

# Fuzzy Deep Learning Approach for the Early Detection of Degenerative Disease

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**Abstract**—Degenerative diseases can impact individuals of any age, encompassing children and teenagers; however, they typically tend to affect productive or adult individuals. Globally, conventional and advanced diagnostic methods, including those developed in Indonesia, have emerged to identify and manage these health conditions. Problems in brain tumor detection are the intricate process of precisely and effectively identifying the presence of tumors in the brain. On the other hand, diagnosing brain tumors in the laboratory poses issues related to time consumption, inaccuracy, lack of consistency, and costliness. This study specifically concentrates on the early detection of brain tumors by analyzing images generated through MRI scans. Unlike the traditional method of manual image analysis conducted by seasoned physicians, our approach integrates fuzzy logic to enable the early identification of brain tumors. The principal objective of this research is to enhance understanding and develop an intelligent, swift, and precise application for diagnosing brain tumors using medical imaging. The segmentation technique provides practical technology for the early detection of brain tumors. Utilizing a dataset comprising over 13,000 data points and undergoing a year-long training process with approximately 1,310 MRI images, the research culminates in the creation of a tool or software application system for the analysis of medical images. Despite the impressive precision score of 0.9992, highlighting its exceptional accuracy in correctly identifying positive instances, the recall value of 0.5767 suggests the potential exclusion of a significant number of actual positive instances in its predictions.

**Keywords**—Degenerative diseases; brain tumor; fuzzy; deep learning

## I. INTRODUCTION

A brain tumor is a severe medical condition that has an impact on the brain, considering the vital role of the brain as one of the essential organs in the body. Disruptions to the brain can have cascading effects on other organs, potentially resulting in fatal consequences. Although brain tumors can impact individuals of any age, including children and teenagers, they typically tend to affect productive or adult individuals [1], [2]. Moreover, as stated in study [3], significant advancements in medical science have introduced sophisticated diagnostic and treatment techniques, offering hope for the survival and improved outcomes of patients grappling with brain tumors. The primary concern for individuals diagnosed with brain cancer or brain tumors is the rate at which they may spread to other areas of the brain or spinal cord, and the potential for successful removal without subsequent recurrence.

Several factors that influence the prognosis (life expectancy) of individuals with brain tumors include the ability for early detection, an accurate understanding of the tumor's location in the brain, and the quality of diagnostic and therapeutic (surgical) technologies, such as Magnetic Resonance Imaging (MRI). Brain cancer arises from the abnormal proliferation of brain cells within brain tissue. There are two distinct types of brain cancer: benign (non-cancerous) and malignant (cancerous). Benign tumors do not have any adverse impact on healthy normal cells or brain tissue, while malignant tumors affect brain tissue and may lead to fatal consequences. Detecting brain cancer early typically involves the use of MRI, although radiologists may encounter challenges in precisely determining the cancer's location within the MRI image. In their study, researchers employed Laplacian of Gaussian filtering to enhance MRI images; achieving approximate 84% segmentation accuracy with the algorithm they devised [4].

As indicated in study [5], brain cancer or tumors can affect people of all age ranges and have the potential to impact the central nervous system. When tumor cells effectively invade the brain, they disturb all bodily functions, posing a substantial risk of mortality. Brain cancer or tumors can affect people of all age ranges and have the potential to impact the central nervous system. When tumor cells effectively invade the brain, they disturb all bodily functions, presenting a substantial risk of mortality. Brain tumors can manifest as either malignant or benign, and in certain instances, the prospects of recovery are minimal, ultimately leading to death. Early detection is crucial for obtaining accurate and precise results, necessitating the use of imaging technology to aid in the diagnosis, treatment, and surgical intervention for brain-related conditions. Moreover, it was stated that research were to provide early warnings to reduce mortality and develop precise and rapid methods for treating brain tumors. They used machine learning to classify malignant tumors, concluding that MML (Machine Learning) is superior to SVM (Support Vector Machine) in terms of PSNR, MSE, fault rate, and accuracy for brain cancer segmentation [6], [7], [8]. Hence, the findings of this study indicate that the integration of artificial intelligence and image processing yields superior outcomes in the segmentation and classification of brain tumors.

In the healthcare sector, computer vision, particularly image processing and segmentation, is widely employed within the realm of Information Technology (IT). Consequently, this research endeavors to create an application as well as proposed segmentation and deep learning methods. The utilized objects

for this application are images extracted from photographs produced through MRI technology. Meanwhile, using image processing techniques [9], it is proposed that conducting statistical analysis, which involves parameters such as mean, standard deviation, and variance derived from object features in images, can offer insights into the state of a healthy or diseased brain. This is achieved by comparing the statistical values derived from images of normal brains with those displaying irregularities. In this research, our objective is to diagnose brain conditions through the application of segmentation and deep learning techniques, and we intend to evaluate the effectiveness of fuzzy deep learning methods in this regard. The developed application is expected to assist medical professionals, especially doctors, in analyzing diseases, particularly generative diseases, using medical MRI images accurately, quickly, and affordably. The urgency of this research lies in the current manual analysis of MRI images, which is not only less accurate but also time-consuming.

As indicated in study [8] SVM is considered one of the premier methods for analyzing image datasets. SVM (Support Vector Machine) generates predictions by reducing the image size while retaining essential information crucial for accurate predictions. The Kernel's model presented in this study achieves a testing accuracy of 98.75%, with the potential for improvement through the addition of more image data. Furthermore, an alternative model employing CNN integrates an automated feature extractor, modified hidden layer architecture, and activation function. Various test scenarios were executed, and the proposed model achieved a precision score of 97.8%, coupled with a low cross-entropy rate [10]

In research [11], the researchers focused on assessing the classification accuracy of cranial MR images using ELM-LRF, achieving a precision rate of 97.18%. The results suggest that the effectiveness of the proposed method exceeds that of recent studies documented in the literature. According to study [10], their proposed model surpasses existing models in accuracy, achieving 99.48% for binary classification models and 96.86% for multi-class classification. In contrast to existing models that encounter difficulties such as substantial computational expenses and restricted generalizability attributed to insufficient training data, our model tackles these challenges by being lightweight, employing cross-validation for enhanced generalizability, and undergoing training on extensive and diverse datasets.

Presented by study [5] and utilizing deep learning algorithms with RG (Radiomics and Geometry) alongside MAKM (Multi-scale Anisotropic Kernels) and U-Nerresults, three distinct experimental setups/cases were presented on the BRATS2015 dataset. The obtained experimental results yielded accuracy values of 89%, 90%, and 80% for case-1, case-2, and case-3, respectively.

The significance of Convolutional Neural Networks (CNNs) in image dataset analysis, emphasizing their efficiency in prediction and image size reduction. An Artificial Neural Network (ANN) achieves a testing accuracy of 65.21%, with potential for improvement through additional image data, was carried out in study [12]. CNN challenges through a lightweight approach and diverse dataset training. State-of-the-

art deep learning algorithms demonstrate robust performance on the BRATS2015 dataset, achieving high accuracy values for various experimental setups, showcasing the versatility of the proposed methodologies. Hence, the cumulative accuracy of the preceding research is 89.83%.

This work introduces the Fuzzy Deep Learning Approach for the Early Detection of Degenerative Diseases. It represents a pioneering integration of fuzzy logic principles with deep learning techniques for disease detection. In contrast to conventional methods, this approach presents a nuanced and adaptive framework that considers uncertainties and imprecise information inherent in medical data. By amalgamating the strengths of deep learning, which excels in learning intricate patterns, with the flexibility of fuzzy logic to handle uncertainty, the model enhances the accuracy and interpretability of early degenerative disease detection. This innovative fusion addresses the inherent complexities and variations in degenerative diseases, offering a promising avenue for more effective and reliable diagnostic tools. The research contributes to advancing the field by presenting a novel and robust methodology that has the potential to revolutionize early disease detection strategies.

## II. RELATED WORKS

### A. Degenerative Diseases

The World Health Organization states that degenerative diseases are the leading cause of death worldwide in the population aged 65 and older, with a higher death toll in developing countries. According to study [13], an estimated 23% of women and 14% of men aged over 65 suffer from degenerative diseases. The global prevalence of hypertension is estimated to be around 15-20%, with a higher incidence in the age group of 55-64 years.

### B. Image Segmentation

Digital image segmentation involves the partitioning and categorization of components within an image into regions or zones that share homogeneity based on specific characteristics. Automated segmentation plays a crucial role in various image processing applications, including object recognition, by enabling the isolation of distinct areas in an image, thereby cutting down on processing time for relevant information, [14], [15]. Furthermore, [5], [16] delineates five primary strategies for image segmentation: thresholding techniques [17], boundary-based methods [18], region-based techniques, clustering-based approaches [19], and hybrid methods [20]. Seeded Region Growing segmentation who used by [5], [21], [22], is a hybrid technique. This method begins by selecting one or more seed pixels as the starting point, denoted as  $A_1, A_2, A_3, \dots, A_n$ . In each iteration, these seeds  $A_i$  expand to include the adjacent pixels  $x$  from the seed region  $A_i$ . The decision on whether the target feature is in the selected seed is made. For example, let  $T$  be all pixels or seeds that are not allocated (unlabeled) and located closest to  $A_i$  after  $m$  iterations, then:

$$T\{x \notin n\}A_i \cap n. A_i \neq \quad (1)$$

In this case,  $N(x)$  refers to the second-order nearest neighbor (8-neighborhood) of pixel  $x$ . If the only intersection

of  $N(x)$  is with region  $i$ , then the label  $L(x)$  is denoted by an index as specified in Eq. (2).

$$N(x) \cap A_i(x) \neq \emptyset \quad (2)$$

Stated by study [23] in specific cases, segmenting color images offers greater benefits compared to grayscale images because of the more extensive feature set present in color images. Color images represent each pixel through a combination of 224 color components of R, G, B, covering both chromatic and intensity aspects. Consequently, the segmentation of color images becomes more intricate. The term "image segmentation" pertains to the division of an image into distinct regions, with a region defined as a collection of pixels exhibiting specific boundaries and shapes, such as circles, polygons, and ellipses. Moreover in study [24], explain that segmentation has two main objectives: i) to divide the image into regions for further analysis, ii) to change the representation of an image. Pixels of an image must be organized into higher-level units that are more meaningful or meaningful for further image analysis. Meanwhile, states that regions contain groups of multispectral or hyperspectral image pixels with similar feature values. Most segmentation methods fall into three classes: (i) feature characteristic [25], (ii) boundary detection, or (iii) region growing.

### C. Image Retrieval Issues

Various problems related to image search have attracted significant attention from researchers, including worked by [26], [27], [28]. Image search is a challenging task closely related to computer vision. Additionally, [26] states that the main problem in evaluating the effectiveness of a CBIR system is how users can clearly determine that the query photo is the same or similar to an image in the database.

### D. Deep Learning-based Image Segmentation

Deep learning addresses the limitations of traditional machine learning methods that can automatically engineer features, commonly referred to as feature engineering [11]. This capability is achieved through deep learning, utilizing algorithms that illustrate sophisticated abstractions within data. Deep learning relies on layers of nonlinear transformation functions arranged in intricate structures. Deep learning is applicable to various domains, including supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, such as tasks like text classification, image recognition, speech recognition, and mor [19], [29].

CNN is a type of machine learning method commonly used in the visual-to-text field. It employs a convolutional layer as a component of a built neural network. The input sequence is padded with zeros to have the same length, enhancing performance by preserving information at the borders.[30] An overview of the CNN process structure is provided in Fig. 1.

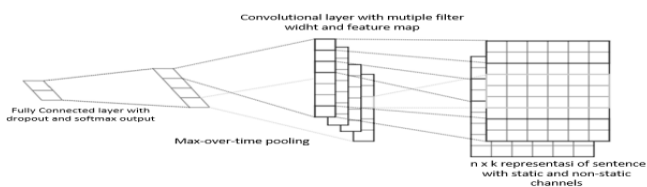


Fig. 1. CNN process structure.

### E. Recurrent Neural Network

According to research [31] and [32], RNN is architecture comprises an input layer, one or more hidden layers, and an output layer. It features a sequential structure resembling a chain, with recurring modules serving as memory to retain crucial information from preceding steps. Additionally, RNN incorporates a feedback loop enabling the artificial neural network to process input sequences. Consequently, the output from step  $t-1$  is reintroduced into the network, influencing the outcome of step  $t$ . Fig. 2 provides a basic depiction of the functioning of the RNN algorithm, involving one input unit, one output unit, and iteratively evolving hidden units.

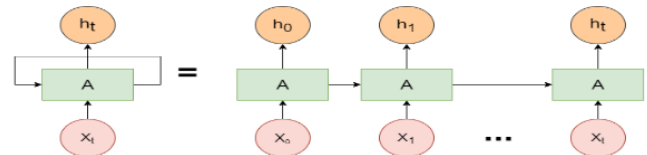


Fig. 2. Overview of how RNN works.

Previous studies have successfully implemented RNN for image processing, such as [33], which successfully implemented LSTM-RNN for plant disease identification, [34], which successfully implemented Attention-Based RNN for plant disease detection, and [35], which used a variation of RNN, namely Dense RNN, for image segmentation of the heart. According to [36], an overall overview of the working mechanism of the RNN method, namely RNN-LSTM, can be seen in Fig. 1. Each LSTM cell receives information from the previous cell and then sends the obtained information to the next cell. Fig. 3 provides a depiction of how RNN-LSTM operates, demonstrating the sequential flow and interactions among input, output, and memory units within the Long Short-Term Memory (LSTM) architecture.

According to [37], LSTM has a memory cell and gate inputs (input gate, forget gate, cell gate, and output gate). In the forget gates, each incoming data is processed and then selected to be discarded or stored; in this gate, the activation function used is sigmoid (if the value is 1, the data is stored; if the value is 0, the data is discarded).

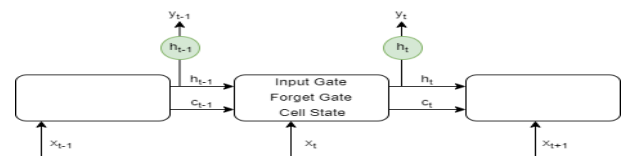


Fig. 3. Overview of how RNN-LSTM works.

Within the domain of computational procedures, the forget gate functions by employing Eq. (3).

$$it = \sigma(Wi[ht - 1, xt] + bi) \quad (3)$$

$$Ct = \tanh(Wc.[ht - 1] + bc) \quad (4)$$

Following that, a new value replaces the current memory cell value on the cell gate. This distinct value is obtained by combining the values acquired from the forget gate and the input gate, as specified in Eq. (4).

$$c_t = f_t * c_{t-1} + i_t * \hat{c}_t \quad (5)$$

Finally, on the output gate, a selection of the value from the memory cell is performed using the sigmoid activation function. The obtained value is then input into the memory cell using the tanh activation function, and the values from both processes are multiplied to produce the output value, as described in Eq. (6) and Eq. (7) in the output gate.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t \tanh(c_t) \quad (7)$$

### F. Fuzzy Logic

Fuzzy logic is a type of logic that has values between true or false, often referred to as fuzzy values or fuzziness. Fuzzy logic can simultaneously have true or false values, but it also has a membership degree ranging from 0 to 1 that determines the existence and accuracy of that value. Fuzzy logic translates a quantity represented using linguistic terms; for example, the speed of a car is represented as slow, moderately fast, fast, and very fast. Unlike classical logic, where a value has only two possibilities—either it is not a member of the set or if the membership degree is 0, or it is a member of the set if the membership degree is 1 [38], [39].

## III. METHODS

In this section, the stages conducted in the research are explained. The preprocessing of MRI images involves resizing, followed by the conversion of color (RGB) images to grayscale. Subsequently, segmentation and deep learning with RNN are performed. An evaluation is then carried out to calculate the accuracy of the algorithm. The overall research stages can be seen in Fig. 4. While Fig. 5 showcase the application of a Recurrent Neural Network in analyzing MRI images that depict the processing of brain tumors.

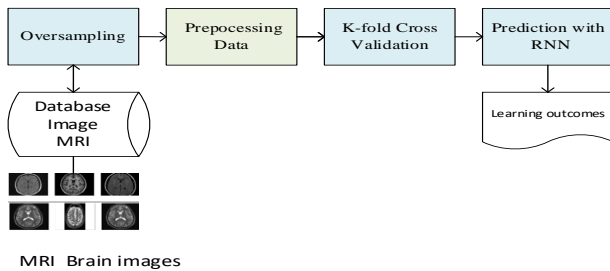


Fig. 4. Research stages.

Query Image contains a set of images for training data.

Pre-processing: Involves two stages for the training images—resizing to achieve uniformity and converting RGB images to grayscale. Cross-validation used to evaluate the performance of the model or algorithm, where data is divided into two subsets: the training process and validation/evaluation data. Learning implemented with the RNN algorithm, a class of artificial neural networks with connections forming a directed graph. RNN comes in different forms, including GRU (Gated Recurrent Units) and LSTM (Long Short-Term Memory Network), which contribute to improved performance. The RNN architecture consists of an input layer, one or more hidden layers, and an output layer. In this study, the RNN utilized is of the LSTM type.

With annotated training data, deep learning is conducted to recognize and identify regions in MRI images containing brain tumors. The learning process flow is depicted in the following diagram:

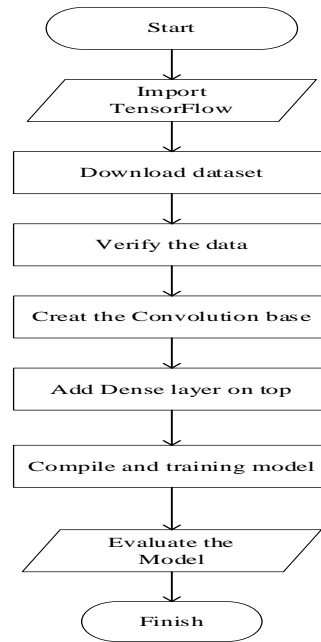


Fig. 5. A diagram illustrating the processing of brain tumor MRI images using a Recurrent Neural Network.

This research uses fuzzy c-means, where the dataset is divided into four clusters: glioma, meningioma, no tumor, and pituitary. The program flow consists of five stages: i) Input Dataset utilizes the OS and OPENCV libraries to process images; ii) Preprocessing involves normalization, data augmentation, and data grouping. Program steps include Image normalization, resizing images to a uniform size. Data augmentation to improve model performance Conversion to a NumPy array for model use Splitting the dataset into training and testing data. Modeling employs clustering with the Fuzzy C-Means (FCM) algorithm. Its stages include flattening Images which conversion of each image into a one-dimensional vector before using the clustering algorithm. Fuzzy C-Means Modeling uses the scikit-fuzzy library to determine FCM parameters and train the FCM model. Model evaluation calculates clustering quality using the Davies-Bouldin index, as clustering was performed earlier. Visualization of Results displays the FCM results plot.

## IV. EXPERIMENTAL RESULTS AND DISCUSSION

### A. Experimental Results

The study utilized a collection of more than 13,000 brain MRI images, which included visuals illustrating conditions like pituitary, meningioma, glioma symptoms, as well as normal or healthy brain images. The dataset was obtained from a nearby public hospital. This work enabled the development of an early detection application for brain tumor diseases, functioning in the following manner: The outcomes reveal accuracy, precision, and recall values and identify the cluster to which the query image pertains.

Evaluating the performance of a classification model involves examining crucial metrics like precision and recall. In our findings, precision stands at an impressive 0.9992, signifying a high level of accuracy in the model's positive predictions. Conversely, a recall value of 0.5767 implies that the model may have overlooked a substantial portion of actual positive instances. To offer a more comprehensive assessment of the model's overall performance, we shift our focus to the F1-score. This metric, derived from the harmonic mean of precision and recall, acts as a balanced indicator that considers both false positives and false negatives. The calculation of the F1-score will further illuminate the harmony between precision and recall and offer a more nuanced perspective on the model's efficacy in making accurate positive classifications.

The findings presented herein reveal crucial metrics such as accuracy, precision, and recall, providing insights into the classification performance. These metrics not only offer a comprehensive evaluation of the model's predictive capabilities but also pinpoint the specific cluster to which the query image is assigned. By analyzing the accuracy, precision, and recall values, we gain a deeper understanding of the model's overall effectiveness in correctly categorizing images. These metrics serve as valuable indicators, shedding light on the model's ability to distinguish between different classes. Furthermore, the identification of the specific cluster to which the query image belongs adds a practical dimension to the assessment, aiding in the interpretation of the model's classification outcomes and their real-world implications.

The analyses presented demonstrate a collection of crucial metrics, each providing valuable insights into the effectiveness of the classification model. The accuracy, measured at 0.5767, reflects the overall correctness of the model's predictions. A precision value of 0.9992 underscores the model's capability to accurately identify positive instances among its predictions. However, the recall value of 0.5767 suggests that the model may have missed a significant portion of actual positive instances during its classification. In examining these metrics collectively, it becomes apparent that while the model excels in precision, its recall performance could be a point of consideration.

The balance between precision and recall is critical for a comprehensive evaluation of a classification model, and further analysis, such as the calculation of the F1-score, may provide additional insights into the model's overall effectiveness. The research results present the Structural Similarity Index (SSIM) for each symptom from the utilized dataset, and the SSIM for each cluster can be observed in Fig. 6, 7, 8, and 9.

Considering the metrics presented, it's clear that achieving a balance between precision and recall is crucial for a well-performing classification model. The high precision value of 0.9992 indicates a strong ability to correctly classify positive instances, minimizing false positives. However, the recall value of 0.5767 suggests that there is room for improvement in capturing the entirety of actual positive instances. Striking a balance between precision and recall is often necessary, depending on the specific requirements of the application. Some applications may prioritize precision, aiming to

minimize false positives, while others may prioritize recall, aiming to capture as many positive instances as possible.

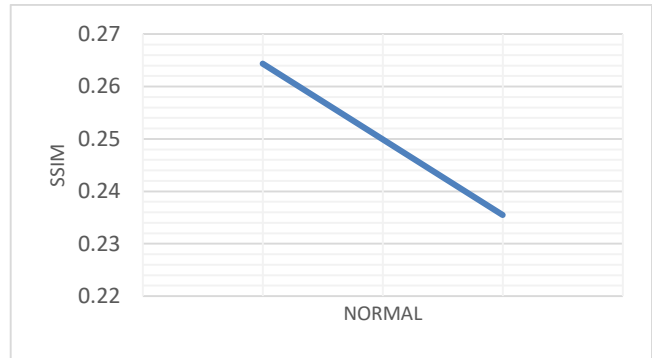


Fig. 6. SSIM normal brain cluster.

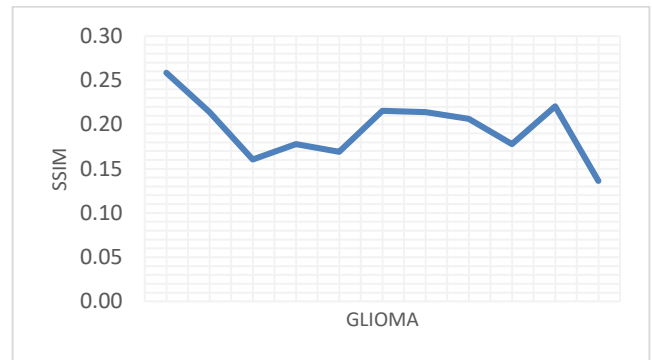


Fig. 7. SSIM glioma brain cluster.

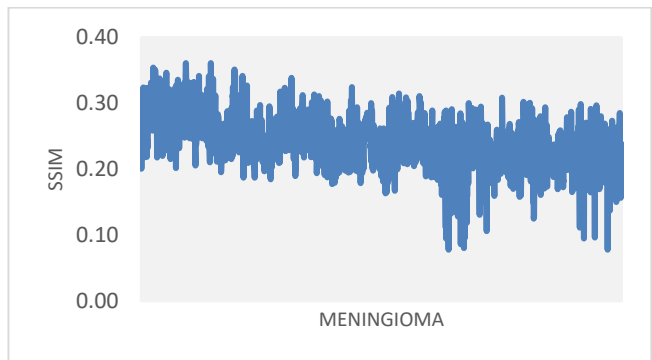


Fig. 8. SSIM meningioma brain cluster.

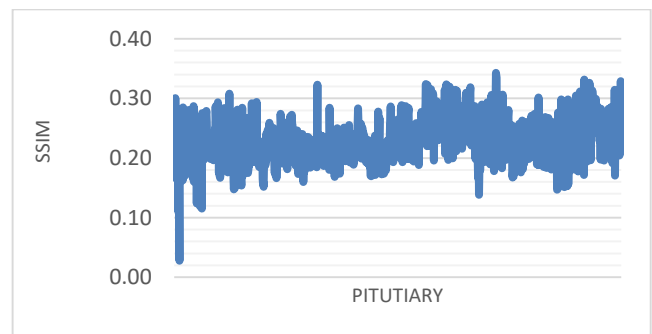


Fig. 9. SSIM pituitary brain cluster.

Furthermore, Fig. 5, 6, 7 and 8 shows that Structural Similarity Index (SSIM) scores indicate a relatively high similarity between the images in normal brain cluster. The SSIM values are close, suggesting consistency in the visual content of the images within this cluster. Cluster Glioma Various similarity scores ranging from 0.1161 to 0.2614. The similarity scores in Clusters glioma are lower compared to Cluster normal. There is a range of values, indicating potential variability in visual content within this cluster. Some images may be less similar to others. Cluster meningioma Various similarity scores ranging from 0.0233 to 0.1511. Similar to Cluster glioma, Cluster meningioma has a range of similarity scores, but the scores are generally lower. This suggests a higher diversity or dissimilarity in visual content within this cluster. Cluster pituitary similarity scores ranging from 0.1995 to 0.2022. The similarity scores in Cluster pituitary are higher compared to Clusters glioma and meningioma but lower than Cluster normal. This cluster seems to have a more consistent level of similarity, though not as high as Cluster normal. Overall cluster normal appears to contain visually similar images with consistently high similarity scores.

### B. Discussion

To provide a more comprehensive assessment, it would be beneficial to calculate additional metrics such as the F1-score, which takes into account both precision and recall, offering a single value that considers the trade-off between these two metrics. This would help in gaining a more nuanced understanding of the model's overall effectiveness and guide potential adjustments to enhance its performance. The provided analyses reveal noteworthy metrics for the classification model. The precision, denoted as 0.9992, highlights the model's exceptional accuracy in correctly identifying positive instances. However, with a recall value of 0.5767, it appears that the model may have missed a substantial portion of actual positive instances during its predictions.

An insightful measure, the F1-score, provides a balanced evaluation by considering both precision and recall. In this context, the calculated F1-score of 0.7311 indicates the harmonic mean of precision and recall, showcasing the model's overall effectiveness in striking a balance between correctly identifying positive instances and minimizing false negatives. These results suggest a strong precision performance but also highlight the importance of addressing recall to ensure a more comprehensive and well-rounded classification model. Further examination and potential adjustments could enhance the model's ability to capture a greater proportion of positive instances while maintaining a high level of precision.

Table I presents an overview of various methods employed in the detection of brain tumors, highlighting their distinctive features and applications. The information is organized to facilitate a clear understanding of each method's strengths, limitations, and overall effectiveness in the realm of medical diagnostics. Starting with Magnetic Resonance Imaging (MRI), this non-invasive technique utilizes magnetic fields and radio waves to generate detailed images of the brain. Known for its high resolution, MRI is particularly effective in providing a comprehensive view for precise tumor detection.

TABLE I. COMPARISON METHODS FOR BRAIN TUMOR DETECTION

No.	Method	Accuracy (%)
1.	Fuzzy Deep learning (propose work)	99.92
2.	Convolutional Neural Network [12]	89.83
3.	ELM-LRF, [11]	97.18
4.	Support Vector Machine [8]	98.75
5.	RG-MAKM [5]	90.00

Whilst the precision of 0.9992 signifies a high accuracy in positive predictions, the recall of 0.5767 points towards a potential improvement in capturing all actual positive instances. The F1-score, as a combined metric, accentuates the need for a balanced approach, yielding a value of 0.7311. These findings prompt a closer examination of the model's performance trade-offs between precision and recall. Depending on the specific objectives and requirements of the application, adjustments may be considered to optimize the model's balance between minimizing false positives and capturing a more comprehensive set of positive. Clusters glioma and meningioma exhibit more variability, with a range of similarity scores indicating diverse visual content. Cluster pituitary shows a moderate level of comparison, but not as high as Cluster normal. It's important to note that the interpretation of these scores depends on the specific context of your analysis and the nature of the images in each cluster.

### V. CONCLUSION

In conclusion, the model's elevated precision value of 0.9992 signifies its remarkable accuracy in predicting positive instances, with a minimal likelihood of false positives. However, the relatively lower recall value of 0.5767 raises concerns about potential oversights in identifying actual positive instances, resulting in false negatives. To comprehensively evaluate the model's performance, the F1-score is crucial, as it takes into account the nuanced equilibrium between precision and recall, addressing the implications of both false positives and false negatives. While the model demonstrates outstanding precision, evaluating the F1-score will offer a nuanced perspective on its overall accuracy, shedding light on the interplay between precision and recall and providing valuable insights for optimal performance in classifying positive instances.

Future works will be addressing the nuanced aspects revealed by the model's precision and recall metrics should be a priority. Researchers can focus on enhancing the recall value to minimize oversights in identifying actual positive instances, possibly through the refinement of model architecture or the incorporation of additional features. Exploring ensemble methods or hybrid models, such as Fuzzy-RNN and Fuzzy-CNN that leverage the strengths of different algorithms may also contribute to achieving a more balanced precision-recall trade-off. Additionally, investigating the impact of varying thresholds on precision and recall and optimizing these thresholds for specific use cases could lead to improvements in overall model performance. Continuous refinement and fine-tuning, guided by the F1-score as a comprehensive evaluation metric, will be essential to ensure the model's robustness in

real-world applications, providing a more holistic perspective on its accuracy and effectiveness in classifying positive instances while mitigating the risks of both false positives and false negatives.

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