# Benchmarking K-Means and EM Algorithms for Spine MRI Image Segmentation

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**Abstract—**
This paper offers an in-depth comparative evaluation of the K-means (K-MEANS) and Expectation-Maximization (EM) algorithms for spine image segmentation. The research aims to assess the algorithms' performance regarding accuracy, robustness, and computational efficiency. Utilizing a dataset of spine images, the study compares segmentation outcomes through various quantitative metrics. The analysis reveals the relative strengths and limitations of K-MEANS and EM, providing valuable insights into their effectiveness in clinical applications. These findings support the enhancement of spine image segmentation techniques, contributing to progress in medical imaging and healthcare. 81

***Keywords:*** ***K-Means Algorithm, Expectation-maximization Algorithm, Segmentation accuracy, Computational Efficiency, Comparative study***
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I. INTRODUCTION

Segmenting medical images, especially for spine imaging, is really important in healthcare. It helps doctors diagnose and plan treatments accurately. Lately, algorithms like K-means and Expectation-maximization have become popular for this task. This paper looks at how these two methods compare when it comes to segmenting spine images. Knowing what each method does well, where it falls short, and how they stack up against each other helps improve segmentation results and makes it easier for doctors to decide on the best course of action for patient care.

The Expectation-Maximization (EM) algorithm is a method used to find hidden patterns or unknown factors in data without needing labeled examples. On the other hand, image segmentation is a process in image processing where pixels with similar characteristics are grouped together. Many studies have explored using the EM algorithm for image segmentation. In this paper, we compare how well the EM algorithm works for image segmentation against the K-Means algorithm, which is used as a benchmark.

II. LITURARY SURVEY

The paper introduces an EM-based algorithm for color image segmentation in the Lab color space, utilizing aGaussian mixture model and color distance-based pixel prioritization for enhanced segmentation quality and structural similarity. Its automatic determination of image classes further enhances its practical applicability in image processing tasks.[1] This research introduces Concurrent Spatial and Channel 'Squeeze & Excitation' (SE) in F-CNNs for image segmentation, offering three SE module versions (cSE, sSE, scSE) that enhance segmentation accuracy across different F-CNN architectures. The spatial squeeze and excitation method show superior performance, highlighting SE blocks' potential for improving neural networks in medical applications.[2] The paper's conclusion underscores the successful utilization of wearable fNIRS technology and unsupervised machine learning, particularly k-means clustering, to analyze brain activation and task performance during working memory tasks, highlighting insights into participant segmentation, variations in task performance, cognitive load assessment, and the potential for real-time cognitive monitoring in high-stakes environments.[3] The paper concludes that an integrated fuzzy k-means RBF method for brain segmentation was successfully developed and tested. This approach achieved high accuracy in identifying white matter, grey matter, and cerebrospinal fluid (CSF) regions, with fewer misclassifications compared to other methods. The system showed better clustering results, proving it is effective at accurately segmenting MRI brain tissue.[4] The research on coffee bean grading and profiling using image processing and neural networks concludes that the method is very accurate for classification. It also suggests ways to improve efficiency and highlights its potential to set new standards for quality control in the coffee industry.[5] The conclusion of the paper "Deep Learning-Based Object Detection Improvement for Tomato Disease" highlights the successful enhancement of the Faster RCNN algorithm for precise tomato disease detection, utilizing k-means for segmentation and ResNet101 for deep feature extraction, demonstrating the potential of deep learning in agricultural disease recognition with improved accuracy.[6] The paper presents a new deep learning technique for semantic segmentation of satellite images that doesn’t require feature extraction or dividing the image into regions. By training SegNet with K-means clustering results and ROI labels, this method provides improved results and reliability in real-world situations, though it does take longer to train.[7] In conclusion, the SMNS model effectively addresses under- and over-segmentation issues and offers robust de-noising capabilities for various types of noise by integrating saliency map and NS theory for image segmentation. While efficient and effective, further optimization is needed for improved objective performance in future work.[8]The conclusion of the study highlights the introduction of new Neutrosophic Set (NS) subsets for enhancing skin lesion segmentation in dermoscopic images, yielding impressive metrics. Future efforts will focus on refining this NS-based segmentation method for broader medical image applications in automated diagnostic systems, even if it will require more time to compute.[9]The paper emphasizes the importance of verifying digital images due to advanced editing techniques and their crucial role as evidence. It highlights the need for sophisticated tools to detect subtle image manipulations that may go unnoticed by the human eye.[10] The study compares EM-Clustering with watershed transform for IR image segmentation, finding EM-Clustering to have high performance due to its robust clustering criterion and insensitivity to contrast issues. Future work is recommended to enhance EM-Clustering's robustness via improved initialization methods.[11] The paper introduces an adaptive method, an EMPCA-MI, for image registration, effectively handling challenges like intensity non-uniformities and large homogeneous regions. Through iterative principal component selection and advanced feature extraction techniques, it surpasses existing MI-based methods in both quantitative and qualitative evaluations across diverse image datasets.[12] The paper introduces the normalized cut criterion as a graph-theoretic measure for image segmentation, emphasizing its ability to capture global scene impressions effectively compared to traditional methods. It's like stepping back to see the whole picture instead of just focusing on small parts. By using math tricks with graphs, they can divide images into meaningful sections that make sense. This approach is useful for tasks like understanding images and can even help with doing math calculations faster when working with lots of data.[13] The paper discovered a good method to find and draw around bone cancer in MRI images. They tried it out and saw that it works well even when tumors are different in size or brightness. This method is useful for looking at medical images, especially for finding tumors. It seems like it could help doctors find and track bone cancer and maybe other types of tumors in medical images.[14] The paper concludes that image segmentation is crucial for various fields, including medical analysis and understanding scenes. Deep learning methods, like recurrent and convolutional networks, are very effective for these tasks. New techniques, such as adversarial networks and attention mechanisms, are being developed to make segmentation even more accurate. Research highlights the importance of designing good network structures and using more data to improve results in semantic segmentation and deep learning. [15] The study concludes with a technique for improving K-means clustering and segmentation rules-based medical volume data visualization. Target features in volumetric datasets are to be precisely extracted and visualized using the suggested methodologies, with a focus on the medical domain. The system can improve user-selected target visualization in a three-dimensional view by employing segmentation, feature extraction, and visualization approaches. Through qualitative and quantitative studies, the paper illustrates the efficacy of the strategy and indicates that the suggested approach can produce precise results that are most similar to the real world. The study also addresses future directions, such as leveraging artificial intelligence techniques to enhance feature extraction and segmentation workflows.[16] The study concludes that the improved fractal texture image analysis method, which applies grayscale morphology to multiple views of MR brain images, yielded positive results. The approach comprised ensemble bagged tree classifiers and KNN for classification, fractal texture analysis for segmentation and feature extraction, and hierarchical transformation. In contrast to traditional techniques, it demonstrated improved segmentation, fewer threshold values, and greater accuracy, sensitivity, specificity, and MCC scores. Additionally, it computed damaged cells and correctly retrieved tumor patches, proving that it could accurately discern diseased from normal tissue in MR brain pictures. Techniques utilizing artificial intelligence to enhance feature extraction and segmentation workflows. [17] The paper proposes a new approach that combines k-means clustering with an improved subtractive clustering technique to improve image segmentation. This update provides k-means with better starting points, leading to better results. The study shows that this new method creates clearer and more accurate segmentations, as shown by better mean square error (MSE) and peak signal-to-noise ratio (PSNR) scores.[18] The paper concludes that two novel techniques for atlas-based image segmentation, integrating diverse classifiers without supervised training, significantly enhance segmentation accuracy. These techniques are particularly advantageous for atlas-based segmentation tasks, avoiding the need for repeated training with new images. By combining registration-based segmentations weighted by EM-based performance estimates, the methods achieve superior accuracy compared to traditional fusion methods. Experimental validation with real atlas-based segmentations confirms the efficacy of EM algorithms in accurately estimating classifier performance parameters for improved segmentation outcomes.[19] The paper examines various methods for segmenting brain tumor MRI images, including basic k-means, k-means with particle swarm optimization (PSO), and k-means with the firefly algorithm (FA). It also explores new ways to improve these methods. Using color and gray labeling techniques enhances the segmentation and region extraction. The results show that k-means with the firefly algorithm is the most effective, offering the best precision, accuracy, f-measure, recall, and quicker segmentation for accurately identifying brain tumors.[20]The paper concludes that their new method, combining K-Means with Morphological Reconstruction and using DPSO for optimization, significantly improves MRI brain tumor segmentation. Their approach surpasses standard techniques and ensures higher accuracy and efficiency, as evidenced by rigorous testing and comparative analysis with state-of-the-art algorithms in medical imaging. Overall, the study highlights the method's effectiveness in overcoming existing limitations and establishes it as a superior choice for MRI brain tumor segmentation.[21] The paper compared two algorithms, K-means and Self-Organizing Maps (SOM), for diagnosing spine issues using data about the pelvis and lower back. They found that SOM was better at this job, being more sensitive, specific, precise, and having a better Negative Predictive Value (NPV) compared to K-means. The SOM model also showed higher agreement, proving it's effective at sorting patients with spine problems. In summary, the study showed that using advanced machine learning like SOM is crucial for accurate and reliable diagnoses in spine health, especially in orthopedics.[22]The paper concludes that combining K-means clustering with an improved watershed algorithm effectively addresses issues like over-segmentation and noise sensitivity in medical image segmentation. This approach reduces over-segmentation in MRI images, produces accurate segmentation results, and shows promise for segmenting anatomical structures like the masseter muscle. Compared to other techniques, the improved watershed algorithm offers advantages and suggests avenues for future research in medical image segmentation.[23]The paper explores image processing techniques for segmenting the spinal cord in MRI scans, crucial for diagnosing spinal cord conditions accurately. It discusses various segmentation methods like thresholding and region-based methods and their role in overcoming challenges in spinal cord injury and disease diagnosis. Through a literature review, the paper highlights advancements in segmentation algorithms, emphasizing their significance in improving automation, accuracy, and reliability in spinal cord analysis.[24] The paper talks about a better way to highlight specific parts of spine CT scans, useful for procedures like facet joint injections. They made a model that understands spine shape and position changes, making it more accurate with fewer settings. Tests on lumbar vertebrae showed very small errors, good for real-world use. This method could be really helpful for guiding medical procedures using CT images. [25]

## III. METHODOLOGY

Our study focuses on improving how we separate different parts of a spine image. We used a method called the EM algorithm to do this and compared its results with another method called K-Means. Instead of using color images, we worked with grayscale ones. To make our segmentation better, we also tried some steps to prepare the images before running the algorithms, and we made a small change to how the EM algorithm works. In our study, we'll explain how the EM algorithm works in general, talk about something called the Gaussian Mixture Model, and explain the specific problem we're trying to solve with these methods

### *A. K-means*

K-means clustering aids spine image segmentation by grouping pixels with similar intensity values, effectively delineating different anatomical structures like vertebrae and soft tissues. It efficiently partitions the image, enabling clinicians to analyze and diagnose spinal conditions more accurately. Additionally, its simplicity and computational efficiency make it suitable for processing large volumes of medical images, contributing to faster diagnostic workflows and treatment planning in clinical practice.

K-means clustering depends on where you start with the centroids, and it might only find a solution that isn’t the best possible. To get a better result, it's usual to run the algorithm several times with different starting points and pick the one that has the smallest total variance within clusters.

K-means clustering holds significance in medical image segmentation by efficiently partitioning image data into clusters based on pixel intensities, aiding in distinguishing between different tissue types or regions of interest. Its computational efficiency and simplicity make it suitable for processinglarge volumes of medical images, facilitating faster analysis and diagnosis. Furthermore, K-means can serve as a foundational step in more advanced segmentation techniques, contributing to the development of accurate and automated medical image analysis systems. Following Fig.1.show the detailed implementation steps of K-mean algorithm.

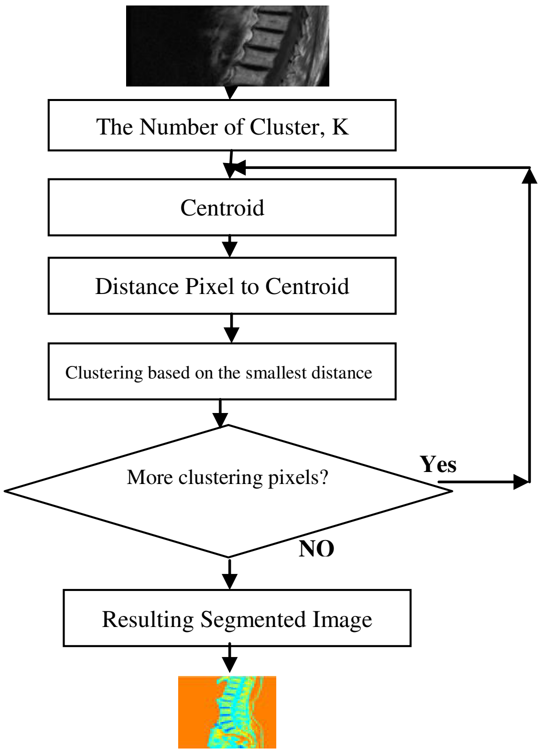



Fig.1. Detailed implementation steps of K-mean algorithm flowchart

We use of the k-means algorithm for spine image segmentation, you would typically include the following details:

Algorithm Overview: Introduce the k-means method and its basic workings. It is an iterative clustering technique that divides data into k clusters according to similarity.

Initialization: Describe how the algorithm initializes k centroids randomly or using a specific strategy, such as k-means++ initialization, to avoid poor local minima.

Assignment Step: In this step, each data point is matched to the closest centroid by measuring the distance, typically using Euclidean distance, during each round of the algorithm.

The K-Means algorithm for spine image segmentation updates centroids by averaging data points, refining clusters iteratively until convergence, where pixels are assigned to the nearest centroid. The segmentation quality is evaluated using metrics like accuracy, precision, and Dice coefficient, compared to ground truth annotations. While K-Means is computationally efficient, it may struggle with noise and complex structures. Comparative analysis suggests it's a strong baseline but could benefit from enhancements like hybrid methods or improved initialization. Future research could explore these improvements to boost segmentation performance.

The K-Means algorithm is easy to understand and works well with large datasets, converging quickly, especially when clusters are well-separated. However, it requires the number of clusters to be defined beforehand and is sensitive to initial centroid placement, which can affect the results. It also struggles with non-spherical clusters and may converge to local minima, potentially reducing clustering accuracy.

*B. EM (Expectation-Maximization)*

The Expectation-Maximization (EM) algorithm is useful for segmenting spine images because it can handle the complex patterns in medical images by using probabilistic models such as Gaussian Mixture Models (GMMs). EM iteratively estimates the parameters of these models, which represent tissue types or regions in the spine image, leading to more accurate segmentation results. Additionally, EM can handle noise and partial volume effects inherent in medical images, enabling finer delineation of anatomical structures crucial for diagnosis and treatment planning in spinal conditions.

The Expectation-Maximization (EM) algorithm is crucial in medical image segmentation due to its ability to handle complex data distributions, such as those encountered in MRI and CT scans, by iteratively estimating parameters and segmenting tissues accurately. Its probabilistic modeling capabilities enable robust segmentation in the presence of noise and partial volume effects, contributing to improved diagnosis, treatment planning, and monitoring in clinical settings. Following Figure 2 show the detailed implementation steps of EM (Expectation-Maximization) algorithm.

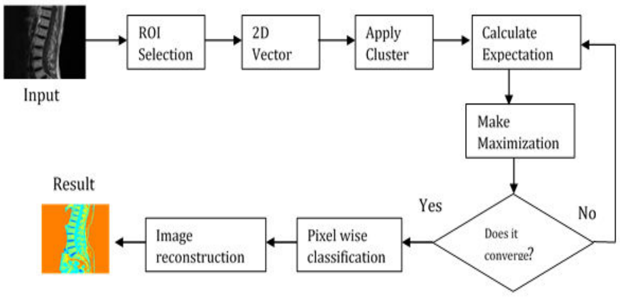



*Figure 2 Detailed implementation steps of EM (**Expectation-Maximization**) algorithm flowchart*

**Fig. 2**. Detailed implementation steps of EM (Expectation-Maximization) algorithm flowchart

In the Expectation-Maximization (EM) algorithm used for spine image segmentation, you would typically write the following components:

**Initialization:** Start by initializing the parameters of the model, such as means and variances for Gaussian mixture models used in EM.

**Expectation Step (E-step):** Using the existing parameters, determine the posterior probabilities (responsibilities) of each data point that belongs to each cluster.

**Maximization Step (M-step):**Revise the model's parameters (such as means, variances, and mixing coefficients) in light of the posterior probabilities that were determined during the E-step.

**Convergence Check:** Repeat the E-step and M-step iteratively until the algorithm converges, meaning that the parameters no longer change significantly between iterations or the likelihood function reaches a maximum.

**Segmentation Process**:Describe how the final segmentation of spine images is achieved by assigning each pixel or region in the image to the cluster with the nearest centroid after convergence.

**Post-processing (Optional):** Optionally, perform post-processing steps such as noise removal or smoothing to improve the final segmented image.

Throughout the algorithm, it's important to handle cases of singularities or degenerate solutions, such as empty clusters or clusters collapsing into single points, to ensure the stability and accuracy of the segmentation results.

Advantages of the EM algorithm: 1) Suitable for data with hidden or latent variables.2) More flexible than k-means as it can model complex data distributions.3) Can handle missing data effectively through the expectation step.4) Produces probabilistic cluster assignments, providing uncertainty information.

Disadvantages of the EM algorithm: 1) it's sensitive to initial guesses, so starting values need to be chosen carefully. 2) It can be slow and demanding on resources, especially with large or complex data. 3) It might only find local solutions, so you often need to run it multiple times with different starting points. 4) It needs prior knowledge or assumptions about how the data is distributed, which might not always be correct.

In summary, while both algorithms have their advantages and limitations, K-means may be preferred for its simplicity and efficiency in initial exploratory analysis, while EM may offer more accurate segmentation results in cases with complex data distributions and overlapping intensity values. However, the choice between the two depends on factors such as dataset size, computational resources, and the specific characteristics of the spine image data.

## IV. EXPERIMENTAL CONFIGURATION

The lumbar MRI dataset, comprising images from 81 participants. The image files are in the "mat_data" folder and have the .mat extension. To simplify image processing due to the large 44 MB size, a MATLAB tool was created to convert these images to .jpg format. Since the study only looks at segmentation methods, all 81 images are used to test how well the segmentation performs. The results for the k-Means and Expectation-Maximization (EM) algorithms were obtained using Matlab 2023a on a Windows 10 computer with an Intel Core i5 650 processor running at 3.20GHz and 8GB of RAM. The segmentation process for a single image typically takes between 3 to 4 seconds to complete. Analyzing all 81 images for segmentation requires approximately 9 to 10 minutes in total.

## V. RESULT

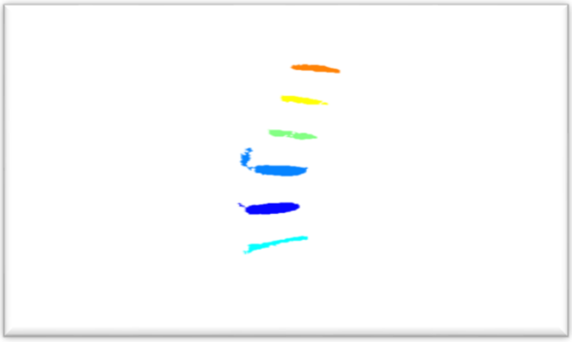
Here are some of the findings as well as the individual accuracy of the EM and K-means algorithms. The following figures display the K-means results: Fig. 3.and EM Results displayed in Fig. 4

A. K-Means results:

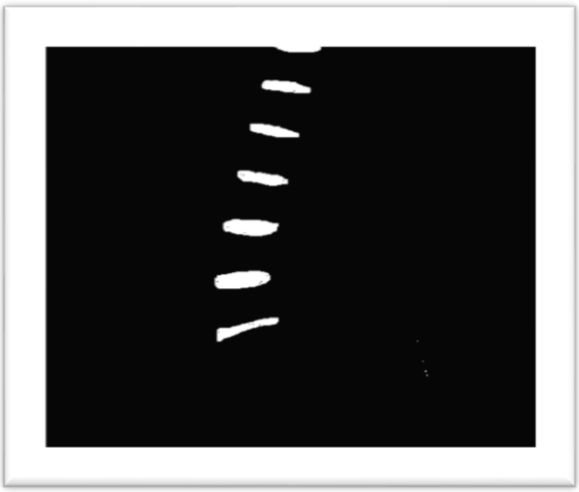
a) Original Image

b) ROI mask image

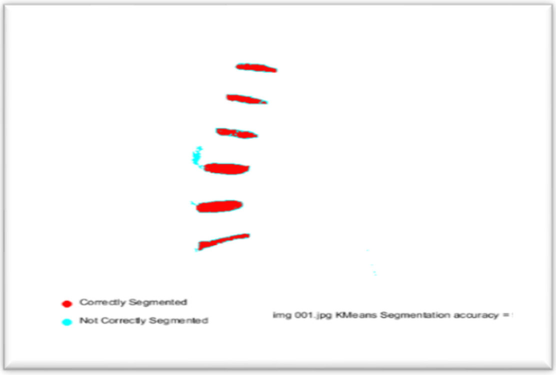




c) Final Disc Segmentation byKmeans



d) Ground Truth jpg image

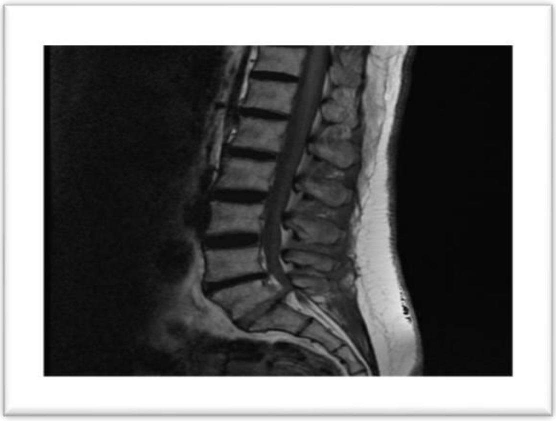



e) K-Means Segmentation accuracy of a spine image = 84.41%

**Fig 3: K**means per step results (a, b, c, d ande) with 5 subfigures of K-Means output.The parts of the image that were correctly segmented are highlighted in red, while those incorrectly segmented are highlighted in blue.(Image sizeis512x512)

As shown in Fig. 3, all of the above a, b, c, d, e, figures show the K-Means algorithm results with a) Original Image b) ROI (Region of interest) mask image c) Final Disc Segmentation byKmeans d) Ground Truth jpg image. e) K-Means Segmentation accuracy = 88.56% using the K-means approach as the red colour was successfully segmented region while the blue colour was wrongly segmented region.

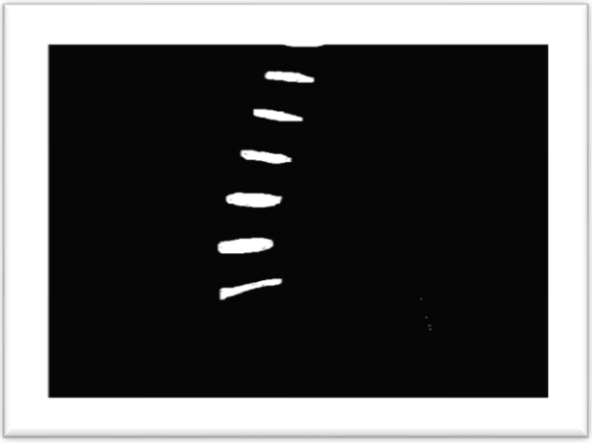
B.EM (Expectation-Maximization) results:



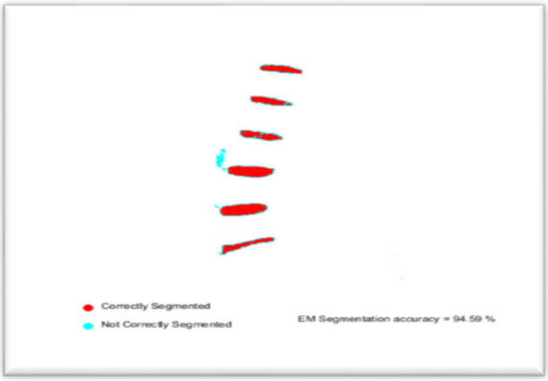
a) Original Image

b) ROI mask image

c) Final Disc Segmentation by EM



d) Ground Truth jpg image




e) EM Segmentation accuracy = 84.41%

**Fig.4: EM** per step results (a, b, c, d and e) with 5 subfigures of K-Means output.The parts of the image that were correctly segmented are highlighted in red, while those incorrectly segmented are highlighted in blue.(Image sizeis512x512)

C.Average segmentation accuracy for both the Kmeans and EM (Expectation-Maximization) methods:

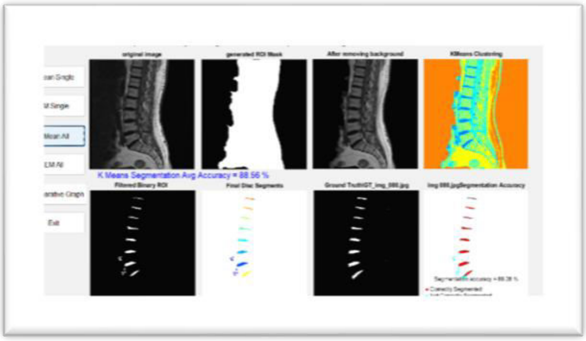


**Fig.5**.Comparative analysis of segmentation of the Spinal cord using Kmeans algorithm.The segmentation average accuracy for this method is 88.56%

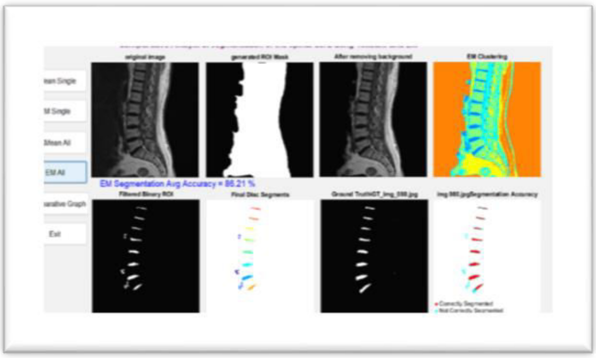
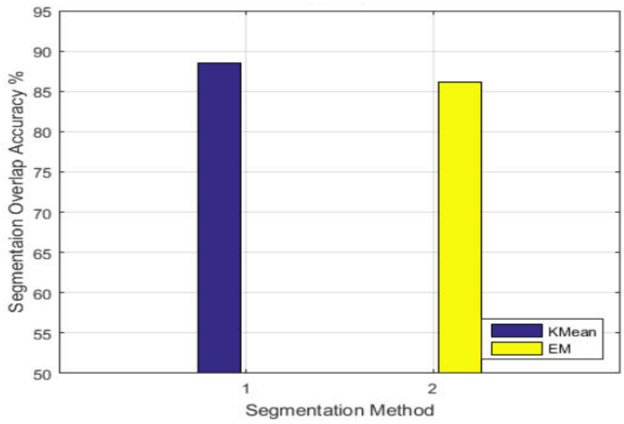


**Fig.6**.Comparative analysis of segmentation of the Spinal cord using EM algorithm. The segmentation average accuracy for this method is 86.21%.

| Segmentation method | Avg Segmentation Accuracy |
|---|---|
| K-Means | 88.56 % |
| EM | 86.21 % |

**Table.1. Comparative analysis of K-MEANS and EM**

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When we used the K-means method on 80 images, it correctly segmented them about 88.56% of the time on average. In comparison, the EM (Expectation-Maximization) method had an average accuracy of around 86.21% on the same images. This indicates that K-means generally performs a bit better than EM in this case.

VI. CONSLUSION

In conclusion, our comparative analysis of K-Means and Expectation Maximization (EM) in spine image segmentation highlights the effectiveness of both algorithms in automatic MRI segmentation for spinal diseases. The study, conducted using a dataset of 80 MR images, demonstrated that while K-Means showed higher segmentation accuracy compared to EM, both methods offered valuable insights into identifying different deformities and abnormalities in the spine. Kmeans technique produces better segmentation results than the EM Expectation-Maximization) technique.

In future work, we plan to improve our method by trying out more segmentation techniques and fine-tuning how we describe the segmented vertebrae to better identify deformities. Overall, this study helps advance automatic spinal MRI segmentation, which supports early detection and accurate diagnosis of spinal misalignments and related health problems.

**Conflict of Interest Statement**

The authors declare that they have no conflicts of interest.

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