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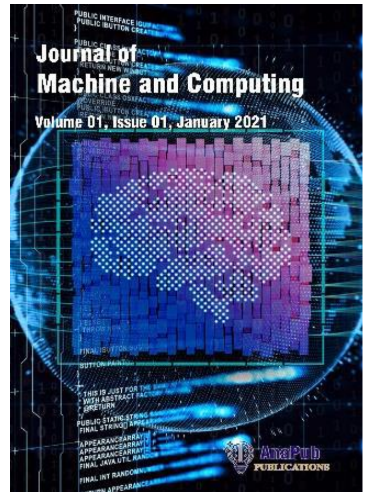

Identification and Delineation of Acquired Brain Anomalies Through Neural Network Classification Technique

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Identification and Delineation of Acquired Brain Anomalies Through Neural Network Classification Technique

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Abstract

Acquired brain anomalies are crucial and life killing disease among the other diseases. As a result, fast and accurate disease diagnosis and classification are critical for human survival. In this research, a machine learning strategy is given for distinguishing and classifying meningioma brain images from non-meningioma brain images. In this paper, the brain pictures are recognized and classified using the Neural Network (NN) classification method. This suggested method comprises of a preprocessing module that uses the shearlet transform for transformation of pixels. Local Binary Pattern (LBP) features are then calculated using the shearlet coefficients. The computed final characteristics are input into the NN classifier to produce classification results. The meningioma detection system using the suggested NN classification approach obtains 9[illegible].45% of SET, 96.57% of SPT, 97.34% of MSA, 97.38% of PR, and 97.3% of FS. The meningioma detection system using the suggested NN classification approach obtains 97.16% of SET, 97.25% of SPT, 97.97% of MSA, 98.19% of PR, and 98. The shearlet transform combined with NN classification algorithm improves the performance of the entire meningioma detection rate.

Keywords: Acquired brain anomalies, Neural Networks, meningioma, shearlet transform, classifier;

1. Introductions

The tumors are formed in the human body due to genetic disorders and abnormal growth of the cells. Due to these certainties, tumors are formed in human brain, which leads to death with different stages. As per World Health Organization (WHO) statement [1], the brain tumors are crucial one such as lung tumors and liver tumors etc., Therefore, it is very important to identify the brain tumors in its earlier stage of development process to save the human life [2]. The brain regions can be scanned using different modalities and these modality techniques scanned the internal regions of brain and produced the quality of images [3]. This method of identifying the brain tumor images are time expensive process and error prone process due to manual examination. These limitations are resolved by developing certain Computer Aided Development (CAD) methods to automate the brain tumor detection process [4]. The CAD technique in modern era uses soft computing algorithms to automate the entire flow work. In this paper, machine learning method is used to detect the brain tumor images from the healthy brain images. The brain tumors are also classified into various classes such as Glioma, Meningioma and Glioblastoma [5]. Among the different classes, Meningioma tumors are crucial and its detection process is more complex than the other classes [6]. Hence, Meningioma tumors are detected and the tumor regions are segmented in this paper used Neural Network (NN) classification process. The brain images for Glioma, Meningioma, and Glioblastoma are displayed in Figure 1(a), Figure 1(b), and Figure 1(c), in that order.

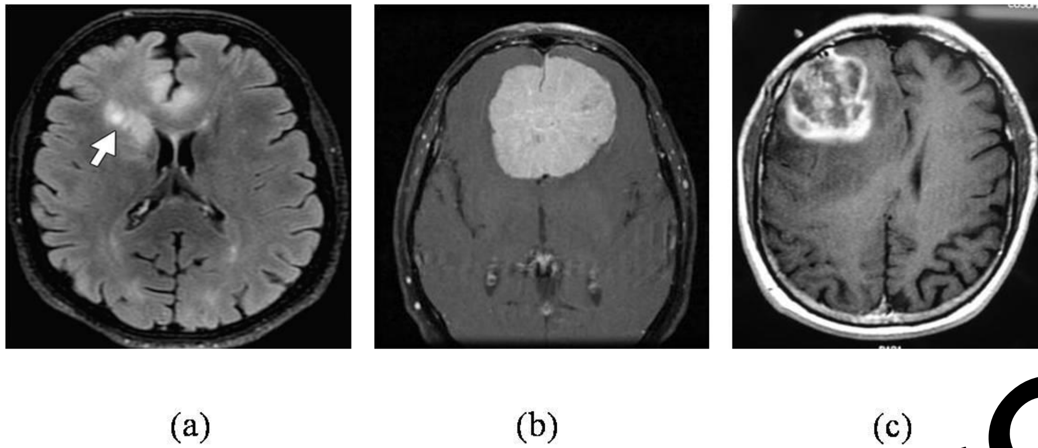


Figure 1(a) Tumor case with Glioma pattern (b) Tumor case with Meningioma pattern (c) Tumor case with Glioblastoma pattern

Győrfi et al. (2021) [7] performed enhancement using Atlas Enhancement process and the enhancement has been used to identify the location of the tumor regions. The authors used ensemble learning approach to classify the normal image from the tumor affected brain MRI images. The authors attained 95.7% of sensitivity rate along with 96.2% of specificity rate on the large number of brain images. Kumar et al. (2020) [8] detected and located the regions which were belonging to tumor cells. The authors used MRI scanning method to capture various regions of brain. The authors used GoogleNet for classifying the abnormal regions in brain images. Further, this method was tested on different imaging datasets BRATS 2018, BRATS 2019 and BRATS 2020. The experimental results of these methods were significantly analyzed with the evaluation metrics. Toğaçar et al. (2020) [9] constructed a new deep learning model BrainMRNet from the conventional deep learning models to overcome the fitting problems. This developed and newly constructed BrainMRNet model was applied and the authors attained 94.2% of sensitivity rate along with 94.2% of specificity rate on the large number of brain images.

Veeramuthu et al. (2019) [10] applied various preprocessing algorithms which was suitable for the detection of tumors. Then, NN classification approach was applied on the collected brain image dataset to identify the abnormal tumor affected brain images from the normal brain MRI images. The authors attained 93.1% of sensitivity rate along with 93.7% of specificity rate on the large number of brain images. Swati et al. (2019) [11] constructed fine tuning rule based algorithm which was worked on the various modes of pixels. The classified pixels in the brain MRI images then used to identify the transfer learning approach. This has been splitted into three different categories. Category 1 contained brain images with low tumor pixels, category 2 contained brain images with high tumor pixels and category 3 contained brain images with moderate tumor pixels. The authors attained 93.2% of sensitivity rate along with 9[illegible].7% of specificity rate on the category 1 dataset brain images. The authors attained 94.2% of sensitivity rate along with 93.8% of specificity rate on the category 2 dataset brain images. The authors attained 95.3% of sensitivity rate along with 94.2% of specificity rate on the category 3 dataset brain images.

The rest of this paper is planned as follows: Section 2 specifics the proposed methodology that includes Shearlet transform, Feature Extraction and Classification. Section 3 describes the results and discussion, comparing the proposed model with the existing approaches across various evaluation metrics. Finally, the Conclusion section summarizes the findings, emphasizes the framework's impact, and outlines potential areas for further research.

2 Methodology

The Nanfang University [12] and BRAINWEB [13] datasets are utilized in this study to assess the tumor classification procedure. There are 571 meningioma and 750 non-meningioma brain images in the Nanfang University collection that are available for use without a license. The 512 x 512 image pixel resolution uses 8-bit quantization. Additionally, the research uses the BRAINWEB dataset to confirm the efficacy of the methods provided in this work. With 8-bit quantization, the image's pixel resolution is roughly 1024 by 1024.

The NN classification approach is used in this study to detect and classify brain pictures that show meningioma and those that do not. This proposed method consists of preprocessing module which uses shearlet transform for the processing flow. Then, LBP features are computed from the shearlet transformed coefficients. The computed final features are fed into NN classifier to obtain the classification results. Figure 2 shows the proposed NN based system.

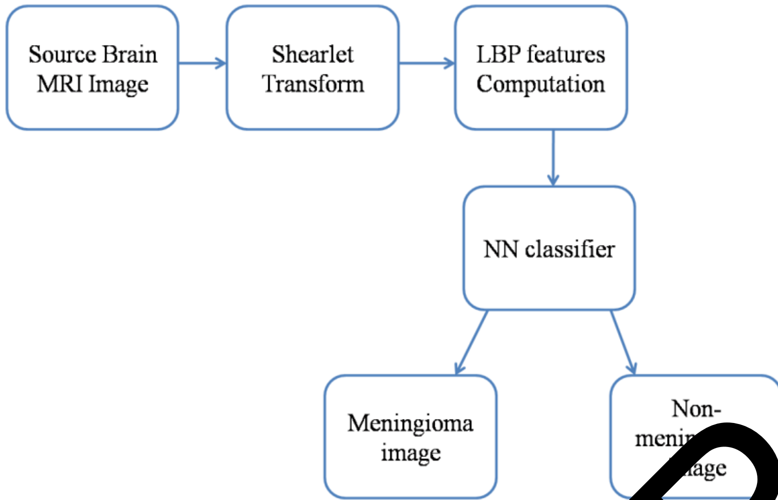


Figure 2 Proposed NN based flow of tumor detection

Shearlet Transform

The non-linear features can be extracted using shearlet transform. It is also called as multi scale systems which are the integration of Laplacian pyramid and shearing filters. The discrete shearlet transform transforms the image into Low Pass (LP) band and Band Pass (BP) band. The LP band is passed through the directional filters which produces shearlet coefficients. Next, the BP band is transformed into LP and BP band and then, BP band is passed through the directional filter in order to obtain the shearlet coefficients. The same process is repeated to decompose the LP and BP band completely. The shearlet coefficients which are obtained from each level in shearlet transform architecture are grouped into matrix. Figure 2 shows the architecture of shearlet transform. The transformation of LP filter and BP filter are represented as H1 and H0, respectively. The response of LP filter at level 1, level 2, level 3 and level 4 are S4, S3, S2 and S1 respectively.

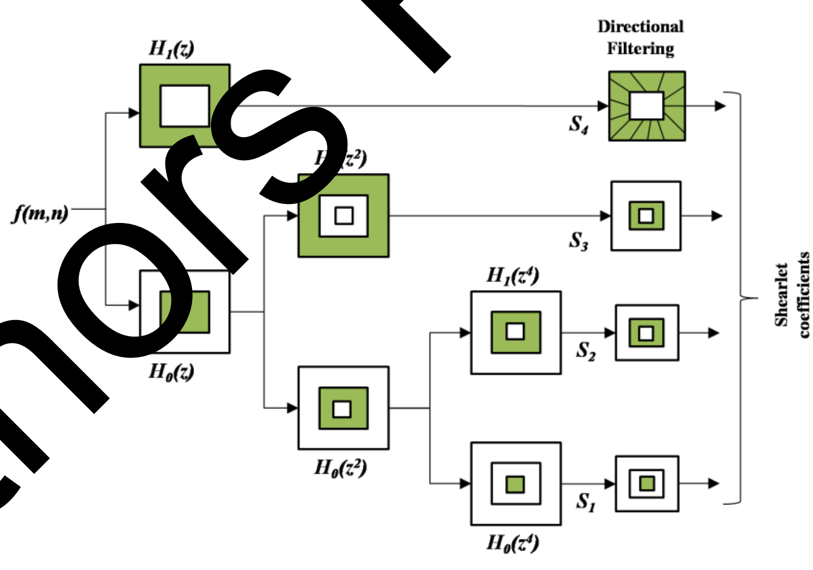


Figure 3 Decomposition architecture of shearlet transform

Figure 3 is the NN classifier architecture which is used in this paper for the classification of meningioma brain image from the non-meningioma brain images. The shearlet features from the decomposition module are fed into the input nodes of the NN classifier which produces the output responses as shown in Figure 4.

Features extraction and classification

The shearlet coefficients which are obtained through the shearlet architecture are stored in 2-dimensional matrix format with M rows and N columns. This work computes features of Local Binary Patterns (LBPs) from the decomposed shearlet coefficients. The 3*3 mask is placed over the computed 2-dimesional matrix and the center pixel in this 3*3 mask region is compared with its surrounding coefficient values. If the value of this center pixel is greater than the value of the surrounding coefficient value, then replace the value of the corresponding surrounding coefficient by 0 else replace it by 1. Then, the mask region is moved to next and the same procedure is followed till the end of the final coefficient value in this matrix. The LBP features are computed during training stage and they are trained with the NN classified which is explained with the following sub section. The size of the computed LBP features is high in size and hence they are not able to process directly with the NN architecture due to its long processing time. Then, the LBP are input into the NN classifier along with the trained patterns, which is obtained during the training stage of the classifier.

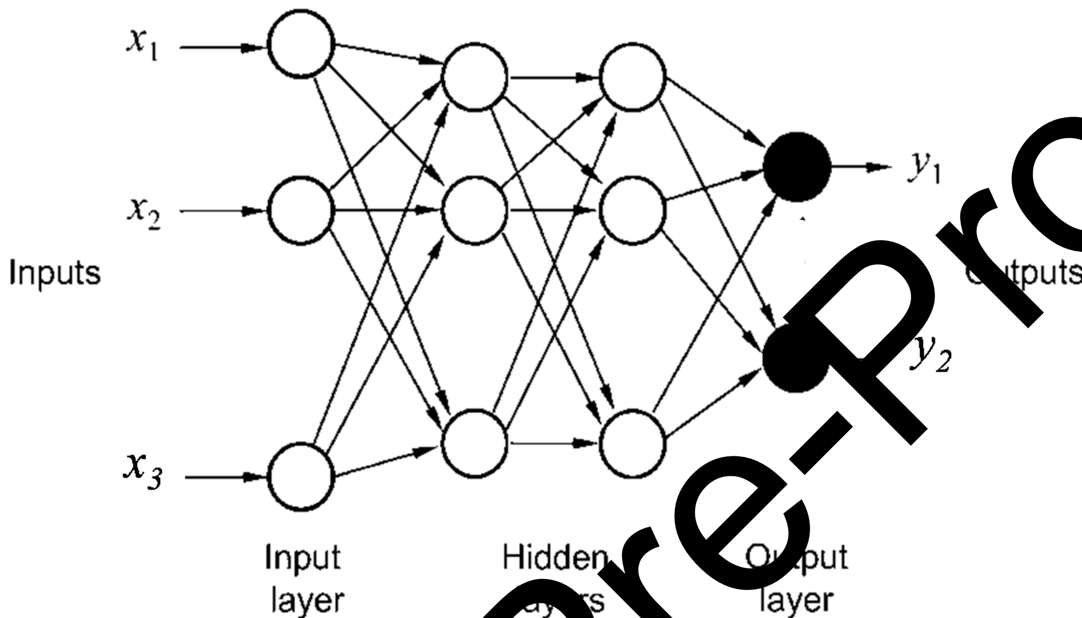


Figure 4 NN classifier

Figure 4 shows the NN classifier architecture with input, hidden and output nodes. The computed features are fed with the nodes in input layer and the final output (y1 and y2) are produced at the end of the output layer. The meningioma brain image is corresponds to the output pattern y1 and the non-meningioma brain image is corresponds to the output pattern y2 as shown in Figure 4. The number of nodes in input, hidden and output layer of the proposed NN classification architecture is depicted in Table 1.

Table 1 shows the NN classifier design specifications for the automated classifications of meningioma and non-meningioma brain images.

Table 1 NN classifier design specifications

Design Parameters	Specifications	Remarks
Number of layers	3	Input layer, hidden layer and output layer
Number of input layer	1	
Number of output layer	1	
Number of hidden layer	18	

Neurons in Input layer	12	
Neurons in hidden layer	20	Each hidden layer is designed with 20 neurons
Neurons in output layer	2	
Epochs	16,000	
Learning rate	0.5*10 (-2)	
Learning rule	Back propagation	

The morphological operators are applied now on the classified meningioma brain image to locate the pixels belonging to tumor. The morphological operators are opening and closing and they are explained in the following equations. The following formula is used to enlarge each pixel's outer layer.

$$Morphological\ open = open\ (I, 0.2) \quad (1)$$

Where, I is the classified meningioma brain image and 0.2 is the circle of radius is to be expanded in each pixel of I.

The following formula is used to reduce each pixel's outer layer,

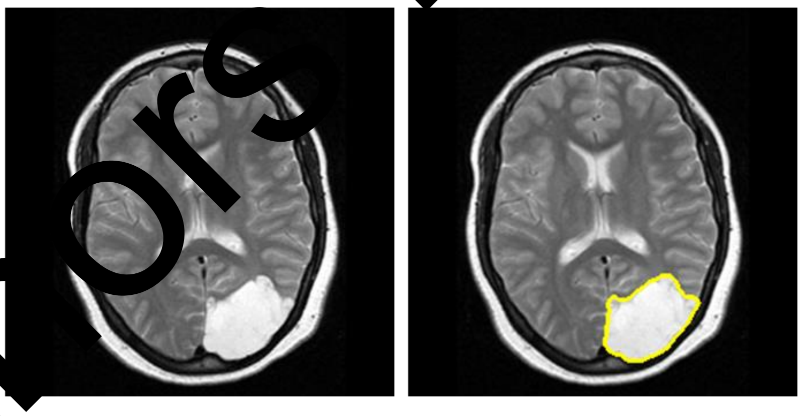
$$Morphological\ close = close\ (I, 0.5) \quad (2)$$

Where, I is the classified meningioma brain image and 0.5 is the circle of radius is to be removed in each pixel of I.

The meningioma brain image's tumor pixels are now segmented using the equation that follows.

$$Tumor\ pixels = Morpholoical\ open - Morphological\ close \quad (3)$$

The categorized meningioma brain image is shown in Figure 5(a), and the tumor region segmented brain image using the suggested method is shown in Figure 5(b).



(a) **(b)**

Figure 5 (a) Classified output (b) Tumor output

3. RESULTS AND DISCUSSIONS

Meningioma Classification Rate (MCR) and Non-Meningioma Classification Rate (NMCR) are used to experimentally examine this meningioma detection approach. Meningioma image count ratio (MCR) is the percentage difference between the total number of meningioma images and the number of detected meningioma images. The ratio, expressed as a percentage, between the total number of non-meningioma images and the number of detected non-meningioma images is known as the non-meningioma count (NMCR).

By accurately identifying 521 meningioma photos over 571 meningioma images, the Shearlet-NN classification algorithm described in this study achieves 91.2% of MCR. In addition, the Shearlet-NN classification algorithm accurately classifies 720 out of 750 non-meningioma pictures, achieving 96.8% of NMCR. Consequently, the Shearlet-NN classification methodology's average Classification Rate (CR) is approximately 94%.The experimental study of the impact of transforms is shown in Table 2.

Table 2 Using Nanfang dataset, an experimental investigation with regard to transformes were conducted.

Transformation model	Meningioma images tested count	Non-meningioma images tested count	Correctly classified meningioma image count	Correctly classified non-meningioma image count	MCR (%)	NMCR (%)
Without shearlet Transform	571	750	521	712	91.2	94.9
With shearlet transform	571	750	553	720	9[illegible].8	96

By accurately categorizing 185 out of 200 meningioma pictures, the Shearlet-NN classification algorithm presented in this research achieves 92.5% of MCR. Moreover, the Shearlet-NN classification algorithm accurately classifies 365 out of 400 non-meningioma pictures, achieving 91.2% of NMCR. As a result, the NN classification method's average Classification Rate (CR) is roughly 91.[illegible]%.

The experimental examination of the BRAINWEB dataset's multi-resolution transforms for the meningioma and non-meningioma detection method is presented in Table 3.

Table 3 Using the BRAINWEB dataset, an experimental investigation with regard to transformes were conducted.

Transformation model	Meningioma images tested count	Non-meningioma images tested count	Correctly classified meningioma image count	Correctly classified non-meningioma image count	MCR (%)	NMCR (%)
Without shearlet Transform	200	400	185	365	92.5	91.2
With shearlet transform	200	400	180	360	90	90

Additionally, an experimental analysis is conducted on the following confusion metrics in relation to the EM[illegible]CNN meningioma detection approach. The accompanying Table 4 defines the confusion metrics, which are created by calculating the real values in terms of positive and negative rate.

The following metrics are obtained from Table 4's confusion matrix to assess how well the Shearlet-NN classification algorithm performs in the meningioma detection system.

$$Sensitivity\ (SET) = \frac{S_{tp}}{S_{tp} + S_{fn}} \tag{4}$$

$$Specificity\ (SPT) = \frac{S_{tn}}{S_{tn} + S_{fp}} \tag{5}$$

$$Meningioma\ Segmentation\ Accuracy\ (MSA) = \frac{S_{tp} + S_{tn}}{S_{tp} + S_{tn} + S_{fp} + S_{fn}} \tag{6}$$

$$Precision\ (PR) = \frac{S_{tp}}{S_{tp} + S_{fp}} \quad (7)$$

$$F1 - Score\ (FS) = \frac{2 * S_{tp}}{2 * S_{tp} + S_{fp} + S_{fn}} \quad (8)$$

Whereas, S_{tp} is number of true positive pixels, S_{tn} is number of true negative pixels, S_{fp} is number of false negative pixels, S_{fn} is number of false positive pixels.

Table 4 Confusion matrix

		Actual values (tumor case)	
		Positive	**Negative**
Predicted values (tested)	Positive	S_{tp}	S_{fp}
	Negative	S_{fn}	S_{tn}

Table 5 presents the results of an experimental investigation using the Nanfang University dataset, utilizing the NN classification approach for meningioma detection. The meningioma detection system using the suggested NN classification approach obtains 96.45% of SET, 96.57% of SPT, 97.34% of MSA, 97.38% of PR, and 97.3% of FS.

Table 5 Experimental analysis of NN classification approach on Nanfang university dataset

Testing images	Numerical results (%)				
	SET	**SPT**	**MSA**	**PR**	**FS**
M1	96.1	96.6	97.2	97.3	97.2
M2	96.7	96.1	97.3	97.1	97.1
M3	96.1	97.3	97.1	97.8	97
M4	96.5	97.1	97.8	97	97.6
M5	96.[illegible]	96.7	97.9	97.2	97.2
M6	96.3	96.3	97.3	97.3	97.1
M7	96.9	96.1	97.1	97.8	97.9
M8	96.7	96	97.4	97.1	97.3
M9	96.2	96.7	97.2	97.8	97.1
M10	96.1	96.8	97.1	97.4	97.5
Mean	**96.45**	**96.57**	**97.34**	**97.38**	**97.3**

The NN classification strategy for meningioma detection system on the BRAINWEB dataset is experimentally analyzed in Table 6. The meningioma detection system using the suggested NN classification approach obtains 97.16% of SET, 97.25% of SPT, 97.97% of MSA, 98.19% of PR, and 98.4% of FS.

Table 6 Experimental analysis of NN classification approach on BRAINWEB dataset

Testing images	Numerical results (%)				
	SET	**SPT**	**MSA**	**PR**	**FS**

M1	96.7	97.3	97.9	98.3	98.3
M2	97.3	97.1	97.8	98.1	98.2
M3	97.1	97.3	97.8	98.3	98.3
M4	97	97.1	97.8	98.2	98.6
M5	97.3	97.9	97.9	98.2	98.7
M6	96.9	97.1	97.7	97.9	98.6
M7	97.9	97.3	98.1	98.3	98.3
M8	97.2	97.1	98.3	98.2	98.6
M9	97.1	97.2	98.1	98.1	98.3
M10	97.1	97.1	98.3	98.3	[illegible]
Mean	**97.16**	**97.25**	**97.97**	**98.19**	**98.4**

The meningioma detection system experimental investigation employing shearlet transform techniques is presented in Table 7.

Table 7 On the Nanfang dataset, an experimental examination of a meningioma detection system using shearlet transform techniques was conducted.

Experimental metrics in %	Meningioma detection system without shearlet transform approach	Meningioma detection system with shearlet transform approach
SET	[illegible].21	96.45
SPT	9[illegible]8	96.57
MSA	94.74	97.34
PR	94.85	97.38
FS	93.28	97.3

The meningioma detection system experimental investigation employing shearlet transform techniques is presented in Table 8. Without using the shearlet transformation approach, the suggested meningioma detection system obtains 93.29% of SET, 94.15% of SPT, 93.28% of MSA, 95.38% of PR, and 95.12% of FS. Additionally, 97.16% of SET, 97.25% of SPT, 97.97% of MSA, 98.19% of PR, and 98.4% of FS are achieved by the suggested meningioma detection technique that uses the shearlet transformation approach.

Table 8 On the BRAINWEB dataset, an experimental examination of a meningioma detection system using shearlet transform techniques was conducted.

Experimental metrics in %	Conventional EMD approach	Proposed MEMD approach
SET	93.29	97.16
SPT	94.15	97.25
MSA	93.28	97.97
PR	95.38	98.19
FS	95.12	98.4

The suggested NN classification method for meningioma detection system is compared with the traditional approaches by Çinar et al. (2020), Kabir Anaraki et al. (2019), Mehrotra et al. (2019), Ahmed et al. (2024), Babu Vimala et al. (2023) and Solanki et al. (2023) in Table 9. Table 9 shows that as compared to traditional meningioma detection methods, the meningioma detection system that uses the NN classification algorithm achieves much higher performance metrics.

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Table 9 On the Nanfang dataset, the suggested NN classification approach for the meningioma detection system is compared to traditional approaches.

Approaches	SET (%)	SPT (%)	MSA (%)	PR (%)	FS (%)
NN classification method	96.45	96.57	97.[illegible]	97.38	97.3
Ahmed et al. (2024) [14]	95.3	94.81	94.[illegible]9	95.12	95.87
Babu Vimala et al. (2023) [15]	94.38	94.[illegible]	94.19	94.10	95.09
Solanki et al. (2023) [16]	94.23	95.19	94.26	94.87	94.02
Çinar et al. (2020) [17]	[illegible]3.28	92.98	94.28	94.07	93.20
Kabir Anaraki et al. (2019) [18]	92.[illegible]	93.29	93.76	93.28	93.16
Mehrotra et al. (2019) [19]	[illegible]3.29	92.17	92.56	93.28	93.27

Table 10 On the BRAINWEB dataset, the suggested NN classification approach for the meningioma detection system is compared to traditional approaches.

Approaches	SET (%)	SPT (%)	MSA (%)	PR (%)	FS (%)
NN classification method	**97.16**	**97.25**	**97.97**	**98.19**	**98.4**
Ahmed et al. (2024) [14]	95.26	94.19	95.56	95.28	95.29

Babu Vimala et al. (2023) [15]	94.76	94.37	95.09	94.15	94.87
Solanki et al. (2023) [16]	94.29	94.87	94.36	95.09	94.38
Çinar et al. (2020) [17]	93.12	93.97	93.28	93.17	94.29
Kabir Anaraki et al. (2019) [18]	93.18	92.29	94.28	93.12	93.28
Mehrotra et al. (2019) [19]	93.76	93.78	94.38	94.01	93.17

4. Conclusions

The meningioma case is detected in this article using a neural network classifier. The source brain picture is subjected to the shearlet transform, and the decomposed shearlet coefficients are used to calculate the LBP features. To classify the features, the acquired LBP features are passed into a NN classifier. By accurately categorizing 185 out of 200 meningioma pictures, the Shearlet-NN classification algorithm presented in this research achieves 92.5% of MCR. Moreover, the Shearlet-NN classification algorithm accurately classifies 365 out of 400 non-meningioma pictures, achieving 91.2% of NMCR. As a result, the NN classification method's average CR is roughly 91.8%. For BRAINWEB open access dataset, the meningioma detection method employing shearlet transform obtains 90% of MCR and 90% of NMCR. The meningioma detection system using the suggested NN classification approach obtains 96.45% of SET, 96.57% of SPT, 9[illegible].34% of MSA, 97.38% of PR, and 97.3% of FS. The meningioma detection system using the suggested NN classification approach obtains 97.16% of SET, 97.25% of SPT, 97.97% of MSA, 98.19% of PR, and 98.

The major strengths of this paper are given in the following points.

- The experimental results of this research work attained optimum results for meningioma detection while comparing with other traditional methods, which could help the radiologist to automate the entire tumor detection process.
- The implementation of shearlet transform could improve the directional slectivity of the pixels, which improves the tumor classification rate.
- The proposed methodologies can be adaptable to any real time clinical dataset irrespective of the modalities of the images.

The limitations of this paper are given in the following points.

- This research work only focused the tumor detection process and not able to further diagnose the severity levels of the tumor regions which are detected and segmented through this proposed method.
- This proposed work provided only optimum experimental results in frequency domain mode instead of spatial resolution mode, which decreases the functional accuracy.
- No validation or statistical test has been involved in this study to validate the proposed results.

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