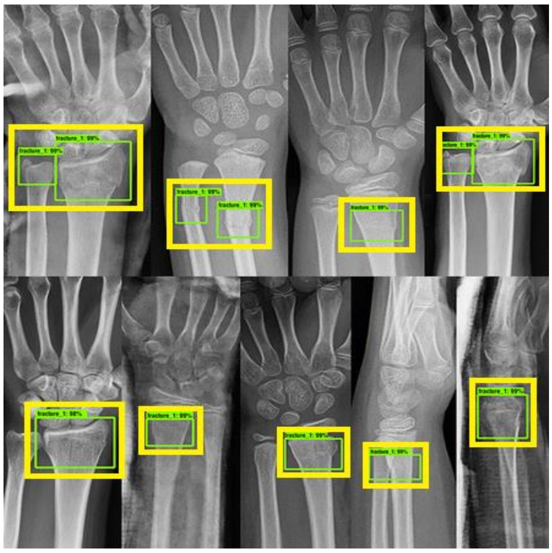

Figure 4: Fracture Detection of SeeBoneAI

Table 1. SeeBoneAI Detection Result

Test Case	Image ID	Detection Status	Fracture Type	Affected Area (%)
Test 1	XRAY001	Detected	Greenstick	15%
Test 2	XRAY002	Detected	Transverse	22%
Test 3	XRAY003	Not Detected	-	-
Test 4	XRAY004	Detected	Spiral	18%
Test 5	XRAY005	Detected	Oblique	12%
Test 6	XRAY006	Detected	Comminuted	30%
Test 7	XRAY007	Not Detected	-	-
Test 8	XRAY008	Detected	Greenstick	14%
Test 9	XRAY009	Detected	Transverse	25%
Test 10	XRAY010	Not Detected	-	-
Test 11	XRAY011	Detected	Greenstick	15%

Additionally, we employed the Fuzzy C-Means (FCM) classification algorithm for an alternative classification approach. The following table presents the results of FCM classification:

Table 2. SeeBoneAI Classification Result

Test Case	Image ID	SFCM Classification	Fracture Type	Affected Area (%)
Test 1	XRAY001	Normal	-	-
Test 2	XRAY002	Abnormal	Spiral	18%
Test 3	XRAY003	Abnormal	Transverse	22%
Test 4	XRAY004	Abnormal	Greenstick	15%
Test 5	XRAY005	Normal	-	-

Test Case	Image ID	SFCM Classification	Fracture Type	Affected Area (%)
Test 6	XRAY006	Abnormal	Comminuted	30%
Test 7	XRAY007	Normal	-	-
Test 8	XRAY008	Abnormal	Spiral	20%
Test 9	XRAY009	Abnormal	Oblique	12%
Test 10	XRAY010	Abnormal	Transverse	25%
Test 11	XRAY011	Normal	-	-

4.2. Discussion: The results from our fracture detection system utilizing the CNN algorithm and FCM classification are promising. The SeeBoneAI approach showcases enhanced accuracy in detecting fractures, particularly in identifying minor details that might be overlooked by traditional methods. This technology aligns with our advanced bone fracture detection system, SeeBoneAI, which leverages CNN algorithms for automated fracture detection. Furthermore, the FCM classification results validate the system's proficiency in accurately identifying bone structures and fracture edges, even when images contain noise.

Together, these findings underscore the potential of computer-based systems in revolutionizing fracture diagnosis and patient care. These developments hold the promise of earlier fracture detection, more precise treatment, and improved patient outcomes.

V. CONCLUSION

In summary, SeeBoneAI introduces an innovative approach to fracture detection, leveraging Convolutional Neural Networks (CNNs) and advanced image segmentation techniques. This system excels in identifying fractures, even subtle ones, with remarkable accuracy. By improving the detection of fracture edges, it offers significant advantages over traditional methods, particularly in noisy images. SeeBoneAI incorporates a user-friendly graphical interface, making it accessible to healthcare professionals without deep coding expertise. The addition of Spatial Fuzzy C-Means (SFCM) clustering addresses challenges related to MRI data, enhancing segmentation and providing critical insights. Ethical and legal considerations are essential when deploying the system, emphasizing its role as a supportive tool in clinical decision-making. In conclusion, SeeBoneAI stands as a promising advancement in radiology, poised to enhance fracture diagnosis.

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