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Fuzzy C Means & Genetic Algorithm for MRI-based Brain Tumor Identification

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***Abstract*:** The method of segmenting pictures of brain tumors is an important part of the medical sector and the processing of medical information. Early diagnosis of brain tumors in patients is the single most important factor in determining the patient's prognosis and treatment options. Finding brain tumors at an earlier stage will improve patients' chances of living longer. Due to the need of automated image fragmentation, a neurologist will commonly employ a physical image classification, which is a method that is challenging and time-consuming. In this research, we discuss various optimization-based proposed that perceived that may be used to identify brain tumors in images obtained from magnetic resonance (MR) scanners. Throughout this investigation, an evaluation of recently reported research is carried out, as well as an attempt is made to develop a brand-new model based on Fuzzy C Means as well as Genetic Algorithm (FCMGA), with both the intention of automatically identifying and classifying brain tumors in MRI images. The objective of the study is to achieve this objective. The modeling was performed between different indicators that analyze the effectiveness of the classification methods, such as K-Means and FCM, as well as some of the hybrid techniques for optimized fragmentation, such as clustering accompanied by Genetic Algorithm (GA), as well as clustering with Particle Swarm Optimization. The above classification methods involve K-Means and FCM (PSO). In order to perform these categorization procedures, first the MRI image must be pre-processed, and then the additional classification or improvement methods must be used in order to get a tumor that is more distinct and simpler to identify. The outcomes of the survey indicate that the model that was developed may be useful in providing accurate detection of brain tumors.

***IndexTerms* - Optimization, Magnetic Resonance, Fuzzy C Means, Genetic Algorithm, K-Means, PSO**

I. INTRODUCTION

The brain is the most important component of the nervous system and is responsible for controlling almost every aspect of the organism. The human brain is the organ with the highest level of complexity [1]. Cancer is a critical public health problem in many parts of the globe. After cardiovascular illnesses, it is the second greatest cause of mortality [2]. BTs may be separated into their own different categories according to the roughness, position, and form of the BTs [3]. Based on this information, doctors are able to determine and diagnose patient perseverance as well as make choices concerning the appropriate therapies. As a result, the grading of the tumor is an important consideration in the process of evaluating and arranging therapy [4,5]. Figure 1 presents examples of several forms of brain tumors.

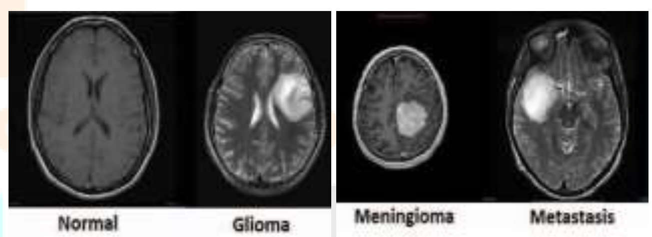

Figure1. Various types of Brain Tumor

Meningiomas and pituitary tumors, which are frequently of a lesser level, are two instances of benign tumors that seldom metastasize, or grow, to healthy neighboring tissue [6]. Brain tumors that are malignant in nature penetrate the neighboring parenchyma with varying degrees of aggressively. Glioblastoma represents the most prevalent and severe kind of malignant brain tumor. It is often categorized as a grade 4 CNS tumor and has a poor prognosis [7]. Primary brain tumors are those that originate in the brain, while secondary brain tumors often originate in a location that is physically separate from the brain. While traditional scanning has significant shortcomings in assessing tumor size, predicting grade, and determining therapeutic outcomes, MRI remains the cornerstone for the evaluation of individuals with brain malignancies [8, 9]. Furthermore, innovative methods to photo editing have already been increasing in popularity because to the quantity of data provided by radiological images [11]. New acquisition methods are now being developed to enhance lesion characterization, treatment evaluation, and maintenance [10]. In this particular setting, the categorization and fragmentation of brain tumors have emerged as essential components of image processing. The categorization of brain tumors may be accomplished via a variety of approaches, involving manual identification and categorization through the use of computer-aided technology. The manual identification of brain tumors requires a significant amount of time [12], and it is also prone to inaccuracy [13]. On the other hand, manual categorization cannot be disregarded since it continues to serve as the gold standard for clinical treatment and is evaluated alongside other methods for purposes of comparison.

MRI is a diagnostic imaging procedure that really is non-invasive, pain-free, and uses high-quality pictures of human body tissues [14]. MRI images may be shown in any version. Since it provides high-resolution pictures of the brain tissues, it is widely used given that it is the most accurate approach for classifying and diagnosing cancer [15,16]. This is the reason why it is so widely applied. Nevertheless, determining the kind of cancer from MRI scans is challenging and fraught with the possibility of inaccuracy. In example, the accuracy is dependent on the years of expertise which the radiologist has, and it is important to keep in mind that the procedure takes a considerable amount of time [17]. In furthermore, a precise analysis assists the patient in swiftly beginning the appropriate therapy, which in turn helps the patient live for a longer period of time [18]. Because of this, there is a large market in the field of artificial intelligence (AI) for the development and design of a novel as well as innovative Computer Assisted Diagnosis (CAD) procedure [19]. In a variety of contexts, neuro-oncologists may benefit from using CAD approaches. The categorization of BTs as well as the timely detection of them is both made easier by CAD approaches [20]. Recent advances in computer technology have led to the creation of powerful tools that may assist in making more accurate diagnoses. Because of these advancements in deep learning-related systems, medical image analysis and decision-making have seen a significant improvement. Particularly technology connected to deep neural networks (DNN) that are used by specialists who have received extensive training [21]. For the aim of diagnosing tumors, clinical practices may make use of a wide variety of scanning procedures, based on the circumstances and the goals of the examination. The terms "ultrasonography" (US), "magnetic resonance imaging" (MRI), and "computed tomography" (CT) are examples of several of these imaging technologies [22]. Since it does not use the potentially harmful ionizing electromagnetic waves of X-rays even during scan, MRI has become the non-invasive imaging method that is most often used.

During the manually classification stage, portions of the tumor are manually found on all continuous slices within which the tumor is thought to exist. This is done in order to provide a complete image. It's not cheap, and it takes a lot of time, and it's a pain to do. They had the idea of inventing a top of the range based on Fuzzy C Means as well as Genetic Algorithm (FCMGA), with the purpose of detecting and recognizing and categorizing the brain tumor in MRI Image, so that we could get around this issue. The process of partitioning an entity into many segments in order to reduce its description into a format that is more intelligible and simpler to analyze is referred to as differentiation. Segmentation is a methodology. Several of the hybrid techniques for optimized fragmentation, including such cluster formation accompanied by Genetic Algorithm (GA) as well as grouping with Particle Swarm Optimization (PSO), can be used. The classification methods include K-Means and FCM, in addition to some of the hybrid techniques for optimized fragmentation. Fuzzy c-means, also known as FCM, is a cluster formation approach that involves the grouping of an information source into N clusters, with each piece of evidence in the information contributing to each cluster to a given degree

The following is the organizational scheme for the next portions of this essay: In Chapter 2, which is named "Literature Review," we explore previous research or publications that apply to emotion reviews. In Chapter 3, we will talk about the methods for collecting reviews, the research design, as well as the technique of grading and classifying feedback depending on the emotion they convey. The results will be provided of Chapter 4, which is the concluding book in the research.

II. Related Study

The relevance of the area of medical imaging is increased by the growing desire for quick and accurate diagnosis that may be performed automatically. In this study, the tumor is located and extracted with the use of the Fuzzy C-means method. Parameters such as segmented area, MSE, and PSNR are determined. After the coefficients of wavelet transform for the magnetic resonance (MR) picture have been extracted using the daubechies three level dissolution of the discrete two-dimensional wavelet transform (DWT), the number of dimensions of the image has been reduced using the principle component analysis (PCA) automated system [23].

Algorithm(s) Used: The fuzzy C means, DWT, PCA, and SVM all come into play. One type of based on the accurate is known as the FCM algorithm. Using this technique, the membership function may be granted to every data emphasis that's also typically linked to each group focus. This is determined by the distance that exists between both the group focus and the data focuses. One sort of linear transformation that may be performed on a data vector in order to change it into a different vector is called DWT. PCA is a sort of statistical technique that may be used to get a condensed number of parameters in the data lattice. This type of procedure is helpful for collecting the greatest amount of variance that is even remotely possible.

Advantages: After the wavelet coefficients from the MR picture have been obtained with the use of Daubechies' three-level breakdown of the two-dimensional DWT, the dimensionality of the picture may then be decreased with the help of the PCA approach. After that, a GLCM is constructed using these coefficients as the input. The SVM classifier was able to reach a high accuracy, which would be helpful in accurately identifying the brain tumor.

Limitation: The outcomes of the proposed system's fragmentation on 14 MR brain pictures are produced, and the operating principles are assessed; however, due to the short size of the dataset, it is not possible to apply this method in a real-time application.

Conclusion: Wavelet decomposition is used to recover the statistical properties, and then the principal component analysis (PCA) technique is used to reduce the dimensions. The learning characteristic database is made up of the features that were retrieved from the pictures that were used for training. Whenever a test input picture is submitted for the purpose of brain tumor classification, this database is utilized.

Brain tumor categorization refers to the process of determining whether a brain tumor is benign or malignant. The suggested supervised learning SVM classification technique is used to 105 magnetic resonance imaging (MRI) scans of the brain in order to identify conditions such as benign and malignant. In the experimental findings, the SVM classifier demonstrated an accuracy of 98.82% along with a sensitivity of 100%, a specificity of 97.83%, and an error rate of 1.17%.

The identification of medical conditions based on images has become an increasingly significant topic in recent years. A brain tumor is defined as an abnormal development of cells that interferes with the brain's ability to perform its usual functions. The primary objective of this study [24] is to identify picture information with both the least amount of inaccuracy that is humanly achievable. The magnetic resonance imaging scan is used to get picture information and to properly identify malignant tissues since, in comparison to other imaging technologies; it produces images of superior quality and higher resolution.

Algorithm(s) Used: Particle Swarm Optimization, Fuzzy C-Mean Clustering, and a Hybrid Method Combining PSO and FCM Fuzzy C means that we are employing a collection of objects that has been partitioned into a number of clusters in dimensional space using fuzzy clusters that have a centroid. Particle swarm optimization involves talking with one another and communicating knowledge about images. In this procedure, the starting location of each particle is allotted, and the velocity is also initialized. The updated velocity and location data are used to calculate the fitness value.

Advantages: During the phase of pre-processing, the efficiency of the mean, the wiener, and the adaptive median filters is evaluated and compared with that of several other methods. This filter uses Wiener to blur an image while simultaneously reducing noise in order to improve the efficiency with which it compresses images. Images that are fed through the median filter are sharpened while also having noise removed from them. This is accomplished by substituting each pixel with the picture's surrounding pixels' median value. The PSO-FCM technique has a higher accuracy rate when it comes to the multiple classification methods that were used to compare the two filtering methods.

Limitation: Due to the fact that it operates in the frequency domain, Wiener filters have a slow speed rate; therefore, they are not appropriate for spackle noise. Therefore, a variety of segmentation strategies will be examined, and the accuracy will be improved.

Conclusion: After making comparisons, the adaptive median filter pre-processing technique was shown to have the best results. In a comparison of four different segmentation methods, the extraction of brain tumors was enhanced in PSO-FCM, which resulted in a greater accuracy rate of 95.79% compared to other segmentation methods.

At this point in time, the application of computer-aided innovation to automatically extract brain tumors through the picture segmentation method has become an extremely essential technique. Support vector machine (SVM) is employed for the categorization of tumor types, as well as combined K-means and fuzzy C-means grouping are researched for brain tumor detection using segmentation [25]. This is done in an effort to enhance efficiency while simultaneously reducing the difficulty of the analysis. Providing evidence that the technique being suggested is effective in separating normal from pathological (i.e. benign or malignant) tissues based on their appearance in MR scans of the brain.

Algorithm(s) Used: integrated K-means, fuzzy C-means (FCM), and support vector machine techniques. Clustering can be done using the fuzzy C-means technique, which permits one piece of information to correspond to two or more clusters at the same time. The fuzzy C-means (FCM) technique, in instance, assigns pixels to fuzzy groups without using labels. Pixels can belong to several clusters using FCM, and the degree to which they belong to each cluster can change. The use of hyper planes to construct decision boundaries that distinguish between data points belonging to distinct classes is the core idea behind support vector machines (SVM). The findings of this study include both normal and abnormal (tumor) images of the brain in their respective categorized forms. These normal data and tumor data can be distinguished from one another using the hyper planes that are available for usage with SVMs.

Advantages: There are four distinct kinds of filters utilized, as well as four distinct kinds of noise (Salt & Pepper, Speckle, and Gaussian, respectively). Finally, we presented the results of a comparison of the effectiveness of four distinct filtering strategies for demising and determined which was the most successful for the research.

Limitation: It is generally agreed that the accuracy of this model, which was determined to be 94.3 percent, is not very good. The accuracy with which this model may predict future events is not very high, and neither is the degree to which it can be relied upon.

Conclusion: Support vector machine (SVM) is utilized for categorization of the supplied test dataset into benign and malignant categories accordingly. K-means and Fuzzy c-means method are employed to divide the raw brain MRI pictures, and support vector machine (SVM) is being used to divide the image information. Wavelet decomposition is used to extract statistical features from MRI pictures, and then the principal component analysis (PCA) technique is used to reduce the dimensions of the data. The trained characteristic collection of MRI images is made up of the selected features that were taken from the training set of pictures. When a test input image is provided, this database is consulted in order to determine if the brain tumor in question is benign or malignant.

Nilesh et.al. [26] examined Berkeley wavelet transformation (BWT) based brain tumor identification in an attempt to improve the effectiveness of the medical picture segmentation algorithm and also to simplify the steps involved in the procedure. In addition, pertinent characteristics are retrieving from every separated tissue in order to increase the accuracy and quality rate of the classification that is based on a support vector machine (SVM). On the basis of accuracy, sensitivity, specificity, as well as the dice similarity index coefficient, the investigational findings of the suggested methodology have been assessed and verified for the quality and performance assessment on magnetic resonance brain images.

Algorithm(s) Used: Support Vector Machines and the Berkeley wavelet transformation are two examples. The Berkeley wavelet transform, often known as the BWT, is a type of triadic wavelet transform that can be applied to either the signal or the image in order to process it. The BWT technique will also execute data processing from a spatial patterns into temporally domains frequencies, similar to the mother wavelet transformation and other families of wavelet transformation. Support vector machines are a category of supervised learning algorithms that can be used to categories data, perform regression analysis, and locate outliers. They are also commonly referred to as SVMs, which stands for support vector machines.

Advantages: Just on foundation of performance initiatives including such sensitivity, specificity, and accuracy, the ANFIS, Back Propagation, and K-NN classifiers are contrasted with the Berkeley wavelet transform (BWT) as well as support vector machine (SVM) classifier that is suggested again for recognition of brain tumors. This method is based just on Berkeley wavelet transform (BWT). When compared to other approaches such as ANFIS, Back Propagation, and K-NN predicated classification, the effectiveness of the suggested methodology has resulted in a considerable improvement in the detection of tumors.

Limitation: It is necessary to use a selected strategy of the classification, which appropriate team members and over one classifier with feature extraction approaches, in order to increase the accuracy of the categorization performed by this work.

Conclusion: The segmentation is performed using the Berkeley wavelet transform, as well as the phase of the tumor is classified using a support vector machine. This is done by examining the relevant features as well as the region of the tumor. In this research, we evaluated characteristics that were dependent on the roughness of the picture as well as the histogram of a picture in conjunction with a well-known classification for the purpose of classifying brain tumors using MR brain images.

It is quite challenging to get insight into the aberrant architecture of the human brain utilizing imaging methods that are straightforward. The neuronal structure of the human brain may be distinguished and elucidated using a method called magnetic resonance imaging. The MRI method incorporates a wide variety of imaging modalities, which enable it to scan and record the interior structure of the human brain. In the research work referred to as [27], the literature focuses on noise reduction techniques, the extraction of GLCM features, and DWT-based brain tumor area developing segmentation in order to minimize the complexity and improve the results.

Algorithm Used: Discrete wavelet transform and probabilistic neural network (PNN). Discrete wavelet transformations, often known as DWT, are an effective method for image retrieval. In order to obtain coefficient of wavelets from MR pictures of the brain, it was employed. The wavelet was able to pinpoint frequency information of the signal function, which was very helpful for categorization. The probabilistic graphical model (PNN) is an offshoot of the Bayesian network and a statistical procedure known as Kernel Fisher discriminate analysis.

Advantages: Using statistical textural characteristics derived from LL and HL sub bands wavelet decomposition, we were able to obtain an accuracy of approximately 100% for training dataset in identifying and classifying normal and abnormal tumors from brain MR images, and 95% for tested dataset.

Limitation: This study used a more limited dataset, which precludes its applicability to real-time settings. By employing a big dataset that covers a variety of situations and integrating more effective segmentation and feature extraction approaches with real-world and clinically-based examples, various classifiers may be utilised to boost accuracy. This can be accomplished by using huge datasets.

Conclusion: The usage of preprocessing, which further leads in an enhancement in signal-to-noise ratio, is what is done in order to get rid of noise and smooth out the picture. Following this, we utilized a discrete wavelet transform to breakdown the pictures, and then extracted textural characteristics from a GLCM before performing morphological operations. The PNN is employed in the process of classifying cancers based on MRI scans of the brain. Performance analysis for segmentation for various existing method is shown in Table 1.

III. Discussion

The grouping of preprocessed MRI images including brain tumors is the primary focus of our work. In order to do this, initially the picture is subjected to preprocessing, which consists of skull stripping and demising it with the use of a median filter. After that, the K-Means and FCM approaches are put to use, and the findings that are acquired are compared. Next, an optimization-based FCM is performed to the same photos by making use of two different algorithms, namely the Genetic Algorithm and the Particle Swarm Optimization, and the results of this method are compared with those of the unoptimized method. Figure 2 presents the FCMGA architecture. Before employing any classification approach to segment the MRI pictures, we have to pre-process this picture by first removing the skull and then extracting the brain from the picture. This will allow us to reduce the amount of noise that is present in the picture. The term "preprocessing" refers to the step of cleaning up a picture by removing unwanted noise and "skull stripping." This stage of our method, known as the pre-processing of an MRI picture, is the first and most critical step. If these processes are skipped, we won't be able to appropriately detect and divide the tumor based on the MRI scan data.

K-Means

It is a method for categorization, in which categories are created based on some type of resemblance that may be found in the information. Its primary goal is to cut down on the total squared distance, known as the Euclidean distance that separates all of the points from the center of the cluster. At the outset, the number of clusters denoted by K is decided upon. After that, K centroids are chosen at random, and each data point is assigned to the centroid that is geographically closest to it depending on the Euclidean distance between them. This leads to the formation of clusters. Just after clusters have been formed, the actual centroids of each cluster are computed, and the previous values of the cluster centroids are replaced with the new ones.

Image No	Paper [23]		Paper [24]		Paper [25]		Paper [26]		Paper [27]	
	MSE	**PSNR**	**MSE**	**PSNR**	**MSE**	**PSNR**	**MSE**	**PSNR**	**MSE**	**PSNR**
1	0.2437	54.26	7.41	31.27	5.78	10.51	1.86	55.45	6.12	14.01
2	0.0975	58.24	7.71	31.86	5.78	10.51	0.58	68.21	3.11	13.82
3	0.1984	55.15	8.02	31.52	5.78	10.51	4.95	56.28	8.06	14.12
4	0.1012	58.07	7.52	32.71	5.78	10.51	1.23	58.79	4.77	13.86
5	0.3923	52.19	8.11	31.65	5.78	10.51	5.06	59.65	5.84	13.79

Table 1: Performance analysis parameters for segmented tissues in various existing papers

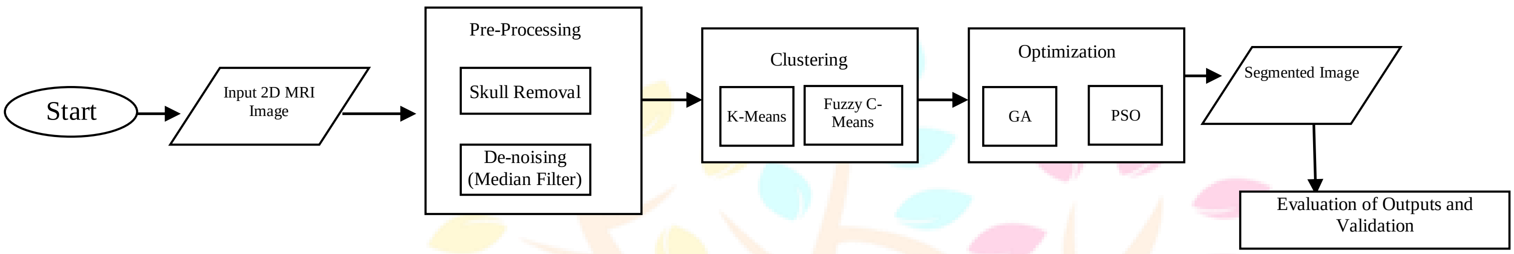

Figure 2. Architecture of FCMGA

Once again, assign the data points to the new centroids that are closest to them. If any of the assignments are different from the one that has previously been carried out, you will need to calculate the new centroid once again and then carry out the procedure again. A fragmentation of the model is regarded as complete if this is not the case. When applied to an image with a resolution of m x n, the K-Means approach divides the picture into k sets, or clusters, with Ck serving as the centroids of each cluster.

Fuzzy C Means

This approach is very similar to K-Means, with the exception that it permits the pieces of information to be a member of more than one grouping rather than mandating that they be a part of just one cluster group. FCM is very similar to K-Means. A fuzzy division is what you get as a consequence of the division. There is a membership function associated with each cluster, which determines the level at which every piece of evidence is a member of the group. It's possible that the locations on the very edge of the clusters are only marginally connected to the rest of it, in comparison to the locations that are considerably closer to the cluster's epicenter. In this step, an iterative search for a collection of fuzzy clusters and corresponding cluster centers that represent the data structure is carried out. FCM separates data into fuzzy clusters by minimizing the squared sum of distance, also known as the Euclidean distance, across classes. This is done with a set number of clusters in mind.

Genetic Algorithm based FCM Clustering

The genetic algorithm is often used to develop achievement and highly optimized answers to search issues by using bio-inspired operators such as mutations, crossings, and selects. This is accomplished via the use of genetic programming. The genetic algorithm is a kind of metaheuristic algorithm that is intrinsically motivated. In GA, every possible solution is modeled as a chromosome, and each chromosome is built up of individual genes. It will be applied to the following iteration, while the incorrect answers will be rejected in favor of the best solution that was applied. We suggest using a classification technique in order to steer the item away from the local minimum and eventually towards a solution that is more neutral. Hill climbing is an example of a local search strategy, and it allows FCM to get to the minimal local level as rapidly as possible on its way to discovering the most optimal answer to the research issue. The difficulties that have been left unsolved by FCM may very well be solved by using GA as an approximation for global optimization. The performance of FCM can be improved by using a genetic algorithm, which we may apply to FCM. The improved method consists of two stages: first, the general algorithm (GA) chooses the initial classification number c automatically, and then, the general algorithm directly calculates the clustering core. PSO will, in most cases, swiftly choose the best broad region in the problem-solving space; nevertheless, it has difficulty doing the fine grain search that is required to locate the absolute optimal location. While in GA, in the hunt for better fitting off springs, the off springs that have previously been picked are discarded.

IV. CONCLUSION

According to our findings, the FCM is superior than the K-means method in terms of its overall effectiveness. When using K-Means, the image is divided into clusters, and each pixel is given a specific cluster to belong to. When using Fuzzy C-Means, on the other hand, the pixels may belong to more than one cluster depending on the membership function, which gives it the ability to detect brain tumors with greater accuracy. We came to the conclusion that the best way to automatically identify and categories a brain tumor in an MRI image was to create a new model that was based on Fuzzy C Means and the Genetic Algorithm (FCMGA). By implementing a tandem FCMGA system, we are able to accomplish the segmentation task with more success and reach a more satisfying conclusion. PSO will, in most cases, swiftly choose the best broad region in the problem-solving space; nevertheless, it has difficulty doing the fine grain search that is required to locate the absolute optimal location. While in GA, in the hunt for better fitting off springs, the off springs that have previously been picked are discarded. The amount of time spent computing will be cut down thanks to FCMGA's repeated selection and rejection. When compared to the FCMGA model, we anticipate that the PSNR values will be greater for the PSO hybrid model and that the related MSE values will be lower.

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