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A Hybrid Framework for Medical X-ray Image Enhancement and Segmentation Using K-Means, Fuzzy C-Means, and Fuzzy Connectivity

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***Abstract* - Accurate medical image processing is essential for clinical diagnosis, as it helps physicians identify conditions early and provide timely treatment. Among its components, medical image segmentation is a particularly important step. However, many existing clustering-based segmentation methods treat image enhancement, segmentation, and spatial refinement as separate tasks. This fragmented approach often results in suboptimal segmentation and reduced anatomical consistency. This study addresses this limitation by introducing an integrated hybrid framework for X-ray image enhancement and segmentation. The proposed approach combines adaptive preprocessing with multi–color-space analysis, applies K-means clustering for initial segmentation, uses Fuzzy C-Means (FCM) to model soft class memberships, and incorporates fuzzy connectivity to refine spatial relationships while preserving anatomical continuity. Experiments on real clinical X-ray images show that K-means offers high computational efficiency, while FCM provides better boundary delineation in areas with unclear tissue transitions. Incorporating fuzzy connectivity further improves segmentation performance by reducing fragmentation and strengthening spatial coherence. Overall, the results demonstrate that the proposed hybrid approach outperforms standalone clustering methods, producing more consistent and anatomically meaningful segmentation results. The developed Python-based graphical user interface facilitates interactive visualization and analysis, highlighting the practical applicability of the framework for research, education, and potential clinical decision-support systems.**

Keywords: Medical Image Segmentation, Image Enhancement, K-Means, Fuzzy C-Means, Fuzzy Connectivity, X-ray Imaging.

I. INTRODUCTION

Image segmentation is an important part of AI and computer vision. It has many uses, such as in medical diagnostics, monitoring crops, and automating factories. In medicine, noise, poor lighting, and low contrast can often make X-rays and MRI scans less clear, which can make it much harder to accurately interpret the results. This shows that there is an urgent need for more advanced computational models that can make images clearer, cut down on noise, and accurately separate anatomical areas [1] [2]. Medical image processing is now an important part of diagnostic imaging. It has greatly improved the accuracy of diagnoses and helped doctors make decisions. Image segmentation is a basic way to analyse images that helps you find important areas of interest, such as bones, soft tissues, or diseased lesions [3]. Segmentation changes raw pixel data into semantically structured representations, making it easier to analyse visual information in a way that is both understandable and measurable.

Clustering algorithms are necessary parts of unsupervised learning methods that are often used in picture analysis. The main goal of these algorithms is to put data points into groups called "homogeneous clusters," where all the points in a cluster have the same qualities [4]. K-Means clustering is a common way to group image pixels based on how similar their colors or brightness levels are. Its "hard" clustering method, which puts each pixel into only one cluster, makes it less useful for medical imaging, since tissue boundaries can sometimes overlap or change slowly [5]. To solve this problem, the Fuzzy C-Means (FCM) method suggests a "soft" clustering approach. FCM works especially well for medical images that have small changes in intensity and complex texture patterns [6]. This is because it lets pixels belong to various clusters with different levels of membership [7]. Pre-processing is very important in the image analysis pipeline. To reduce noise while keeping important edge information, Gaussian, Median, and Bilateral filters are used. Furthermore,

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deliberate conversions to the LAB color space [8], which distinguishes perceived lightness (L) from chromatic components, enhance feature separation and grouping efficacy. This study introduces an enhancement technique based on the Lattice Boltzmann Method (LBM), which optimizes the L channel through edge-guided diffusion to improve illumination uniformity and emphasize structural details [9].

Despite extensive research on clustering-based medical image segmentation, many existing methods struggle with low-contrast X-ray images, overlapping tissue intensities, and limited spatial coherence. Most studies address enhancement, clustering, or refinement separately, leaving a gap for an integrated approach that jointly improves segmentation accuracy, anatomical consistency, and practical usability. The main contributions of this paper are:

(1) The development of a hybrid framework that integrates image enhancement, K-Means clustering, Fuzzy C-Means, and fuzzy connectivity for accurate medical X-ray image segmentation;
(2) The application of fuzzy connectivity to improve spatial coherence and preserve anatomical continuity in challenging X-ray images; and
(3) The validation of the proposed approach on real clinical X-ray images, supported by an interactive Python-based graphical user interface for visualization and analysis.

II. LITERATURE REVIEW

A. Overview of Clustering and Fuzzy-Based Segmentation Methods

The K-Means Clustering Algorithm is a way to divide a dataset into K separate, non-overlapping clusters using centroids. This is a hard clustering method, which means that each data point only goes to the cluster with the closest centroid. The method always makes the sum of squares in each cluster as small as possible [10]:

$$J = \sum_{i=1}^{k}\sum_{j=1}^{n} | x_j - \mu_i |^2 \qquad (1)$$

To update the cluster centroids, the average of the allocated points is used:

$$\mu_j = \frac{1}{|C_j|}\sum_{x_i \in C_i} x_i \qquad (2)$$

The method is easy to use and works well, although it is sensitive to the choice of the first centroid and does not work well with clusters that are not spherical or that overlap [11]. Fuzzy C-Means is a soft clustering extension that lets data points have membership degrees from 0 to 1, which means they can belong to more than one cluster. This strategy works well when the data has fuzzy edges. FCM can be used to minimize weighted objective function [12].

$$J_m = \sum_{i=1}^{N}\sum_{i=1}^{C} u_{\{ij\}}^{m} | x_i - v_j |^2 \qquad (3)$$

Iteratively update cluster centroids and membership data.

$$v_j = \frac{\sum_{i=1}^{N} u_{i\ j}^{m}\, x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \qquad (4)$$

FCM is great at handling overlapping clusters, but it needs more computing power and is more sensitive to noise [13].

All variables used in Equations (1) – (4) are defined as follows: $\boldsymbol{x_j}$ denotes the feature vector of the $\boldsymbol{j^{th}}$ pixel, $\boldsymbol{k}$ and $\boldsymbol{c}$ represent the number of clusters in K-Mean and FCM respectively, $\boldsymbol{\mu_i}$ and $\boldsymbol{v_i}$ denote cluster centroids, and $\boldsymbol{u_{ij}}$ represents the fuzzy membership degree of a pixel to a cluster.

B. Related Work in Medical Image Segmentation

Segmentation of medical images is an important part of computer-aided diagnosis systems and has been studied a lot. Clustering-based methods have become very popular in unsupervised segmentation techniques because they are easy to use and don't need labelled training data [14]. Early studies used strict clustering methods like K-Means a lot. Nonetheless, numerous studies indicate that these methods struggle with overlapping intensity distributions and ambiguous tissue boundaries in medical imaging [8].

Fuzzy C-Means (FCM) clustering usually does a better job than K-Means at separating medical images, especially if the edges are blurry or unclear. FCM works well for things like spotting breast tumours because it's better at handling uncertainty [15]. This means a pixel can kind of belong to more than one group, and group sizes can change. One study showed that K-Means was quicker at separating retinal images, but FCM was more precise. FCM did a better job finding small blood vessels and other tiny details, and it also understood how the tissues worked [16]. These findings suggest to use both methods together. Combining them can get you a system that's both fast and correct at image separation.

The fuzzy concept lets pixels connect based on how alike they are statistically and how strong their links are, not just if they're nearby. This helps keep anatomical info steady, even with tough medical images, while still keeping things spatially consistent. These simple ideas were formalized and used a lot in fuzzy stuff for splitting up 3D medical images, which led to

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adding handy tools to common medical imaging tools like SimpleITK [17].

New studies are trying out mixing different FCM models or using multi-step segmentation to make things more solid. These results tell us that there's no simple solution for all the problems in splitting up medical images, so hybrid systems are becoming common. They mix regular clustering ways with new features, limits, and simple interfaces, deep studies into segmentation methods prove this [18].

FCM has been good at making tissue easier to spot and marking borders in tricky medical imaging like CT scans. Fuzzy setups that think about both location and brightness can use flexible color choices to split up areas, which makes segmentation more accurate [19].

Even with these adjustments, many new studies only test one way of sorting info or just try to simplify systems without really pushing boundaries [20]. This research is special because it's a full, multi-method setup that puts together fuzzy improvements, K-Means clustering, fuzzy C-Means segmentation, and image improvement in one easy visual interface. This all-in-one approach mixes fuzzy models with real medical image tests to build segmentation tools that are better and easier to work with.

III. PROPOSED METHODOLOGY

This study employs a systematic and comprehensive technique to formulate a cohesive strategy for enhancing the segmentation of medical X-ray images. The proposed methodology incorporates pre-processing, color space analysis, clustering-based segmentation, fuzzy logic, and spatial optimization within an interactive computational framework. Algorithm 1 shows the full workflow of the method.

A. Dataset Description and Experimental Setup

To be clinically relevant and accurately assessed, this study used a dataset that was gained through Al-Ghaydah Hospital in Al-Mahrah Governorate, Yemen. The data comprises 30 true clinical X-ray images that belong to different body parts which include the foot, shin, forearm, knee, and thigh. The selection of such pictures was to depict authentic diagnostic challenges, including uneven light distribution, low contrast, noises, overlapping intensity distributions in different body parts. All the pictures were saved in JPEG format with 8 bits depth and three-color channels (RGB).

The picture resolutions were between 460 x 404 pixels and 780 x 1040 pixels which indicate that different equipment was used to take the pictures and the settings were also different to take the pictures. This randomness renders the experimental evaluation to be stricter. Table 1 illustrates a clear understanding of how the photos employed in this study are like. All the experiments were carried out in Python programming language. To simplify the task of users to engage, view and examine the outcome of the experiment Tkinter toolkit was employed to create an interactive graphical user interface (GUI) to make the results easier to view and analyse.

Table 1: X-ray images characteristics

No	Body area	Size	Dimensions
Image 1	Feet	38.48 KB	460*404 px
Image 2	Forearm	39.11 KB	780 *1040 px
Image 3	Shin	32.32 KB	780 *1040 px
Image 4	Thigh	21.46 KB	780 *1040 px

Algorithm 1:

Hybrid Framework for X-ray Image Enhancement and Segmentation

Input: *Medical X-ray image I*
Output: *Refined segmented image S*

Step 1: Image Acquisition

1. $I \leftarrow \text{Input X} - \text{ray image}$

Step 2: Preprocessing

2. *Apply Gaussian or Median filtering:*
$I1 = F_{gm}$
$I_2 = F_{bf}(\boldsymbol{I1})$
3. *Apply Bilateral filtering:*
$$I_2 = \mathcal{F}_{bf}(I_1)$$

Step 3: Image Enhancement

4. *Brightness and contrast adjustment:*
$$I_3 = \mathcal{E}_{bc}(I_2)$$
5. *Lattice Boltzmann Method (LBM)–based enhancement:*
$$I_4 = \mathcal{E}_{lbm}(I_3)$$

Step 4: Initial Segmentation

6. *K-Means clustering (k=3k = 3k=3):*
$$S_k = \mathcal{K}\text{-Means}(I_4, k = 3)$$
7. *Fuzzy C-Means clustering:*
$$S_f = \mathcal{FCM}(I_4)$$

Step 5: Segmentation Refinement

8. *Combine clustering results:*
$$S_c = \mathcal{C}(S_k, S_f)$$
9. *Apply fuzzy connectivity for spatial refinement:*
$$S = \mathcal{FC}(S_c)$$

Step 6: Visualization and Analysis

10. *Display(S)*

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B. Image Preprocessing and Enhancement Techniques

The pre-processing is an important procedure that enhances the image quality before segmentation. To minimize noise and retain significant anatomical edges, in this work three filtering techniques were used:

1. Random noise was suppressed with the help of Gaussian filtering.
2. To eliminate the impulse (salt-and-pepper) noise, a median filtering was used.
3. Bilateral filtering has been used to smooth area portions that are homogeneous and retain edge information.

The brightness and contrast enhancement were done after the removal of noise to enhance the visibility of some fine anatomical structures. Also, a sophisticated enhancement method that is based on the Lattice Boltzmann Method (LBM) was used. The method was applied to L channel of LAB color space and local contrast enhancement is achieved, preserving the color properties of the image. X-ray images are black and white in nature but changing them into other color space can assist you to isolate features and make segmentation stronger.

This experiment involved transformation of pictures into various color spaces e.g., RGB, HSV, LAB and YCrCb. The changes allow obtaining free information on brightness and intensity that can be used in clustering. We have also conducted a statistical analysis with the help of the histograms to observe the way the intensity of the pixels is distributed. This comparison assists us to realize the dissimilarity among soft tissues, background areas, and bones which are the high-density structures.

C. Segmentation Framework

C.1 Initial Segmentation Using K-Means Clustering

In this study, K-Means clustering is used as an initial segmentation step to rapidly partition X-ray images into three coarse regions representing background, soft tissue, and bone. The choice of k=3 reflects the dominant anatomical intensity distributions observed in X-ray images and provides an efficient initialization for subsequent refinement.

C.2 Boundary Refinement Using Fuzzy C-Means Clustering

Fuzzy C-Means clustering is applied following K-Means to refine region boundaries by modelling pixel-level uncertainty. The soft membership assignment improves segmentation performance in areas with overlapping intensities and gradual tissue transitions, which are common in medical X-ray images.

C.3 Spatial Refinement Using Fuzzy Connectivity

Fuzzy connectivity is employed as a final refinement stage to enforce spatial coherence and anatomical continuity. By propagating connectivity from selected seed points based on similarity and spatial consistency, fragmented regions are reduced and anatomically meaningful structures are preserved.

D. Integrated Clustering and Refinement Strategy

K-Means clustering was applied to separate each X-ray image into three major clusters (k = 3). The reason behind such choice is that X-ray pictures tend to present soft tissues, bones, and the background. K-Means simplifies the work with the subsequent steps as it fast and conveniently creates crude categories into which the data is placed.

FCM helped us sub-divide things in a more sophisticated manner, therefore, to avoid the same issues with hard clustering. FCM is more effective with medical images whose edges are not clear or have a fade in and out effect since the pixel can be a member of multiple clusters with varying membership levels. This paper used FCM in classifying item into three groups:

- **Cluster 0:** Extremely quiet and noisy places in the background.
- **Group 1:** Body parts closely related to soft tissues: These are referred to as group 1.
- **Group 2:** very dense places such as the inside of bones, the interior of breaks or things that do not belong there.

This hazy representation allows finding the correct segmentation in the areas where the lines are not clear to be by far simpler to accomplish in comparison to hard clustering techniques. Lastly, fuzzy connectivity was introduced to enhance the anatomical consistency and spatial coherence.

The method requires that the user selects a seed point himself. Fuzzy affinity is subsequently applied to locate regions that are joined by the degree of their resemblance and the consistency of their area. This process removes anatomically inconsistent regions that are either long or do not fit with each other such as the bones or parts of a broken bone. It also leaves the segmentation less fragmented.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this area, we will show, and compare our results with those of another research that are similar.

A. Qualitative and Quantitative Results

Figure 1 illustrates the qualitative findings of the suggested framework for breaking up medical images into

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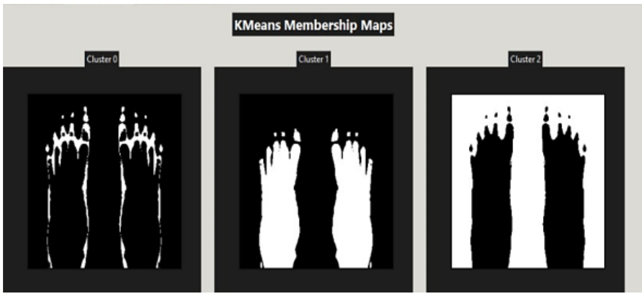
parts. The picture gives a full visual comparison of the several steps in the procedure. More particularly, the original X-ray image, which has low contrast and overlapping anatomical components, is shown. The enhanced image in shows better contrast and sharper bone boundaries after the pre-processing pipeline was used.

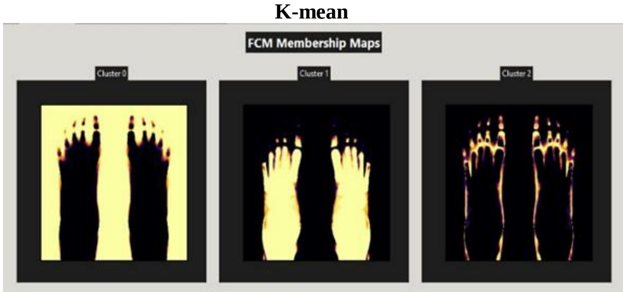
(a) (b)

Figure 1: A side-by-side look at the original and enhanced X-ray images. (a) Original X-ray image and (b) Improved X-ray image after using the suggested preprocessing

After we improved the image, we did a number of color actions, such as altering the color schemes and picking the right color based on the method we had just talked about. Lastly, we used two alternative algorithms to do segmentation operations. We started by using the K-means method with a K value of three. The segmentation behaviour of K-Means and FCM differs significantly (see Figure 2).



K-mean



FCM

Figure 2: Creation of different membership maps for segmenting X-ray images using K-Means and Fuzzy C-Means clustering

The final result from combining FCM with fuzzy connection has better spatial coherence and better preservation of anatomical continuity. This means that the segmentation is more accurate and visually consistent than if it were done using clustering-based methods alone. The latter part of each algorithm is shown in Figure 3.

B. Comparison with Existing Methods

The results of this study are in accordance with the previous studies conducted in medical image segmentation, and it seems that hard clustering algorithms such as K-Means are not optimal for images with overlapping intensity distributions [14], [20]. It has been already shown that K-Means has a tendency of creating different borders and misclassifications in transitional zones [17] which was also observed in the segmentation results of our research. These limitations point out the difficulty in using hard clustering algorithms for medical images with small changes in tissue.

The experimental results demonstrate that while K-Means clustering provides fast and coarse segmentation, its hard assignment strategy leads to abrupt boundaries and frequent misclassification in regions with overlapping intensity distributions. In contrast, Fuzzy C-Means (FCM) achieves superior performance by allowing pixels to belong to multiple clusters with varying membership degrees, resulting in smoother transitions and more accurate boundary representation, particularly around soft tissue and bone interfaces. However, FCM alone may still produce fragmented regions due to noise and local intensity variations.

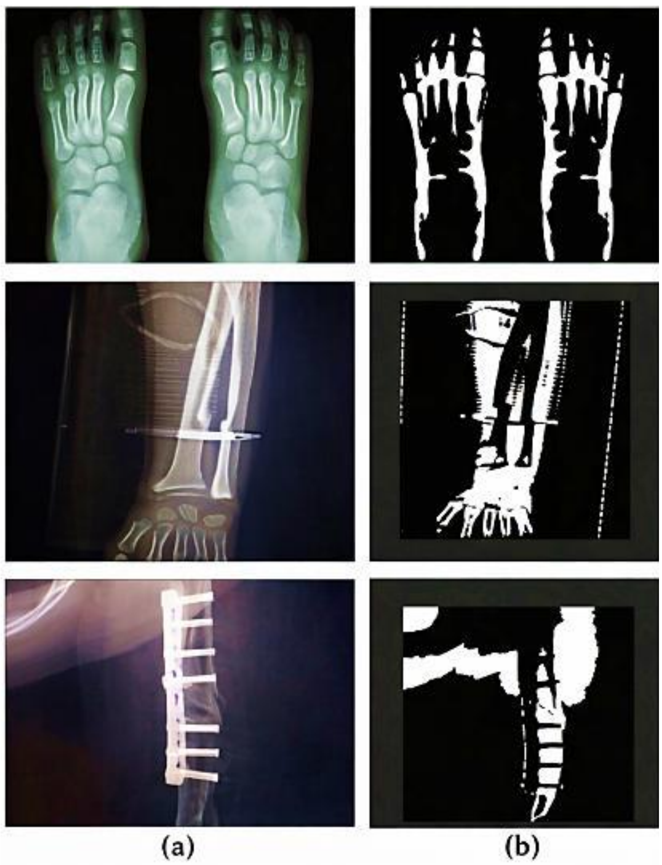


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Figure 3: X-ray image segmentation. (a) Original images, (b) K-means segmentation, (c) FCM segmentation, (d) Fuzzy connection segmentation

The integration of fuzzy connectivity addresses this limitation by enforcing spatial coherence based on pixel similarity and connectivity strength, thereby reducing fragmentation and preserving anatomical continuity. This combined approach produces segmentation results that are both visually consistent and anatomically meaningful, outperforming standalone clustering methods.

V. CONCLUSION AND FUTURE WORK

This study proposes an integrated hybrid framework for enhancing and segmenting medical X-ray images by combining classical image processing techniques with fuzzy clustering and connectivity-based refinement. The proposed method performs effectively for typical problems in medical picture processing including low contrast, noise, and indistinct tissue borders. Experimental results show that K-Means gives fast initial segmentation but FCM gives better boundary representation by using soft membership modelling. Adding fuzzy connection makes the spatial coherence even better and keep the anatomical continuity. Both qualitative and quantitative evaluation approve that the proposed hybrid paradigm produces more reliable and anatomically coherent segmentation results than independent clustering techniques.

Future endeavors will focus on extending the proposed framework to cover larger and more heterogeneous datasets including medical images of multimodal degraded scans such as CT, MRI etc.; to further establish its generalization efficacy. Using automated parameter optimization methods and deep learning-based models such as convolutional neural networks also could help to make segmentation more accurate and independent of manual first initialization. Enhancement of the graphical user interface to facilitate sophisticated interactive analysis and introduction into real clinical scenarios are important opportunities for future studies, with the goal of enhancing usability and adoption in computer-aided diagnostic use cases.

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AUTHOR CONTRIBUTIONS

Conceptualization, K.H.M.B, M.A.A., and A.A.B..; Methodology, A.S.B., and M.O.B.; Validation, M.F.A.; Writing Original Draft Preparation, M.A.A, A.A.B, and M.O.B.; Writing Review & Editing, K.H.M.B. and M.F.A.; Supervision, K.H.M.B. and A.S.B.

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