Brain Tumor Classification Using Relief Algorithm Based Convolutional Neural Network

Dr. R.Karthik[a], and A.Kavitha[b]

[a] Assistant Professor Department of Computer science engineering, Sri Krishna College of technology, Coimbatore-641042.
[b]ME Department of Computer science engineering, Sri Krishna college of technology, Coimbatore - 641042.

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: The brain is another vital organ in humans for running a standard life. In this fast-paced world, brain damage is caused by eating habits and their personal lifestyle. In such a case, the current development in medical and imaging technology could be a boon for treating diseases. At the early stage, the tumour part is not very visible, which can be identified by the variation in texture and the small limits of the image. The conventional method used the edge representation and deep learning convolutional neural network for the classification process. Its accuracy of classification is solely depends on the parameters of the network. This problem is overcome in the first phase of research by using gray scale properties based feature extraction and Galactic swarm based Convolutional neural network for the tumour classification. But, it requires high computational time for attribute selection and it does not describe about the tumour pattern. Hence, in this, a fast processing and pattern based convolutional neural network is proposed. Here, the images are subjected to pre-processing using inverse filtering and then the pattern oriented features were extracted using local binary pattern and histogram oriented gradients. Then, the extracted features are ranked using the Relieff algorithm. Then, top most ranked feature is used for the classification process using convolutional neural network. The whole process is realized on the figshare tumour dataset in MATLAB R2018a under windows10 environment. Then, its performance is compared with the existing techniques based on accuracy, sensitivity and specificity. The proposed Pattern based CNN can achieve high accuracy of 99.7% with smaller processing time of less than 10 minutes as compared to existing techniques.

Keywords: Brain tumour, deep learning, optimization, pattern oriented, Relieff

1. Introduction

Brain tumor is the collection of abnormal cells in the brain. Brain tumor is a life-threatening disease when the tumor begins to grow in size and shape every day and is not detected at an early stage. Cancer cells from other parts can also spread to the brain, this is called a secondary brain tumor.

There are different types of tumors depending on its location and types, namely benign and malignant. Three types of tumours are considered for classification, which help the doctor diagnose and treat patients early. Another advantage of this type image classification is the non-invasive method for the patient. This imaging process reduces the need for biopsies and also gives an early idea of the diseases.

The classification of the tumour is based on the brain images captured by the medical imaging systems. The medical imaging modalities of the brain are PET, MRI, and CT. Among these three modalities, magnetic resonance imaging of the brain is suitable for tumour classification because the MRI images can properly observe the tissue.

The tumours are life-threatening one if they are not treated early. The tumours are glioma, meningioma, and pituitary tumours. Glioma occurs between the spinal cord and the brain. Meningioma is a tumour that grows on the meningeal membrane and grows more slowly compared to other tumours. This tumour shows symptoms after developing a tumour in a large size. The pituitary tumour is not cancerous if the hormone produced by the pituitary is not significantly changed. This work consists in differentiating these tumours at an early stage using the MRI image properties of the brain and the tumour area using texture information extracted with the help of pattern features.

Anitha and Murugavalli (2016) used the two phase classification for detecting the brain tumour. Here, the segmentation process is performed to detect the brain tumour region using adaptive K-means segmentation. Then, the wavelet transform is used to extract the features. Finally, the extracted features is trained with self-organizing neural network and its output is again is trained with K-nearest neighbour. The testing is also done in the two phases. Due to this, processing time is high.

Thara and Jasmine (2016) proposed a segmentation based tumour detection in the MRI brain image. Here, the input image is processed with clustering algorithms like Fuzzy c-means and K-means clustering. Among these two clustering, the fuzzy c-means is best due to the extraction of the information effectively from the image. Then, the classification of tumour and normal image is performed based on the properties like amplitude, direction. The probabilistic neural network and generalized regression neural network is used for the classification. Based on its performance evaluation, the fuzzy c-means based probabilistic neural network is best for the classification of tumour.

Shenbagarajan et al. (2016) proposed the segmentation based classification of tumours as normal, cancerous and abnormal. Here, "Segmentation: Active contour model. Textural and shape feature descriptors were extracted. Classifier: Neural network with LM algorithm is used. Good accuracy and Error rate. Feature extraction and selection can be improved. Mohankumar (2016) analysed the different types of wavelet families in classification of brain tumour using support vector machine algorithm. It compared three wavelet families like daubechies8, symlet8 and biorthogonal3.7 for the analysis. Among these, daubechies8 is the best for the classification process.

Subramaniam and Radhakrishnan (2016) proposed the region oriented tumour classification. First, it extract the tumour region. Then, features were extracted from the tumor region. It is trained with the bee colony based neural network and traditional neural network to compare its performance.

Abbadi and Khadim (2017) also used the artificial neural network for the tumour classification. Here, the gray scale properties like gray level co-occurrence matrix and Gray level run length matrix were used for the feature extraction process. Latha and Surya (2017) proposed the Clustering and neural network classifier to classify the brain tumours. Here, "Segmentation: K-means segmentation. Feature extraction: dual tree complex wavelet transform. Feature reduction: principal component analysis. Classifier: Neural network. Types of tumours are not considered.

Lavanyadevi et al. (2017) Proposed the probabilistic neural network based tumour detection. Here, "Segmentation: K-means segmentation. Feature extraction: Gray level co-occurrence matrix. Feature reduction: principal component analysis. Classifier: Probabilistic Neural network. Tumour phase only classified.

Angulakshmi and Lakshmipriya (2017) conducted a survey on the tumour segmentation techniques. It listed about all the techniques used for the tumour segmentation in all types of image modalities like MRI, PET, CT and multimodal. It also listed about the evaluation metrics for the segmentation process.

1.1 Recent techniques for tumour classification

Shahzadi et al. (2018) [9] proposed CNN-LSTM based network for the brain tumour classification. In this, High grad or low grade Tumour classification of glioma is performed. VGG-16 net is used for the feature extraction and is best as compared to Alexnet and Resnet. The classification is performed on 3D images. It processed only 60 volumes. The accuracy is less with longer processing steps.

Malathi and Sinthia (2018) [10] proposed the hybrid clustering and back propagation network to classify the tumour in brain. The tumour region is first segmented using hybrid C-means clustering approach. Then, Wavelet transform and back propagation network is used for the classification. The drawbacks of this approach is types of tumour is not considered. Clustering may result different output in repeated iterations

Abd-Ellah et al (2018) [11] proposed the Multi model for tumour classification. First, convolutional neural network for feature extraction. Error correcting code based Support vector machine for classification. Regional convolutional neural network for tumour localization. Processing time is high due to multiple CNNs. Soltaninejad (2018) [12] also suggested the Supervoxel and Random forest for brain tumour classification. Supervoxel based feature extraction is performed. Random forest classifier is used for classification. Identification of tumour core is high. Super voxels applying on smaller image is good. But, for larger image processing time is high.

Abir et al (2018) [13] utilized the Probabilistic Neural network based tumour classification. Here, discrete cosine transform to remove redundant data. Gray level co-occurrence matrix is used for feature extraction. PNN is used for classification. It performed well for malignant detection. Spread factor selection is important for classification.

Thejaswini et al. (2019) [14] proposed the Clustering and Hybrid classifier to classify the brain tumours. Here, "Segmentation: Adaptively Regularized Kernel-Based Fuzzy C-Means (ARKFCM)". Classifier: combination of SVM and ANN. Good accuracy and Error rate. Feature extraction and selection can be improved. Hemanth and Anitha (2019) [15] proposed the brain tumour classification based on Modified Genetic algorithm. Genetic algorithm is improved by using different types of operators on MRI brain images. Its merit is higher accuracy and demerit is binary operators tend to vary.

Rehman et al. (2019) [16] proposed the regional based classification of tumours. Here, Regional based features like Statistical, histogram and fractal were used to extract features from the brain. Classifiers used in this are as follows: SVM, Adaboost and RF based regional classifier. Among these best classifier is RF based regional classifier. But, it requires more number of features for training the network.

Kavitha and chellamuthu (2019) [17] used the optimization process based neural network. Here, segmentation: Modified region growing and two-dimensional wavelet. Feature extraction: Gray Level Co-Occurrence Matrix. Feature selection: self-learning Particle swarm optimization. Classifier: Feed forward neural network. Its limitation is Feature extraction is limited. Abiwinanda et al. (2019) [18] also used the Convolutional neural network based classification. Here, convolutional neural network alone. No prior image processing operations which can improve the accuracy further.

Sriramakrishnan, et al. (2019) [19] used the probalisitic ternary patterns technique for brain tumour segmentation. Here, first phase: SVM to classify tumour or non –tumour. Second phase: FCM to segment the tumour region. Third phase: probabilistic local ternary pattern. Overall performance is good in terms of accuracy and dice score. Computational time is high even though the GPU and parallel process is used.

Kumar et al. (2019) [20] utilized the genetic algorithm for the tumour classification. Here, "Segmentation: Adaptively Regularized Kernel-Based Fuzzy C-Means (ARKFCM). Feature extraction: Hybrid Feature extraction. Feature selection: genetic based K-nearest neighbour. Classifier: deep neural network. Overall accuracy is above 90% for three types of glioma, meningioma and pituitary computational time is high due to more stages of processing

Rehman et al. (2020) [21] use the data augmented based CNN. Here, CNN: google net, Alexnet and VGGnet used for data augmentation. Data augmentation is performed with pre-defined cnn for classification. Its drawback is computational time is high.

Paper is organized as follows: The existing method and its shortcoming are mentioned in section 2. The proposed method procedure is mentioned in the section 3. Section 4 discuss about the proposed results and in comparison with the existing methods. Section 5 describes about the summary of the proposed method results. Section 6 concluded the paper with its future enhancement.

2. Convolutional Neural network based tumour classification:

Devi and Gomathi (2020) performed brain tumour classification using convolutional neural network [22]. Here, the pre-processing is performed to extract the edges of the image using canny edge operator. Then, the extracted images are represented through Saliency Image representation (SIP). The modified minimum barrier distance and nonlinear diffusion at multiple level used to represent to SIP. Then, the features are extracted and classified using convolutional neural network. Due to the deep learning process, the accuracy of the tumour detection is high as compared to other existing techniques mentioned in related works. The major drawback is detection of tumour types is based on the selection of parameters in the convolutional neural network. This problem is overcome in the first phase of research by using gray scale properties based feature extraction and Galactic swarm based Convolutional neural network for the tumour classification. But, it requires high computational time for attribute selection and it does not describe about the tumour pattern. The shortcomings of the existing techniques is as follows:

- The features from the pre-trained network and the feature from the convolutional layers are combined and processed for the classification.
- The feature reduction process requires more processing time.
- Galactic swarm optimization not able to optimize for larger features reduction process.
- The features are mostly concentrated on the gray scale values.

3. Pattern based convolution neural network for tumour classification

In this, the classification of tumour is performed by extracting the patterns between the pixels in the image rather than its gray scale properties as in the existing techniques. Here, three techniques were applied to the image to extract the pattern. Then, the dominant pattern feature is determined through ranking method. Finally, the classification of tumour is performed through convolutional neural network. The objectives of the proposed method is as follows:

Improve the accuracy of tumour detection.

- To improve the faster processing time
- Accurate information about the pixels in the MRI image due to pattern oriented features

The process in the proposed method is shown in the following flow diagram figure 1.

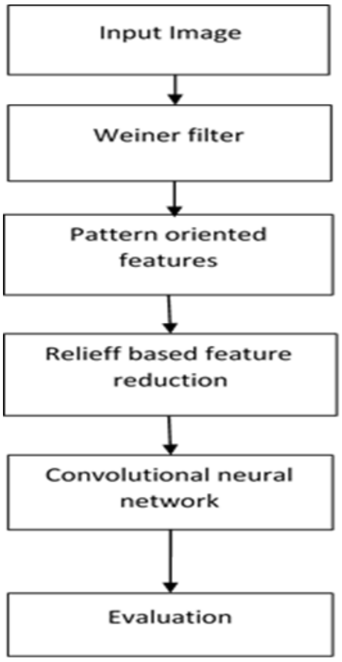

Figure 1. Pattern based tumour detection using CNN

3.1 Dataset

The input image is the T1-weighted MRI brain image, which consists of three categories of images, namely meningioma, glioma, and pituitary tumor. It is downloaded from openly available public dataset called fig share [23]. A total of 174 pictures and 58 pictures were taken in each category. This input image is a contrast-enhanced image which is further improved in the preprocessing stage for better feature extraction. The sample image of the three types of tumor is shown in figure 2.a, 2.b and 2.c.

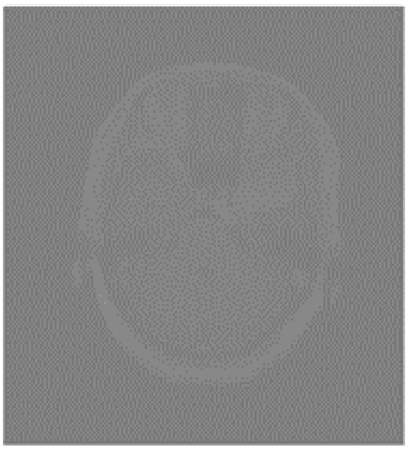	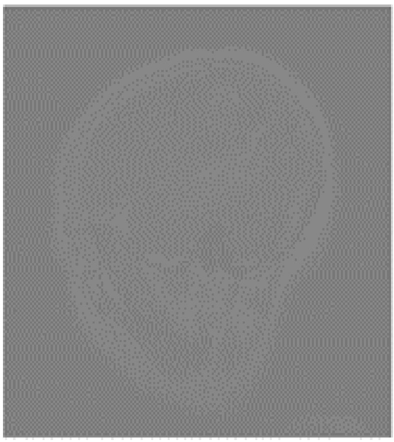	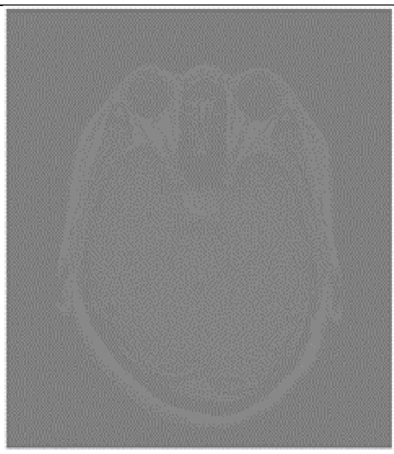
Figure 2.a Meningioma	Figure 2.b Glioma	Figure 2.c Pituitary Tumour

Figure 2. Sample input images

3.2 Pre-processing

Here, the input image has lower contrast resolution. To improve its quality, the image is viewed in its own pixel values and it saved in png format for the further feature extraction process. Here, the noise smoothing is carried out with the help of inverse filtering [24]. The Wiener filter is used for inverse filtering, which performs both blur removal and noise smoothing. The Weiner filter is applied to the images along with the noise from the power spectra of the image. The periodogram is the method of estimating the spectrum of the image, and the filtering process is named as follows in equation 1.

$$W = \frac{1}{H}\frac{SP_{JJ}^{p} - SP_{\eta\eta}}{SP_{JJ}^{p}} \qquad 1$$

The term 〖SP〗_JJ^p denotes the periodogram of the image. It is calculated using Fourier transform based on [24]. Similarly, the enhanced image for the three types of tumours is shown in figure 3.a, 3.b and 3.c.

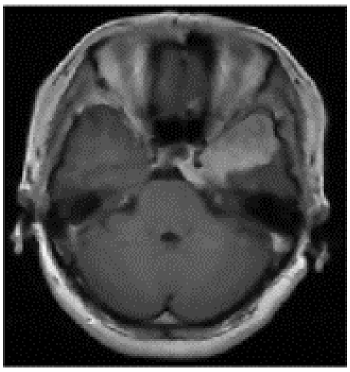	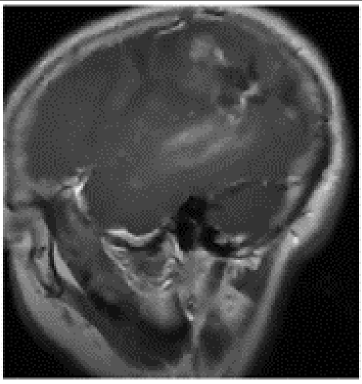	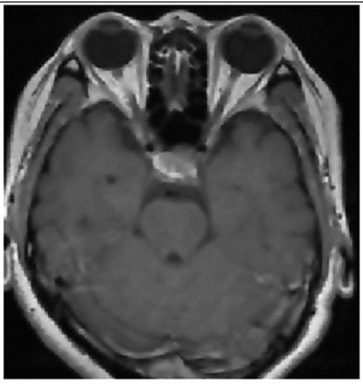
Figure 3.a Filtered Meningioma	Figure 3.b Filtered Glioma	Figure 3.c Filtered Pituitary Tumour

3.3 Pattern based feature extraction

In this, the pre-processed image produces a noise free and enhanced image as output. It is then subjected to the feature extraction process to extract the characteristics from the image. Here, the features are extracted based on three methods. Among these methods, one is the gray level co-occurrence matrix property Homogeneity, it is selected from the first phase of the work. Then, the remaining two properties were based on the extraction of the pattern from the image. Local binary pattern and Histogram oriented gradients were used for the feature extraction.

3.3.1 Local binary pattern

The simplest form of the LBP feature vector is created as follows:

Divide the image into multiple cells (for example, each cell is 16x16 pixels). For each pixel in the cell, compare it with its 8 neighbouring pixels (at its upper left, middle left, lower left, upper right, etc.). Follow the pixels in a circle (that is, clockwise or counter clockwise). If the value of the centre pixel is greater than the value of the neighbouring pixels, write "0". Otherwise, write "1". This gives an 8-bit binary number (it is usually converted to decimal for convenience). Calculate a histogram of the frequency of each "number" that appears on the cell (ie, the frequency of each combination where the pixel is smaller and greater than the centre). The histogram can be regarded as a 256-dimensional feature vector. Concatenate (normalize) the histogram of all cells. This gives the feature vector of the entire image.

A sample calculation of the Local binary pattern for window size of three is shown in the figure 4.

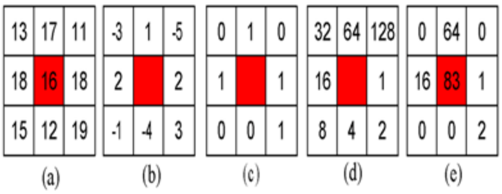

Figure 4. LBP feature calculation

Figure 4 shows the sample calculation for the LBP feature vector based on window size 3. In figure 4.a the centre pixel value is highlighted. In 4.b the pixel value is compared with its neighbouring pixel in all directions. In figure 4.c the negative values are replaced by zero and positive values are one. Then, the histogram of the window size is shown in figure 4.c. Finally, the histogram of the image and binary pattern is multiplied and it's shown in figure 4.d. The same procedure is followed for the window size 16.

3.3.2 Histogram oriented gradients

For edge features, we only identify whether the pixel is an edge. HOG can also provide edge direction. This is done by extracting the gradient and direction (or size and direction) of the edge. In addition, these directions are calculated in the "Localization" section. This means decomposing the complete image into smaller regions and calculating the gradient and direction for each region. The sample format for calculating gradients in an image is shown in figure 5.

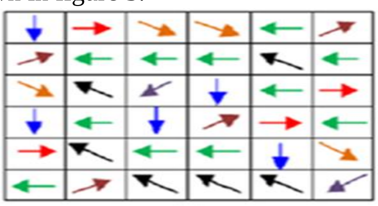

Figure 5. Gradient calculation

Finally, HOG will generate histograms for each of these regions separately. The histogram is created using the gradient and direction of pixel values, hence the name "Directed Gradient Histogram". The calculation of histograms is shown in the figure 6.

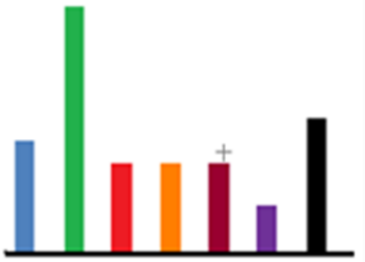

Figure 6. Histogram count of gradients.

Based on this count, the feature descriptor is formed for the image.

3.4 Relief based feature reduction

Relief will calculate a feature score for each feature, and then apply it to the ranking and select the feature with the highest score for feature selection. Alternatively, these scores can be used as feature weights to guide downstream modelling. The relief feature scoring is based on the recognition of the feature value differences between the closest pairs of instances. If a feature value difference ("hit") is observed in adjacent pairs of instances with the same category, the feature score will decrease. Alternatively, if a feature value difference ("missing") is observed in pairs of adjacent instances with different category values, the feature score increases. The weight for the feature vector is given in equation 2

$$Weights = weights - (x - hit)^2 + (x - miss)^2 \qquad 2$$

3.5 Convolution neural network

Here, the convolutional neural network is used for only the classification purpose. The input for the CNN is the dominant attribute selected from the relief algorithm. The output will be the three types of tumour. CNN is also a kind of neural network, but it has different levels to correlate input and output. In traditional neural networks, hidden layers and hidden neurons will be used to correlate input and output. Based on this, the following explains the layer used to associate output with input in the proposed technique: By converting a single attribute to a four-dimensional format, the input layer should be four-dimensional. The convolutional layer is used with a convolutional filter of size [1 1]. Then, behind it is the pooling layer. Then, use a fully connected layer of size 3. Because the tumour types is 3. Finally, use the classification layer before the softmax layer

i. Layer functionalities:

The input is specified in the first layer. Perform convolution on the second layer to improve the information from the first layer. Perform consolidation to limit information to scope. The fully connected layer is used to define input labels. The remaining two layers are used to indicate the nature of the CNN's work, namely the classification process. The Convolutional neural network architecture is shown in the figure 7.

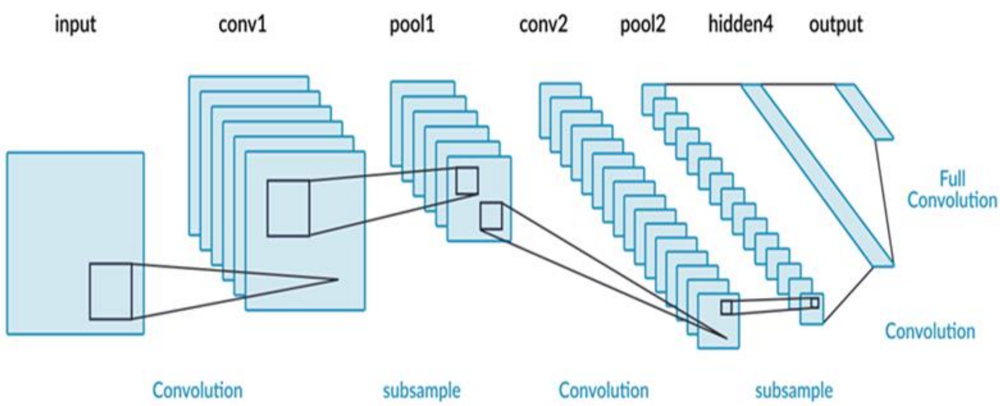

Figure 7. Convolutional neural network

3.6 Evaluation metrics

The Evaluation parameters are calculated based on the following terms in table 2.

Table 2. Terms used in Evaluation

Term	Purpose
True positive (TP_T)	Identification of particular tumour correctly
True negative (TN_T)	Identification of other tumour with respect to true positive correctly
False Positive (FP_T)	Interpreting the other class tumour into true positive
False negative (FN_T)	Interpreting the true positive class as negative class.

Based on the above terms, the accuracy, sensitivity and specificity were calculated.

3.6.1 Accuracy

It is used to determine the tumour classes accurately. It is calculated based on the equation 3.

$$Accuracy = \frac{TP_T + TN_T + FP_T + FN_T}{Total\ tumour\ cases} \quad 3$$

3.6.2 Sensitivity

Sensitivity indicates the identification of the true negative tumour classes correctly. It is calculated using the following formula 4,

$$Sensitivity = \frac{TN_T}{TN_T + FP_T} \quad 4$$

3.6.3 Specificity

Specificity indicates the identification of the true positive tumour classes correctly. It is calculated using the following formula 5,

$$Specificity = \frac{TP_T}{TP_T + FN_T} \quad 5$$

4. Implementation and Discussion

In this, the MATLAB R2018a software and windows 10 environment were used for simulating the proposed method. The proposed method is simulated on the dataset taken from the site [23]. In this, the sample output for the proposed method on a single image is discussed.

The input image without any pre-processing step is shown in the figure 8.

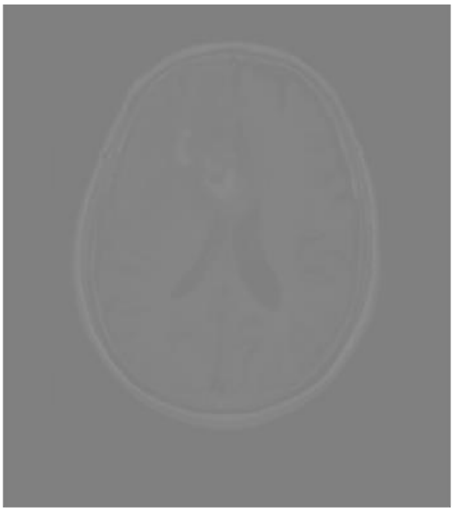

Figure 8. Input image.

The visual quality of the image is poor and it cannot be processed directly to extract the features. In order to improve its quality, the pre-processing step mentioned in section 3.b is performed on the input image. Then, the output of the pre-processed image is shown in figure 9.

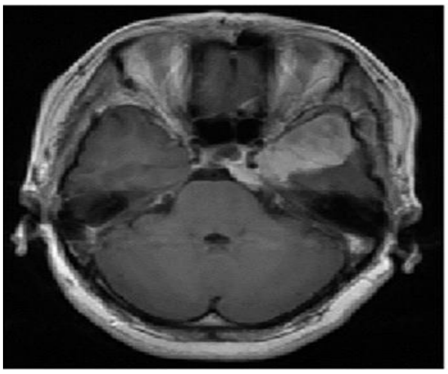

Figure 9. First stage of pre-processing

Figure 9 shows clear MRI brain image as compared to the figure 8. It is due to the conversion of image format of input image from .tiff to .png format.

Due to the image conversion, the noise will be added to the image in the form of disturbance. Those disturbances were removed with the help of wiener filter. The output of inverse or wiener filter is as shown in the figure 10.

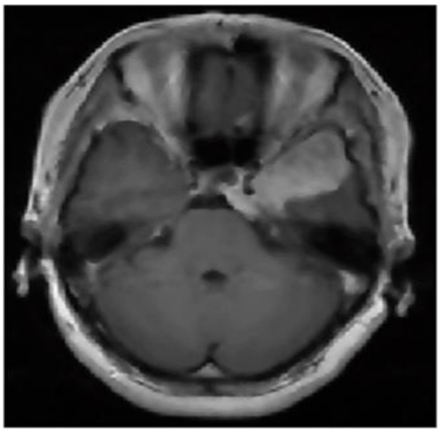

Figure 10. Filtered Image using inverse filtering

The patterns of each pixels were extracted from the pre-processed image figure 10 as per in the section 3.c for all the tumour images. The features of the image is shown in the matrix format in figure11.

Variables - brain_features

brain_features

174x46631 single

	1	2	3	4	5	6	7
1	0.0111	0.0399	0.0323	0.2768	0.6662	0.5557	0.1270
2	0.0065	0.0825	0.0093	0.4144	0.1447	0.5112	0.3685
3	0.0079	0.0856	0.0089	0.4098	0.1430	0.5075	0.3677
4	0.0079	0.0821	0.0075	0.3972	0.1342	0.4964	0.3452
5	0.0079	0.0843	0.0069	0.3967	0.1372	0.4955	0.3491
6	0.0100	0.1021	0.0109	0.4616	0.1601	0.4875	0.4243
7	0.0092	0.1120	0.0102	0.4590	0.1548	0.4875	0.4222
8	0.0089	0.1089	0.0100	0.4591	0.1505	0.4962	0.4158
9	0.0062	0.0742	0.0064	0.3609	0.1197	0.4977	0.3159
10	0.0059	0.0686	0.0060	0.3485	0.1121	0.5018	0.2994
11	0.0055	0.0662	0.0048	0.3389	0.1130	0.5011	0.2917
12	0.0060	0.0663	0.0058	0.3577	0.1188	0.4987	0.3073

Figure 11. Feature Pattern of MRI Tumour dataset

At the top of the window in figure 11 shows that 174 * 46631. Here, 174 indicates the input images and 46631 indicates the feature vectors extracted using Local binary pattern, histogram oriented gradients and homogeneity.

Then, the extracted features were processed with the relief algorithm to rank its importance in classifying the tumour. The output for the feature reduction is shown in figure 12.

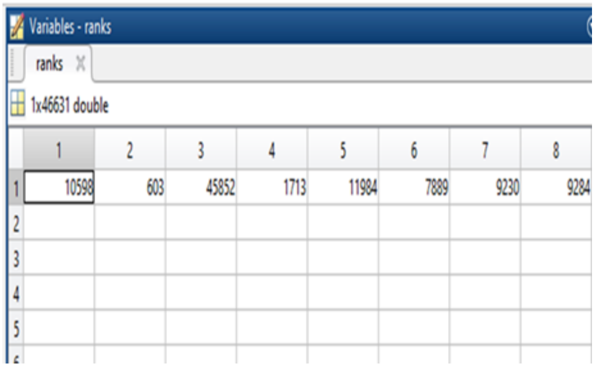

Figure 12. Ranking of features using Relief

Figure 12 shows that each attribute gets its own individual rank based on the Relief algorithm using four as nearest neighbour option. The attributes were ranked from 1 to 46631.

The topmost ranked attribute is used for the training and testing of the convolutional neural network for the tumour classification process. The training process is done on 70% of training data obtained from the dataset using hold-out approach with 0.3%. The training process result is shown in the figure 13.

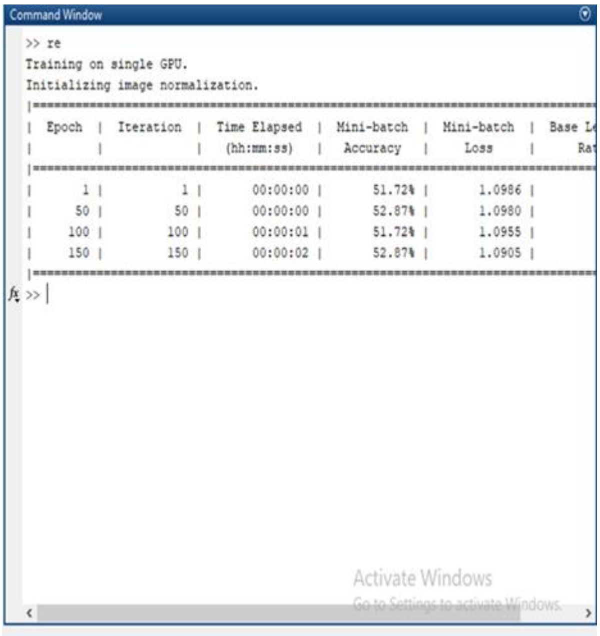

Figure 13. CNN training process

The CNN can achieve accuracy of 52.87% for the mini-batch size of training data. The mini-bath size is 10. Then, the trained CNN is used to test the remaining 30% of the data. Then, the tested output were evaluated using the metrics mentioned in 4.6. Based on the evaluation, the proposed method performance is tabulated in the table 3.

Table 3. Proposed Pattern-CNN performance

Metric	**Proposed Pattern -CNN (%)**
Accuracy	99.8
Sensitivity	98.2
Specificity	98.6

Based on the table 3, it is observed that the proposed method can predict the tumour types exactly by having accuracy of 99.7. In order to evaluate its performance, the proposed method is compared with the existing convolutional neural network based classification of tumour based on accuracy and computational time. The comparison of proposed method with the existing techniques using the same dataset is shown in the table 4.

Table 4. Performance comparison.

Technique	**Accuracy in %**	**Time consumption (minutes)**
CNN with ADAM	0.99	>10
CNN with SGD	0.9687	10-15
Existing (GSO-CNN)	0.995	<10
Proposed (Pattern-CNN)	0.998	<8

Table 4 shows that all the techniques were can accurately detect the type of tumours with 95% and above. But, the processing time (testing time) of the techniques is differed. Based on its processing time, the proposed Pattern – convolutional neural network can detect the tumour accurately and also use lesser processing time for the detection.

Based on both performance and processing time, the proposed pattern based convolutional neural network can classify the tumour effectively as compared to the other deep learning approaches.

5 Conclusion

In this, pattern oriented classification of tumour is performed using deep learning approach called convolutional neural network. This approach observes the pattern in each pixel and features were extracted using local binary pattern and histogram oriented gradients. Due to the pattern based feature extraction, abundant features were extracted. It is reduced with the Relieff algorithm. Then, trained and tested with the reduced features using convolutional neural network. Relieff –CNN has the following merits as compared to the existing system.

- It classifies the types of tumour as compared to binary classification of tumours.
- It extracts abundant features for analysis, but for classification it limited the features using Relieff
- Also, it reduces the computational time for feature reduction as compared to the existing techniques with higher accuracy of 99.7%.

6 Future enhancement

In future, the proposed method can be further enhanced by using hybrid algorithms.

References

1. Anitha, V., & Murugavalli, S. J. I. C. V. (2016). Brain tumour classification using two-tier classifier with adaptive segmentation technique. IET computer vision, 10(1), 9-17.
2. Thara, K. S., & Jasmine, K. (2016, March). Brain tumour detection in MRI images using PNN and GRNN. In 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET) (pp. 1504-1510). IEEE.
3. Shenbagarajan, A., Ramalingam, V., Balasubramanian, C., & Palanivel, S. (2016). Tumor diagnosis in MRI brain image using ACM segmentation and ANN-LM classification techniques. Indian Journal of Science and Technology, 9(1), 1-12.
4. Mohankumar, S. (2016). Analysis of different wavelets for brain image classification using support vector machine. International Journal of Advances in Signal and Image Sciences, 2(1), 1-4.
5. Subramaniam, S., & Radhakrishnan, M. (2016). Neural Network with Bee Colony Optimization for MRI Brain Cancer Image Classification. International Arab Journal of Information Technology (IAJIT), 13(1).
6. El Abbadi, N. K., & Kadhim, N. E. (2017). Brain cancer classification based on features and artificial neural network. Brain, 6(1), 123-134.
7. Latha, M., & Surya, R. (2017). Brain tumour detection using neural network classifier and k-means clustering algorithm for classification and segmentation. Eur J Appl Sci, 9(2), 66-71.
8. Lavanyadevi, R., Machakowsalya, M., Nivethitha, J., & Kumar, A. N. (2017, April). Brain tumor classification and segmentation in MRI images using PNN. In 2017 IEEE International Conference on Electrical, Instrumentation and Communication Engineering (ICEICE) (pp. 1-6). IEEE.

9. Angulakshmi, M., & Lakshmi Priya, G. G. (2017). Automated brain tumour segmentation techniques—a review. International Journal of Imaging Systems and Technology, 27(1), 66-77.
10. Shahzadi, I., Tang, T. B., Meriadeau, F., & Quyyum, A. (2018, December). CNN-LSTM: Cascaded framework for brain Tumour classification. In 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES) (pp. 633-637). IEEE.
11. Malathi, M., & Sinthia, P. (2018). MRI brain tumour segmentation using hybrid clustering and classification by back propagation algorithm. Asian Pacific Journal of Cancer Prevention: APJCP, 19(11), 3257.
12. Abd-Ellah, M. K., Awad, A. I., Khalaf, A. A., & Hamed, H. F. (2018). Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks. EURASIP Journal on Image and Video Processing, 2018(1), 1-10.
13. Soltaninejad, M., Yang, G., Lambrou, T., Allinson, N., Jones, T. L., Barrick, T. R., ... & Ye, X. (2018). Supervised learning based multimodal MRI brain tumour segmentation using texture features from supervoxels. Computer methods and programs in biomedicine, 157, 69-84.
14. Abir, T. A., Siraji, J. A., Ahmed, E., & Khulna, B. (2018). Analysis of a novel MRI based brain tumour classification using probabilistic neural network (PNN). Int. J. Sci. Res. Sci. Eng. Technol., 4(8), 65-79.
15. Thejaswini, P., Bhat, M. B., & Prakash, M. K. (2019). Detection and classification of tumour in brain MRI. Int. J. Eng. Manufact.(IJEM), 9(1), 11-20.
16. Hemanth, D. J., & Anitha, J. (2019). Modified Genetic Algorithm approaches for classification of abnormal Magnetic Resonance Brain tumour images. Applied Soft Computing, 75, 21-28.
17. Rehman, Z. U., Naqvi, S. S., Khan, T. M., Khan, M. A., & Bashir, T. (2019). Fully automated multi-parametric brain tumour segmentation using superpixel based classification. Expert systems with applications, 118, 598-613.
18. Kavitha, A. R., & Chellamuthu, C. (2019). Brain tumour detection using self-adaptive learning PSO-based feature selection algorithm in MRI images. International Journal of Business Intelligence and Data Mining, 15(1), 71-97.
19. Abiwinanda, N., Hanif, M., Hesaputra, S. T., Handayani, A., & Mengko, T. R. (2019). Brain tumor classification using convolutional neural network. In World congress on medical physics and biomedical engineering 2018 (pp. 183-189). Springer, Singapore.
20. Sriramakrishnan, P., Kalaiselvi, T., & Rajeswaran, R. (2019). Modified local ternary patterns technique for brain tumour segmentation and volume estimation from MRI multi-sequence scans with GPU CUDA machine. Biocybernetics and Biomedical Engineering, 39(2), 470-487.
21. Kumar, V. V., Krishna, K. S., & Kusumavathi, S. (2019). Genetic algorithm based feature selection brain tumour segmentation and classification. International Journal of Intelligent Engineering and Systems, 12(5), 214-223.
22. Rehman, A., Naz, S., Razzak, M. I., Akram, F., & Imran, M. (2020). A deep learning-based framework for automatic brain tumors classification using transfer learning. Circuits, Systems, and Signal Processing, 39(2), 757-775.
23. Devi, K. U., & Gomathi, R. (2020). Brain tumour classification using saliency driven nonlinear diffusion and deep learning with convolutional neural networks (CNN). Journal of Ambient Intelligence and Humanized Computing, 1-11.
24. https://figshare.com/articles/brain_tumor_dataset/1512427/5 dated on 21 July.
25. Kumar, S., Kumar, P., Gupta, M., & Nagawat, A. K. (2010). Performance comparison of median and wiener filter in image de-noising. International Journal of Computer Applications, 12(4), 27-31.