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# A STUDY OF CATEGORIZATION TECHNIQUES FOR BRAIN TUMOURS USING MRI IMAGING

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**Abstract**

Brain tumours are formed by aberrant brain cells. Depending on where they are and what they are, they may be benign or malignant. The tumours are being classified, which will aid doctors in early diagnosis and patient treatment. This will not give the patient any discomfort. Brain scans are used to classify cancers using medical imaging technologies. Brain MRI is the best approach for tumour categorization since it can clearly view the tissue and detect cancers in the brain. Tumors include gliomas, meningioma, and pituitary tumours. Glioma is a kind of cancer that affects the spinal cord and the brain. Meningioma grow slowly on the meninges in comparison to other types of tumours. This study presents a preliminary assessment for differentiating these cancers using magnetic resonance imaging brain and tumour area characteristics generated from pattern features.

***Keywords:*** Brain tumour, MRI, machine learning, types, CNN, features.

## 1. Introduction

A brain tumour is a collection of aberrant brain cells. It is a life-threatening disease when a brain tumour begins to grow in size and shape on a daily basis and is not detected at an early stage. Cancer cells from other parts of the body can travel to the brain, becoming a secondary brain tumour.

Tumours are classified as benign or malignant based on where they are located and their nature. Three types of tumours are studied for classification that assists clinicians with early diagnosis and intervention of patients. Additional advantage of this sort of image classification is that this is simple for the patient.

The brain scans acquired by medical imaging technologies are used to classify the tumour. PET, MRI, and CT are medical imaging techniques for the brain. MRI of the brain is the most suited of these three modalities for tumour categorization since the MRI scans can effectively view the tissue.

If tumours are not treated promptly, they can be fatal. Glioma, meningioma, and pituitary tumours are the types of tumours. Glioma is a cancer that develops between the spinal cord and the brain. Meningioma is a tumour that develops slowly on the meningeal membrane in comparison to other tumours. This tumour manifests symptoms after it has grown to a significant extent. If the hormone generated by the pituitary gland is not considerably altered, the pituitary tumour is not malignant.

This work includes a preliminary survey for differentiating these tumours using magnetic resonance imaging characteristics of the brain and the tumour region obtained with the use of pattern features.

Senthilkumaran and Thimmiaraja (2014) examined MRI brain imaging enhancement techniques. The techniques under discussion are built on pixel intensity level counting, often known as histogram count. Global and local histogram equalisation, as well as adaptive and brightness-preserving dynamic histogram equalisation, is all techniques to equalisation.

Saritha et al. (2013) successfully classified brain images by using a probabilistic neural network. The wavelet entropy and spider web plot features are used to train the network. It achieved 100 percent accuracy thanks to the combo stage feature extraction approach.

Natarajan et al., (2012) utilised basic image processing methods such as equalisation, filtering, morphological and thresholding techniques and the subtraction process to find the tumour in the brain.

The classification of a brain tumour was done by Huang et al. (2012) using content-based image retrieval. The CBIR technique has a 91 percent accuracy rate in predicting brain tumour categories. CBIR is made up of a bag of visual terms that is intensity-based and region-specific.

Rajini and Bhavani (2011) used the Haar wavelet to find significant information from brain scans and classified them. The wavelet coefficients are employed to collect the features, which are then reduced using PCA. With the combined KNN and BPN network, it achieved 99 percent accuracy.

Wavelet and BPN were also used by Zhang et al., (2011) to classify normal and pathological brain images. However, the scaled conjugate gradient technique is used to update the BPN weights in order to categorise the images. Because of this weighting strategy, the network can provide 100% accuracy for both training and testing images categorization.

El-Dahshan et al. (2010) used the wavelet transform to extract the characteristics from the MRI brain image categorization. Principal component analysis is used to decrease the number of characteristics. The two step classifiers, feed forward neural network and k- closest neighbour, with 97 percent and 98 percent accuracy, are used to classify normal and pathological brain images.

Badran et al., (2010) categorised healthy and unhealthy brain scans, which were then further divided into main and secondary tumours. Segmentation techniques such as thresholding, edge detection such as canny edge, and Harris operators are used to carry out the procedure. For the two forms of categorization, it used a two-stage neural network.

Using computer assisted design software, Kaus et al. (2001) achieved automated segmentation of low-grade brain tumours such as glioma and meningioma. It is likened to segmentation by hand. Adaptive template moderated classification was utilised to automate the process.

Dhamodharan and Raghavan (2015) presented a tumour classification system based on segmentation. The MRI brain scan is initially divided into several areas depending on tissues and normal and pathological regions. The neural network is then trained using the retrieved characteristics from the regions. The trained network can then distinguish between normal and pathological brain imagery.

The neuro-fuzzy was utilised by Renjith et al. (2015) to categorise tumour types as normal, malignant, and benign. The precise tumour area is then retrieved using Otsu's thresholding. The features retrieved from the grey level co-occurrence matrix and the dual tree complex wavelet transform are utilised for classification.

The categorization of tumours was done by Gaikwad and Joshi (2015) using a probalisitic neural network. Principal component analysis was used to decrease the number of features retrieved from the images. Then, to categorise the tumours, the reduced characteristics were trained using a probabilistic neural network.

Convolutional neural networks were utilised by Pan et al. (2015) to grade the tumour in MRI brain scans. The convolutional neural network is used for both feature extraction and grading in this case. In comparison to other feature-based classifiers, the whole process is dependent on layer selection.

To categorise the tumours, Karthik et al. (2015) employed a variety of pre-processing and feature extraction methods. The skull is stripped here to remove only the brain area from the slice. The tumour area is then extracted using a watershed-based method. Finally, support vector machine is used to classify the features derived from the grey level co-occurrence matrix and curvelet transform.

The two-phase classification was utilised by Anitha and Murugavalli (2016) to detect the brain tumour. The segmentation technique is used to discover the brain tumour area utilising adaptive K-means segmentation in this case. The features are then extracted using the wavelet transform. Finally, the extracted features are trained using a self-organizing neural network, and the output is trained using K-nearest neighbour once again. The testing is done in two parts as well. As a result, processing time is lengthy.

Thara and Jasmine (2016) suggested a tumour detection method based on segmentation in an MRI brain imaging. Clustering techniques such as Fuzzy c-means and K-means clustering are used to process the input image. The fuzzy c-means clustering is the better of the two since it successfully extracts information from the image. Then, using characteristics such as amplitude and direction, the tumour and normal images are classified. The categorization is done using a probabilistic neural network and a generalised regression neural network. The fuzzy c-means based probabilistic neural network is the best for tumour classification, according to its performance evaluation.

Shenbagarajan et al. (2016) presented a segmentation-based categorization system for tumours, dividing them into three categories: normal, malignant, and abnormal. "Segmentation: Active contour model" is used here. Descriptors for texture and shape were retrieved. The classifier is a neural network with the LM algorithm. Accuracy and error rate are both good. It is possible to enhance feature extraction and selection.

Using the support vector machine method, Mohankumar (2016) investigated the different types of wavelet families in the categorization of brain tumours. For the investigation, it examined three wavelet families: daubechies8, symlet8, and biorthogonal3.7. Between these, daubechies8 is the most suitable for categorization.

The region oriented tumour categorization was suggested by Subramaniam and Radhakrishnan (2016). It starts by extracting the tumour area. The tumour region's characteristics were then retrieved. To compare its performance, it is trained with a bee colony based neural network and a standard neural network.

The artificial neural network was also utilised by Abbadi and Khadim (2017) to classify tumours. For the feature extraction procedure, grey scale characteristics such as grey level co-occurrence matrix and grey level run length matrix were employed.

To classify brain tumours, Latha and Surya (2017) suggested the Clustering and neural network classifier. In this case, "K-means segmentation is a type of segmentation. Dual tree complex wavelet transform is used to extract features. Principal component analysis is a technique for reducing the number of features. Neural network is a type of classifier. Tumor types aren't taken into account.

The probabilistic neural network-based tumour identification was proposed by Lavanyadevi et al. (2017). In this case, "K-means segmentation is a type of segmentation. Gray level co-occurrence matrix was used to extract a feature. Principal component analysis is a technique for reducing the number of features. Probabilistic Neural Network is a type of classifier. Only the tumour phase is categorised.

A survey of tumour segmentation strategies was done by Angulakshmi and Lakshmipriya (2017). It detailed all of the approaches for tumour segmentation in several image modalities, including MRI, PET, CT, and multimodal imaging. It also included information on the segmentation process's assessment measures.

The following is how the paper is laid out: Section 2 discusses the current technique and its shortcomings. The section 3 discusses the assessment metrics and compares them to existing techniques. Section 4 summarised the paper, while section 5 discussed potential improvements.

## 2. Recent tumour classification approaches

Shahzadi et al. (2018) presented a CNN-LSTM-based network for classifying brain tumours. This procedure is used to classify glioma tumours as high or low grade. The VGG-16 net is being used for extracting the features and outperforms Alexnet and Resnet. The categorization is done on three-dimensional pictures. It only handled 60 volumes. With lengthier processing stages, accuracy suffers.

To classify brain tumours, Malathi and Sinthia (2018) presented a hybrid clustering and back propagation network. A hybrid C-means clustering method is used to segment the tumour area initially. The Wavelet transform and back propagation network are then utilised to classify the data. The disadvantage of this technique is that tumour kinds are not examined. Clustering may yield different result in repeated rounds.

The Multi model for tumour categorization was proposed by Abd-Ellah et al (2018). First, a convolutional neural network is used to extract features. Error-correcting coding that is based on categorization, use a support vector machine. For tumour localisation, a regional convolutional neural network is used. Due to the numerous CNNs, processing time is lengthy.

For brain tumour classification, Soltaninejad (2018) recommended the Supervoxel and Random forest models. The extraction of features based on supervoxels is done. For classification, a random forest classifier is employed. The likelihood of finding the tumour core is high. It's a fantastic idea to use super voxels on a smaller image. However, the processing time for bigger images is lengthy.

The Probabilistic Neural Network-based Tumor Classification was used by Abir et al (2018). Discrete cosine transform is used to eliminate superfluous data in this case. For feature extraction, a grey level co-occurrence matrix is employed. For classification, PNN is employed. It was effective at detecting cancer. The selection of spread factors is critical for categorization.

To diagnose brain tumours, Thejaswini et al. (2019) suggested the Clustering and Hybrid classifier. Segmentation is done by using Adaptively Regularized Kernel-Based Fuzzy C-Means (ARKFCM)" is the title of the paper. Combination of SVM and ANN are good as a classifier. Accuracy and error rate are both good. It is possible to enhance feature extraction and selection.

Hemanth and Anitha (2019) proposed using the Modified Genetic algorithm to classify brain tumours. Using several sorts of operators on MRI brain pictures improves the genetic algorithm. It has the advantage of more precision, but the disadvantage is that binary operators tend to fluctuate.

The regional-based categorization of tumours was proposed by Rehman et al. (2019). To extract characteristics from the brain, regional-based features such as statistical, histogram, and fractal were employed. The following are the classifiers that were used: Regional classifier based on SVM, Adaboost, and RF. RF based regional classifier is one of the finest classifiers. However, it necessitates a greater amount of characteristics for the network to be trained.

Kavitha and Chellamuthu (2019) utilised a neural network based on the optimization method. Modified region growth and two-dimensional wavelet are used for segmentation in this case. Gray Level Co-Occurrence Matrix was used to extract a feature. Self-learning was chosen as a feature. Optimization of particle swarms. Feed forward neural network as a classifier. Its drawback is that feature extraction is restricted.

Convolutional neural network-based categorization was also utilised by Abiwinanda et al. (2019). Only a convolutional neural network is used here. There have been no previous image processing techniques that could enhance the accuracy even more.

For brain tumour segmentation, Sriramakrishnan, et al. (2019) utilised the probalisitic ternary patterns method. The initial phase is to use SVM to categorise tumours and non-tumors. The second phase involves using FCM to segment the tumour area. Probabilistic local ternary pattern in the third phase. In terms of accuracy and dice score, the overall performance is good. Even with the GPU and parallel processing, the computation time is long.

The genetic method was used by Kumar et al. (2019) to classify tumours. Segmentation is performed using AdaptivelyRegularized Kernel-Based Fuzzy C-Means in this case (ARKFCM). The Hybrid Feature extraction approach was used for feature extraction. The genetically based K-nearest neighbour method is used to pick features. A deep neural network is used to classify the data. For three kinds of glioma, meningioma, and pituitary tumours, accuracy rate seems to be above 90%. Because there are additional steps of processing, the computing time is longer.

Rehman et al. (2020) employ a data-augmented CNN to solve their problem. For data augmentation, CNN employed Google Net, Alexnet, and VGGnet. For categorization, data augmentation is done with pre-defined CNN. Its disadvantage is that it takes a long time to compute.

**Table1. Literature survey**

| s.no | Author | Paper | methodology | Advantages | Drawbacks |
|---|---|---|---|---|---|
| 1 | Hemanth, D. J., & Anitha, J. (2019) | Modified Genetic Algorithm approaches for classification of abnormal Magnetic Resonance Brain tumour images | Genetic algorithm is improved by using different types of operators on MRI brain images | high Accuracy | the binary operators tend to vary |
| 2 | Devi, K. U., & Gomathi, R. (2020). | Brain tumour classification using saliency driven nonlinear diffusion and deep learning with convolutional neural networks (CNN). | pre-processing : canny edge.<br>Saliency Image representation: modified minimum barrier distance and nonlinear diffusion at multiple level<br>Feature Extraction and Classification: Convolutional neural network | High accuracy | classification is purely depends on selecting the convolutional neural network parameters. |
| 3 | 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. | Regional based features like Statistical, histogram and fractal were used<br>Classifiers: SVM,Adaboost and RF based regional classifier<br>best classifier: RF based regional classifier | High pixel level classification high dice score to the result | more number of features for training the network |
| 4 | 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. | first phase: SVM to classify tumor or non -tumour<br>second phase: FCM to segment the tumor region<br>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 |
| 5 | Kumar, V. V., Krishna, K. S., & Kusumavathi, S. (2019). | Genetic algorithm based feature selection brain tumour segmentation and classification. | Segmentation: Adaptively Regularized Kernel-Based Fuzzy C-Means (ARKFCM)<br>Feature extraction: Hybrid Feature extraction<br>feature selection: genetic based K-nearest neighbour<br>classifier: deep neural network | overall accuracy is above 90% for three types of glioma, meningoma and pitutary | computational time is high due to more stages of processing |
| 6 | Thejaswini, P., Bhat, B., & Prakash, K. (2019). | Detection and classification of tumour in brain MRI. | Segmentation: Adaptively Regularized Kernel-Based Fuzzy C-Means (ARKFCM)<br>Classifier: combination of SVM and ANN | good accuracy and reduced the error rate | Feature extraction and selection can be improved. |
| 7 | Kavitha, A. R., & Chellamuthu, C. (2019) | Brain tumour detection using self-adaptive learning PSO-based feature selection algorithm in MRI images. | segmentation: Modified region growing and two-dimensional wavelet<br>Feature extraction: GLCM<br>feature selection: self learning PSO<br>classifier: Feed forward neural network | High accuracy | feature extraction is limited. |
| 8 | Abiwinanda, N., Hanif, M., Hesaputra, S. T., Handayani, A., & | Brain tumor classification using convolutional neural network. | Convolution neural network alone | good accuracy for un trained data also | No prior image processing operations which can improve the |

| | | | | | |
|---|---|---|---|---|---|
| | Mengko, T. R. (2019). | | | | accuracy further |
| 9 | Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., & Baik, S. W. (2019). | Multi-grade brain tumor classification using deep CNN with extensive data augmentation. | segmentation: CNN<br>30 augmented data using 8 techniques<br>classifier: pre-defined cnn with augmented data | overall classification is good for three grades | feature set is high. Accuracy for fourth grade is also less even if high number of features are obtained. |
| 10 | 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 | CNN: google net, Alexnet and VGGnet<br>data augmentation<br>data augmentation is performed with pre-defined CNN for classification | VGGnet performs better as compared to the other classification | computational time is high |

**3. Performance Evaluation**

**4.** The accuracy, sensitivity, and specificity were computed using evaluation parameters are determined using the terms in table 2 as a guide.

Table2. Terms for Evaluation

| **Term** | **Purpose** |
|---|---|
| True positive ($TP_T$) | Correct identification of a specific tumour |
| True negative ($TN_T$) | Correct identification of additional tumours with relation to true positives |
| False Positive ($FP_T$) | Taking the other class tumour and converting it to a true positive |
| False negative ($FN_T$) | The real positive class is interpreted as a negative class. |

### 3.1.1 Accuracy

It is used to correctly classify tumours into several categories. The equation 1 is used to compute it.

$$Accuracy = \frac{TP_T + TN_T + FP_T + FN_T}{Total\ tumour\ cases} \qquad (1)$$

### 3.1.2 Sensitivity

Sensitivity shows that the genuine negative tumour classifications were properly identified. The following formula 2 is used to compute it,

$$Sensitivity = \frac{TN_T}{TN_T + FP_T} \qquad (2)$$

### 3.1.3 Specificity

The term "specificity" refers to the ability to accurately identify genuine positive tumour classifications. It is computed using the formula 3 below.

$$Specificity = \frac{TP_T}{TP_T + FN_T} \qquad (3)$$

Using the formulas 1, the performance comparison of tumour classification using svarious approaches is shown in table 3.

**Table3. Accuracy comparison**

| **Technique** | **Accuracy in %** |
|---|---|
| CNN with ADAM | 0.99 |
| CNN with SGD | 0.9687 |
| Existing (GSO-CNN) | 0.995 |
| Region specific CBIR | 89 |

A simple comparison of CNN for tumour classification is shown in the table 4.

**Table4. CNN evaluation**

| **Metric** | **Pattern -CNN (%)** |
|---|---|
| Accuracy | 99 |
| Sensitivity | 98.2 |
| Specificity | 98.6 |

Table 3 demonstrates that utilising a convolution neural network, all of the approaches can properly diagnose the kind of tumour 95% of the time. In comparison to previous machine learning techniques, the suggested convolution neural network can successfully categorise the tumour.

## 5. Conclusion

The advancement of imaging technology and processing aids in improving brain tumour diagnosis, identification, and classification. This study succeeded its goal by categorising brain tumours, which aids in better identification and treatment without the need of intrusive methods. This study discovered two findings: first, the spread function value plays a role in machine learning techniques for classification, and second, texture information combined with edge is significant for brain tumour detection. The tumour component of the picture is not as evident at this stage, as seen by the textural diversity and tiny borders in the image. This issue is solved, and the picture is readily categorised using the convolutional neural network approach.

## 6. Future work

In the future, the categorization and tumour segmentation will be enhanced to capture the features in more depth.

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