EFFICIENT CLUSTERING OF BRAIN TUMOR SEGMENTS USING LEVEL-SET HYBRID MACHINE LEARNING ALGORITHMS

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Abstract. Cluster computing is an essential technology in distributed environments for practical data analysis in complex datasets like tumor segmentation, disease classification etc. Today real-world applications like medicine and transport are needed for big data analytics environments. This research article considers complex image data environments like brain tumor segmentation based on advanced clustering techniques for effective tumor prediction. An a-state-of-art analysis used Hierarchical clustering to extract initial tumor segments from the image. The next segment is further refined using novel Noise detection-based level-setting techniques. The unsupervised Fuzzy C-means and k- means clustering is used to segment the diseases affected region to enhance noise detection used in the level set. Effective features are extracted using gray level co-occurrence matrix and redundant discrete wavelet transform. Finally, classifying malignant and benign brain tumor images is done using deep probabilistic neural networks. Publicly available datasets are used to validate the proposed algorithms. Experimental results prove that proposed pipeline techniques have effective performance in tumor segmentation and classification model.

Key words: Cluster computing, Distributed environment, brain tumor segmentation, deep learning classification, Hierarchical clustering, Fuzzy C-means, and k- means clustering.

1. Introduction. Recently cluster computing has emerged as a high performance in complex data operation. Normally, image segmentation [22] allows a vast number of data for efficient processing. This segmentation algorithm usually requires numerous pixel data to give better results. It needs more time to address more effective output. By using clustering techniques, the processing splits into multiple clusters (or) nodes and makes it possible quickly. This results in entirely satisfactory solutions with high-resolution images.[19, 2]. Clustering technique is essential in medical diagnosis like tumor segmentation, disease segmentation etc.

Brain tumor segmentation is a critical component of medical diagnosis and treatment planning. Still, it is a complex task due to the variability in tumor size, shape, and location and the similarity in intensity values between healthy and tumor tissue. To overcome these challenges, machine learning and deep learning-based methods have emerged as powerful tools that have significantly improved segmentation accuracy.

Deep learning, in particular, has demonstrated impressive results in overcoming segmentation errors and enhancing accuracy. One key advantage of deep understanding is that it can automatically learn features from the input data, allowing it to identify complex patterns that may be difficult to capture using traditional segmentation techniques. Furthermore, deep learning can perform feature extraction and segmentation in a single end-to-end process, eliminating the need for hand-crafted feature extraction. These advancements in deep learning-based techniques have greatly enhanced the accuracy and flexibility of brain tumor segmentation in clinical applications. With improved segmentation, medical professionals can make more informed diagnoses and treatment plans, monitor the tumor's progression and evaluate the treatment's effectiveness over time.

Medical imaging plays an essential role in diagnosing what the actual problem is and also use to treat diseases. Image segmentation using the clustering model plays a vital role in this process. The past day's image segmentation process mainly produced unsatisfied results, which is normal, because image segmentation includes a large amount of noised pixel data. Here we discuss Brain tumor image segmentation using a pipeline of clustering models for efficient tumor image segmentation[20]. Especially in this type of segmentation, the

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image can vary in shape and size. To meet such demand, we suggest combining clustering techniques for better results. So here we recommend using the below-mentioned techniques to reach an accurate destination.

The initial step in the segmentation process involves Noise Detection, which is crucial for removing any unwanted fluctuations in the intensity values of the input image. This pre-processing step is essential to ensure accurate results. Subsequently, we applied the Fuzzy C Means and K Means algorithms to handle noisy data[4]. The Fuzzy C Means algorithm uses a membership function to determine the similarity between data points and cluster centers, whereas the K Means algorithm uses the Euclidean distance[21]. The Fuzzy C Means approach offers a more flexible clustering technique, while K Means is faster and simpler to produce satisfactory results [25].

Brain tumor prediction and classification is regarded as a challenging research issue. This research considers A-State-of-art techniques and chooses the best strategy to process the brain tumor MRI image. The image is always composed of enormous noises. Hierarchical clustering is widely used in various image segmentation or tumor segmentation process. The algorithms for noise detection in this approach leverage their strengths to provide robust and accurate segmentation results. This noise detection and correction method with the hybrid Fuzzy C Means and K Means algorithms is highly effective for brain tumor segmentation in medical imaging. It helps in accurate diagnosis and proper treatment planning in clinical applications. We recommend using this method for optimal results.[12, 7].

The proposed methodology contribution to image segmentation is as follows:

1. Levelling the feature by removing noises appropriately using fuzzy c & K-means clustering methods.
2. Involves (GLCM) Gray Level Co-occurrence Matrix for future (feature) extraction for calculating co-occurrence of pixel intensities in the image and Involves (RDWT) Redundant Discrete Wavelet Transform for decomposing the image.
3. Deep learning for the final classification process is used with probability techniques.

The paper is further organized as follows: The related study is discussed in section 2 of the article. Section 3 has proposed algorithms and their working details. Next, 4th section details the evaluated results, and finally, in section 5 whole research work is concluded.

2. Related Work. The authors[22] proposed a method for detecting brain tumors through MRI using image thresholding and K means clustering. They used an adaptive median filter to increase image clarity in the pre-processing stage. The results showed their method produced a high accuracy rate in detecting brain tumors. In paper [19], researchers discussed fuzzy c means optimization for brain tumor segmentation. They emphasized the importance of using membership to handle complex data to achieve better results. This work [2] presented an adaptive kernel fuzzy mean and clustering algorithm for brain tumor segmentation. The results showed that the proposed method effectively improved the accuracy of brain tumor segmentation. The paper [20] proposed a method for brain tumor detection using template-based K-means clustering. They found that using the TK template-based k means algorithm produced high-accuracy results for brain tumor diagnosis and treatment planning. The author[4] discussed using common fuzzy c means clustering techniques and concepts for MRI image segmentation. They used a fluctuation tracker to select images for segmentation and showed that using SVM improved the accuracy of brain tumor segmentation.

The proposed approach for liver tumor segmentation [21] utilized a 2D slice-based U-net for liver localization, a 3D patch-based network. For segmentation refinement, and unsupervised Fuzzy c means clustering for tumor estimation. In contrast, [25] proposed using Fuzzy c hyper means clustering to overcome traditional FCM disadvantages for breast tumor segmentation. The methods[24] applied Fuzzy c means and integrated K means clustering techniques for brain tumor classification using Fusion net HFCMIK segmentation. Based on these related works, we propose to use clustering techniques for brain tumor segmentation to improve the accuracy and robustness of the output. Authors in[12] proposed using the Superpixel fuzzy clustering and lattice Boltzmann method to obtain better results for Brain tumor segmentation.

According to authors [7] brain tumor classification is performed under a hybrid deep autoencoder with the Bayesian fuzzy clustering concept. For the preprocessing stage, using a mean filter for noise detection, the Bayesian method is used for brain segmentation. Article [11] motivation presents the deep learning approach to classify brain MRI images to assist medical practitioners. Also, it includes the k means clustering method for preprocessing. The paper[5, 14, 6, 23, 8] analyzes tumor localization by performing operations using k-
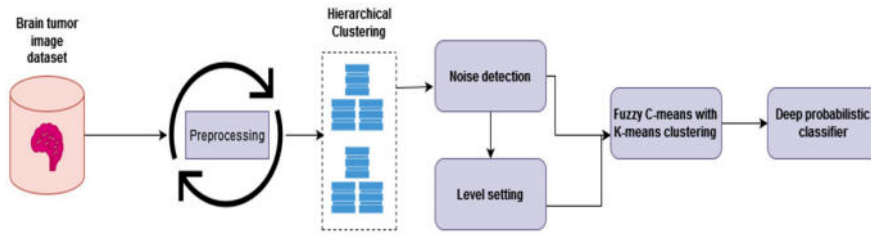
Fig. 3.1: Proposed HFCMKM Techniques for Brain tumor segmentation

means clustering techniques. The proposed method of [15] tumor segmentation is classified under Linear contrast enhancement. Deep learning feature extraction. Based on this strategy, they obtained the segmented output. Machine learning techniques for efficient brain tumor detection[17] Hybrid clustering techniques for brain tumor segmentation[9]. Categorization of brain tumors under MRI images under CNN and SVM[1]. Brain tumor segmentation under machine learning approach[10, 13].Brain tumor classification tumor detection: a long short-term memory (LSTM)-based learning model[18, 16].

3. Proposed system model. The research overview on accurate tumor segmentation and classification model is presented in this section. Figure 3.1 describes the architecture of the proposed work. Medical results based on computer-aided diagnosis have proven most accurate by physicians, and more technological perspective is needed to improve the detection and classification. The grayscale MRI image is considered in this research. The idea requires an effective preprocessing model to remove unwanted noises in the dataset. This research uses median filters to remove noise from the dataset. Then the tumor groups are recognized using hierarchical clustering. Further, our proposed noise-based level set function ideology is computed with hybrid machine learning techniques called Fuzzy C-means and k-means clustering (HFCMKM). In this process, tumor features are accurately segmented from the input image before final classification. The proposed HFCMKM model for MRI image segmentation involves a series of steps to enhance the quality of the input image and extract relevant features for accurate segmentation.

Medical imaging heavily relies on accurate image preprocessing. In the case of brain tumor image segmentation, the focus is on achieving high accuracy. The primary objective of image segmentation is to eliminate the noise present in the image, enhancing its quality and accuracy. This is achieved through three stages: changing the image mode, improving image quality, and analyzing intensity distribution. Image preprocessing includes various sub-stages:

(1) Converting the input image into grayscale.

(2) Smoothing the images to provide noise-free data. This can be achieved by extracting the brain's surface and de noising the images using Median filtering.

Median filtering works by replacing the intensity of each pixel with the median value of powers in its nearest pixel. The size of the filter kernel can be specified, and the entire image is evaluated using the filter kernel. The resulting image is then used to enhance the quality of the image and identify the noise-affected regions, improving the accuracy of the other segmentation process.

This research model employs a noise level set-based hybrid approach with Fuzzy C-means and K-means clustering algorithms to improve the accuracy of segmentation results. This approach overcomes the limitations of traditional fuzzy clustering and produces satisfactory output images. Finally, a post-processing step is performed to eliminate small and isolated regions in the segmented image, resulting in a more accurate and precise image for analysis.

3.1. Hierarchical clustering . The preprocessed image is further processed using hierarchical clustering to segment the image. This clustering method groups similar data points into clusters based on a similarity metric and is commonly used in brain tumor segmentation. Hierarchical clustering is a machine-learning technique that can be used for brain tumor segmentation. Brain tumor segmentation is identifying and delineating

the boundaries of tumor tissue within medical images, such as Magnetic Resonance Imaging (MRI) scans. Hierarchical clustering is an unsupervised learning algorithm that groups similar data points in a hierarchical tree-like structure.

In brain tumor segmentation, hierarchical clustering can group pixels or voxels within the MRI scan with similar intensity values. The algorithm starts by considering each pixel or voxel as a separate cluster and then iteratively merges them based on their similarity. The similarity between two groups is determined using a distance metric, such as Euclidean or correlation distance. The algorithm continues to merge the clusters until a stopping criterion is met, such as a desired number of clusters or a threshold value for the distance metric.

Once the hierarchical tree-like structure is created, a threshold can be applied to the distance metric to cut the tree at a particular level, creating a set number of clusters. These clusters can then be labeled as tumor or non-tumor tissue based on their location within the MRI scan.

The process of hierarchical clustering can be outlined as follows:

Step 1: Initially, each item is assigned to its cluster, resulting in N clusters. The distance between each group is the same as the distance between the items.

Step 2: Similar clusters are identified and merged into one cluster to reduce the overall number of clusters.

Step 3: The distance between each new cluster and every other cluster is calculated.

Step 4: Steps 2 and 3 are repeated until all clusters have been merged into a single cluster, resulting in a hierarchical tree structure.

3.2. Noise Removal using Level Set Function. The 99th percentile minimum and maximum [25] technique reduces noise in Magnetic Resonance Imaging (MRI) images for detecting brain tissue and tumor presence. This technique involves identifying intensity values that correspond to the 99th percentile of the intensity distribution in the MRI image. A piecewise linear transformation is applied to segment the image into different regions, and a linear transformation is separately applied to each region. This process helps enhance or modify the image's appearance by separating brain tissues based on contrast, adjustment, and color. The equation 3.1 state the condition,

$$
y = \left\{ \begin{array}{ll} \left\{ \begin{array}{c} 0 \\ \frac{x - T_{low}}{T_{high} - T_{low}} \quad , \quad x < \\ 1 \\ T_{low} < x < T_{high} \\ X > T_{high} \end{array} \right. & T_{low} \end{array} \right\} \tag{3.1}
$$

Let I be a cropped MRI image defined on a domain Ω. Tumor formed with zero level set
$C = \{(x \in \Omega \mid (x) = 0)\}$
Points inside the contour is $\emptyset(x) < 0$ and outside $\emptyset(x) > 0$
Level set Function $\emptyset : \Omega \to R$ [22] energy function is $\epsilon(\emptyset)$ is defined in equation 3.2

$$
\epsilon(\emptyset) = \mu \mathcal{R}_p + \lambda \mathbf{L}_g(\emptyset) + \alpha A_g(\emptyset) \tag{3.2}
$$

where $R_p(\emptyset) \triangleq \int \Omega \frac{1}{2} (\nabla \emptyset - 1)^2 dx$ The regularization term, which includes $|\nabla \emptyset| \simeq 1$ the length term $\mathscr{L}(\emptyset) = \int \Omega g^\delta(\emptyset) |\nabla \emptyset| dx$ and involves the function g integrated along the zero level contour, is represented dx. The area term is then computed as $\mathcal{A}(\emptyset) = \int \Omega g^H(-\emptyset) dx$

The method is tested on MRI images to segment tumors in a slice-by-slice manner. The segmentation is refined using the contour representation of the tumor formed with the zero level set.

3.3. Applying Hybrid Fuzzy C means and K means clustering:. The Fuzzy C Means (FCM) is a unsupervised technique that is utilized to distinguish between the background tumor-affected region and healthy brain tissue. Hybrid Fuzzy C-K means (HFCKM) provides several advantages over traditional Fuzzy C Means (FCM) by ensuring smooth and continuous segmentation and avoiding the creation of isolated regions in the image. HFCKM involves pre-processing, initialization, cluster assignment, spatial regularization, cluster update, iteration, and segmentation, which provides more accurate results than traditional FCM. This increased accuracy allows for improved diagnosis and more effective treatment planning for patients.

Algorithm 1: Pseudocode for Fuzzy C-Means and K-Means

Step 1:	The image is pre-processed to remove noise and artifacts.
Step 2:	The number of clusters is determined, and the cluster centers are initialized randomly.
Step 3:	Each pixel is assigned a membership value to each cluster, indicating the degree to which the pixel belongs to the cluster.
Step 4:	The membership values are calculated using the Euclidean distance metric, which controls the degree of membership of each pixel to each cluster.
Step 5:	Spatial regularization is included to ensure that nearby pixels have similar membership values. This can be validated using a Gaussian filter.
Step 6:	The cluster center is updated based on the new membership values.
Step 7:	Steps 3 to 6 are repeated until all the clusters are covered.
Step 8:	Finally, the membership values are thresholded to create the segmented results.
Step 9:	Additionally, the K means the concept is applied to HFCM.
Step 10:	Each pixel in the image is assigned to the nearest cluster center based on the Euclidean distance between data points and the cluster.
Step 11:	The cluster center is updated based on the values of each pixel assigned to each cluster.
Step 12:	Steps 2 and 3 are repeated until all the clusters have been covered.
Step 13:	Finally, the tumor-affected area is represented based on the identified clusters.

To perform HFCMKM, the following steps are presented in Algorithm 1.

The proposed HFCMKM technique is applied in two steps. In the first step, the hybrid FCM algorithm assigns a membership value to each pixel for each cluster based on the degree to which the pixel belongs to the cluster. Spatial regularization is included to ensure that nearest pixels have similar membership values. The Euclidean distance metric is used to calculate membership values, and a Gaussian filter can validate the results.

Next, the K means technique is applied to represent brain tissues as K clusters. Each pixel is assigned to the nearest cluster center based on the Euclidean distance between data points and the cluster. Finally, the HFCMKM technique combines the advantages of both FCM and K means clustering to obtain robust and flexible results.

Overall, the proposed HFCMKM technique (Algorithm 2) provides an efficient and effective way to handle complex data in brain image segmentation. It overcomes the limitations of traditional FCM and K means techniques and can lead to accurate diagnosis and treatment planning for clinical applications.

Finally, the tumor values are clustered using following equations

$$\bigcup_{j=1}^{n} = \sum_{i=1}^{n} W_i \ X_i \tag{3.5}$$

W_i denotes the weightage of X_i

For n data points, the number of U values are estimated in equation 3.6

$$\bigcup_{j=1}^{m} \begin{pmatrix} U_1 \\ U_2 \\ U_n \end{pmatrix} \tag{3.6}$$

The data points U_i are sorted by distance and weighted. Then, they are divided into k equal sets, where k represents the number of clusters. The mean value of each set is taken as the initial centroid. The proposed approach, named HFCMKM, utilizes the distance metric to determine the value of the members in each group. The suggested weighted algorithm selects centroids based on the following formula, which improves the selection of initial centers. HFCMKM divides the image into clusters and employs the centroids to represent the artificially constructed clusters, followed by a re-estimation of the segmented output.

Algorithm 2: HFCMKM

Step 1 Input MRI images [I_n] // cleaned level set images
Step 2: $U^1 = [U_{nj}]$
Step 3: Fix number of clusters C
Step 4: Fix Max Iteration =T
Step 5: Fix delta value ϵ
Step 6: Initialize randomly U^0
Step 7: t=1 to T do

$$U_{nj} = \frac{1}{\sum_{k=1}^{C} \left(\frac{I_n - C_j}{I_n - C_k} \right)} \quad \frac{2}{m-1} \tag{3.3}$$

Calculate the new cluster center C_j

$$C_j = \frac{\sum_{i=1}^{N} U_{nj}^m \cdot I_n}{\sum_{i=1}^{N} U_{nj}^m} \tag{3.4}$$

Calculate the new objective function.
if $|J^1 - J^{t-1}| < \in$ then
Break;
else
Continue;
end if
end for

3.4. Hybrid Feature Extraction using GLCM and RDWT.

3.4.1. Gray level Co-occurrence Matrix. There are several characteristics that aid in distinguishing brain tumors, including statistical color features, GLCM texture-based features, and RDWT-based low-level features [12]. GLCM, which represents the frequency of pairs of pixel values in an image, has been particularly useful in characterizing the texture of brain tumors. By using GLCM as a feature extraction method, the texture properties of a brain image can be captured and utilized in a machine learning model for classifying different regions of the image. This process involves several steps, such as image preparation, gray level quantization, co-occurrence matrix calculation, feature extraction, and machine learning model training[12].

$$\text{Contrast} = \sum_{a,b=0}^{N-1} S_{a,b}(a-b)^2 \tag{3.7}$$

$$\text{Homogeneity} = \sum_{a,b=0}^{N-1} \frac{S_{a,b}}{1 + (a-b)^2} \tag{3.8}$$

$$\text{Correlation} = \sum_{a,b=0}^{N-1} S_{a,b} \left[\frac{(a-\mu_a)(b-\mu_b)}{\sqrt{(\sigma_a^2)(\sigma_b^2)}} \right] \tag{3.9}$$

$$\text{Angular Second Moment (ASM)} = \sum_{a,b=0}^{N-1} s_{a,b}^2 \tag{3.10}$$

$$\text{Energy} = \sqrt{ASM}[12] \tag{3.11}$$

3.4.2. Redundant discrete wavelet transform. Next step involves RDWT, It is a popular technique used under the feature extraction of image processing. RDWT is a method of decomposing an image in to wavelet coefficients. It includes Lower level and higher level frequency bands. Lower level represents the features where as higher level represents the finer details. It also used to extract the features for further analysis. This redundancy allows more flexibility and accurate feature extraction results under segmentation process.

$$\text{Mean}(\mu) = \frac{1}{N^2} \sum_{i,j=1}^{N} I(i,j) \tag{3.12}$$

$$\text{Standard Deviation}(\sigma) = \sqrt{\frac{\sum_{i,j=1}^{N} \left[I\left(i,j\right) - \mu^2\right]}{N^2}} \tag{3.13}$$

Finally, the features of both GLCM and RDWT are combined and produce the result in the form of hybrid feature matrix[12]. The Proposed HFCMKM is a highly accurate segmentation technique that ensures smooth and continuous segmentation, avoids creating isolated regions in the image, and provides more accurate results than traditional FCM. These advantages lead to improved diagnosis and effective treatment planning for patients

3.5. Deep Learning Based Probabilistic Neural Network (DPNN). The deep probabilistic neural network (DPNN) is a type of neural network that combines the strengths of deep learning and probabilistic modeling, making it a valuable tool in feature extraction and classification. In the context of brain tumor image segmentation, the DPNN can differentiate between tumor and non-tumor tissue based on features such as intensity, texture, and shape. During the feature extraction process, the DPNN learns to assign a probability value to each class based on their features. When presented with a new image, the DPNN uses these probabilities to classify each pixel as either tumor or non-tumor[3] The DPNN performs these classification operations once, learning to train with the input's local characteristics at a higher level. The network also provides information on each layer, such as its size, parameters, and filters. By combining all layers, the DPNN achieves a satisfactory output. Overall, the DPNN is a powerful tool for accurately segmenting brain tumors from medical images.

4. Result Discussion. This system utilizes the BraTS-2020 dataset to give a full evaluation of findings and efficacy compared with previous techniques. Moreover, assessments of numerous objective outcomes as well as visual objective achievements are offered. The MatlabR2021a tool was used in combination with a GPU processor to perform this study. Here on the dataset, the algorithms are taught in realistic scenarios. The experiments are executed using a Windows 10 operating system equipped with a NVIDIA Tesla P100 CPU. The 10-fold cross-validation method is used for learning the suggested model. All of the algorithms were developed using Matlab R2021a with a learning rate of 0.02 and 10-fold cross validation over 1000 iterations.

4.1. Dataset Used for Evaluation. The BraTS-2020 dataset is used to evaluate the proposed network's efficiency. There are 369 images used for training, 125 for validation, and 169 for testing in multi-modal brain MRI studies. Each study contains 80 T1-weighted (T1) images, 80 T1ce-weighted (T1ce) images, 80 T2-weighted (T2) images, and 209 Flair sequence images. The annotation for training studies is made available for online evaluation and the final segmentation competition, but not for validating and test runs.

The proposed HFCMKM method evaluates the brain tumor dataset with following parameter metrics such as accuracy, precision, recall, f1-score and confusion matrix. The proposed method HFCMKM is compared with existing methods such as MCA-CS [2], LDNSD [2] and DB-CNN [2].

Accuracy. It is used to evaluate the classification of correct brain tumor images accurately.

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} X 100 \tag{4.1}$$

Table 4.1: Metric measures for classification of brain tumor image

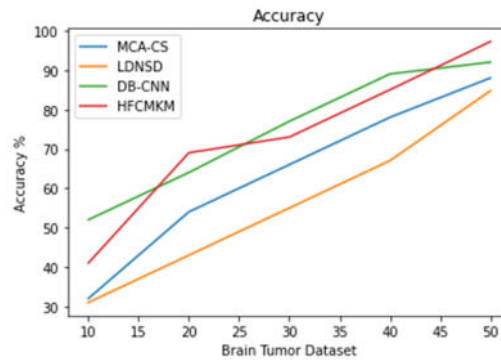| Methods Used	Accuracy	Precision	Recall	F1-score
MCA-CS	88	79	89.45	92
LDNSD	84.76	76	87	94.75
DB-CNN	92	88	91	93.09
HFCMKM	**97.23**	**93**	**95.78**	**97.88**

Fig. 4.1: Accuracy

Precision.

$$precision = \frac{TP}{TP + FP} X100 \qquad (4.2)$$

Recall.

$$recall = \frac{TP}{TP + FN} \qquad (4.3)$$

Table 4.1 shows that Classification of four types of brain tumor images like T1-weighted, T1ce-weighted, T2-weighted and Flair sequences using proposed work.

Table 4.1 presents the results of an evaluation of four different machine learning models for a specific task. The task is not specified, but it is assumed to be a classification problem, as the metrics reported are accuracy, precision, recall, and F1-score. These metrics are commonly used for evaluating the performance of classification models.The four models evaluated are MCA-CS, LDNSD, DB-CNN, and HFCMKM. For each model, the table reports the accuracy, precision, recall, and F1-score achieved by the model.

Accuracy is the percentage of correctly classified instances out of all instances. Precision is the percentage of correctly classified positive instances out of all instances classified as positive. Recall is the percentage of correctly classified positive instances out of all actual positive instances. F1-score is the harmonic mean of precision and recall.

Based on the results in the table, the highest accuracy is achieved by the HFCMKM model with a score of 97.23%. The highest precision is achieved by the DB-CNN model with a score of 88%. The highest recall is achieved by the HFCMKM model with a score of 95.78%. Finally, the highest F1-score is achieved by the HFCMKM model with a score of 97.88%.

Figure 4.1 shows the graphical representation of the accuracy which is compared with existing methods. X-axis represents number of images in dataset and Y-axis represents accuracy percentage for tumor prediction.

The HFCMKM model outperforms the other models evaluated in terms of accuracy, recall, and F1-score. However, the DB-CNN model achieves the highest precision score. The choice of the best model will depend on the specific requirements of the task at hand and the trade-off between different performance metrics.
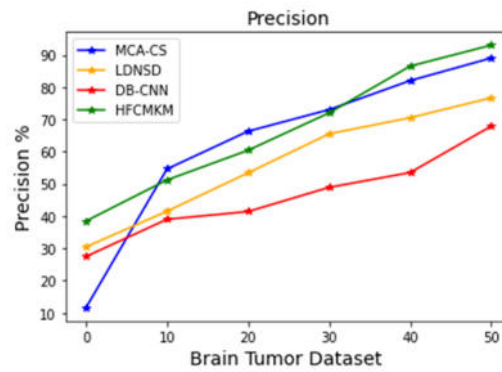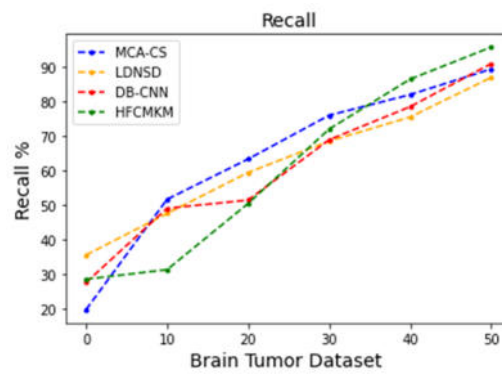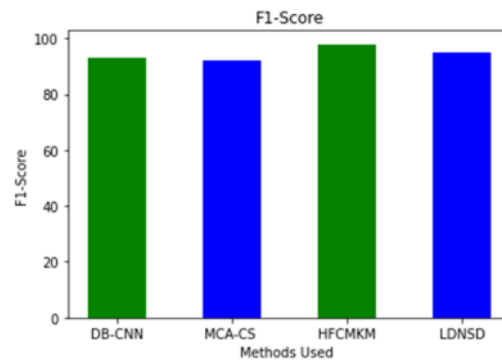
Fig. 4.2: Precision

Fig. 4.3: Recall

Fig. 4.4: F1-Score

The confusion matrix classified the correct and incorrect classification of brain tumor images. The Classification of four types of brain tumor images like T1-weighted, T1ce-weighted, T2-weighted and Flair sequences evaluated in confusion matrix and shown in figure 4.5.

The use of larger datasets can result in high computational complexity. The proposed approach of combining HFCMKM segmentation and classification performance needs to be improved. There are various metric methods
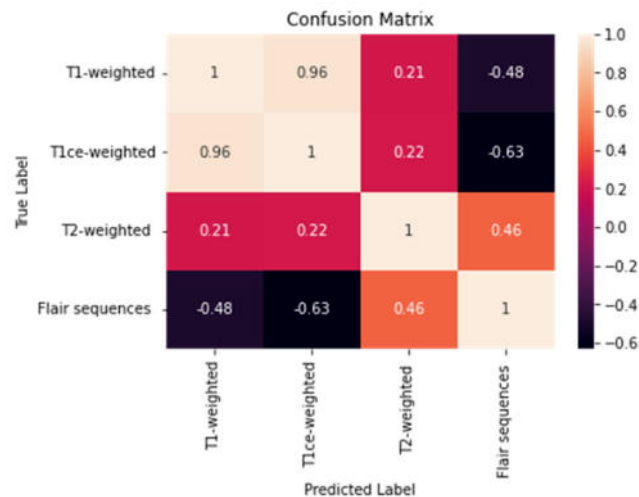
Fig. 4.5: Confusion Matrix

that have been published under DLPNN, but their main limitation is their high complexity. This paper proposes a novel approach that combines clustering methods. Traditional clustering methods have limitations that can affect their accuracy in providing the desired output. By combining the strengths of adaptive clustering methods, high-quality results can be obtained. Therefore, this paper presents a new approach, the HFCMKM method, which involves preprocessing, noise detection using Level Set, applying FCMKM, and finally, combining these strengths to improve the tumor region's accuracy.

5. Conclusion. Finally, this paper we proposed HFCMKM approach to enhance the quality and accuracy of the MRI Brain image to identified the tumor region perfectly based on the above features as we discussed while. It performs in a good way and lead to correct path for clinical diagnosis. This method also helps to localize the tumor location accurately. Initially this work implemented the Hierarchical Clustering to enhance the quality of the image. In addition, Level set function used to remove noise and pre-processing of the source images. Finally combining strengths of both HFCM and K means based segmentation is used to localize the tumor. Furthermore, Hybrid features is extracted from the segmented images using GLCM and RDWT approaches. Finally, DLPNN is used to classify benign and malignant by using this feature. Finally, the proposed method is compared with the various existing methods to prove that the proposed method can be adopted for real time application.

REFERENCES

[1] S. Deepak and P. Ameer, *Automated categorization of brain tumor from mri using cnn features and svm*, Journal of Ambient Intelligence and Humanized Computing, 12 (2021), pp. 8357–8369.

[2] R. S. Devi, B. Perumal, and M. P. Rajasekaran, *A hybrid deep learning based brain tumor classification and segmentation by stationary wavelet packet transform and adaptive kernel fuzzy c means clustering*, Advances in Engineering Software, 170 (2022), p. 103146.

[3] Q. Hu, S. Hu, and F. Zhang, *Multi-modality medical image fusion based on separable dictionary learning and gabor filtering*, Signal Processing: Image Communication, 83 (2020), p. 115758.

[4] M. K. Islam, M. S. Ali, M. S. Miah, M. M. Rahman, M. S. Alam, and M. A. Hossain, *Brain tumor detection in mr image using superpixels, principal component analysis and template based k-means clustering algorithm*, Machine Learning with Applications, 5 (2021), p. 100044.

[5] A. R. Khan, S. Khan, M. Harouni, R. Abbasi, S. Iqbal, and Z. Mehmood, *Brain tumor segmentation using k-means clustering and deep learning with synthetic data augmentation for classification*, Microscopy Research and Technique, 84 (2021), pp. 1389–1399.

[6] M. A. Khan, I. Ashraf, M. Alhaisoni, R. Damaševičius, R. Scherer, A. Rehman, and S. A. C. Bukhari, *Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists,*

Diagnostics, 10 (2020), p. 565.

[7] A. Khosravanian, M. Rahmanimanesh, P. Keshavarzi, and S. Mozaffari, *Fast level set method for glioma brain tumor segmentation based on superpixel fuzzy clustering and lattice boltzmann method*, Computer Methods and Programs in Biomedicine, 198 (2021), p. 105809.

[8] S. Maheswaran, S. Sathesh, G. Saran, and B. Vivek, *Automated coconut tree climber*, in 2017 International Conference on Intelligent Computing and Control (I2C2), IEEE, 2017, pp. 1–6.

[9] K. Maheswari, A. Balamurugan, P. Malathi, and S. Ramkumar, *Hybrid clustering algorithm for an efficient brain tumor segmentation*, Materials Today: Proceedings, 37 (2021), pp. 3002–3006.

[10] M. A. Naser and M. J. Deen, *Brain tumor segmentation and grading of lower-grade glioma using deep learning in mri images*, Computers in biology and medicine, 121 (2020), p. 103758.

[11] P. S. Raja et al., *Brain tumor classification using a hybrid deep autoencoder with bayesian fuzzy clustering-based segmentation approach*, Biocybernetics and Biomedical Engineering, 40 (2020), pp. 440–453.

[12] M. Ramprasad, M. Z. U. Rahman, and M. D. Bayleyegn, *A deep probabilistic sensing and learning model for brain tumor classification with fusion-net and hfcmik segmentation*, IEEE Open Journal of Engineering in Medicine and Biology, 3 (2022), pp. 178–188.

[13] Z. U. Rehman, M. S. Zia, G. R. Bojja, M. Yaqub, F. Jinchao, and K. Arshid, *Texture based localization of a brain tumor from mr-images by using a machine learning approach*, Medical hypotheses, 141 (2020), p. 109705.

[14] S. Rinesh, K. Maheswari, B. Arthi, P. Sherubha, A. Vijay, S. Sridhar, T. Rajendran, Y. A. Waji, et al., *Investigations on brain tumor classification using hybrid machine learning algorithms*, Journal of Healthcare Engineering, 2022 (2022).

[15] L. Rundo, L. Beer, S. Ursprung, P. Martin-Gonzalez, F. Markowetz, J. D. Brenton, M. Crispin-Ortuzar, E. Sala, and R. Woitek, *Tissue-specific and interpretable sub-segmentation of whole tumour burden on ct images by unsupervised fuzzy clustering*, Computers in biology and medicine, 120 (2020), p. 103751.

[16] V. Sabitha, J. Nayak, and P. R. Reddy, *Withdrawn: Mri brain tumor detection and classification using kpca and ksvm*, 2021.

[17] V. Sanjay and P. Swarnalatha, *A survey on various machine learning techniques for an efficient brain tumor detection from mri images*, IJEER, 10 (2022), pp. 177–182.

[18] K. S. Sankaran, M. Thangapandian, and N. Vasudevan, *Brain tumor grade identification using deep elman neural network with adaptive fuzzy clustering-based segmentation approach*, Multimedia Tools and Applications, 80 (2021), pp. 25139–25169.

[19] C. J. J. Sheela and G. Suganthi, *Accurate mri brain tumor segmentation based on rotating triangular section with fuzzy c-means optimization*, Sādhanā, 46 (2021), p. 226.

[20] R. Sindhiya Devi, B. Perumal, and M. Pallikonda Rajasekaran, *A robust hybrid fusion segmentation approach for automated tumor diagnosis and classification in brain mr images*, Journal of Intelligent & Fuzzy Systems, 42 (2022), pp. 6063–6078.

[21] R. Vankdothu and M. A. Hameed, *Brain tumor segmentation of mr images using svm and fuzzy classifier in machine learning*, Measurement: Sensors, 24 (2022), p. 100440.

[22] A. Verma, M. Ansari, P. Tripathi, R. Mehrotra, and S. A. Shadab, *Brain tumor detection through mri using image thresholding, k-means, and watershed segmentation*, in Computational Intelligence in Healthcare Applications, Elsevier, 2022, pp. 267–283.

[23] B. Vivek, S. Maheswaran, P. Keerthana, S. Sathesh, S. Bringeraj, R. A. Sri, and S. A. Sulthana, *Low-cost raspberry pi oscilloscope*, in 2018 international conference on intelligent computing and communication for smart World (I2C2SW), IEEE, 2018, pp. 386–390.

[24] L. Xiao, H. Qi, C. Fan, and Z. Ai, *Energy noise detection fcm for breast tumor image segmentation*, IEEE Access, 8 (2020), pp. 62895–62904.

[25] Y. Zhang, B. Jiang, J. Wu, D. Ji, Y. Liu, Y. Chen, E. X. Wu, and X. Tang, *Deep learning initialized and gradient enhanced level-set based segmentation for liver tumor from ct images*, IEEE Access, 8 (2020), pp. 76056–76068.