Enhanced Brain Tumor Diagnosis through Differential and Canonical Quadri –Partitioned Neutrosophic Set Classification Methods: A Comparative Study

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Abstract

An early cancer diagnosis is carried out for adequate management of diseases. Magnetic resonance imaging (MRI) is most commonly preferred method for cancer diagnosis. Due to the uncontrolled and rapid growth of cells, brain tumor is occurred. If not treated at a preliminary phase, it may lead to death. Thus, a noteworthy prerequisite for a successful treatment outcome is an early and precise diagnosis.Many conventional methods are discussed for performing efficient tumor detection. But, conventional classification methods not distinguish MRI as primary and metastases tumors in an accurate manner. Therefore, the performance comparison of deep learning-based classification (i.e., Differential Quadri-Partitioned Neutrosophic Interval-valued Polynomial Attention-based Deep CNN (DQNI-PADCNN) method and Canonical Quadri-Partitioned Neutrosophic Set based Otsuka–Ochiai Deep Recurrent Neural Network (CQNS-ODRNN) method) is introduced to provide exact image classification results. The brain MRI images are considered as an input. MRI image classification is carried out through CNN and RNN to find the brain tumor disease. Before the classification process, input images are de-noised. The noise-removed images are get segmented to identify the region of interested regions. Later, the images are classified into four classes such as glioma, meningioma, no tumor, and pituitary classes to detect the brain tumor. Both classification methods use Quadri-Partitioned Neutrosophic set for categorizing the images. Depending on CNNs and RNNs achievement in handling intricate tasks, an optimal multi-class brain tumor diagnosis is carried out. Experimental evaluation is implemented using MATLAB 2017 for brain tumor detection with the Brain Tumor MRI dataset. To the total number of MRI images, the various performance metrics are calculated in terms of sensitivity, specificity, accuracy, and time for the detection of brain tumors.

Keywords: Cancer Diagnosis; Magnetic Resonance Imaging; Recurrent Neural Network; Convolutional Neural Network; Quadri-Partitioned Neutrosophic set.

1. Introduction

Tumor tends to repeat itself and increase over the specific region. Brain tumor happens when abnormal cell growth within the brain. The aberrant cells that arise during the replication phase proliferate when brain cells replenish

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themselves. Brain tumors can be classified as either malignant/secondary (glioma) or benign/primary (pituitary or meningioma).

Machine learning and deep learning-based approaches for analysis of brain MRI images to detect brain tumors obtaining interest due to their self-learning capability. Non-Sequential Recurrent Model Ensemble (NSRME) was introduced in [1] to predict the stages of tumors despite their origin. NSRME employed a heterogeneous collection of tumor images that were classified consistent with their respective stages. However, the detection accuracy was not improved by using NSRME. A deep learning method was introduced in [2] to detect brain tumors through preprocessing, segmentation, feature extraction, optimization, and detection. Threshold and histogram methods performed image segmentation. The current deep learning approach did not, however, reduce the amount of time required.

Mutual information-accelerated singular value decomposition (MI-ASVD) was introduced in [3] to recognize the MRI brain images into dissimilar classes. The intelligent system classified the MRI brain images through smoothening by Gaussian kernel filters. The sensitivity level was not improved by MI-ASVD. A co-active adaptive neuro-fuzzy inference system (CANFIS) was developed in [4] for brain tumor recognition and segmentation. The brain MRI images were combined using dual-tree complex wavelet transform. Then, image attributes were extracted and classification was carried out to categorize brain MRI image as normal or abnormal. But, the computational cost was not reduced.

The triangular fuzzy median filtering method was developed in [2] to develop the image quality for tumor detection using extreme learning machine (ELM). Gabor features were extracted for every candidate lesions and similar texture (ST) features were measured. Though designed method reduced computational time, it lacked in attaining higher peak signal-to-noise ratio. An innovative possibilistic fuzzy c-means (FCM) technique was presented in [6] to increase the MRI brain image segmentation performance. It was efficient one for data clustering with non-spherical allocation. Through local label information, image noise was not removed accurately.

A novel automatic cell segmentation count framework was designed in [7] to segment the cell images by labeled diverse cell images. But, the computational complexity was not reduced. A review on various segmentation as well as attribute extraction methods were developed in [8] with medicinal images for preprocessing. But, PSNR was not improved by existing method. The eXtreme Gradient Boosting (XGBoost) approach was designed in [9] for reliable brain tumor classification. K-Means algorithm partitioned the images into sections. Feature selection was carried out using Particle Swarm Optimization (PSO). The accuracy level was not at the required level through XGBoost approach.

A Composite Network called CR-Unet was developed in [10] to segment the ovary and follicles in Transvaginal ultrasound (TVUS). The deep supervision approach was designed with effective and efficient training model. But, the detection time was not reduced by CR-Unet. A novel correlation mechanism using learning technique included CNN in [11]. The support neural network aided CNN for recognizing the pertinent filers in pooling and convolution. The neural classifier convergence speed was confirmed to guarantee high efficiency. However, the correlation method did not reduce the error rate.

A new classification technique was intended in [12] for MRI brain tumor finding. Threshold function was employed to perform pre-processing and segmentation. MR Image features were collected through discrete wavelet transformation (DWT). But, the computational time was not minimized by the classification method.

The problems identified from existing research are lesser detection accuracy, higher detection time, higher error rate, higher computational complexity, lesser specificity, lesser sensitivity, and so on. To address these existing issues, deep learning techniques are reviewed in this paper.

The article's primary contribution is listed as follows:

- The performance analysis of deep learning-based classification (i.e., Convolutional Neural Network and Recurrent Neural Network) is carried out to provide exact image classification results.

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- CNN is the neural network for performing efficient image classification with strong self-learning, adaptability, and generalization ability.
- RNN finds active temporal behaviors in random lengths of large-scale series data. RNN is competent in learning intricate temporal behaviors with sparse representations. By using RNN, the image classification is accurately performed with a minimal number of features for disease detection.
- Depending on CNNs and RNNs' achievement in handling intricate tasks, an optimal multi-class brain tumor diagnosis is carried out.

The remaining portion of the work is divided into five sections. The associated studies on the detection of brain tumors are reviewed in Section 2.Section 3 describes the performance analysis of CNNs and RNNs including a neat diagram. Section 4 presents the experimental scenario and corresponding results for four parameters are discussed. The conclusion comes at last in Section 5.

2. Related Work

To gather the crucial feature distributions as class-unbalanced brain MRI images, a unique convolutional variational model with generative basis for brain tumor identification and categorization was introduced in [13].The designed model synthesized the brain MRI images for every class. A sizable, balanced dataset was utilized to train the classifier to recognize cancers of the brain in MRI scans. In [14], a fully autonomous deep learning technique for reliable, highly accurate medical image segmentation was created.An encoder-decoder CNN forward system predicted the input image segmentation outcome. FCN basis context feedback system was employed to encode the forward system predicted probabilistic output.

In [15], a CNN-based automatic segmentation algorithm with size variability was created.For tumorous slices pixel-wise classification, CNN basis encoder-decoder UNET model was used. A multi-inception-UNET model was employed to augment UNET model scalability. To classify and segment images, the deep learning technique was created in [16]. In Medical Image Processing, Fuzzy Sets were analyzed in [17] to provide detailed analysis of fuzzy sets utilization in the medical image processing field. It emphasized the fuzzy set capability to handle uncertainty and vagueness with medical image data.

A brain tumor recognition method that is accurate, automatic, and based on deep learning has been presented in [18].The designed method employed an SVM classifier and activation algorithms to cross-check. To diagnose and treat BT, a deep learning model was developed in [19].For efficient processing and analysis, the transformer self-attention method computed the relationships among the input data. Precise attention was employed to enhance the tumor accuracy. In [20], Deep Transfer Learning Networks were developed for MR Image-Based Brain Tumor Detection.The dissimilar deep learning classifiers were used for identifying the brain tumor from MR images with high accuracy performance.

"Theory and Applications of Fermatean Neutrosophic Graphs" is a noteworthy contribution to the field of neutrosophic sets and systems. The authors successfully introduce and develop the concept of FNGs, providing a robust framework for handling complex uncertainties [31]. In [32] the authors successfully extend the concept of FNGs to CFNGs, providing a robust and flexible structure for representing and managing complex uncertainties. Despite its complexity, the paper's thorough exploration of both theoretical and practical aspects makes it a valuable resource for researchers and practitioners looking to apply advanced neutrosophic concepts to decision-making processes.

In [33] Authors Broumi, Raut, and Behera present a novel integration of ACO with neutrosophic sets to better manage and solve complex routing problems under uncertainty.In [34] IVFNS extend Fermatean Neutrosophic Sets by allowing the membership values (truth, indeterminacy, and falsity) to be intervals rather than exact numbers. This enhances the ability to model and manage uncertainty in complex decision-making scenarios.And aim to provide a more accurate and flexible method for handling uncertainty and imprecision in the evaluation process. In [35] the authors Broumi, Krishna Prabha, and Vakkas Uluçay propose a novel method to address

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uncertainty and imprecision in the shortest path problem by leveraging the characteristics of IVFNS and introducing a score function to facilitate decision-making.

Two deep learning techniques were designed in [21] for recognizing normal and multiclass brain tumors with high classification accuracy. The different radiographic image modalities were used within dissimilar types of brain tumors. Despite using a high number of MRI scans for training, there was no decrease in uncertainty.

To classify and identify brain tumor images, the deep learning technique was created in [22]. The proposed foundation for support values utilizing adaptive deep neural network identification, the brain image was classified as either abnormal or normal.During preprocessing, skull stripping was employed to separate the desired brain region. (BrainMRNet) residual network was employed in [23] for brain tumor detection. In BrainMRNet, a concentration module and hypercolumn technique were used to preprocess the image. Every layer attribute was collected from the BrainMRNet model.Ensemble Method for Classifying Medical Images In [24], a bio-inspired Evolutionary DenseNets model was created using several evolutionary DenseNet-121s.The designed model was considered with network width reduction. To extract the texture characteristic from the MR images, a composite Neutrosophic-Slantlet Transform Domain was used in the development of an inventive brain tumor intelligence screening method [25]. To distinguish between malignant and benign brain tumors, a novel brain tumor Gray Level Run Length Matrix feature was created using composite NS-SLT data. An extreme learning machine (ELM) employed to detect tumors, the triangular fuzzy median filtering method was introduced in [26] to enhance the image quality. It extracted the Gabor features to determine the similar texture (ST) features.

Tripartite Generative Adversarial Network (Tripartite-GAN) was introduced in [27] for accurately detecting the tumor. An end-to-end framework was employed for an efficient tumor detection process. The deep classification method was first used in [28] to identify malignancies inside brain magnetic resonance imaging.The classifier performance was examined with principal component analysis to reduce the feature vector dimensions. To separate the input images into tumor and non-tumor categories, the DL model was introduced in [29].

The image presentation was carried out at the preprocessing phase. The high-pass filter was selected to employ the input image edges. In [30], a K-means clustering technique combined using the Fuzzy C-means (KMFCM) technique is described for very accurate tumor segmentation.

3. Methodology

Deep learning is a fit and better approach in many fields for medical image segmentation. Deep learning-based classification is important to provide exact categorized results of images. A traditional data mining method that depends on machine learning is classification. Every item in the data collection is sorted using the classification technique into a single of the pre-established class categories.

Convolutional Neural Network (CNN) is a commonly used neural network in DL for image classification. In addition, a Recurrent Neural Network (RNN) is a powerful method to identify the active temporal behaviors in random lengths of large-scale series data. RNN is competent in learning intricate temporal behaviors promptly comprising sparse representations. RNN is used through convolutional layers to extend efficient pixel regions. By using RNN, image classification is accurately performed as it uses less number of features for disease detection. Depending on the achievement of CNN and RNN in handling different intricate tasks, an improved framework obtained the optimal multi-class brain tumor diagnosis by detecting interested regions in the image.

Using effective transfer learning, the identification of brain tumors is divided as the tumor area and the non-tumor zone.However, CNN and RNN are not integrated to address the data uncertainties. Therefore, CNN and RNN methods are introduced with QNS for accurately classifying and detecting the tumor images. The block diagram of tumor detection using CNN and RNN methods is illustrated in above figure 1.

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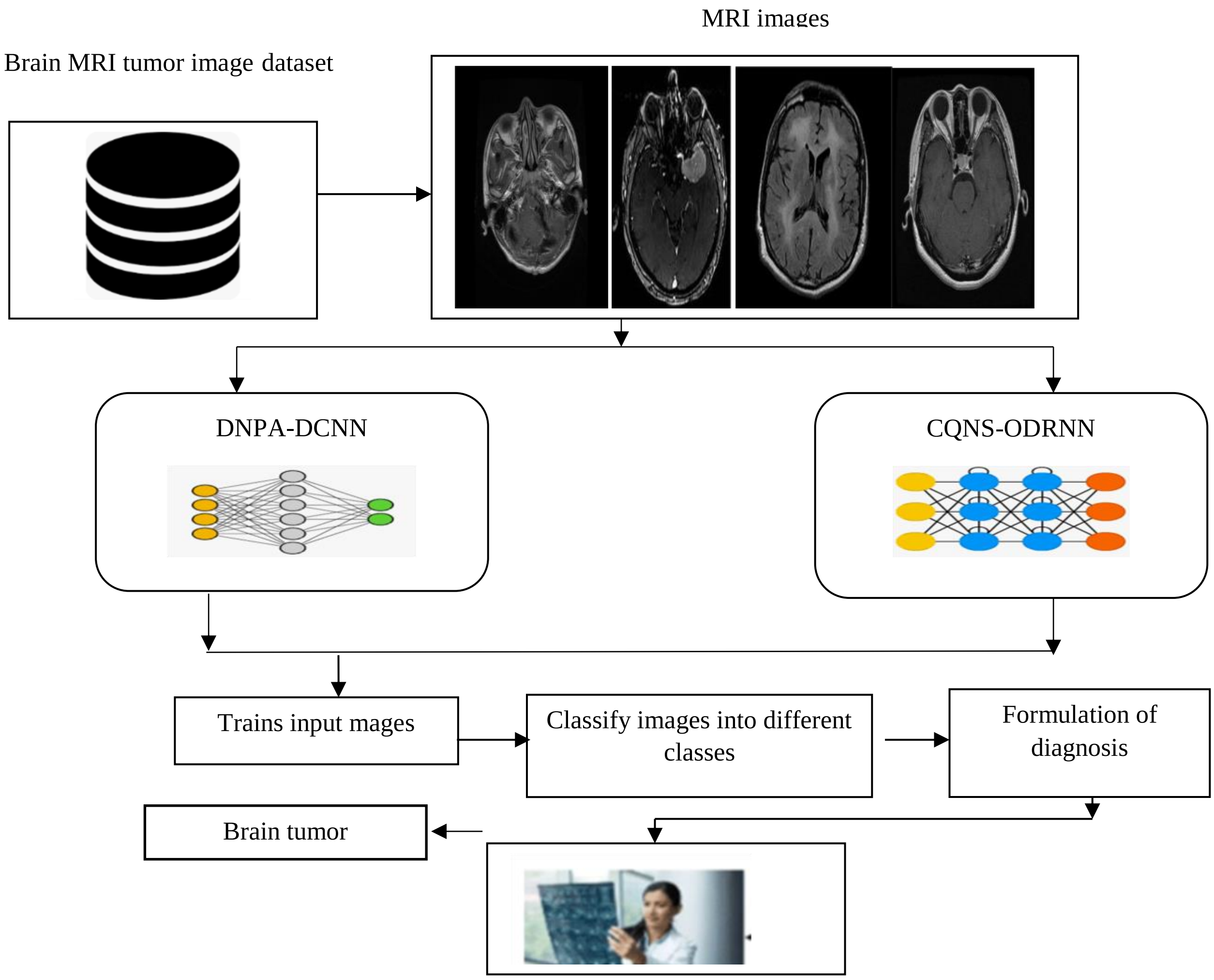

Figure 1. Block Diagram of Brain Tumor Detection using Convolutional and Recurrent Neural Network

The overall process involved in the above-mentioned methods are described as follows.

4. Differential Quadri-Partitioned Neutrosophic Interval-Valued Polynomial Attention-Based Deep CNN

A Differential Quadri-Partitioned Neutrosophic Interval-valued Polynomial Attention-based Deep CNN (DQNI-PADCNN) is developed to detect brain tumor accurately. DQNI-PADCNN method segmented the images as input from morphological operations with a Quadri-Partitioned Neutrosophic set. With this input, Region of Interest (RoI) identification and image classification are performed for brain tumor detection. RoI identification is carried out by using Differential Quadri-Partitioned Neutrosophic Sets on input-segmented brain MRI images. There are four measures like truth, false, contradiction, and indeterminate outputs are acquired without concerning others in the decision-making process for identifying the RoI. The uncertainty involved in raw brain tumor MRI dataset is reduced. After finding RoI, classification of brain images are carried out by Interval-valued Quadri-Partitioned Neutrosophic Polynomial Attention-based Deep Convolutional Neural Network.

Interval-valued Quadri-Partitioned Neutrosophic Polynomial Attention-based CNN model comprised different kinds of layers like pooling layers, convolutional layers, and fully connected layers. The convolutional layer accomplishes feature maps by taking RoI brain tumor images. The feature maps are sampled down and given to the second layer of the Interval-valued Quadri-Partitioned Neutrosophic Polynomial Attention-DCNN model (i.e., pooling layer). Ultimately, the fully linked layer uses the ELU activation function at varying intervals to display the categorization outcomes for four distinct types of brain cancers.

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Lastly, glioma, meningioma, no tumor, and pituitary tumor classes are accurately identified from the output generated from fully connected layers. In this way, the DQNI-PADCNN method's accuracy for tumor detection is raised.

The pseudocode for Interval-valued Quadri-Partitioned Neutrosophic Polynomial Attention-based Deep Convolutional Neural Network is illustrated as,

Algorithm 1: Interval-valued Quadripartitioned Neutrosophic Polynomial Attention-based Deep Convolutional Neural Network
Input: Dataset ‘DS’, Brain MRI Image ‘$BI = \{BI_1, BI_2, \ldots, BI_N\}$’ **Output**: Efficient brain tumor detection
1: **Initialize** ‘N $(sample\ instances)$’, region of interest ‘RoI’ **2**: **Begin** **3: For** each Dataset ‘DS’ with Brain MRI Image ‘BI’ and region of interest ‘RoI’ **//Convolutional layers** **4**: Determine the magnitude of the convolution layers **5**: Calculate the Quadri-Partitioned convolution layer for every RoI brain tumor image **6**: Compute Polynomial Attention Coefficient function **//Pooling layer** **7**: Estimate ELU function **8**: Attain output from ELU layer for Quadri-Partitioned membership subset **9**: Obtain output from the ELU layer **//Fully connected layers** **10**: Generate the output produced from fully connected layers **//Error evaluation** **11**: Measure the error rate using the fitness function **12**: Display the detected results (‘glioma’, ‘meningioma’, ‘no tumor’, ‘pituitary’) **13**: **End for** **14**: **End**

As illustrated in the above algorithm, Differential Quadri-Partitioned Neutrosophic brain MRI RoI detected outputs are sent to the classification process for achieving computationally efficient outputs. The deep CNN is divided into convolution layers where different magnitude convoluted outputs are attained through Interval-valued and Polynomial Attention Coefficient functions for all differential Quadri-Partitioned neutrosophic brain MRI RoI detected outputs. After that, the convoluted output is transmitted to the pooling layer to minimize the feature map dimension through the ELU activation function depending on various intervals. In this way, an efficient classification between four distinct classes (i.e., glioma, meningioma, no tumor, and pituitary) is carried out based on the fitness function with the output produced from fully connected layers efficiently.

5. Canonical Quadri-Partitioned Neutrosophic Set Based Otsuka–Ochiai Deep Recurrent Neural Network

The Canonical Quadri-Partitioned Neutrosophic Set based Otsuka–Ochiai Deep Recurrent Neural Network (CQNS-ODRNN) method is introduced to efficiently determine the brain tumor disease. The CQNS-ODRNN approach performed two functions: tumor detection classification and region of interest identification. The segmented pictures obtained from morphological operations using a Quadri-Partitioned Neutrosophic set are used as the input for the CQNS-ODRNN technique.With segmented images, the region of interest is identified through

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a Canonical Censored Regressive Quadri-Partitioned Neutrosophic Set. The images are transformed into the Quadri-Partitioned Neutrosophic domain. Then, the relationship between pixels is recognized for finding the interested region of the pixel through Canonical correlated censored regression. Upon identifying the RoI portions from MRI images, the Otsuka–Ochiai Deep Recurrent Neural Network is used to categorize the images into different classes. The RNN comprises several layers input layer, hidden layers, and output layer. Each layer has several neurons. Neurons in one layer are linked to the other layer neurons. RNN used the unit delay to study the identified RoI images and sent them back into the input layer. The input layer collects the RoI-detected images as input. Subsequently, the various buried layers receive input.

The images get examined to classify the images into different classes through the Otsuka–Ochiai index. Finally, the classified outputs are sent to the output layer through the Gaussian activation function. Depending on classified results, gliomas, meningiomas, no tumors, and pituitary tumors are classified accurately. The algorithmic process of Otsuka–Ochiai deep RNN is described as follows

Algorithm 2: Otsuka–Ochiai Deep Recurrent Neural Network
Input: Dataset 'S', Brain MRI Image '$I = \{I_1, I_2, \dots, I_n\}$', RoI detected image $RI = \{RI_1, RI_2, \dots, RI_n\}$ **Output**: Accurate brain tumor detection

Initialize the number of region of interest images 'RI_i'
Begin
For each Dataset 'S' with Brain MRI Image 'I' and region of interest 'RI_i'
Assign weight 'δ_x' and bias 'b'
Identify activity of neuron at input layer
Formulate the activity of neuron at hidden layer
Compute Otsuka–Ochiai index 'φ'
Formulate recurrent behavioral of deep RNN classifier
Hidden layer forwards Otsuka–Ochiai index results to the output layer
Output layer applies Gaussian activation function 'α'
If ($\alpha = 1$) **then**
Images are correctly classified into gliomas, meningiomas, no tumors, and pituitary tumors
Else
Images are not correctly classified
End if
Return brain tumor detection results
End for
End

As discussed in the above algorithm, Otsuka–Ochiai Deep Recurrent Neural Network is used to categorize the image into different classes for tumor detection. For increasing the tumor detection performance with less error rate, the Otsuka–Ochiai index is employed to determine the association between training and testing images. Depending on these results, the Gaussian function is used to recognize the different classes of brain tumor images. In this way, classification accuracy is increased in the proposed CQNS-ODRNN method.

6. Performance Comparison of DQNI-PADCNN and CQNS-ODRNN

The performance of the proposed DQNI-PADCNN and CQNS-ODRNN methods are implemented using a MATLAB simulator. Using the Brain Tumor MRI dataset, the outcomes of brain tumor identification are examined.The dataset is collected from https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset. The designed dataset includes three datasets namely figshare, SARTAJ, and Br35H correspondingly.

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There are 7023 images of human brain MRIs in the brain tumor MRI collection. The dataset's photos are categorized into four groups: pituitary, glioma, meningioma, and no tumor.

The performance of both proposed classification methods such as DQNI-PADCNN and CQNS-ODRNN method are compared with conventional deep learning and Non-Sequential Recurrent Model Ensemble (NSRME) method. The results of classification methods are validated under different performance metrics as,

- Brain tumor detection accuracy
- Sensitivity
- Specificity
- Brain tumor detection time

6.1 Results of Brain Tumor Detection Accuracy

Brain tumor detection accuracy is described as the proportion of samples that are correctly categorized for disease detection. It is computed in terms of percentage (%). It is mathematically computed as,

$$BTD_{acc} = \sum_{i=1}^{N} \frac{S_{AD}}{S_i} * 100 \qquad (1)$$

From (1), 'BTD_{acc}' indicates the brain tumor detection accuracy, 'S_{AD}' refers a brain tumor samples accurately classified, and 'S_i' refers a brain tumor samples. When the accuracy is high, the performance of brain tumor detection is improved. The comparison of DQNI-PADCNN, CQNS-ODRNN method, deep learning, and NSRME methods in terms of brain tumor detection accuracy is provided in table 1.

Table 1: tabulation of brain tumor detection accuracy using DQNI-PADCNN, CQNS-ODRNN, deep learning and NSRME

Sample Brain MRI images	Brain tumor detection accuracy (%)			
	Existing NSRME	Existing deep learning	Proposed DQNI-PADCNN	Proposed CQNS-ODRNN
50	89.00	92.00	96.00	98.65
100	84.63	89.25	95.35	98.53
150	83.28	88.65	93.10	98.41
200	82.00	86.45	92.25	98.86
250	80.31	85.35	90.45	98.73
300	78.52	84.25	89.75	97.96
350	75.00	82.35	88.45	97.89
400	74.63	79.10	87.65	97.77
450	73.31	78.35	86.10	96.93
500	72.00	76.65	85.25	96.84

Table 1 shows the comparative analysis of brain tumor detection accuracy for proposed and existing classification methods with the Brain Tumor MRI dataset.The accuracy of detecting brain tumors utilizing the suggested DQNI-PADCNN and CQNS-ODRNN methods is compared to current deep learning and NSRME methods.
By analyzing the above tables, the brain tumor detection accuracy of the proposed methods is found to be higher than the existing methods. As compared to the DQNI-PADCNN method, the proposed CQNS-ODRNN method provided higher accuracy during the brain tumor detection. Graph for brain tumor detection accuracy using four methods is depicted in figure 2.

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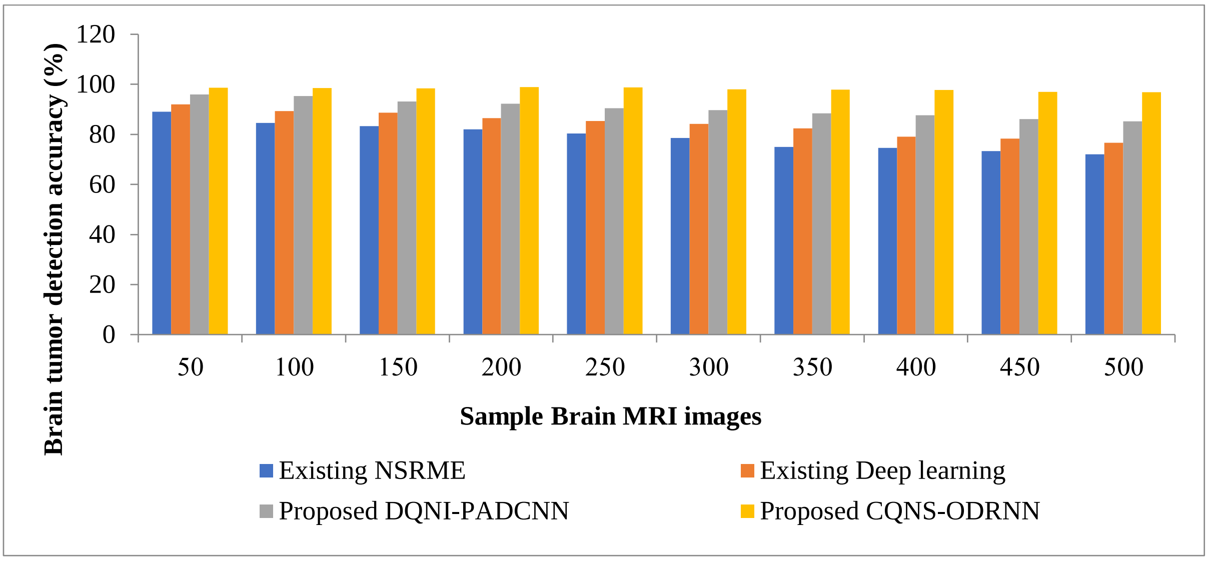

Figure 2. Results of brain tumor detection accuracy versus different sample brain MR images

Figure 2 illustrates the show analysis of brain tumor detection accuracy for proposed and existing classification methods for different numbers of brain MRI images ranging from 50 to 500. The brain tumor detection accuracy results of the proposed DQNI-PADCNN method and CQNS-ODRNN method are determined with existing deep learning and existing NSRME. In figure 2, the x-axis represents the sample brain MRI images as input and the y-axis symbolizes brain tumor detection accuracy. Through comparing existing and proposed methods, the performance of brain tumor detection accuracy using the proposed CQNS-ODRNN method is higher than any other methods. This is because of using recurrent neural networks with several layers to analyze the input images for brain tumor detection. The input layer comprised the RoI-detected images. Then, the hidden layer employed the Otsuka–Ochiai index to determine the similarity between training and testing images. Afterward, Gaussian activation is used at the output layer for image classification into four different classes. Consequently, the brain tumor disease finding accuracy is improved in CQNS-ODRNN than the DQNI-PADCNN and existing methods. The experimental result of the proposed CQNS-ODRNN method improves the brain tumor detection accuracy by 9% as compared to the proposed DQNI-PADCNN method. Furthermore, the suggested DQNI-PADCNN approach outperforms the current deep learning and NSRME in terms of brain tumor detection accuracy, improving it by 17% and 24%, respectively.

6.2 Results of sensitivity

Sensitivity is determined based on the computation of true positives and false negatives of brain MRI image detection. Sensitivity is estimated in terms of percentage (%). Sensitivity is mathematically estimated as,

$$Sensitivity = \frac{TP}{TP+FN} * 100 \qquad (2)$$

From (2), 'TP' denotes the True Positive, and 'FN' symbolizes the False Negative. A sensitivity comparison of four different classification methods is provided as given below.

Table 2: tabulation of sensitivity using DQNI-PADCNN, CQNS-ODRNN, deep learning and NSRME

Sample Brain MRI images	Sensitivity (%)			
	Existing NSRME	Existing deep learning	Proposed DQNI-PADCNN	Proposed CQNS-ODRNN
50	88.00	90.00	97.00	98.00
100	86.00	89.31	95.86	96.00
150	85.00	88.00	93.91	94.00

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200	83.00	87.21	92.25	93.00
250	82.00	86.00	91.25	92.00
300	80.00	85.00	91.00	92.00
350	79.00	84.00	90.00	91.00
400	78.00	83.00	89.63	90.00
450	77.00	82.63	88.53	89.00
500	75.00	81.00	87.63	88.00

Table 2 describes the comparative analysis of sensitivity based on sample brain MRI images for the proposed DQNI-PADCNN method, CQNS-ODRNN method, existing deep learning, and NSRME. The number of brain MRI pictures is adjusted between 50 and 500 to do the sensitivity analysis.As shown in the above figure, a decreasing trend is monitored when increasing the number of sample brain MRI images. Though all the methods decrease the sensitivity, the proposed methods comparatively give better average sensitivity during brain tumor detection. In addition, the proposed CQNS-ODRNN method attained higher sensitivity than the existing methods. Graphical results of sensitivity based on the sample brain MRI images are provided in below figure 3.

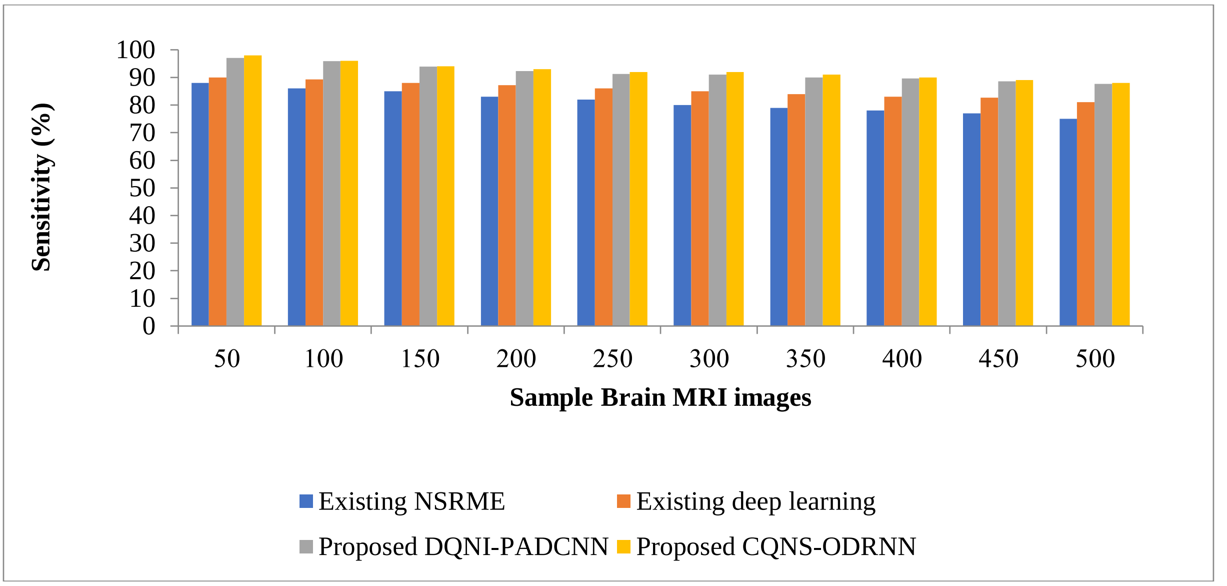

Figure 3. Results of sensitivity versus different sample brain MR images

The comparative examination of sensitivity for various numbers of samples brain MRI images obtained from the Brain is shown in Figure 3. Tumor MRI dataset. While comparing the proposed DQNI-PADCNN method, and CQNS-ODRNN method with existing deep learning and NSRME, the proposed CQNS-ODRNN method attained higher sensitivity. The total number of sample brain MRI pictures is shown on the x-axis in the above figure, while the y-axis displays the sensitivity findings for both suggested and current approaches.

The higher sensitivity is attained through the Otsuka–Ochiai Deep Recurrent Neural Network. RNN comprises multiple layers such as input, hidden layer, and output layer. The input layer collects the RoI-identified images as input. In the hidden layer, the Otsuka–Ochiai index is employed to compute the similarity between the training image (i.e., RoI identified) and the testing image. Besides, the Gaussian activation function is used to categorize the images into four different classes. With this, sensitivity in tumor detection is increased in the CQNS-ODRNN method. As a result, the suggested CQNS-ODRNN method's average sensitivity is raised by 8% and 14%, respectively, in comparison to the current deep learning and NSRME.

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6.3 Results of specificity

Specificity is defined as the possibility of a test to identify people without brain tumor disease exactly. It is computed as the ratio of true negative values to the true negative values and false positive values. Specificity is computed in terms of percentage (%). The specificity is given below.

$$Spe = \frac{TN}{TN+FP} \quad (3)$$

From (3), 'Spe' denotes the specificity, 'TN' represents the true negative values (i.e., nontumor patients accurately predicted as patients with nontumor), and 'FP' denotes the false positive values (i.e., healthy people wrongly predicted as tumor patients) respectively.

Table 3: tabulation of specificity using DNPA-DCNN, CQNS-ODRNN, deep learning and NSRME

Sample Brain MRI images	Specificity (%)			
	Existing NSRME	Existing deep learning	Proposed DQNI-PADCNN	Proposed CQNS-ODRNN
50	86	90	92	94
100	83	86	89	92
150	82	85	88	91
200	81	84	88	90
250	80	84	88	89
300	78	84	87	89
350	77	82	87	88
400	76	82	85	88
450	75	80	84	87
500	73	78	83	86

Table 3 illustrates the comparative results of specificity through proposed and existing methods depending on sample brain MRI images from the given input dataset. The results of specificity for the DQNI-PADCNN method and CQNS-ODRNN method are evaluated with traditional deep learning and NSRME methods. In the above table, the numbers of sample brain MRI images are indirectly proportional to true positive rate results. When increase in sample brain MRI images, the true positive rate gets reduced. However, the proposed DQNI-PADCNN method and CQNS-ODRNN method give a higher true positive rate than the existing methods. Among the two proposed methods, the CQNS-ODRNN method attained comparatively higher specificity while identifying the brain tumor.

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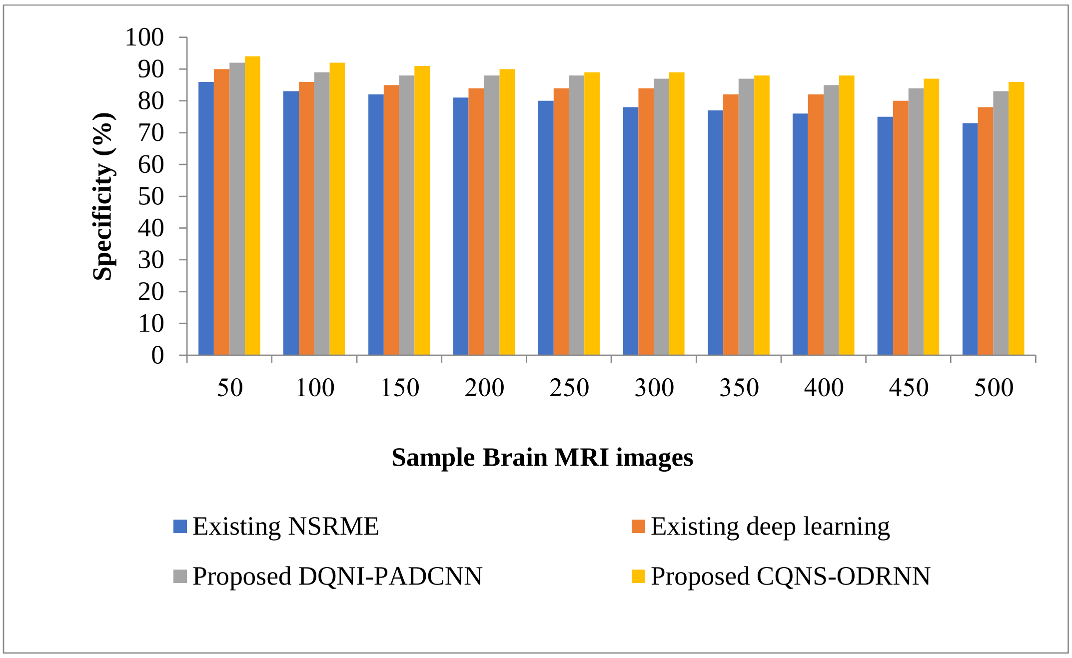

Figure 4. Results of specificity versus different sample brain MR images

Figure 4 illustrates a graph of specificity for four different methods to compute the performance of classification methods. The different colors in the above graph represent specificity results for two proposed and two existing methods. In the above figure, the horizontal direction symbolizes the sample brain MRI images and the vertical direction symbolizes the output of specificity using four methods. As compared to existing methods such as deep learning and NSRME methods, the proposed DQNI-PADCNN method, and CQNS-ODRNN method attained higher specificity. Predominantly, the CQNS-ODRNN method attained improved specificity than the DQNI-PADCNN method. This is due to the application of two processes RoI identification and brain tumor image classification. Canonical Censored Regressive Quadri-Partitioned Neutrosophic Set is used to identify the region of interested portions in the image. After that, the Otsuka–Ochiai Deep Recurrent Neural Network is used to classify the input images. Otsuka–Ochiai coefficient and Gaussian activation function are used to classify the input images into four different classes. The specificity of the CQNS-ODRNN method is improved than the proposed DQNI-PADCNN and existing methods. As a result, compared to the suggested DQNI-PADCNN approach, the specificity results obtained with the CQNS-ODRNN method are 3% higher. Also, the proposed CQNS-ODRNN method increases the specificity by 7% and 13% as compared to existing deep learning and existing NSRME respectively.

6.4 Results of Brain Tumor Detection Time

Brain tumor detection time is computed as the time taken to identify the brain tumor images by classification process. The brain tumor detection results are calculated in milliseconds (ms). The following is how brain tumor detection times are calculated.

$$BTD_{time} = \sum_{i=1}^{N} S_i * Time\ (ff) \qquad (4)$$

From (4), 'BTD_{time}' represent the brain tumor detection time. 'S_i' symbolizes the number of samples and '$Time\ (ff)$' refers a time for tumor detection. Table 4 compares the time it takes to detect brain tumors using proposed and current categorization techniques.

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Table 4: tabulation of brain tumor detection time using DQNI-PADCNN, CQNS-ODRNN, deep learning and NSRME

Sample Brain MRI images	Brain tumor detection time (ms)			
	Existing NSRME	Existing deep learning	Proposed DQNI-PADCNN	Proposed CQNS-ODRNN
50	24.00	22.50	15.50	13.00
100	36.52	30.35	16.25	14.52
150	45.25	36.55	20.10	18.00
200	50.21	48.15	23.45	20.34
250	68.10	60.65	26.25	22.63
300	92.52	68.05	33.25	29.14
350	100.52	80.15	37.45	32.24
400	108.62	90.25	53.05	46.62
450	122.52	100.05	60.25	54.71
500	134.25	110.25	70.85	62.52

The comparative analysis of brain tumor detection time depending on the number of samples is given in table 4. The validation of the proposed DQNI-PADCNN method and CQNS-ODRNN method is carried out through comparison with existing deep learning and NSRME. Ten different runs are carried out with various ranges of sample brain MRI images like 50, 100, 150,..., 500. The results from the table confirm that the CQNS-ODRNN method consumed less time than DQNI-PADCNN method, deep learning, and NSRME. The graphical view of brain tumor detection time for four different methods is illustrated in the below figure.

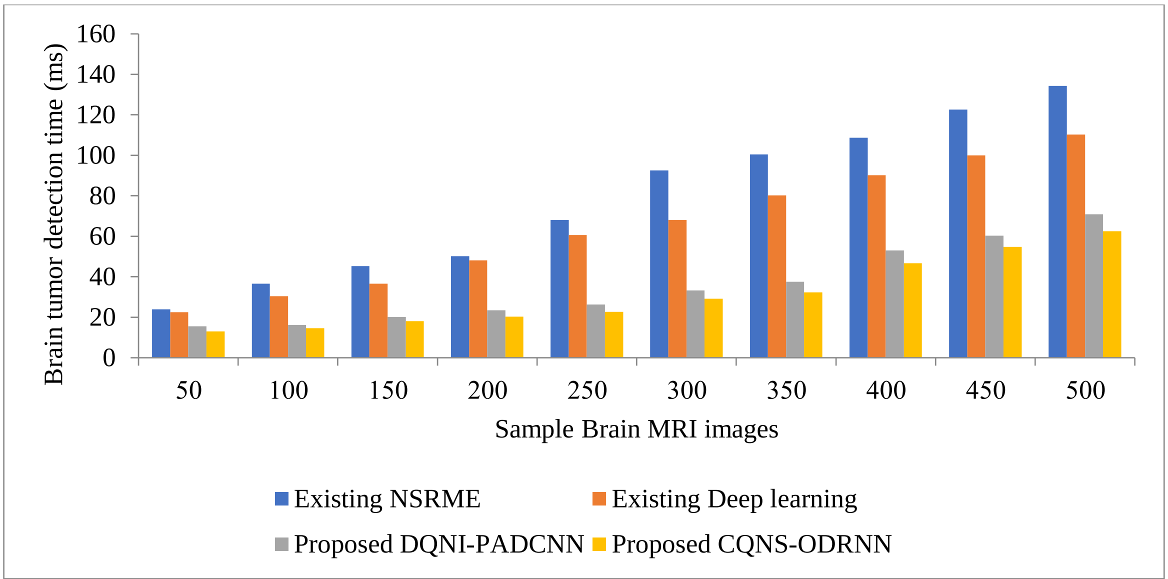

Figure 5. Results of brain tumor detection time versus different sample brain MR images

Figure 5 illustrates the results of brain tumor detection time for the proposed DQNI-PADCNN method, CQNS-ODRNN method, deep learning, and NSRME. From the above figure, the horizontal axis considered 500 sample brain MRI images, and the vertical axis gives brain tumor detection time for suggested and existing methods. The graph of brain tumor detection time is gradually increased with an increasing number of input sample brain MRI images. In addition, the proposed CQNS-ODRNN method takes a lower outlier detection time than the existing

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methods. The brain tumor detection time consumption is minimized through canonical censored regressive Quadri-Partitioned Neutrosophic set-based RoI detection. The sample input images are modified into the Quadri-Partitioned Neutrosophic domain. Canonical censored regression analysis is carried out to identify similar pixels to determine the RoI. The time consumed for brain tumor detection is reduced in the CQNS-ODRNN method than in the DQNI-PADCNN method, deep learning, and NSRME method. As a result, the brain tumor detection time of the suggested CQNS-ODRNN method is reduced by 12% than the DQNI-PADCNN method as well as decreased by 52% and 59% when compared to existing deep learning and existing NSRME respectively.

7. Conclusion

The overall performance analysis of two proposed methods as DQNI-PADCNN method and the CQNS-ODRNN method are carried out in this article for efficient brain tumor detection. The DQNI-PADCNN approach is first presented as a means of effectively classifying brain tumors utilizing Differential Quadri-Partitioned Neutrosophic. Sets and Interval-valued Quadri-Partitioned Neutrosophic Polynomial Attention-based Deep Convolutional Neural Network DQNI-PADCNN method increased the brain tumor detection accuracy with lesser time. Through RoI identification using differential QNS, the time and complexity during the classification process get reduced. In addition, deep CNN is used to categorize the images into glioma, meningioma, no tumor, and pituitary classes based on ELU activation function. Secondly, the CQNS-ODRNN method is introduced to perform accurate brain tumor disease diagnosis using Canonical Censored Regressive Quadri-Partitioned Neutrosophic Set and Otsuka–Ochiai Deep Recurrent Neural Network. With the help of regression-based QNS, more interested regions in the images are detected. The classification method is carried out to identify the brain tumor disease with higher accuracy. The performance of the two proposed methods is computed against conventional deep learning and NSRME. The findings of the brain tumor detection procedure are examined in terms of specificity, sensitivity, accuracy, and duration of the tumor's identification. From the experimental results, the proposed methods give better results in brain tumor detection. Among the two proposed methods, the CQNS-ODRNN method gives higher brain tumor detection accuracy, sensitivity, and specificity with less time than the DQNI-PADCNN method. CQNS-ODRNN has a simple structure to provide enhanced output based on the previous computation. Therefore, CQNS-ODRNN provides good results in brain tumor detection.

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