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A MODIFIED FUZZY C MEAN-BASED LIVER TUMOR SEGMENTATION

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ABSTRACT

Early detection of the liver cancer disease prediction reduces the risk factor of the patients. Several conventional segmentation techniques are proposed to detect the liver tumor like Gaussian mixture model, NS, FCM, and Watershed. But most of the Conventional models difficult to detect liver tumor in the early stages and to improve the life of patients segmenting the liver tumor is essential in detecting and managing liver cancer. This study suggests using the modified fuzzy c means (MFCM) algorithm to segment liver Tumors. In this work, proposed a modified Fuzzy C Mean algorithm to do the liver segments depends on the region of interest over the filtered image. The suggested technique enhances the segmentation accuracy, and robustness by including spatial information in the conventional fuzzy c means algorithm. The performance of the suggested algorithm was assessed on a dataset of CT scans of the liver that was made available to the public. The results demonstrate that the MFCM algorithm surpasses the conventional fuzzy c means technique and several other advanced segmentation approaches regarding segmentation accuracy, sensitivity, specificity, and dice similarity coefficient. Clinicians can benefit significantly from the proposed algorithm's assistance in detecting and managing liver cancer. The results show that the suggested model works, which outperformed many existing algorithms, attained 98% accuracy.

1.INTRODUCTION

Early detection of the liver cancer disease prediction reduces the risk factor of the patients. Several conventional segmentation techniques are proposed to detect the liver tumor like Gaussian mixture model, NS, FCM, and Watershed. But most of the Conventional models difficult to detect liver tumor in the early stages and to improve the life of patients segmenting the liver tumor is essential in detecting and managing liver cancer. This study suggests using the modified fuzzy c means (MFCM) algorithm to segment liver Tumors. In this work, proposed a modified Fuzzy C Mean algorithm to do the liver segments depends on the region of interest over the filtered image. The suggested technique enhances the segmentation accuracy, and robustness by including spatial information in the conventional fuzzy c means algorithm. The performance of the suggested algorithm was assessed on a dataset of CT scans of the liver that was made available to the public. The results demonstrate that the

MFCM algorithm surpasses the conventional fuzzy c means technique and several other advanced segmentation approaches regarding segmentation accuracy, sensitivity, specificity, and dice similarity coefficient. Clinicians can benefit significantly from the proposed algorithm's assistance in detecting and managing liver cancer. The results show that the suggested model works, which outperformed many existing algorithms, attained 98% accuracy.

Identifying tumors, spotting damaged tissue, preparing for surgery, and diagnosing anatomical features are just a few of the medical jobs where picture segmentation is useful. Its usefulness comes from its capacity to identify damage-causing regions, which helps medical experts choose the best treatment plans for dealing with these problems. The early detection and diagnosis of liver cancer rely heavily on the segmentation of liver Tumor in medical image processing. The segmentation process in medical images like CT or MRI scans involves separating the liver Tumor area from the neighboring healthy tissues. This task is challenging because liver Tumor differ in size, morphology, and degree of severity. Yasmeen Al-Saeed [1] proposed a computer aided diagnosis system to identify the tumor by using fuzzy c means method and then tumor is either labelled as benign and malignant by using support vector machine (SVM) method. The accuracy obtained to the proposed methodology is 96.75%.

1.1 SEGMENTATIONTECHNIQUESON LIVER TUMOR

In order to extract fine features from images, image segmentation is a critical component of image processing. With each pixel being the smallest component of an image, this method allows us to fully comprehend images at the pixel level. To create discrete segments inside the image, the main objective is to group pixels that have comparable properties. We can recognize items and draw borders within the photos using this segmentation technique. Image segmentation ultimately produces a group of segments that, when put together, recreate the entire image, improving its overall clarity and visibility.

The MFCM algorithm is a modified version of the fuzzy c-means (FCM) algorithm. By adding geographical information to the clustering process, MFCM improves on FCM.Based on a pixel's intensity and spatial position, the MFCM-based liver Tumor segmentation algorithm allocates each pixel in the medical Picture to a particular cluster. Until a convergence requirement is satisfied, the algorithm iteratively updates each pixel's membership value and cluster center. A binary picture that distinguishes the location of the liver Tumor from the healthy liver tissue is the outcome of the segmentation process. MFCM to segment liver tumors is a powerful method for identifying and treating liver cancer. It can assist medical professionals in precisely identifying the position and size of liver Tumors, which is crucial for treatment planning and tracking the course of the disease.There are some research gaps in the papers we reviewed. So, we are trying to overcome some gaps in our proposed model. It is also essential to get the best results with our proposed model. Some of the research gaps are mentioned below. Many researchers used small-size datasets, leading to their model's underfitting. Many researchers didn't consider the poor-quality images; they were removed as noise. Existing models can detect the presence of Tumors but fail to identify the proper region.

A clustering approach called fuzzy C-means (FCM) gives data points membership degrees, allowing them to belong to numerous groups simultaneously. FCM provides benefits, but there are also several limitations to take into account:

- The clusters are thought to be convex and isotropic using FCM. When working with datasets that have non-convex or irregularly structured clusters, it may run into problems. FCM may yield unsatisfactory findings or need to capture intricate cluster formations accurately.
- The data points are supposed to be evenly dispersed throughout the cluster centers, according to FCM. FCM is susceptible to data noise or outliers because of this supposition. Outliers have a significant impact on where the cluster centers are located, which affects the clustering outcome.
- The fuzziness of the clusters is managed via the fuzziness parameter (m) introduced by FCM. The partition matrix, in turn, impacts the clustering outcome depending on the value of m. However, there is no clear-cut formula for choosing the ideal value of m; instead, this is frequently an empirical determination.

Modified fuzzy c-means (MFCM) clustering is one method for liver Tumor segmentation. MFCM is a variation of the conventional fuzzy c-means (FCM) clustering technique commonly used in picture segmentation. By combining spatial data and prior knowledge into the clustering process, the MFCM method improves the performance of FCM. The medical image is initially pre-processed to improve contrast and eliminate noise before being segmented using MFCM for liver Tumors. Then, the MFCM method is used to group the picture pixels into regions that contain Tumors and those that do not. To enhance clustering performance, you should consider the following suggestions., the method adjusts various parameters, such as the cluster count, the fuzziness parameter, and the spatial penalty factor.The liver Tumor and surrounding tissues are distinguished in a binary image produced by the MFCM algorithm. Many metrics, including the dice coefficient and the sensitivity and specificity measurements, can be used to gauge how accurate the segmentation is.Overall, the segmentation of liver Tumors using MFCM clustering is a promising method that can deliver precise and effective outcomes for medical diagnosis and therapy planning.

2. METHODOLOGY

The proposed model designated with Modified Fuzzy C Mean algorithm to detect the liver tumor over noise and low resolute images. Figure 3.1 shown the hierarchical view of the proposed model and it designated with four stages.

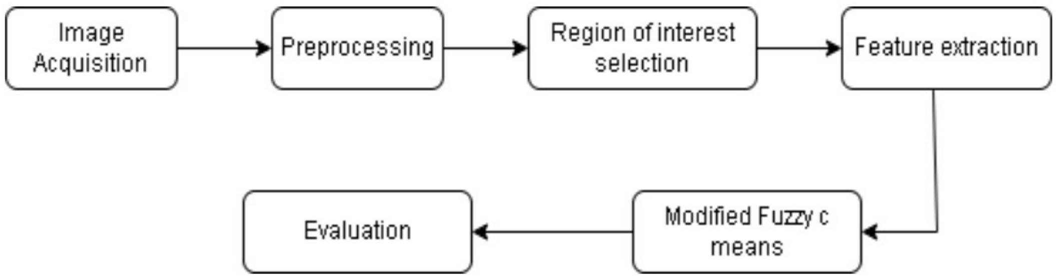

Fig. 1. Architecture of Liver Tumor Segmentation

Stage1: Pre-Processing

Pre-handling is fundamental for the division of liver growths. To improve the accuracy of the analysis results and enhance the quality of the data at initial stage the raw CT images are pre-processing using curve let transformation to improve the contrast and resolution.

1. Curvelet Transform:

The segmentation of liver Tumors can be pre-processed using the signal-processing method known as the curvelet transform. The multiscale, multi-directional curvelet can capture the image transform's

directional information and textural elements. It can break down an image into a collection of curvelet coefficients, which can subsequently be applied to the image to improve particular characteristics or lessen noise.With an input image, the curvelet algorithm applies the discrete wavelet transform (DWT) and the inverse discrete wavelet transform (IDWT). This technique breaks the image down into its frequency components, which can be helpful in several image processing operations like denoising, compression, and feature extraction, as shown in the equation below.

$$\mathrm{C} = pywt.dwt2(img, 'bior1.3')$$

Performs the DWT on the input image using the biorthogonal1.3 wavelet. The dwt2 function decomposes the image into four components: the estimate coefficients (CA), even detail coefficients (CH), vertical detail coefficients (CV) and inclining coefficients (Album). The result C is a tuple of these four parts.Performs the IDWT on the extracted components using the same wavelet. The dwt2 function reconstructs the image from the four components, producing an output image. The np. Unit8 function converts the output to an 8-bit unsigned integer representation, the format used for most images.

Stage2: Region of Interest on Pre-processed image

ROI plays elementary role on image segmentation to extracting the important image features in form of segmented object from the various regions on the image. In this work internal representations are used to compute the cubic similarity based 5X5 kernel to identify the curves of the image regions.

Cubic Similarity Measure = $((c_1 - c_2)^3 + (d1 - d2)^3)^{1/3}$ ------- (1)

Where (c_1, d_1) and (c_2, d_2) are pixels of the image.

Thresholding Segmentation:

New image = Blurred image < 0.8

Stage3: Liver Tumor Segmentation using Hybrid Modified Fuzzy C Means

At this stage, the chosen characteristics are changed into a fresh set of features that may be applied to the particular application. Principle component analysis (PCA), discrete wavelet changes (DWT), and profound learning-based approaches like convolutional brain organizations can be in every way used to do this (CNN).In many machine learning and computer vision applications, feature extraction is a pivotal stage that fundamentally affects the Accuracy and execution of the last framework. A method for automatically locating and segmenting liver and Tumor locations in medical pictures is called modified fuzzy c-means clustering. Statistical techniques are utilized. This method determines the correlation coefficients between pairs of significant image attributes, such as intensity levels, texture, and shape.

The final step is to delete any redundant features that might not significantly improve the segmentation accuracy and to discover any significant correlations between features using the generated correlation matrix. The liver and Tumor regions in the image are segmented using the chosen characteristics, after which they are fed into the modified fuzzy c-means clustering method. The modified fuzzy c-means clustering technique divides the image into many clusters according to how similar they use the image attributes.

Modified fuzzy c means algorithm.

1. Activate the medical image that shows the liver and the Tumor.
2. Enhance the contrast between the liver and the Tumor regions by pre-processing the image to remove any noise.

3. Select the number of clustersperformed in the MFCM Algorithm (i.e., two clusters for liver and Tumor regions).

4. Each pixel will be randomly assigned to one of the two clusters to begin the MFCM process.
5. Calculate the membership function for each pixel, which establishes how closely a pixel is related to each cluster.

$$\mu_{ij} = [\frac{d_{ij}}{\sum Dk}(d_{ik})]^\wedge(\frac{2}{m-1}) \quad \text{-----}\ (2)$$

6. Each cluster's centroid should be updated based on the membership function.
7. Use a Liver-Tumor model to get the prior probability for each cluster. The objective is to assess the probability of each pixel belonging to a cluster representing either the liver or cancer. The perfect is trained on a dataset of liver and tumor images.
8. Incorporate the prior probabilities into the membership function to obtain a modified membership function.
9. When convergence or the centroids and membership functions stop changing noticeably, repeat steps 5-8.
10. Assign each pixel to the cluster with the most fantastic membership value to create the segmented image.

At final stage evaluate the quality of the segmented region and test the algorithm on over different liver tumor and nontumor CT images.

3. RESULTS

The openly available Liver Growth Division (LiTS) dataset was created and tested for liver cancer division calculations. The Liver Growth Division Contest, supported by the Radiological Society of North America (RSNA), highlighted the dataset's presentation in 2017.The LiTS dataset incorporates 131 difference-improved CT sweeps of the liver with no less than one sore that two qualified radiologists have physically distinguished. There are 201 liver lesions in total in the dataset, with 101 of them being malignant and 100 of them benign. Slice thicknesses range from 1 to 5 mm, and images have a resolution of 512x512 pixels. The LiTS dataset has significantly contributed to developing cutting-edge segmentation algorithms and has advanced the field of liver Tumor segmentation. It is still a valuable tool for scientists and doctors researching the detection and treatment of liver cancer.

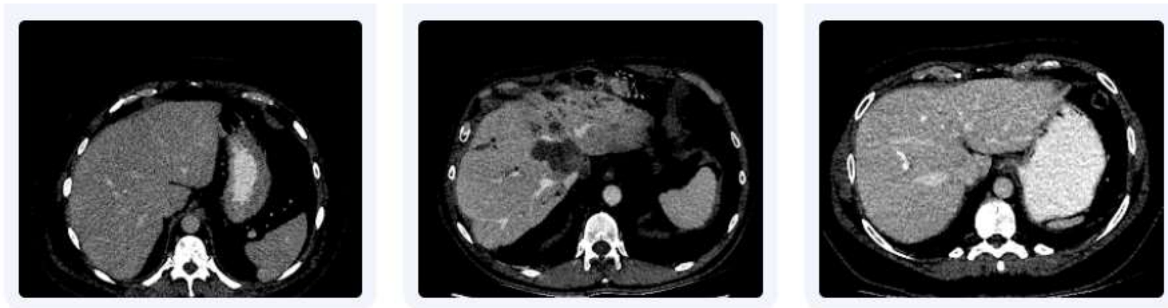

Fig. 2. CT images from the LITs Dataset

Segmenting the liver Tumor in medical image analysis is a critical step that can help with the detection and management of liver cancer. A clustering-based method for liver Tumor segmentation called the

Modified Fuzzy C-Means (MFCM) algorithm has been successfully employed. Reporting the MFCM

algorithm's performance in terms of parameters like the Dice coefficient, sensitivity, specificity, and Accuracy is crucial for the results section. These metrics demonstrate the algorithm's success in locating and classifying liver cancers in the photos. The objective is to demonstrate the superiority of the MFCM algorithm in comparison to other segmentation strategies. It is crucial to evaluate how well it performs compared to those strategies. The study's findings are interpreted, and their ramifications are explored in the discussion section. The MFCM algorithm's benefits and drawbacks are analyzed, and recommendations for future developments are offered. Also, the clinical significance of the liver Tumor segmentation data is explored, and possible clinical applications of the algorithm are considered. Lastly, the study's importance to medical image analysis is underlined.

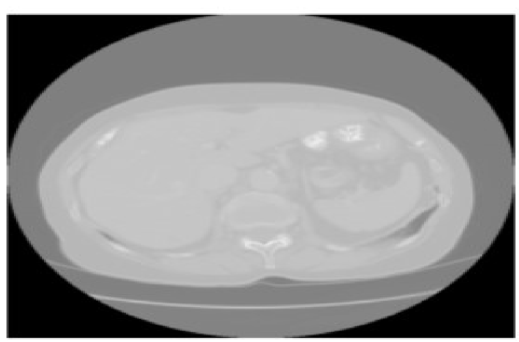

Fig. 3. Sample Image

A dataset that has undergone pre-processing is usually better organized, consistent, and in a more straightforward format. Pre-processing may involve deleting excessive or redundant data, addressing missing data, converting data to a numerical representation, normalizing or scaling characteristics, and encoding categorical variables.Pre-processing is a crucial stage in data analysis and machine learning since it can significantly increase the precision and efficacy of models created from the data. Furthermore, it is crucial to validate the pre-processing procedures and ensure they don't cause overfitting or any other problems with the model.

Fig.3. Pre-prosed Image

The proposed modified fuzzy c means to segment the liver Tumor image. And they then saved the images to represent the Tumor. With high contrast between the object of interest and the backdrop, thresholding is a quick and easy segmentation approach that works well for photographs. Region-growing algorithms help segment images with more complicated features, including Tumors with

uneven shapes. Techniques for edge detection work well in pictures where the object and background delineate boundaries. Images with little contrast and noise respond well to clustering methods like MFCM.For the clustering, they used modified fuzzy c means, passed those images through the segmented image, and found the Accuracy of the images. For the clustering, it did the dataset was tested and trained. The test accuracy of this model is 98 per cent.

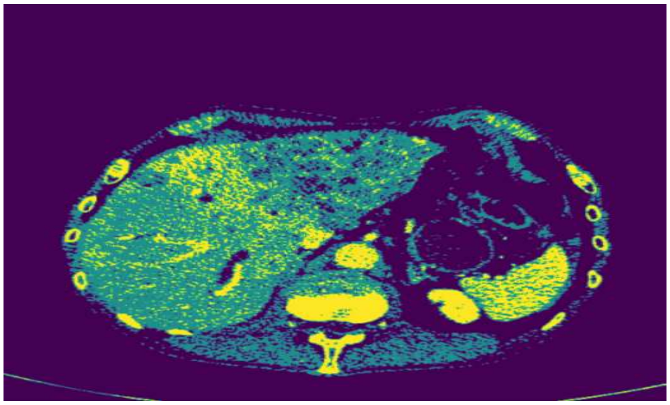

Fig. 4. Segmented Image

Table 1: Comparison of Existing model with our model

S. No	Author	Accuracy
1.	Lamia N. Mahdy [16]	96.86%
2.	Dong Yang [14]	95%
3.	Grzegorz Chlebus [15]	90%
4.	Modified FCM	98%

In the below graph, the liver Tumor segmentation using Modified Fuzzy C Mean achieved greater Accuracy than other existing techniques. This bar graph can explain the benefits of our model.

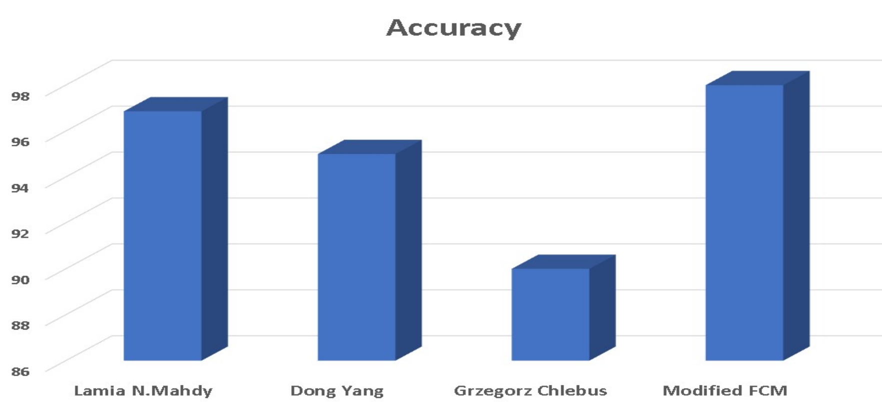

Fig. 5. Graph for Comparison of Existing model and Proposed model

A correlation matrix is a table that displays the correlation coefficients between several variables. A correlation matrix can be utilized to examine the connections between various picture features and how they might affect the segmentation outcomes in the context of liver tumor segmentation using modified fuzzy c-means clustering. A standard method for segmenting images is modified fuzzy c-means clustering, which seeks to divide a picture into groups according to its component features' similarity.

The image features used in liver tumor segmentation may include the intensity values, texture, form, and other qualities of the liver and tumor regions.

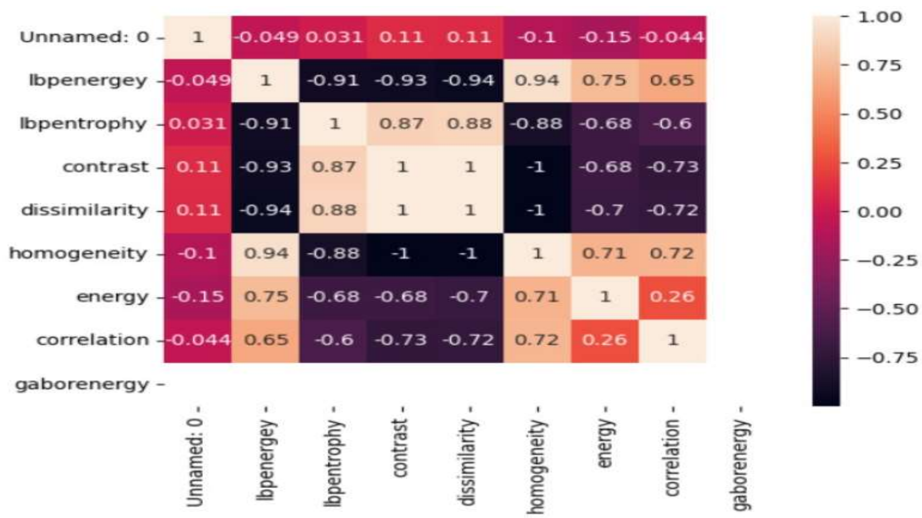

Fig.6. Co-relation matrix of Liver Tumor Segmentation

4. CONCLUSION

The segmentation of liver Tumors is a vital stage in medical image analysis that has significant clinical ramifications for the detection and management of liver cancer. A popular and successful method for segmenting liver tumor is the modified fuzzy c-means (MFCM) algorithm, which has received extensive research in the literature. The proposed MFCM algorithm enhances the traditional fuzzy c-means (FCM) algorithm's performance and robustness in handling noisy and low resolute data. By incorporating traditional segmentation techniques, the proposed segmentation model achieved optimistic accuracy over liver tumor detection. The proposed model improved the increase accuracy at 98.01% and decrease false positives rate. Overall, the MFCM algorithm is a powerful and widely useful technique for liver Tumor segmentation that can provide valuable insights into diagnosing and treating liver cancer. With further advancements and improvements in this field, the MFCM algorithm can be an even more powerful tool for liver Tumor segmentation by integrating with deep learning models.

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