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Original Article

Gaussian Weighted Deep CNN with LSTM for Brain Tumor Detection

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Abstract *- Brain tumor is contemplated as a cruel illness in which the accuracy of images has a vital task. Accurate identification of tumor aid in exactly finding the injured portion and so decrease the mortality rate. Given that, learning the hidden pattern is significant to get an enhanced diagnosis and image quality. But, acquiring accurate diagnosis considering different lesion cases is a key concern. To overcome existing works problem, the automatic detection of brain tumor patients from their tumor images, Gaussian Weighted Deep Convolutional Neural Network with LSTM (GWDeepCNN-LSTM), is introduced. GWDeepCNN-LSTM technique includes many layers. First, brain MR images are collected from the given database. The image preprocessing is performed using a Gaussian weighted non-local mean filter where the noisy pixels are eliminated. Then, the segmentation is employed Hartigan's segmentation method to partition the image into similar regions. Followed by feature extraction is performed to extract the more informative features, such as texture, color and intensity, from the segmented image. Later, the classification of brain MR images is executed via Long short-term memory (LSTM). From that, the input image is classified as normal or tumor with higher accuracy. GWDeepCNN-LSTM performs better with an accuracy of disease detection and minimal time and error rate.*

Keywords *- Brain tumor, Convolutional Neural Network* (*CNN), LSTM.*

1. Introduction

A tumor is the abandoned augmentation of cancerous tissues in humans. A tumor is partitioned into various classes depending on the aspects and the inconsistent healing. Among all the sorts of tumors, brain tumor is pondered as the riskiest illness. It must be clearly analyzed by a medical practitioner who could sort the tumor rigorously. For that reason, image processing schemes are broadly exploited in classifying and detecting tumor images. The detection of brain tumors by way of MRI is a noteworthy part of healing. This procedure renders data associated with anatomical formations for preparing to heal. Tumor segmentation is positive for modeling the brains and building the brain's maps. Also, classification using deep learning methods has great attention in brain tumor detection.

Convolutional Auto-encoder Neural Network (CANN) was applied to find brain tumors. CANN categorize tumor into Astrocytoma, Meningioma, Pituitary, and Glioma [1]. Though the network retrieves the features, the time taken for tumor detection was not minimized. Dolphin- Sine Cosine Algorithm-based Deep CNN (Dolphin- SCA-based Deep CNN) was described to identify the brain tumor [2]. However, the accuracy of tumor detection was not improved. Multimodal information fusion and CNN-depended on brain tumor discovery were carried out in [3]. But, the error rate was not reduced. To diminish the error rate, CNN is integrated with feature learning in [4,5] for brain tumor identification. However, texture, color and intensity features are not accurately performed. The enhanced Deep Learning Approach was designed to categorize the brain images for tumor detection [21,30,31]. But, the number of parameters used in the network was not reduced. Depending on the integration model called neural autoregressive distribution estimation (NADE) and CNN, a deep learning technique was developed for tumor detection [6]. However, computational complexity has remained higher.

Deep learning and transfer learning models were presented to render accurate automatic segmentation and detect tumors [7]. Also, a grading model was applied to grade the tumors, but the feature extraction was not focused. A new deep CNN model designed through a hypercolumn masking scheme was described for brain tumor MRI classification [8]. However, computation complexity was not addressed. Based on the Snake Model and Fuzzy C-Means optimization, robust brain tumor segmentation was done in [9]. Though preprocessing was performed, image quality was not improved. Combined Neutrosophy and CNN (NS-CNN) were designed to discover tumor images [10]. However, segmentation was not performed. Semantic segmentation technique via CNN was introduced to automatically segment brain tumor [11]. But, the accuracy of segmentation was not improved. A combined CNN-SVM threshold segmentation scheme for tumor identification and classification was developed in [12]. However, the time for tumor diagnosis was not reduced. A novel Deep network model was introduced using ResNet-50 and global average pooling for holding the gradient and over-appropriate problem during the tumor discovery [13]. The accuracy analysis was not accurate. A VGG Net-Based Deep Learning structure was designed for tumor discovery on MRI Images with lesser time [32,33]. However, the false positive rate failed to be minimized. An ensemble segmentation scheme was employed to partition the tumor portion of the brain image [14,15]. But, similarity-based segmentation was not carried out.

An extended local fuzzy active contour model was employed for performing Super pixel-based segmentation [16]. However, the time taken for segmentation was high. Kernel-based SVM (K-SVM) was described to categorize the brain MR images [17]. Independent component analysis was used to get the relevant features. Computation overhead was not reduced. Hybrid CNN architecture was introduced to detect the tumor [18]. Though sensitivity was improved, the error rate was not decreased. The ensemble learning method was designed to classify tumors or neoplasms via MRI [19]. But, the time complexity was not reduced. Automated brain tumor detection and classification schemes were designed to predict the brain tumor [20]. But, the accuracy of tumor detection was not sufficient. Deep learning was designed to forecast the input slices as tumor and non-tumor images [34]. However, the false positive rate was unable to be reduced. A novel automated method was designed to detect and segment anomalous tissue [22]. However, the time complexity was not minimized.

An ensemble method was designed to detect and categorize brain tumor [23]. But, the accuracy was not sufficient. A noise removal technique was introduced in [24]. But, the image quality still needed to be improved for further process. A deep learning method was introduced for image segmentation and classification [25,27]. But, the computational cost was not reduced. An intelligent clinical decision support system was presented in [26] to find and sort the brain tumor image. But, the accuracy was not improved efficiently. A cost-effective stochastic method was discussed in [35] to discover brain tumors automatically. However, the time needed for disease detection remained higher. A modified fractal texture feature analysis was carried out in [28] by employing grayscale images to sort the images into normal and abnormal robustly. Relevant features failed to be extracted in the above analysis. In [29], a discrete wavelet transform coefficient was introduced to fuse the images. Though the PSNR was improved, sensitivity was not analyzed. The hybrid segmentation scheme was presented in [36] based on k-means clustering and modified subtractive clustering, but overall segmentation performance still needed improvement.

To solve these issues, a novel deep CNN-based technique is designed for brain tumor detection. The work aims to introduce a brain tumor detection technique called GWDeepCNN-LSTM. The work's main novelty is a tumor discovery via deep CNN. It is deliberated below:

- The performance of brain tumor detection is improved by introducing the GWDeepCNN-LSTM technique. GWDeepCNN-LSTM technique is modified by Deep CNN with LSTM, which it was recently designed using Hartigan's method and the Schutz index. GWDeepCNN-LSTM technique is modified to find the tumors from the MR images.
- To increase brain tumor detection accuracy, a Gaussian weighted non-local mean filter is applied to eradicate the noisy pixels in the image and improve the image's quality.
- Hartigan's segmentation method is employed inGWDeepCNN-LSTM to lessen the brain tumor detection time through similar grouping pixels. This is done by computing the hamming distance between the pixels.
- The Schutz index is computed to classify brain MR images using LSTM. It finds the similarity between extracted features and testing features for finding normal and tumor images.

The residue of the manuscript is prepared as follows: GWDeepCNN-LSTM is developed in Section 2. Results and discussion is given in section 3. Section 4 bestows the conclusion.

2. Proposed Method

A brain tumor is a dreadful kind of cancer that introduces severe problems in individuals. Exact analysis of the brain tumor lessens the mortality rate. Nevertheless, it is tricky to conquer precise analysis of dissimilar tumors. Accordingly, providing better tumor detection through deep learning is the main step for assisting early brain tumor detection. Conventional methods depending on brain tumor discovery are explored, and the inadequacies of technique push the inspiration to intend a new brain tumor detection approach. Therefore, Gaussian Weighted Deep Convolutional Neural Network with LSTM (GWDeepCNN-LSTM) is introduced to carry out brain tumor detection with higher accuracy and lower time. The architecture of GWDeep CNN-LSTM is shown in figure 1.

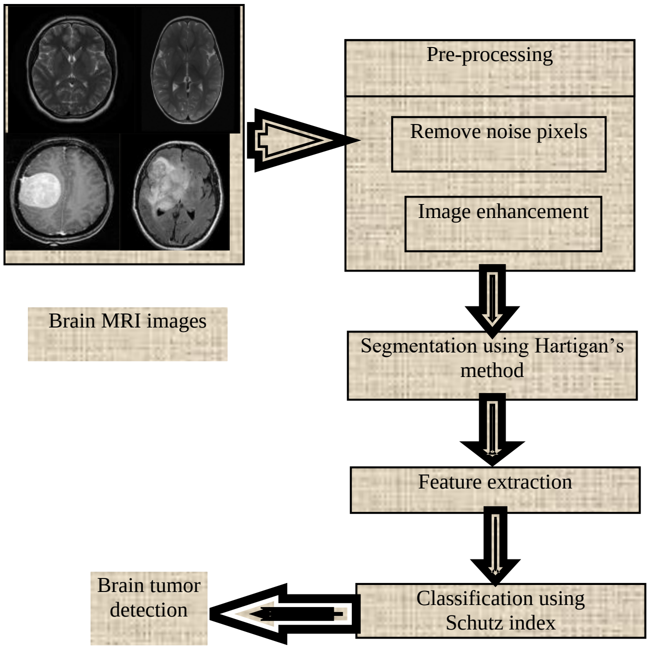

Fig. 1 Architecture of GWDeep CNN-LSTM

The overall process involved in brain tumor detection via GWDeepCNN-LSTM is demonstrated in figure 1. The number of brain MR images is gathered from the database. The input images are primarily preprocessed using a Gaussian weighted non-local mean filter to prepare the image apt for ensuing processing. Then segmentation module is employed where the de-noised image is segmented via Hartigan's algorithm. After that, feature extraction is carried out, pondering each segment. Features like shape, gray level intensity, and color are retrieved from each segment. Extracted features acquired from the segment are subjected to the classification process where LSTM is applied to categorize the brain tumor images. This, in turn, leads to the accuracy of tumor detection being improved with lower time.

3. Methods

GWDeep CNN-LSTM is designed based on the Deep Convolutional Neural Network with LSTM, as shown in figure 2.

Figure 2 depicts the construction of deep CNN for training brain MR images for tumor detection. In the deep learning concept, brain MR images are used as input in the input layer. The input images are fed into the input layer of deep CNN. The layers incorporate neurons like nodes linked from one layer to a consecutive layer. The input images in the layer are transformed into the next layer with different adjustable weights. Input is sent to the hidden layer, which involves image de-noising by Gaussian weighted non-local mean filter. Then, the de-noised image is given to the second hidden layer to execute image segmentation in which a similar region is extracted. Followed by the classification process is carried out via LSTM. With this, normal and abnormal image classification is done with better accuracy.

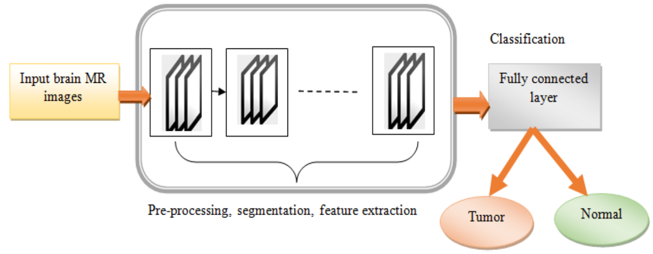

Fig. 2 Deep Convolutional Neural Network with LSTM

3.1. *Image De-noising*

With the diverse intensity values, MRI images are affected via bias domains. A dynamic intensity normalization method is established to form MRI examinations of numerous patients and vary the bias domain of data. With the rise of MRI image compression, the compression of tumor disclosure usually has noisy nature, and minimal contrast relies on the region of interest (ROI). Thus, de-noising is enforced to protect the quality of the image and feature value. Various filters are exploited for image filtering and ruin the image's tiny data. Certain knowable filters achieve image flattening and lessen the edges of the image. For enhanced clarity of data, de-noising is answerable. Therefore, a Gaussian-weighted non-local mean filter is applied to diminish the noise. It revises the weight score of the mean pixels. According to the distance between the target pixel and the intensity grey level vector, the weight of every pixel is computed. Each pixel is brain MR images is derived by,

$$I(a) = \sum_{j \in I} w\,(a, b) I(b) \tag{1}$$

Where, $I(b)$ is the noise image, $I(a)$ is the de-noised image, and $w\,(a, b)$ is the weight based on the similarity among pixels a and b and assures the common conditions $0 \le w\,(a, b) \le 1$and $\sum_j w\,(a, b) = 1$. The weighted function $w\,(a, b)$ finds how closely related the image at the pixel a is to the image at the pixel b. In the proposed technique, weights are defined using the Gaussian function as follows,

$$w\,(a, b) = e^{-\frac{|G(a)-G(b)|^2}{h^2}} \tag{2}$$

Where, h is the degree of filtering and $G(a) - G(b)$ is the intensity gray level vector. The pixel with a comparable grey-level neighborhood to $G(a)$ include large weights in the average. With this, the de-noised image is obtained. As a result, the noise in the input images is removed and obtain the contrast-enhanced image. Then the preprocessed image is sent to the hidden layer.

3.2. Segmentation

In the first hidden layer, segmentation of the input image is performed. Brain tumor segmentation is a procedure of splitting the tumor from normal brain images. In medical practice, it gives favorable data for analysis and treatment preparation. However, it is still difficult with uneven form and confusing boundaries of tumors. Various methods have previously planned semi and fully involuntary schemes to partition images. Among them, Hartigan's method is significant for finding the region of interest of probable tumor. Simplicity and degree of human direction decide the medical acceptance of Hartigan's segmentation method.

Hartigan's segmentation method primarily partitions the image into many parts according to the pixel intensity. Hartigan's segmentation method partitions the image into various regions based on similar pixel characteristics. Here, all the de-noised brain MR images are separated into the diverse region $R_i = R_1, R_2, \ldots, R_z$ depended on the pixel similarity. Hartigan's segmentation method partition image regions into R_z clusters are groups for the nearest mean. Let's ponder the number of pixels in an image $p_1, p_2, p_3, \ldots p_m$. Later, the objective function is calculated for segmenting the de-noised image. In GWDeepCNN-LSTM, the objective function is computed as the similarity between the pixels using a distance measure. In the proposed segmentation process, hamming distance is computed to find the similarity between the pixels. It is given by,

$$H_{xy} = \sum_{x=1}^{n} \sum_{y=1}^{m} \left| p_x - p_y \right| \tag{3}$$

Where, H_{xy} point out the hamming distance between two pixels, p_x point outs the preprocessed image pixel and p_y point out the adjacent pixel. In Hartigan's segmentation method, the smallest objective function (distance) is considered to group the pixel for a particular region. This can be viable if it decreases the objective function and therefore increases the total quality of clustering the region.

3.3. Feature Extraction

The feature is extracted by pondering every section of the de-noised image. Retrieval of features promises better tumor identification where significant aspects are modified. Every portion is personalized to guarantee enhanced accuracy in tumor identification. In the second hidden layer, feature learning is accomplished. The features extracted from segments include texture, color and intensity. The spatial information of pixel intensities is acquired from the texture feature.

$$T = \frac{\sum_i \sum_j (p_i - m_i)(p_j - m_j)}{\delta_i \times \delta_j} \tag{4}$$

Where T point outs the texture feature, m_i and $m_j$point outs a mean of the pixels p_i, p_j and deviations are δ_i andδ_j. Then the intensity feature is extracted as follows,

$$In_g = \sum_i \sum_j \left| p_i - p_j \right|^2 \tag{5}$$

Where, $In_g$is a gray-level intensity contrast. Later, color features are acquired, and it is given as follows,

$$C = \frac{In_g}{p_Z} \tag{6}$$

Where, $p_Z$is the total pixels in the image, and C is the color feature. It is retrieved via transferring the RGB image into HSV color spaces. From that, the texture, color and intensity features are extracted for tumor detection.

3.4. Classification

Once the feature extraction is completed, image classification is performed. The proposed work uses LSTM to classify the input MR images. The structure of LSTM comprises an input gate, an output gate, and a forget gate. The input gate gets the extracted features as input from the second hidden layer. The activation function is applied to eradicate the significant information from the cell state in the forget gate. It is also employed to generate the result to show the outcome in a certain time. Later, the output gate provides the outputs. Hence, forget gate is formulated by,

$$FG\ (t) = \alpha\ (w_k * F_E + v_k * y_{t-1} + b) \tag{7}$$

Where, $FG\ (t)$point out as a result of the forget gate in time t,α is the activation function, F_E are the input extracted features, w_k and v_k is the weights between the connections, y_{t-1} is the previous layer output, b is the bias and '$*$' indicates the convolution operator. The softmax activation function is employed to examine the extracted features through the testing data by the Schutz index. The Schutz index is employed to compute the similarity among extracted feature values and test disease feature values. It is given by,

$$S_I = \frac{\sum_i \left| F_i - F_j \right|}{2 \sum_i F_i} \tag{8}$$

Where, S_I point out the Schutz similarity coefficient, $F_i$point out an extracted feature, F_j indicates a testing feature value. The similarity coefficient provides the outcomes in the ranges from 0 to +1, where +1 indicates the higher similarity, and 0 represents the low similarity. The estimated similarity value is provided to the output layer. According to the similarity value, the brain MR images are classified with better accuracy. The activation function is accountable for deciding whether values are stored or removed from the cell state. The activation function returns the output as '1' refers forget gate and keeps the results at a certain time step.

Otherwise, forget the particular values in the cell state. Thus, the classification output using the activation function is obtained as,

$$\alpha = \begin{cases} 1; & input\ image\ is\ classified\ as\ tumor \\ 0; & input\ image\ is\ classified\ as\ normal \end{cases} \quad (9)$$

Where, α denotes an activation function result where the result is varied from 0 to 1. From the above equation, the activation function provides '1' as output, image is categorized as a tumor image. If not, the image is normal. Based on classification results, accurate tumor detection is performed.

Algorithm 1. Gaussian Weighted Deep Convolutional Neural Network with LSTM

```
Input: Brain tumor images
Begin
Get the brain tumor images I_i
For each I_i
   Carry out Gaussian weighted non-local mean filter
     De-noise the image using w(a,b)
End
 For each de-noised I_i
 For each adjacent pixel p_i
    EstimateH_xy
    Group the pixels
    Get different regions of the image
  End for
End for
  For each segmented portion
     Extract the texture, color and intensity
   End
    For extracted features with brain images
      Compute the Schutz similarity coefficient. 'S_I'
    For each time step 't'
       Derive FG(t)
         If (α = 1) then
            monitor classification results
        Else
           Forget other class results
        End if
         Get the classification output
     End for
End for
Output: Improve tumor detection accuracy
```

Algorithm 1 demonstrates the procedure of brain tumor detection with higher accuracy and lesser time by applying deep learning concepts. The deep learning concept uses different layers to perform tumor detection. The input layer receives the different brain MR images as input. Then the unwanted noise in an image is eliminated and obtains the de-noised image in the first hidden layer by using Gaussian weighted non-local mean filter. After that, image segmentation is performed in the second hidden layer with the help of Hartigan's segmentation method. This segmented region is sent to the next hidden layer in which the significant feature extraction is employed. Based on extracted features, image classification is done at the subsequent layer through the LSTM. Lastly, the classified result is displayed at the output layer where the brain tumor image is classified into normal and tumor images with minimum error rate.

4. Results and Discussion

The implementation of GWDeepCNN-LSTM technique, Convolutional Auto-encoder Neural Network (CANN) [1] and Dolphin- SCA based Deep CNN [2] are done in MATLAB simulator. Brain MRI Images for the brain tumor detection database is used as input. The input database includes 253 files, which comprise different brain MR images. The simulation output of the proposed GWDeepCNN-LSTM technique is validated against previously published works. Testing metrics pondered for examining methods such as Brain Tumor Detection Accuracy (BTDA), Brain Tumor Detection Time (BTDT) and false positive rate.

4.1. BTDA

It is described as the proportion of no. of MR images accurately classified to the images. Brain tumor detection accuracy is estimated by,

$$BTD_{acc} = \sum_{i=1}^{n} \frac{I_{AD}}{I_i} * 100 \quad (10)$$

Where, BTD_{acc} is the brain tumor detection accuracy, I_{AD} indicates accurately classified brain MR images and I_i is the total images.

4.1.1. BTDT

It is computed by the amount of time consumed through the algorithm for tumor detection. It is given by,

$$BTD_{time} = \sum_{i=1}^{n} I_i * Time\,[BTD] \quad (11)$$

Where, BTD_{time} is the brain tumor detection time and $Time\,[BTD]$ denotes the time needed for brain tumor detection.

4.1.2. False-positive Rate

It is described as the proportion of wrongly detected images in the classification. It is measured by,

$$R_{FP} = \sum_{i=1}^{n} \frac{I_{ID}}{I_i} * 100 \quad (12)$$

Where, R_{FP} is the false-positive rate and I_{ID} is the wrongly detected images.

4.1.3. Sensitivity

It is the measure of positive predictions. The formula for sensitivity is given as follows,

$$S_e = \sum_{i=1}^{n} \frac{TP}{TP+FN} * 100 \tag{13}$$

Where, S_e is the sensitivity, TP is the true positive values of correctly detected tumors, and FN denotes the false negative.

4.1.4. Specificity

The ratio of correctly identified negatives is defined as specificity. It is computed as follows,

$$S_p = \sum_{i=1}^{n} \frac{TN}{TN+FP} * 100 \tag{14}$$

Where,S_p is the specificity, TN is the true negative, and FP is the false positive. Specificity is computed in percentage (%).

4.1.5. Matthews Correlation Coefficient (MCC)

The correlation between actual and predicted values are described as MCC. It is expressed by,

$$MCC = \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \tag{15}$$

Where TP is the true positive, TN is the true negative, FP is the False positive, and FN is the false negative.

The performance of the proposed GWDeepCNN-LSTM technique, CANN [1] and SCA-based Deep CNN [2] is evaluated by modifying the training image. In addition, the training image for both the GWDeepCNN-LSTM technique and existing methods is considered to promise the efficiency of the proposed technique. Table 1 shows the results of BTDA for proposed and existing methods.

Table 1. Results of BTDA

Number of brain MRI images	Brain tumor detection accuracy (%)		
	Dolphin-SCA-based Deep CNN	CANN	GWDeepCNN-LSTM
25	88	92	96
50	84	88	92
75	88	89	93
100	87	88	91
125	88	90	94
150	84	88	91
175	85	87	93
200	86	88	94
225	84	86	93
250	86	88	95

Table 1 demonstrates the performance results of brain tumor detection accuracy for the proposed GWDeepCNN-LSTM technique, existing [1] and [2]. The experiment is conducted based on the number of brain MR images used from 25 to 250. Brain tumour detection accuracy results using the proposed technique are compared with conventional methods. According to the number of brain MR images, various brain tumor detection accuracy results are obtained for three methods. Compared to conventional CANN and Dolphin- SCA based Deep CNN, the number of MR images accurately classified is improved in the GWDeepCNN-LSTM technique. Let us consider 250 images; brain tumor detection accuracy of the proposed GWDeepCNN-LSTM technique is obtained as 95%, whereas existing CANN and Dolphin- SCA based Deep CNN obtained 88% and 86% of accuracy. In the simulation, ten runs are conducted. For comparison purposes, the average value is considered. Thus, the average brain tumor detection accuracy of the proposed GWDeepCNN-LSTM technique is enhanced by 5% and 8% than the CANN [1] and Dolphin- SCA based Deep CNN [2] correspondingly. A comparison graph of brain tumor detection accuracy for different methods is provided in figure 3.

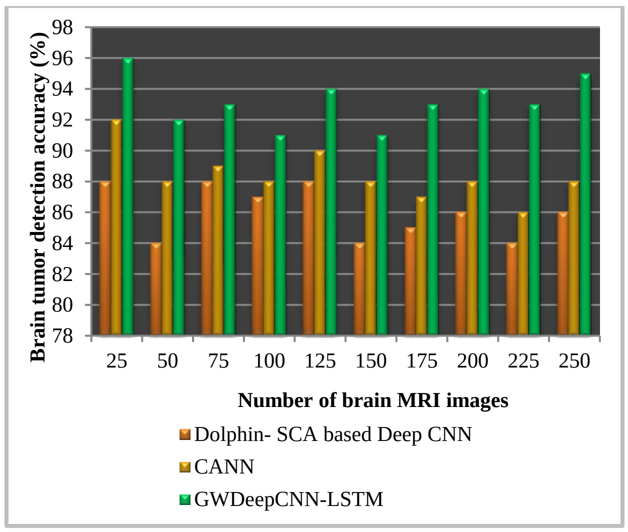

Fig. 3 Comparison of Brain Tumor Detection Accuracy

A comparison graph of accuracy for tumor diagnosis is shown in figure 3. As observed in the above figure, three different colors indicate the brain tumor detection accuracy of the GWDeepCNN-LSTM technique, existing CANN and Dolphin- SCA based Deep CNN. X-co-ordinates number of brain MR images as input, and the Y-co-ordinates provide the corresponding accuracy results. From that, brain tumor detection accuracy results in the proposed GWDeepCNN-LSTM technique are said to be higher than the other methods. Contrary to conventional methods, GWDeepCNN-LSTM uses the novel preprocessing technique called Gaussian weighted non-local mean filter, where the background pixels are removed to enhance the image quality. Also, Hartigan's segmentation method is employed to segment the input images. In addition, LSTM is applied to accurately classify the brain MR images as normal or tumor. Above said processes help to increase the accuracy of brain tumor detection accuracy.

The performance of the false positive rate for the proposed GWDeepCNN-LSTM technique, existing CANN and Dolphin- SCA-based Deep CNN are described in table 2.

Comparative analysis of false positive rates for different brain tumor detection methods based on deep CNN is reported in table 2. The false positive rate results using the current GWDeepCNN-LSTM technique are validated against previously published works such as CANN [1] and Dolphin- SCA-based Deep CNN [2]. The false positive rate of the GWDeepCNN-LSTM technique is calculated based on the input of brain MR images. 250 brain MR images are considered ten iterations. By noticing the above table, the false positive rate of all three methods is reduced when detecting the brain tumor. However, the proposed GWDeepCNN-LSTM technique reduces the false positive rate compared to other methods. 4%, 8% and 12% of the false positive rate is obtained when taking 25 images as input for GWDeepCNN-LSTM technique, CANN [1] and Dolphin- SCA-based Deep CNN [2], respectively.

Similarly, 8%, 12% and 16% false positive rates are obtained for both proposed and conventional methods when taking 50 images. Likewise, the false positive rates for the remaining iterations is obtained and compared with each other. Simulation results of false positive rate using GWDeepCNN-LSTM technique are reduced by 41% than the CANN [1] and 51% than the Dolphin- SCA based Deep CNN [2], respectively. Based on the table values, a graphical view of the false positive rate is shown in figure 4.

Table 2. Results of False Positive Rate

Number of brain MRI images	False Positive rate (%)		
	Dolphin-SCA-based Deep CNN	CANN	GWDeepCNN-LSTM
25	12	8	4
50	16	12	8
75	12	11	7
100	13	12	9
125	12	10	6
150	16	12	9
175	15	13	7
200	14	12	6
225	16	14	7
250	14	12	5

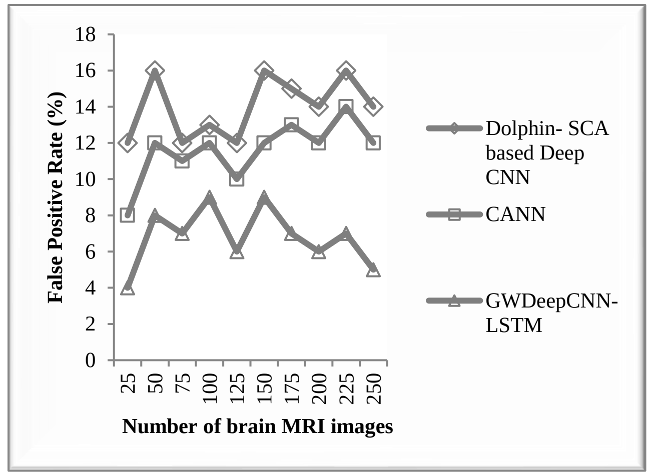

Fig. 4 Comparison of False Positive Rate

The false positive rate for various deep CNN-based brain tumor detection is given in figure 4. As the figure shows, brain MR images are pondered on the x-axis, and the corresponding results of false positive rates are provided on the y-axis. The false positive rate of the GWDeepCNN-LSTM technique is validated with existing CANN [1] and Dolphin-SCA-based Deep CNN [2]. While taking various sets of images, the rate of false positives varies. These results show that the false positive rate of the GWDeepCNN-LSTM technique is highly decreased than the CANN [1] and Dolphin-SCA-based Deep CNN [2].

On contrary to conventional methods, various layers are involved in the developed GWDeepCNN-LSTM. The designed deep CNN uses the many hidden layers where the preprocessing, segmentation, feature extraction and classification are performed. Here, classification is carried out using LSTM, where the Schutz similarity coefficient is applied. With this coefficient, the similarity between extracted features and testing features is computed. It aids in classifying the brain's MR images accurately. Also, the error rate for each classified result is computed. From that, the minimum error rate result is used to detect the brain tumor. As a result, the false positive rate of the GWDeepCNN-LSTM technique is considerably reduced.

The results of brain tumor detection time for GWDeepCNN-LSTM technique, CANN and Dolphin- SCA based Deep CNN are given in table 3.

Table 3 describes the performance outcome of time to discover the brain tumor based on the number of brain MR images considered as input. Input brain MR images are considered in the ranges of 25, 50, 75, ….,250. Totally ten runs are conducted in the simulation.

Table 3. Results of BTDT

Number of brain MRI images	Brain tumor detection time (ms)		
	Dolphin-SCA-based Deep CNN	CANN	GWDeepCNN-LSTM
25	4.62	3.4	2.8
50	6.12	5.2	3.3
75	6.48	5.8	4.51
100	7.6	6.3	5.52
125	8.12	7.5	6.4
150	9.6	8.6	7.3
175	11.5	10.2	8.46
200	12.6	11.3	9.05
225	13.4	12.4	10.5
250	14.6	12.8	11.4

Simulation outcomes of brain tumor detection time for the proposed GWDeepCNN-LSTM technique are compared with existing CANN [1] and Dolphin-SCA-based Deep CNN [2]. While increasing the number of brain images, the time for finding the brain tumor also increased. Here, a measure of time is directly relative to the MR images. From that, GWDeepCNN-LSTM, CANN [1], and Dolphin-SCA-based Deep CNN [2] use the minimal time for tumor detection. Comparatively, GWDeepCNN-LSTM consumes minimal time than the other methods. For instance, 2.8ms, 3.4ms and 4.62ms of brain tumor detection time are acquired using the GWDeepCNN-LSTM technique compared with existing CANN [1] and Dolphin-SCA-based Deep CNN [2] while processing 25 images. In the same manner, brain tumor detection time up to 250 images is computed and compared. Compared values show that the minimal time is utilized in the GWDeepCNN-LSTM technique than the [1] and [2]. Figure 5 illustrates the graph for BTDT for three methods.

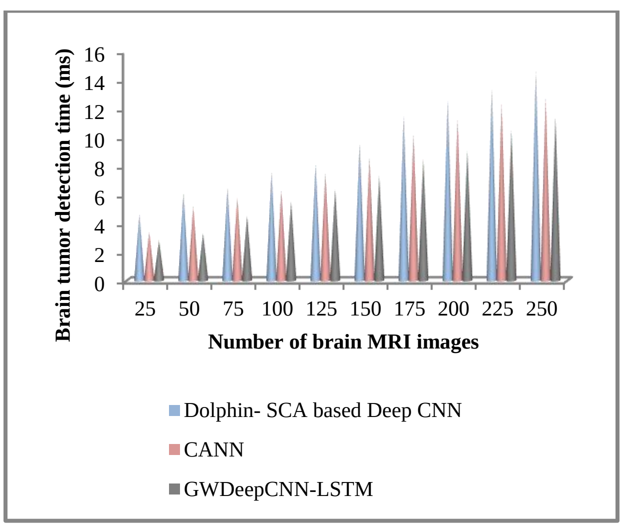

Fig. 5 Comparison of BTDT

Figure 5 illustrates a comparison graph of BTDT versus no. of brain MR images. As demonstrated in the above figure, brain tumor detection time for three methods, such as the GWDeepCNN-LSTM technique, is compared with existing CANN [1], and Dolphin-SCA-based Deep CNN [2] is obtained. The figure shows that the amount of time needed to detect the brain tumor is greatly diminished in the proposed GWDeepCNN-LSTM technique than in the other method. Applying a Gaussian-weighted non-local mean filter significantly eradicates the image's noisy pixels. This, in turn, increases the contrasts of the image is improved. Followed by, Hartigan's segmentation method is used to partition the image into similar pixel regions. This is done by computing the hamming distance. In addition, relevant features such as texture, color and intensity feature were extracted for tumor detection. Above said methods make easier and faster brain tumor detection. Therefore, the GWDeepCNN-LSTM technique uses less time for tumor detection than the other methods.

The results of sensitivity using GWDeepCNN-LSTM technique, CANN [1], and Dolphin-SCA-based Deep CNN [2] are provided in table 4 and figure 6.

Figure 6 illustrates the outcomes of sensitivity using the proposed GWDeepCNN-LSTM technique and existing CANN [1] and Dolphin-SCA-based Deep CNN [2] methods based on brain MRI images. Comparative sensitivity results using GWDeepCNN-LSTM are analyzed with existing CANN [1] and Dolphin-SCA-based Deep CNN [2]. On contrary to existing works, GWDeepCNN-LSTM gets higher sensitivity in tumor detection. This is due to the application of LSTM in GWDeepCNN-LSTM, where the images are accurately classified with better accuracy. As a result, the sensitivity of the proposed GWDeepCNN-LSTM technique is improved by 9% and 16% compared to existing CANN [1] and Dolphin-SCA-based Deep CNN [2].

Table 4. Results of Sensitivity

Number of brain MRI images	Sensitivity (%)		
	Dolphin-SCA-based Deep CNN	CANN	GWDeepCNN-LSTM
25	74.14	83.15	91.02
50	79.53	86.34	93.65
75	82.53	86.84	95.21
100	83.64	87.14	98.24
125	88.23	91.63	98.94
150	85.47	90.45	98.11
175	85.04	88.54	98.75
200	86.54	89.21	98.14
225	88.14	90.14	98.57
250	86.24	92.87	98.21

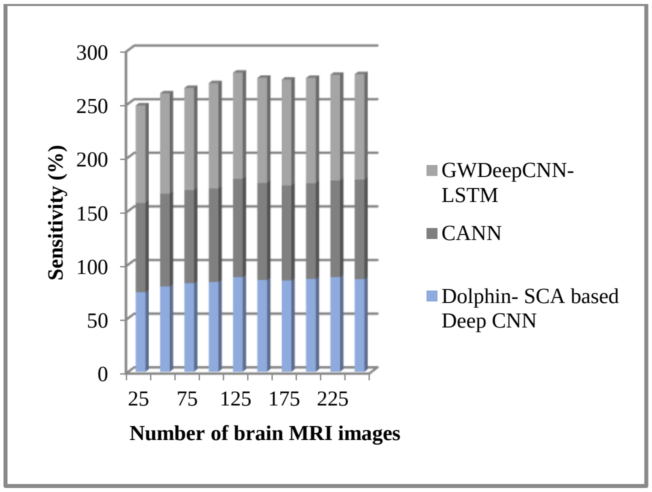

Fig. 6 Comparison of Sensitivity

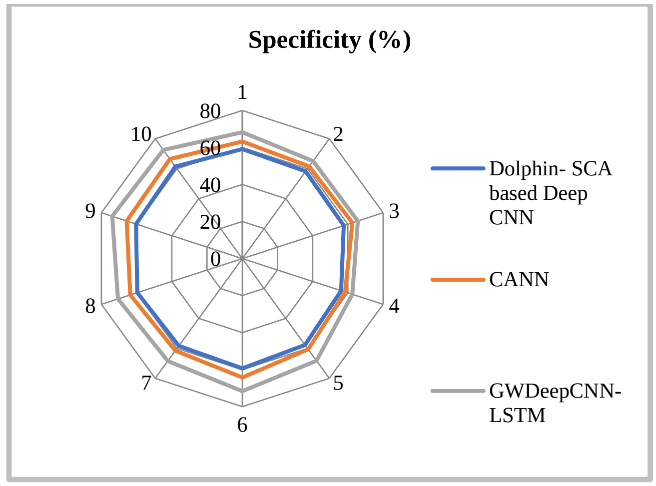

Fig. 7 Comparison of Specificity

The results of specificity using proposed and existing methods are demonstrated in table 5 and figure 7.

Figure 7 represents the results of specificity using previously published works with proposed works. As observed in the figure, the specificity of GWDeep CNN-LSTM is said to be higher than the existing CANN [1] and Dolphin-SCA-based Deep CNN [2]. Specificity comparison of GWDeepCNN-LSTM is made with CANN [1] and Dolphin-SCA-based Deep CNN [2]. Among the three methods, GWDeepCNN-LSTM provides better specificity in tumor discovery. The higher specificity is achieved using the classification process. Here, the activation is employed to measure the similarity between the features. From that, the tumor is effectively identified. Thus, the specificity of GWDeepCNN-LSTM is improved by 9% and 17% compared to the existing CANN [1] and Dolphin-SCA-based Deep CNN [2].

Table 5. Results of Specificity

Number of brain MRI images	Specificity (%)		
	Dolphin-SCA-based Deep CNN	CANN	GWDeepCNN-LSTM
25	59.15	63.24	68.25
50	58.24	61.53	65.12
75	57.64	62.54	65.64
100	56.15	58.46	62.48
125	57.64	60.54	68.24
150	59.34	64.25	71.64
175	58.28	61.48	68.41
200	59.64	63.63	70.56
225	60.33	65.64	73.84
250	61.47	66.42	72.54

The results of the Matthews Correlation Coefficient using GWDeepCNN-LSTM, CANN [1], and Dolphin-SCA-based Deep CNN [2] are shown in table 6 and figure 8.

Figure 8 demonstrates the results of the Matthews Correlation Coefficient for GWDeepCNN-LSTM, existing CANN [1], and Dolphin-SCA-based Deep CNN [2], where the performance of classification methods is identified. Matthews Correlation Coefficient is determined for input images to observe the classification outcome. The higher correlation refers to the efficient performance of the method said to be. In the figure, GWDeepCNN-LSTM gets a greater correlation than the existing CANN [1] and Dolphin-SCA-based Deep CNN [2]. The average results of the Matthews Correlation Coefficient using GWDeepCNN-LSTM are improved by 20% and 41% compared to the existing CANN [1] and Dolphin-SCA-based Deep CNN [2], respectively. The results of the confusion matrix are demonstrated in table 7.

Table 6. Results of Matthews Correlation Coefficient (MCC)

Number of brain MRI images	Matthews Correlation Coefficient (MCC)		
	Dolphin-SCA-based Deep CNN	CANN	GWDeepCNN-LSTM
25	0.3472	0.4658	0.4685
50	0.4064	0.4726	0.5782
75	0.4321	0.5318	0.6581
100	0.4125	0.5564	0.7015
125	0.5264	0.5684	0.7068
150	0.4985	0.5971	0.7285
175	0.5681	0.6245	0.7384
200	0.5891	0.6474	0.7648
225	0.5982	0.6684	0.7935
250	0.6254	0.6723	0.8671

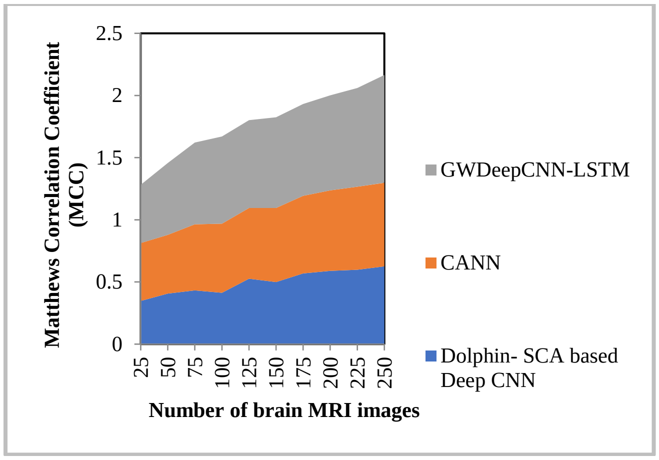

Fig. 8 Comparison of Matthews Correlation Coefficient

Table 7. Confusion matrix

	Total population= 25	Actually positive	Actually negative
Predicted Condition	Predicted Positive=18	True Positive (TP) =13	False positive(FP)=5
	Predicted Negative=7	False-negative (FN)=3	True negative (TN)=4

The outcome of the confusion matrix is depicted in table 7. The confusion matrix is determined for input images to the actual positive and actual negative predicted condition. With the total population of 25 images, the predicted positive class of true positive is 13; false positive is 5. The predicted negative class of false negative is 3, and the true negative is 4 using the classification of proposed GWDeepCNN-LSTM to find the brain tumor.

5. Conclusion

A brain tumor detection method through the classification is implemented for discovering tumor areas from the MRI images by developing the GWDeepCNN-LSTM technique. To begin with, the MRI images are fed into the de-noising to eradicate noise-contributed pixels. Followed by images segmented via Hartigan's segmentation, where the pixels with different intensities are combined. The result of Hartigan's segmentation is given to the feature extraction process. In this stage, the more helpful features for tumor detection are extracted. Lastly, LSTM is designed to classify the images depending on their features. The performance of the proposed GWDeepCNN-LSTM is examined and demonstrates the enhanced accuracy performance. Also, the time and error rate involved in tumor detection is optimized using GWDeepCNN-LSTM.

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