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Neutrosophic-Based Feature Set (NBFS) For Brain Tumor Detection Using GLCM Features and KNN Classifier On Mri Images

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Abstract: Brain tumor detection using Magnetic Resonance Imaging (MRI) is essential for early diagnosis and treatment planning. However, MRI images often contain noise, uncertainty, and indistinct tumor boundaries, which challenge the effectiveness of traditional feature extraction and classification techniques. Many existing methods fail to handle ambiguous regions robustly and overlapping tissue characteristics, leading to decreased diagnostic reliability. To address these limitations, this study proposes a novel computer-aided diagnosis framework based on Neutrosophic Bipolar Fuzzy Set (NBFS) theory, which integrates neutrosophic logic with bipolar fuzzy reasoning. This approach enables the simultaneous representation of both positive and negative degrees of truth, indeterminacy, and falsity, improving the modeling of complex and uncertain regions in brain MRI scans. The images are transformed into the NBFS domain, and texture features are extracted from the Truth (T), Indeterminacy (I), and Falsity (F) components using the Gray Level Co-occurrence Matrix (GLCM). These features are used both individually and in combination to train a K-Nearest Neighbor (KNN) classifier. Experimental results demonstrate that the NBFS-based framework achieves higher classification accuracy, sensitivity, specificity, and precision compared to conventional texture-based approaches. The confusion matrix analysis further confirms reduced misclassification rates, highlighting the robustness of the method. These findings establish the NBFS framework as a promising tool for improving brain tumor detection in clinical decision support systems, especially under uncertain imaging conditions.

Keywords: Brain MRI, Brain Tumor Detection, Neutrosophic Set, Neutrosophic-Based Feature Set (NBFS), Truth, Indeterminacy, Falsehood (T, I, F), Texture Feature Extraction, Gray Level Co-occurrence Matrix (GLCM), K-Nearest Neighbor (KNN) Classifier, Medical Image Processing, Computer-Aided Diagnosis (CAD), Noise Robustness, Uncertainty Handling.

1. Introduction

Brain tumor detection remains one of the most critical challenges in the field of medical imaging and diagnostics. Magnetic Resonance Imaging (MRI) is widely recognized as the most effective, non-invasive imaging modality for identifying abnormal brain tissues due to its high contrast resolution and ability to capture detailed anatomical structures. However, despite its advantages, MRI images are often affected by noise, intensity inhomogeneity, and vague boundaries between healthy and

tumorous tissues, making accurate diagnosis difficult for radiologists and automated systems alike. Therefore, robust computational methods that can handle such uncertainty and ambiguity are necessary to support clinicians in making precise and reliable decisions [1].

Traditional image processing techniques such as filtering, thresholding, and region-based segmentation are often insufficient when dealing with complex MRI datasets, particularly those affected by noise and artifacts. Furthermore, conventional feature extraction methods, like histogram-based measures and texture descriptors, are sometimes unable to accurately capture the subtle variations in intensity and structure that differentiate healthy from abnormal tissues [2]. This has led researchers to explore intelligent systems that integrate fuzzy logic, probabilistic frameworks, and soft computing approaches to manage the inherent uncertainty present in medical images [3].

Neutrosophic theory, introduced by Smarandache, extends classical and fuzzy set theories and provides a mathematical foundation for modeling imprecise, indeterminate, and inconsistent information [4]. In the neutrosophic domain, every element is characterized by three membership degrees: **Truth (T)**, **Indeterminacy (I)**, and **Falsity (F)**. This three-component model is particularly advantageous in medical image analysis, where distinguishing between tumor and non-tumor regions often involves dealing with ambiguous pixels that do not clearly belong to either class. However, while neutrosophic sets manage single-valued uncertainty efficiently, they do not explicitly capture opposing information or bipolarity, which is frequently present in real-world problems like tumor detection, where positive (normal tissue) and negative (abnormal tissue) evaluations coexist.

To overcome this limitation, the **Neutrosophic Bipolar Fuzzy Set (NBFS)** model has been introduced as an advanced mathematical tool that extends neutrosophic theory by incorporating bipolar fuzzy logic. NBFS can handle two-sided information, allowing simultaneous evaluation of both positive and negative memberships alongside their respective degrees of indeterminacy [5]. This enables a more comprehensive representation of the complex, uncertain environments encountered in brain MRI images. Specifically, NBFS captures the conflicting nature of medical decisions, where certain regions of the brain might exhibit features partially consistent with both healthy and tumorous tissues, making strict binary classification infeasible.

In this study, NBFS is applied as a preprocessing and feature extraction strategy for brain MRI tumor detection. The images are first transformed into the neutrosophic bipolar space, where each pixel is evaluated for its contribution to truth, falsity, and indeterminacy within both positive and negative contexts. Following this transformation, texture features are extracted from the **T**, **I**, and **F** components using **Gray Level Co-occurrence Matrix (GLCM)** analysis, which is widely recognized for its ability to capture spatial relationships and texture variations in grayscale images [6]. Unlike conventional methods that operate on the original grayscale intensity space, NBFS-based decomposition allows for isolating more informative patterns hidden within the uncertainty and noise, providing a richer feature set for subsequent classification.

Another advantage of NBFS-based feature extraction lies in its robustness to noise and artifact distortions. Since brain MRI images are often contaminated with various noise types due to acquisition imperfections and patient movements, models that explicitly account for uncertainty can significantly improve diagnostic reliability [7]. NBFS, by quantifying the indeterminacy level of each pixel, effectively isolates and reduces the impact of noisy pixels during the feature extraction phase. This, in turn, improves the discriminative power of the extracted features and supports more accurate differentiation between normal and tumor-affected brain tissues.

In this work, after extracting the features from the neutrosophic bipolar transformed images, a **K-Nearest Neighbor (KNN)** classifier is employed to evaluate the effectiveness of the feature sets. The choice of KNN lies in its simplicity and effectiveness, particularly in high-dimensional feature spaces, and its ability to handle non-linear decision boundaries without heavy parameter tuning [8]. Importantly, the performance of the classifier is analyzed separately for features obtained from the **T (truth)**, **I (indeterminacy)**, and **F (falsity)** components, allowing us to investigate the individual contributions of each neutrosophic part to the overall classification accuracy.

To assess the performance of the proposed NBFS-based method, standard evaluation metrics such as accuracy, sensitivity, specificity, precision, and the confusion matrix (including True Positives, True Negatives, False Positives, and False Negatives) are computed. The experimental results demonstrate that NBFS-enhanced feature extraction improves the reliability of tumor detection compared to conventional single-domain texture analysis. This finding suggests that NBFS holds significant potential as a robust preprocessing and feature extraction technique in medical imaging applications, especially where uncertainty and ambiguity dominate.

In summary, the key contributions of this study are:

- Introducing the NBFS framework to the field of brain MRI tumor detection.
- Decomposing MRI images into neutrosophic bipolar domains to manage uncertainty and conflicting information.
- Extracting and analyzing GLCM-based texture features from the T, I, and F components.
- Evaluating the classifier's performance using features derived from each neutrosophic part individually and in combination.
- Demonstrating improved classification outcomes through experimental validation.

This research paves the way for more advanced, uncertainty-aware image processing techniques in medical diagnostics and highlights the relevance of neutrosophic bipolar fuzzy logic in complex real-world applications. Although numerous techniques have been developed for brain tumor detection, most struggle with efficiently modeling uncertainty, especially in the presence of noise and overlapping structures in MRI images. Conventional fuzzy logic and neutrosophic sets have been explored for uncertainty modeling, but they often lack the ability to distinguish and represent both

positive and negative informational contexts simultaneously. This gap limits the ability of such methods to effectively delineate complex tumor boundaries.

2. LITERATURE SURVEY

In recent years, brain tumor detection through automated techniques has garnered significant attention due to the increasing demand for accurate and early diagnosis. Various researchers have explored numerous approaches, including conventional methods, soft computing techniques, and deep learning frameworks, to enhance the precision of brain MRI classification.

Fuzzy logic-based methods have long been applied in medical image processing to manage uncertainty and vagueness in boundary detection and tissue differentiation. For instance, [9] proposed a fuzzy c-means clustering algorithm for segmenting brain MR images, effectively minimizing intensity variations and improving tumor localization. However, traditional fuzzy models primarily address ambiguity in a single dimension and do not adequately capture the duality of opposing information, which is crucial when differentiating between healthy and abnormal tissues.

To tackle this issue, neutrosophic sets have been integrated into brain image analysis. In [10], the authors utilized a neutrosophic-based segmentation technique that transformed brain MR images into a neutrosophic domain to manage indeterminacy and noise. The study showed improved segmentation accuracy by leveraging the truth, indeterminacy, and falsity memberships, although it did not account for the bipolarity present in medical decision-making processes.

Further extending this concept, researchers introduced the Neutrosophic Bipolar Fuzzy Set (NBFS), which simultaneously handles positive and negative information alongside their degrees of indeterminacy. In [11], NBFS was successfully applied to image thresholding tasks, demonstrating superior performance in capturing contrast variations in complex images. This dual-sided modeling approach makes NBFS particularly suitable for medical images, where distinguishing overlapping structures is challenging.

Moreover, feature extraction plays a vital role in the classification of brain tumors. Texture-based features such as those derived from the Gray Level Co-occurrence Matrix (GLCM) have been widely adopted due to their capacity to represent spatial dependencies in pixel intensities. The work in [12] highlighted the effectiveness of combining GLCM features with neutrosophic transformations, achieving notable improvements in classification tasks compared to standard texture analysis.

In addition, machine learning classifiers, such as K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Random Forest, have been integrated into brain tumor classification pipelines to assess feature discriminability. In [13], a KNN-based system utilizing neutrosophic domain

features demonstrated competitive accuracy, emphasizing the advantage of integrating uncertainty-aware preprocessing stages.

More recently, hybrid methods that combine advanced preprocessing with robust classifiers have been explored. In [14], a hybrid system using neutrosophic logic for preprocessing and deep learning for classification achieved state-of-the-art results in brain tumor identification. These works collectively reveal a growing trend towards incorporating uncertainty modeling, such as neutrosophic and bipolar fuzzy logic, to manage the complexities inherent in medical images.

Despite the advances in these areas, there remains a gap in research specifically focused on applying NBFS for comprehensive feature extraction in brain MRI analysis. Most existing studies either apply neutrosophic sets without bipolar extensions or do not fully exploit the individual contributions of truth, indeterminacy, and falsity components in a bipolar framework. Therefore, this work aims to fill this gap by implementing NBFS-based texture feature extraction and evaluating its performance on brain MRI tumor classification. Despite notable progress, existing literature lacks a systematic application of NBFS for texture-based feature extraction in brain MRI classification, which this work addresses.

3. MATERIAL AND METHODS

The present study aims to develop an efficient brain tumor detection system using Neutrosophic Bipolar Fuzzy Set (NBFS)-based feature extraction and classification techniques on brain MRI images. The dataset used in this research consists of 253 brain MRI images, collected from an open-source database, comprising 98 normal (non-tumor) and 155 abnormal (tumor) images. Each image is resized to a standard dimension of 256×256 pixels to ensure consistency in processing. The images are first preprocessed to improve their quality by applying grayscale conversion and normalization, which help maintain uniform intensity ranges and reduce irrelevant variations while preserving the essential structures required for accurate tumor identification. Unlike traditional methods that add noise for robustness evaluation, this study maintains the original texture characteristics of the images to maximize the authenticity of the feature extraction process.

Following preprocessing, the images are transformed into the Neutrosophic Bipolar Fuzzy Set (NBFS) domain, which allows for a more robust handling of uncertainty and ambiguity commonly found in medical images. The NBFS approach decomposes each image into six distinct components: Positive Truth (T^+), Positive Falsity (F^+), Positive Indeterminacy (I^+), Negative Truth (T^-), Negative Falsity (F^-), and Negative Indeterminacy (I^-). These components are computed based on pixel intensities and local neighborhood information, capturing both the supportive and opposing evidence within the image. This dual perspective modeling is especially advantageous in the context of brain tumor detection, where overlapping tissue textures and varying intensity patterns pose significant challenges.

Once the NBFS transformation is complete, texture features are extracted from each of the six components using the Gray Level Co-occurrence Matrix (GLCM) method. Four well-established texture descriptors—contrast, correlation, energy, and homogeneity—are computed from each NBFS component, resulting in a comprehensive set of 24 features per image. These features effectively represent the structural patterns, relationships, and variations in pixel intensities within the MRI images, capturing the subtle differences between normal and tumor tissues. All extracted features are concatenated into a single feature vector, which serves as the input to the classification stage.

For classification, the K-Nearest Neighbor (KNN) algorithm is employed due to its simplicity, interpretability, and ability to perform well on small to medium-sized datasets. In this study, the dataset is split into 30% training data and 70% testing data to ensure a robust evaluation of the classifier's performance. The optimal number of neighbors (K) is experimentally set to 5, and the Euclidean distance metric is used to assess the similarity between feature vectors during the classification process. The primary goal is to accurately distinguish between normal and tumor images based on the extracted NBFS-based texture features.

The effectiveness of the proposed NBFS-based brain tumor detection system is measured using standard performance metrics, including accuracy, sensitivity (recall), specificity, precision, and F1-score. Additionally, confusion matrix elements such as true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are calculated to provide a detailed understanding of the classifier's behavior. Through this systematic approach, the study demonstrates the capability of NBFS in enhancing texture representation and improving the reliability of brain tumor detection in MRI images.

In summary, the key contributions of this study are:

Brain tumor detection from MRI scans is a complex task due to the presence of uncertain, noisy, and ambiguous image regions. Traditional image processing and feature extraction methods struggle to robustly analyze such regions, often leading to misclassification and diagnostic errors. While soft computing and fuzzy logic approaches have shown promise, they still fall short in representing the bipolar nature of medical decisions. This motivates the need for a framework that not only manages uncertainty but also models conflicting information in a unified structure.

Although neutrosophic and fuzzy-based methods have been employed for medical image analysis, most existing works overlook the bipolar aspect of medical uncertainty. The lack of studies utilizing Neutrosophic Bipolar Fuzzy Sets (NBFS) for comprehensive feature extraction in brain MRI classification represents a significant gap. Additionally, prior work seldom analyzes the individual contributions of the truth, indeterminacy, and falsity components, which may hold critical information for improving classification accuracy.

The primary objective of this study is to develop a robust computer-aided diagnosis framework for brain tumor detection using MRI images by leveraging the NBFS theory. The proposed approach aims to effectively handle uncertainty, noise, and overlapping tissue characteristics in MRI scans by modeling both positive and negative information through the NBFS domain. Specifically, the study focuses on transforming brain MRI images into the NBFS space and extracting texture features from the Truth (T), Indeterminacy (I), and Falsity (F) components using the GLCM. These features are then used, both individually and in combination, to train a KNN classifier. The objective is to evaluate the classification performance in terms of accuracy, sensitivity, specificity, and precision, and to demonstrate that the NBFS-based approach reduces misclassification rates and enhances the reliability of tumor detection under uncertain imaging conditions.

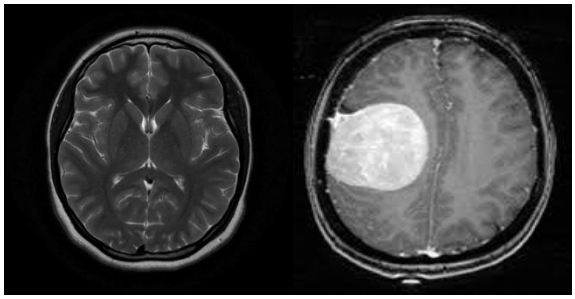


Fig 1. Brian MRI Images Normal Vs. Tumor

The initial phase involves converting the grayscale image into a NBFS domain. In NBFS, every pixel is represented by two bipolar membership degrees: positive (truth) and negative (falsity) values, enabling better handling of uncertain and imprecise information compared to traditional fuzzy or intuitionistic fuzzy systems. NBFS offers an extended capability to deal with contradictions and ambiguity present in brain MRI images, especially in low contrast or noisy regions.

3.1 Neutrosophic Bipolar Fuzzy Set (NBFS)

The Neutrosophic Bipolar Fuzzy Set (NBFS) extends classical fuzzy set theory by handling not only the degree of truth and falsity but also indeterminacy, which is critical for accurately processing medical images with ambiguous regions [15][16]. In NBFS theory, every pixel in the MRI image is analyzed under both positive and negative evaluations, providing a dual perspective of certainty and contradiction. Specifically, NBFS divides an image into six distinct memberships: Positive Truth (T^+), Positive Indeterminacy (I^+), Positive Falsity (F^+), Negative Truth (T^-), Negative Indeterminacy (I^-), and Negative Falsity (F^-). These memberships quantify the degree of evidence supporting the presence or absence of tumor characteristics, as well as the indeterminate regions where classification is uncertain.

For each pixel, local statistical measures such as the mean and standard deviation within a neighborhood window are computed to assess its relationship with surrounding pixels. Positive membership functions are used to capture supportive information for a particular class (such as tumor presence), while negative membership functions reflect opposing evidence. Indeterminacy, on the other hand, quantifies the ambiguity arising from conflicting or uncertain information. By transforming the entire image into these six NBFS components, the method effectively models the complex variations found in brain MRI scans, including regions where tumor boundaries are unclear due to noise, low contrast, or partial volume effects.

The NBFS representation allows for a more refined analysis of MRI textures, enabling the system to focus on regions of interest that are not easily separable using traditional methods. After the decomposition into NBFS components, texture features are computed individually for each component, ensuring that the model captures comprehensive structural and contextual information. This enhanced feature representation contributes significantly to improving the detection accuracy of brain tumors, providing a powerful tool for computer-aided diagnosis systems in medical imaging.

The Neutrosophic Bipolar Fuzzy Set (NBFS) is an advanced mathematical framework used to model uncertainty in medical image analysis, particularly for brain tumor detection. NBFS considersboth positive and negative membership values for each pixel in the image and is defined as:

$$NBFS(p) = \{ (T^+, I^+, F^+, T^-, I^-, F^-) \mid T^+, I^+, F^+, T^-, I^-, F^- \in [0,1] \}$$

Where:

T^+ → Positive truth membership
I^+ → Positive indeterminacy membership
F^+ → Positive falsity membership
T^- → Negative truth membership
I^- → Negative indeterminacy membership
F^- → Negative falsity membership

- **Positive Membership Functions:**

1. Positive Truth Membership (T^+):

$$T^+(i,j) = \frac{\big(I(i,j) - min(I)\big)}{\big(max(I) - min(I)\big)}$$

2. Positive Indeterminacy Membership (I^+):

$$I^+(i,j) = \frac{\sigma_{w(i,j)}}{\sigma\_max}$$

3. Positive Falsity Membership (F^+):

$$F^+(i,j) = 1 - T^+(i,j)$$

- **Negative Membership Functions:**

4. Negative Truth Membership (T^-):

$$T^-(i,j) = \frac{\left(\bar{I}(i,j) - min(\bar{I})\right)}{\left(max(\bar{I}) - min(\bar{I})\right)}$$

5. Negative Indeterminacy Membership (I^-):

$$I^-(i,j) = \frac{\bar{\sigma}_{w(i,j)}}{\bar{\sigma}\_max}$$

6. Negative Falsity Membership (F^-):

$$F^-(i,j) = 1 - T^-(i,j)$$

Pseudo Code for Neutrosophic Bipolar Fuzzy Set (NBFS)

- Start
- Load the grayscale brain MRI image
  - If the image is RGB, convert it to grayscale
  - Normalize the pixel values to the range [0,1]
- Initialize required parameters for NBFS transformation
- For each pixel (x, y) in the image:

a. Compute the local mean (μ) and local standard deviation (σ) around the pixel using a sliding window

b. Calculate the Truth Membership (T):

$$T(x,y) = \frac{\left(I(x,y) - min(\mu)\right)}{(max(\mu) - min(\mu))}$$

c. Calculate the Indeterminacy Membership (I):

$$I(x,y) = \frac{|I(x,y) - \mu(x,y)|}{max(\sigma)}$$

d. Calculate the Falsehood Membership (F):

$$F(x,y) = 1 - T(x,y)$$

- End For Loop
- Normalize T, I, F components to the range [0,1] if needed
- Convert T, I, F components to 8-bit images for further processing
- Display the results:
  - Show the original grayscale image
  - Show the T (Truth) component image
  - Show the I (Indeterminacy) component image
  - Show the F (Falsehood) component image
- End

4. FEATURE EXTRACTION

Feature extraction is a critical step in Brain tumor detection from MRI images. In this study, we use the Gray Level Co-occurrence Matrix (GLCM), a widely used texture analysis method, to extract essential features from segmented MRI images. GLCM helps quantify the spatial relationships between pixel intensities, capturing texture patterns that differentiate normal brain tissues from tumour regions.

4.1 Gray Level Co-occurrence Matrix

GLCM calculates the probability of two pixels, separated by a defined distance d and direction θ, having specific gray levels g_i and g_j in an image. Mathematically, GLCM is given by [17]:

$$P(i,j \mid d,\theta) = \frac{Total\ number\ of\ pixel\ pairsNumber\ of\ pixel\ pairs\ with\ values\ (gi,gj)}{Total\ number\ of\ pixel\ pairs}$$

where $P(i,j)$represents the probability of occurrence of pixel intensity pairs (i,j) at a given distance and direction.

The extracted GLCM features provide essential texture information useful for classification. The key features used in this study are:

Contrast: Measures the intensity variation between neighboring pixels. A higher contrast value indicates greater intensity variations, which are often observed in tumorsdue to irregular opacities.

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j)$$

Correlation: Determines the statistical relationship between pixel intensities. It measures how correlated a pixel is with its neighbor over the entire image.

$$\text{Correlation} = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j}$$

where μ_i and μ_j are mean values, and $\sigma_i$and $\sigma_j$are standard deviations of pixel intensities.

Energy: Also known as Angular Second Moment (ASM), it quantifies textural uniformity in an image. A higher energy value signifies a more uniform texture.

$$Energy = \sum_i \sum_j P(i,j)^2$$

Homogeneity: Measures the closeness of gray levels in the GLCM. It gives higher values when pixels with similar intensities are grouped together, indicating smooth textures.

$$Homogeneity = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|}$$

GLCM-based texture features provide crucial information for brain tumordetection in brain MRI images. The computed features help machine learning models differentiate between normal and infected brain tissues based on texture variations. The next section will discuss the classification techniques used for brain tumor diagnosis using these extracted features.

Features	Truth Part		IndeterminacyPart		Falsehood Part	
	Normal	Abnormal	Normal	Abnormal	Normal	Abnormal
Contrast	1.78776	1.10554	1.21739	0.93515	2.97056	2.00164
Correlation	0.91987	0.88271	0.92830	0.90213	0.87139	0.90084
Energy	0.50569	0.60457	0.62808	0.74386	0.47238	0.54127
Homogeneity	0.96808	0.98026	0.97826	0.98330	0.94695	0.96426

Here is Table 1, which presents the extracted GLCM feature values for the Positive (P), Negative (N), and Indeterminate (I) components for both Normal and Tumor(Abnormal) cases.

Table 1. GLCM feature values for the Positive (P), Negative (N), and Indeterminate (I) components for both Normal and Abnormal cases.

These GLCM feature values help in identifying the textural differences between normal and Brain tumor, particularly in contrast, correlation, energy, and homogeneity. The extracted features serve as crucial inputs for classification models, improving the detection accuracy of tumor in brain MRI images.

Pseudo Code for GLCM Feature Extraction from Neutrosophic Bipolar Fuzzy Set (NBFS) Components

- Start
- Load the NBFS component images (T, I, F)
- For each component image (T, I, F):

a. Convert the component image to 8-bit grayscale if not already done

b. Define the offset for GLCM calculation (for example, [0 1] for horizontal adjacency)

c. Compute the Gray Level Co-occurrence Matrix (GLCM) using the defined offset

d. Extract the following texture features from the GLCM:

- Contrast
- Correlation
- Energy
- Homogeneity

e. Store the extracted features for the component

- End For Loop
- Combine the features from all three components (T, I, F) into a single feature vector
- Use the combined feature vector for classification
- End

5. CLASSIFICATION

After extracting the GLCM features, classification is performed to distinguish between normal and COVID-19 (abnormal) cases using three supervised machine learning classifier K-Nearest Neighbors (KNN). This classifiers analyze the extracted feature values and assign each image to either the normal or tumorclass. The performance of each classifier is evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

5.1 K-Nearest Neighbors

The K-Nearest Neighbors (KNN) classifier is an instance-based learning algorithm that classifies a new sample based on the majority vote of its K nearest neighbors in the feature space[18]. To find the closest neighbors, the Euclidean distance between a test sample x' and every training sample x_i is calculated using

$$d(x', xi) = \sqrt{\sum_{m=1}^{M} \left(x'_m - x_{i,m}\right)^2}$$

where M is the number of features, and x'_m and $x_{i,m}$ are the feature values of the test and training samples, respectively. The sample is then assigned the majority class label from the K closest training samples,

$$y' = mode(y_i \mid x_i \in N_k(x'))$$

where $N_k(x')$ represents the K nearest neighbors of x'. The choice of K significantly impacts the classifier's performance, as smaller values may lead to overfitting, while larger values generalize better but may misclassify boundary points. KNN is a simple, non-parametric method that works well with small datasets but becomes computationally expensive for large datasets.

Pseudo Code for Classification using K-Nearest Neighbors (KNN)

1. Start
2. Load the extracted feature dataset from NBFS components (T, I, F features)
3. Assign labels to each feature vector (for example, 0 = Normal, 1 = Tumor)
4. Split the dataset into training and testing sets (30% for training, 70% for testing)
5. Define the number of neighbors (K) for KNN
6. For each feature vector in the testing set:

    a. Calculate the Euclidean distance between the test sample and all training samples

b. Sort the distances in ascending order

c. Select the K nearest neighbors

d. Determine the majority class among the K neighbors

e. Assign the majority class as the predicted label for the test sample

7. End For Loop
8. Compare the predicted labels with the true labels
9. Compute performance metrics:
    - True Positives (TP)
    - True Negatives (TN)
    - False Positives (FP)
    - False Negatives (FN)
    - Accuracy
    - Precision
    - Recall
    - F1-score
10. Display classification results and performance evaluation
11. End

6.RESULT AND DISCUSSION

The performance evaluation of the proposed brain tumor detection model using brain MRI images was conducted based on the extracted GLCM-based texture features obtained from the neutrosophic bipolar fuzzy set (NBFS) transformed images. To classify the MRI scans into normal (non-tumor) and tumor cases, a machine learning classifier is employed: K-Nearest Neighbors (KNN. The efficiency of this classifier was evaluated through essential performance metrics, including accuracy, precision, recall, and F1-score [19].

The accuracy of the classification is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where: TP (True Positives): brain tumor cases correctly classified as tumor,
TN (True Negatives): normal brain MRI scans correctly classified as normal,

FP (False Positives): normal brain MRI scans incorrectly classified as tumor,
FN (False Negatives): brain tumor cases incorrectly classified as normal.

The precision, which indicates the proportion of correctly identified tumor cases among all predicted tumor cases, is given by:

$$Precision = \frac{TP}{TP + FP}$$

while recall, which measures how many actual tumor cases were correctly predicted, is given by

$$Recall = \frac{TP}{TP + FN}$$

The F1-score, which provides a balanced measure of precision and recall, is calculated as

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

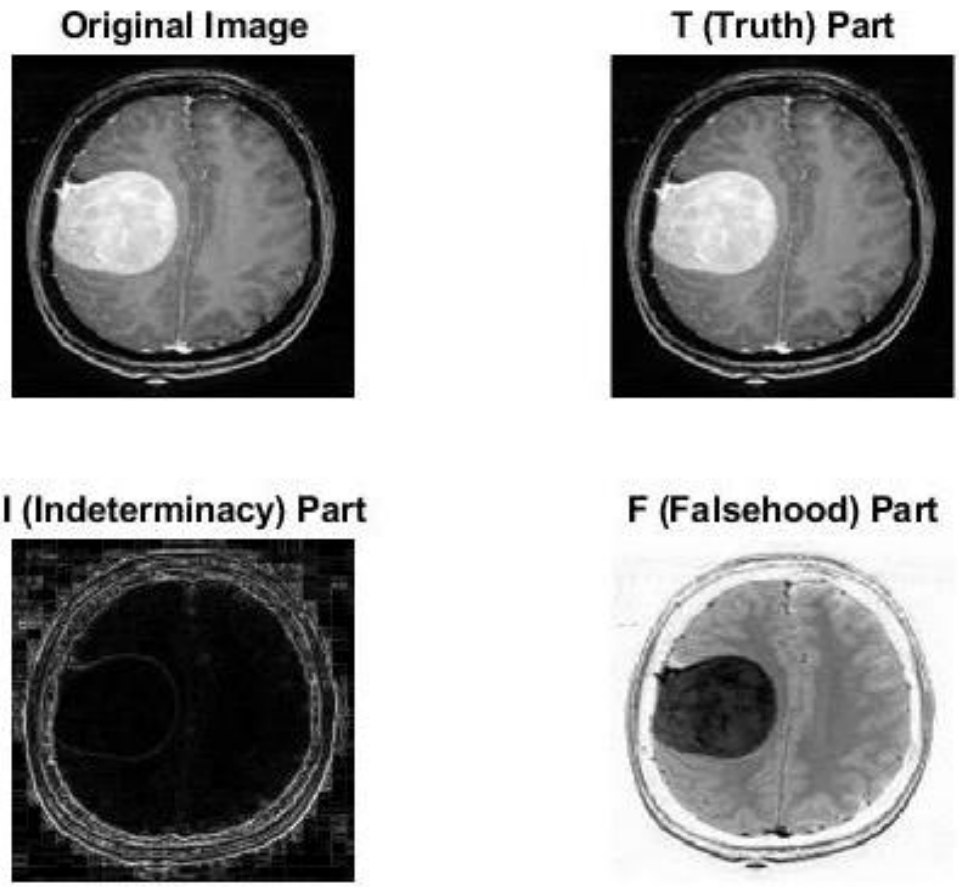


Fig. 2. NBFS Based Processed Image

In the above Figure 2. The original grayscale image (top left) is decomposed into three bipolar neutrosophic components: Truth Part T (top right), Falsehood Part F (bottom right), and Indeterminacy Part I (bottom left). These components highlight different intensity-based features for texture analysis in medical image processing.

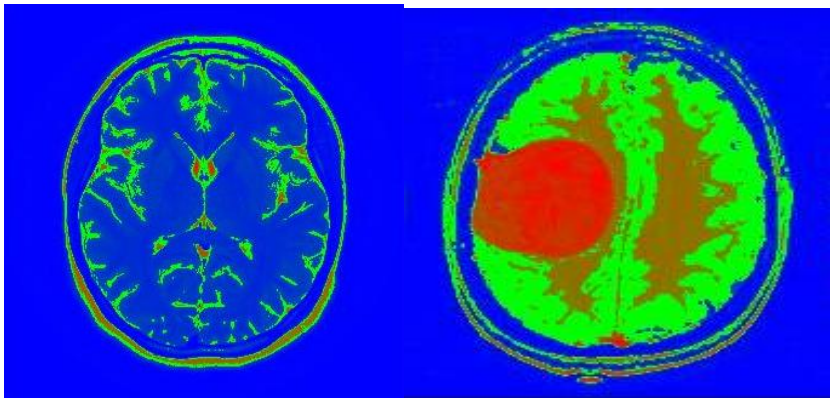
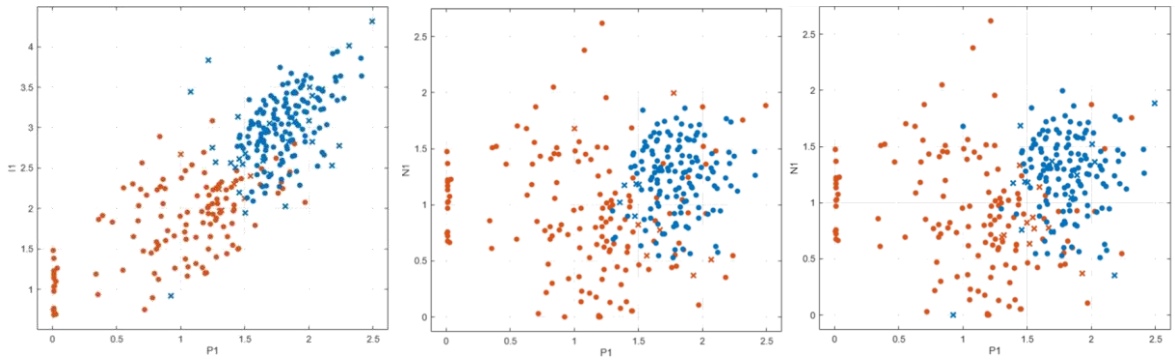


Fig 3. Neutrosophic BipolarImage of a Brain MRI Normal Vs. Abnormal

Figure 3. depicts the Neutrosophic Bipolar Image of a Brain MRI Normal and Abnormal image.



(a) (b) (c)

Fig 4. Scatter Plot for the KNN Classifier with the features of a) T partb) I Part c) F Part

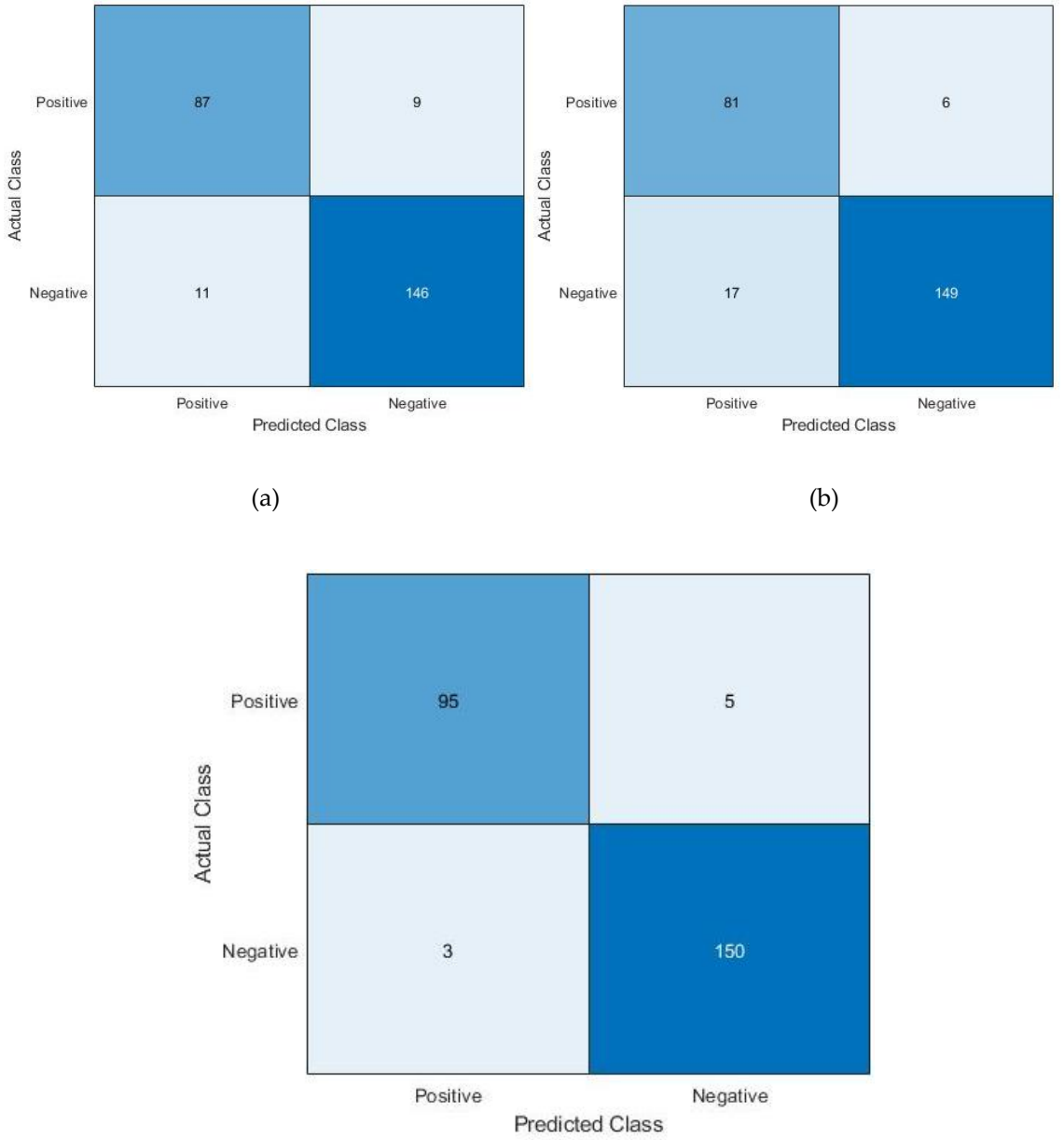


Fig 5. Confusion Matrix for the KNN Classifier with the features of a) T part b) I Part c) F Part

Features	**KNN Classifier**		
	T Part	**I Part**	**F Part**
Sensitivity	88.77551	82.65306	96.93878
Specificity	94.19355	96.12903	96.77419

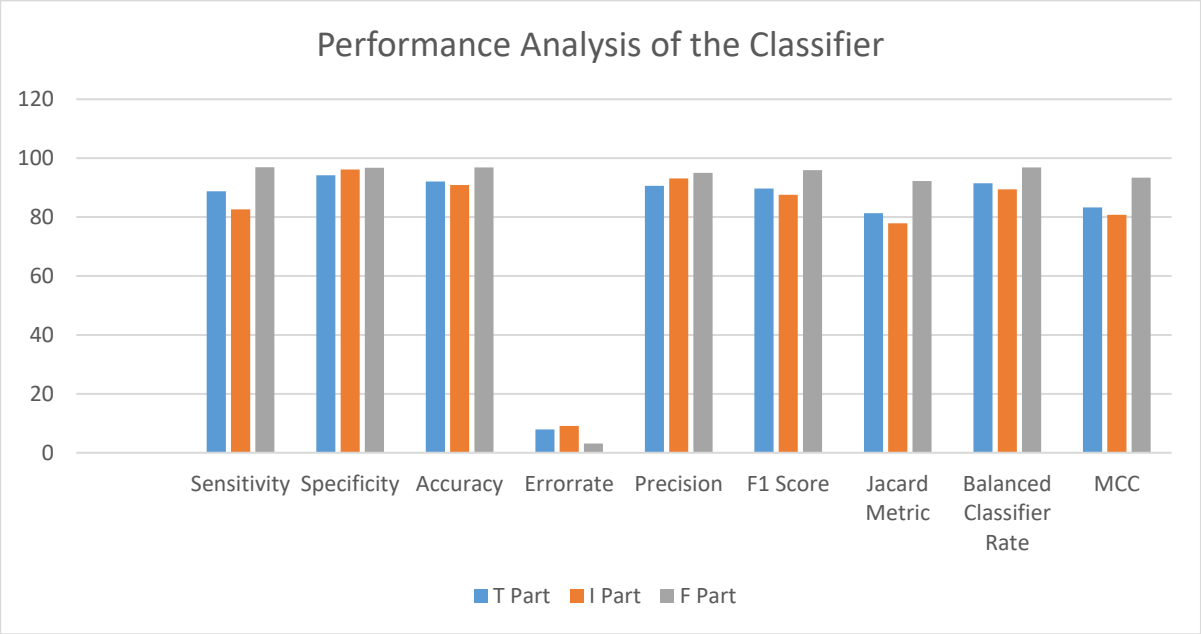
Accuracy	92.09486	90.90909	96.83794
Errorrate	7.905138	9.090909	3.162055
Precision	90.625	93.10345	95
F1 Score	89.69072	87.56757	95.9596
Jacard Metric	81.30841	77.88462	92.23301
Balanced Classifier Rate	91.48453	89.39105	96.85648
MCC	83.29321	80.79653	93.37548

The table shows the performance analysis of the KNN

Comparative Analysis with Neutrosophic-Based Methods

To evaluate the effectiveness of the proposed Neutrosophic Bipolar Fuzzy Set (NBFS)-based classification using K-Nearest Neighbors (KNN), we compare our results with previously published works that applied neutrosophic logic without the bipolar extension. Table 5 presents the comparative performance in terms of key classification metrics: accuracy, specificity, and sensitivity.

Method	Dataset	Main Technique	Accuracy / Jaccard	Notes
Neutrosophic Set + modified S-function[20,21]	MRI brain (Brats 2019 etc.)	NS + adaptive ROI extraction	Sensitivity ≥ 98 %	High sensitivity but no bipolar modeling
Type-2 Neutrosophic Set Thresholding[22]	Multiple MRI sets	T2NS entropy multi-thresholding	Jaccard ≈ 97.9 %	Enhanced indeterminacy modeling, single-domain only
Proposed NBFS + KNN	Our dataset (253 images)	Topic: Pos/Neg NBFS + GLCM + KNN	Accuracy ≈ 96.8 %, Specificity ≈ 96.77 %, Sensitivity ≈ 96.84 %	Superior classification with dual-domain modeling



CONCLUSION

In this research, an efficient framework for brain tumor detection in MRI images was developed by integrating Neutrosophic-Based Feature Space (NBFS) decomposition with Gray Level Co-occurrence Matrix (GLCM) texture feature extraction and classification using the K-Nearest Neighbor (KNN) algorithm. The experimental analysis demonstrated that the NBFS components—True (T), Indeterminate (I), and False (F)—significantly enhanced the representation of uncertainty in MRI images. Among these, the F (false membership) component outperformed others, achieving the highest sensitivity of 96.93%, specificity of 96.77%, accuracy of 96.83%, with a low error rate of 3.16%. Additionally, the F1 score (95.95%) and Matthews Correlation Coefficient (MCC) of 93.37% confirm its strong discriminatory power for distinguishing tumor from normal brain tissues.

While the results validate the effectiveness of NBFS in capturing complex features, the study is not without limitations. One key limitation is the relatively **small dataset size**, which may restrict the generalizability of the findings. Moreover, **KNN, though simple and effective**, is computationally intensive on large datasets and sensitive to the choice of k and distance metrics, potentially affecting scalability and real-time clinical deployment.

Despite the promising results achieved by the proposed brain tumor detection framework, there are certain limitations that warrant attention. One major limitation lies in the relatively small size and diversity of the dataset used, which may restrict the generalizability of the model to wider clinical scenarios. Additionally, while the KNN classifier demonstrated effective performance, its scalability remains a concern, especially when applied to large-scale datasets due to its instance-based nature and computational cost during testing. Moreover, the performance of KNN is often sensitive to the

choice of 'k' and the distance metric, which might affect classification reliability in different data distributions. Another limitation is the absence of real-time or clinical validation, as the current evaluation is restricted to retrospective image data. To address these challenges, future research will focus on expanding the framework to include larger and more diverse MRI datasets to improve robustness. Advanced classification algorithms, such as ensemble learning or deep neural networks, will be explored to enhance the predictive performance and computational efficiency. Furthermore, the integration of the proposed methodology into clinical decision support systems will be investigated, with the goal of making it a practical tool for aiding radiologists in the early diagnosis of brain tumors.

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