AN EFFICACIOUS APPROACH FOR BRAIN TUMOUR DETECTION IN MR IMAGES

Daulat Kunwar Chauhan[a], Kalpana Jain[b]
[a]Department of Computer Science and Engineering, College of Technology and Engineering, MPUAT
Udaipur, Rajasthan, India
E-mail: daulatchauhan51195@gmail.com
[b]Department of Computer Science and Engineering, College of Technology and Engineering, MPUAT
Udaipur, Rajasthan, India
E-mail: kalpana_jain2@rediffmail.com

Abstract: The diagnosis of brain tumours in a timely and efficient manner will assist in making better treatment decisions and will increase the patients' survival rate. Magnetic resonance imaging (MRI) segmentation plays a critical role in detecting brain malignancies. Because of the huge number of MRI images generated during cancer detection, manual image segmentation will be a time-consuming task. For medical analysis and interpretation, precise and automated classification of brain MRI images is critical. A hybrid methodology for brain tumour classification is suggested, based on kernel fuzzy c-means and Convolutional Neural Networks (CNN). Pre-processing and segmentation are applied to the captured image. Then there's feature extraction, which is followed by classification. The proposed methodology is intended to distinguish between normal and cancerous brain (benign or malign).

Keywords: MRI, Classification, Segmentation, CNN, KFCM, Feature Extraction.

1. INTRODUCTION

A tumour is a mass of tissue that grows uncontrollably, despite the presence of normal growth-controlling factors. Tumors can develop in any body part, interfering with the proper functioning of the system, but they are fatal when they develop in the brain, which is the most sophisticated portion of our body. Brain tumours are abnormal cell development in the brain that develop within or next to the brain. Some can be treated with surgical resection, but many can't be healed with existing treatments, and while they're disabled, neurological impairments are common.

Tumors are characterised based on two factors: cancerous potential and origin. When cancer tissues begin to grow and stay in the same site and position, they become primary tumours. It's a problem that starts in the brain. Primary brain tumours frequently transmit malignant cells to other sections of the central nervous system (brain or spine), but they seldom spread to other sections of the body. Primary brain tumours are named for the cell types that gave rise to them. Secondary or metastatic brain cancers are tumours that have spread from another part of the body to the brain. Secondary brain tumours are three times more prevalent than initial brain tumours. Primary tumours are classified as benign (slow-growing, less aggressive, and noncancerous) or malignant (fast-growing, aggressive, and cancerous). A benign tumour is one that grows slowly and does not spread to other tissues. A benign tumour does not return once it has been removed. The majority of benign brain tumours have clean borders, which means they do not infect nearby tissues. Malignant brain tumours normally dominate nearby tissues but rarely spread to other parts of the body, though they may reoccur following therapy. Because these are difficult to identify, they can be life threatening. They compress/displace brain tissues to create way for the expanding mass, and as the tumour grows, it causes brain swelling, increasing the pressure within the skull.

In addition to these fundamental data, treatment planning is influenced by grade and tissue cell information, which is often obtained via a biopsy procedure. Tissue cell type defines the cells that gave rise to the tumour, while tumour grade determines how aggressive the tumour is. Tumors are generally graded at different phases of their development.

The fast advancement of non-invasive brain imaging technology over the last few decades has opened up new avenues for analysing and studying brain architecture and function. Magnetic resonance imaging (MRI) has made huge strides in gaining access to brain damage and understanding brain structure (MRI). Advances in brain MR imaging have also resulted in a vast volume of high-quality data. For clinicians who have to manually extract critical information from these massive and complicated MRI datasets, processing has become a tiresome and hard undertaking. Due to numerous inter- or intra-operator variability studies, this manual examination is sometimes time-consuming and prone to errors. These challenges in analysing brain MRI data necessitated the development of computational approaches to better disease detection and testing. Computerized

MR image segmentation, registration, and visualisation approaches are now widely employed to aid doctors in making qualitative diagnoses.

2. RELATED WORK

The researchers have suggested a number of segmentation and classification techniques for brain tumor detection in the medical field. A brief evaluation of a few significant segmentation and classification techniques are presented in this section.

Zhong-dong et al. (2003) proposed FKCM which is a fuzzy kernel C-means clustering algorithm based on the typical fuzzy C-means clustering approach (FCM). FCM is combined with the Mercer kernel function in this novel FKCM technique, which addresses some concerns in fuzzy clustering. The features of the new methods are demonstrated. The FKCM algorithm is successful not only for spherical clusters, but also for non-spherical clusters such as annular rings.

Sachdeva et.al. (2013) used a varied dataset of 428 post-contrast T1-weighted MR images from 55 patients to perform multiclass brain tumour classification Principal component analysis (PCA) is used to reduce the dimensionality of the feature space, and artificial neural networks are then utilised to classify the classes (ANN). As a result, this method is known as the PCA-ANN method.

Kannade and Gumaste (2015) The current state of semi-automated and automated approaches for segmenting anatomical medical images is evaluated critically, with the benefits and drawbacks highlighted. They use testing and database training to detect the brain tumour and characterise the stages of the tumour. Spatial FCM is used to segment for testing purposes.

Praveen and Amritpal Singh(2015) A new hybrid technique based on the support vector machine (SVM) and fuzzy c-means for brain tumor classification is proposed. The purposed algorithm is a combination of support vector machine (SVM) and fuzzy cmeans, a hybrid technique for For brain tumour classification, a new hybrid methodology based on the support vector machine (SVM) and fuzzy c-means is proposed. The intended methodology is a hybrid methodology for brain tumour prediction that combines support vector machine (SVM) with fuzzy cmeans. The image is upgraded using enhancement techniques such as contrast improvement and mid-range stretch in this approach. Skull striping is done via double thresholding and morphological processes. To find the suspicious region in a brain MRI picture, fuzzy c-means (FCM) clustering is employed for image segmentation. The grey level run length matrix (GLRLM) is utilised to extract features from the brain image, and then SVM is used to classify them.

Jain and Jain (2016) proposed a method to remove anomalies and to properly handle and analyze missing data values. Their method provides more accurate and efficient results and reduces distortion of results when entering missing data. Theoretical analysis and empirical results showed the superiority of their proposed methodology.

Sujan et al. (2016) suggested a new threshold-based approach for morphological image analysis to detect brain cancers. The colour image is first converted to grayscale, and then the noise in the grayscale image is removed using a filtering algorithm. To accurately segment the tumour component, the grayscale image was transformed to a binary picture and a threshold of 0.3 was added to the Otsu threshold. Then, using morphological operations, look for brain tumours that have the brightest spots on magnetic resonance imaging (MRI). In the process of detecting and segmenting brain tumours from 61 individuals, our approach only obtained 84.72 percent accuracy

VishwaPriya and Shobrani (2016) The Contextual Clustering based segmentation methodology, proposed by them, covers picture pre-processing and tumour segmentation. The whole noise in the image is removed, and the borders are corrected, using image pre-processing. The tumour portion is segmented from the raw MR images using the Contextual Clustering technique. This paper proposes an automatic technique of tumour detection and localization in brain MRI that minimises spurious segmentation and enhances accuracy.

Ameta and Jain (2017) discussed kidney disease which is one of the leading causes of death worldwide. They suggest for applying Supportive Vector Machine (SVM) classification for HRS diagnosis. Outcomes were evaluated using real-world data from the hospital. RBF, Kernel functions are applied to SVM. The result shows a fairly high accuracy of 95%.

Pant and Jain (2017) presented a technique for calculating sentiment in a movie review dataset to improve the overall performance of model. This model trains and tests the model to find performance constraints. First preprocess the dataset, then select the feature, and then rank the features to check the performance.

Jain (2017) presented a survey of state-of-art techniques for feature selection.

Usman and Rajpoot (2017) develop a segmentation and classification system for brain malignancies using multimodal MRI. From the preprocessed image, extract the intensity, local neighbourhood, intensity variance, and wavelet texture. Following that, the random forest classifier is given all of the information to predict five categories: background, necrosis, edoema, unimproved tumour, and enhanced tumour. These labels are used to categorise three separate areas based on whether the tumour is intact, active, or improved. The proposed technique achieved a dice overlap of 88 percent across the tumour area, 75 percent in the central tumour area, and 95 percent in the increased tumour area.

Raju et al. (2018) On the basis of brain tumours, they proposed a Bayesian Fuzzy Clustering (BFC) approach and identified brain tumours using the HCS optimization algorithm based on the SVNN classifier. To evaluate the amount of brain tumours, this classification approach employs the features of the segments formed by the BFC algorithm.

Shahriar Sazzad et al. (2019) An automated methodology for brain tumour detection was proposed in this research work, which included MRI gray-scale pictures. This research offered an automated method that involves initial enhancement to reduce gray-scale colour fluctuations. To aid improved segmentation, a filter operation was employed to remove as much unnecessary noise as feasible. Because the images in this investigation were grayscale, threshold-based OTSU segmentation was employed instead of colour segmentation. Finally, pathology experts gave information that was used to establish the study's focus areas (brain tumour region).

Gurbina et al. (2019) They proposed a method which is intended to distinguish between normal and cancerous brain (benign or malign). Brain magnetic resonance imaging is used to examine some types of brain malignancies, such as metastatic bronchogenic carcinoma tumours, glioblastoma, and sarcoma (MRI). Different wavelet transforms and support vector machines are used in the identification and categorization of MRI brain cancers.

Hemanth et al. (2019) This study presents a method for automatic segmentation that uses CNN (Convolution Neural Networks) to determine small 3 x 3 kernels. Segmentation and classification are achieved by combining this single methodology. CNN (a machine learning methodology) is derived from NN (Neural Networks), and it uses layers to classify outcomes.

Tyagi (2019) explained which classification technique is better for detection of brain MRI data set. The CNN improves the accuracy of detection for normal and abnormal brain MRI compared to existing classification methods.

Divyamary et al.(2020) presented a Naive Bayes Classifier for early detection of brain tumours Noise removal, segmentation-based morphological operations, feature extraction, and the Naive Bayes classifier are among the project's different steps.

3. METHODOLOGY

The proposed methodology consists of a set of stages commencing from gathering brain MRI images. The main steps are depicted in figure 1.

Preprocessing, segmentation, feature extraction, and training the CNN classifier utilising MRI images with GLCM features are the primary processes in this hybrid methodology.

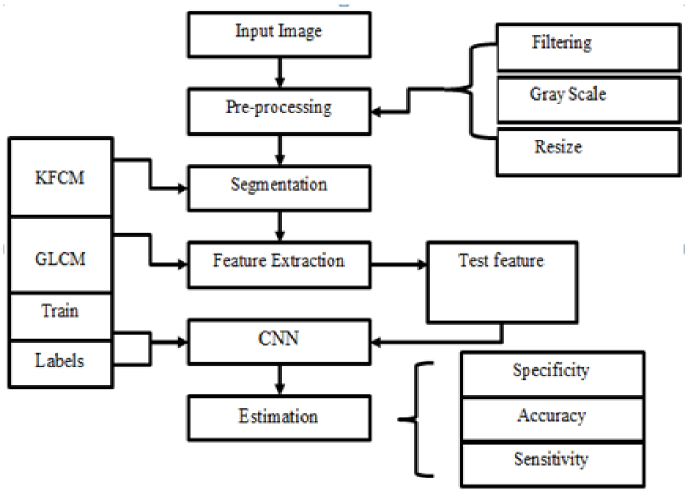


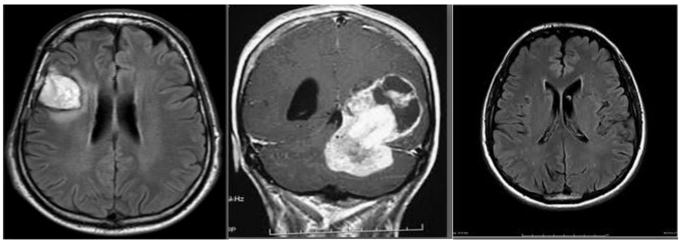
Figure1: The proposed methodology architecture.

3.1 Preprocessing:

Image pre-processing refers to actions on images at the lowest level of abstraction with the goal of improving the image data by suppressing unwanted distortions or enhancing some critical image attributes for future processing. Image repetition is used in image pre- processing. Pre-processing is required to prepare the image data for model input. For example, in a fully connected layer of a convolutional neural network, all images must be arrays of the same size. Image preprocessing can also speed up model inference and reduce model training time. If the input image is too large, then shrinking the image will greatly reduce the model's training time without affecting the model's performance. Filters are mainly used in image processing to remove high frequencies from an image. i.e. Smooth the image or remove low frequencies from the image. i.e., it enhances or detects edges. The first step is to convert the image to the frequency domain, multiply it by the frequency filter function, and then return the output to the spatial domain. The filter function is designed to reduce some frequencies and increase others.

Gaussian filters are widely used for filtering different types of surfaces. This type of filtering is the first choice for filtering in many applications due to the simplicity of the algorithm, ease of implementation, and robustness of the results. Gaussian linear filters are widely used in surface characterization, have become the filtration standard in the industry, and are widely used by researchers. One can apply a Gaussian filter to the input region by transforming the measurement region using the Gaussian weighting function.

.



(a) (b) (c)

Figure 2: sample images (a) benign tumour image (b) malignant tumour image (c) no tumour.

3.2 Segmentation:

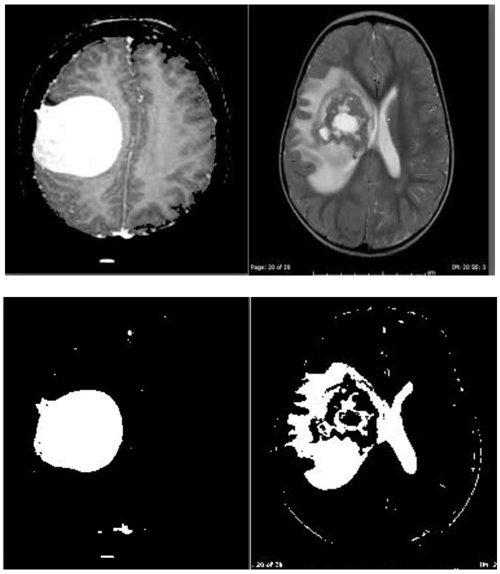
Image segmentation is the process of partitioning a digital image into several segments (sets of pixels, also known as image objects) in digital image processing and computer vision. In most cases, image segmentation is used to locate objects and boundaries (lines, curves, and so on) in images.

Clustering algorithms are unsupervised segmentation algorithms that divide an image into clusters of similar-intensity pixels/voxels without the use of training images. Clustering techniques, in effect, train themselves using the available picture data. Iterating between two steps: data clustering and determining the properties of each tissue class, segmentation and training are done in tandem. The k-means clustering and fuzzy C-means clustering methods are the most often used clustering algorithms.

Fuzzy C-Means is a data aggregation approach in which the data set is divided into n groups and each data point in the data set belongs to some degree in one of the groups. For example, a data point in the center of a group has a high degree of membership or membership in that group, and a data point far from the center of the group has a low degree of membership or membership in that group.

Clustering models exist in large areas of features without explicit interpretation, which is one of the primary limitations of the FC technique. FCM works well with compact and well-separated spherical groups, but the problem is that the non-spherical and the data overlap a lot.

Kernel Fuzzy C-Means aims to address this deficiency. Kernel-based fuzzy C (KFCM) is used to aggregate large amounts of data and is applied to the original dataspace, which is a transactional database. To improve ensemble quality, kernel-based fuzzy means (KFCM) methods are applied to annotated learning objects. The main advantage of using KFCM is that you can use nonlinear transformations to map the input data to a higher dimensional feature space and implement FCM in that feature space. Therefore, after non-linear separation, the non-linear complex data structure can be easily separated in the input space and can be linearly separated in the feature space.



(a) (b)

Figure 3: sample segmentation output (a) benign tumour (b) malignant tumour.

3.3 Feature Extraction:

Texture analysis makes it easy for humans and machines to distinguish between healthy and diseased tissue. It also shows the difference between malignant tissue and normal tissue that is not visible to the naked eye. Accuracy is improved by selecting appropriate quantitative characteristics for early detection. In the early stage, we extracted information about the statistical features of the underlying structure analysis from the image intensity graph and measured the grayscale frequency at random image positions. No correlation or coexistence of pixels is taken into account. In the second stage, we extracted secondary texture analysis features based on the probability of gray levels at random intervals and the orientation of the image series.

Gray-level concurrence matrix (GLCM), also known as spatial grayscale dependence matrix, is a method of describing spatial relationships between pixels of different gray levels. GLCM is a two-dimensional graph, where the element (p, q) represents the number of times event p occurs when event q occurs. It is a function of the distance S = 1, angle (0 (horizontal), 45° (positive diagonal), 90° (vertical) and 135° (negative diagonal), and the gray levels y and q. Determines how many times a pixel appears from the p intensities of another pixel q in distance S and direction.

Texture properties such as variance, correlation, energy, homogeneity, entropy, and variance were determined using this method starting from a gray level co-occurence matrix.

3.4 Classification:

CNN is a deep learning model that uses a grid pattern to interpret data. The image can be segmented without the need of a convolutional neural network. It is based on multiple layers such as convolutional, pooling, dropout, and fully connected layer, and it can detect normal and pathological brain MRI with the assistance of these layers. When compared to other classifiers, CNN provides superior accuracy, and it performed well when the data set was enormous since it readily decreases the dimension of data size.

3.5 Performance measures:

The following formulas were used to determine classification, sensitivity, specificity, and accuracy:

• True Positive (TP): A brain that is abnormal is appropriately identified as such.

• True Negative (TN): Normal brain identified accurately as normal.

• False Positive (FP): A healthy brain is mistakenly labelled as abnormal.

• False Negative (FN): An abnormal brain is seen for normal.

(1) Sensitivity = TP/ (TP+FN) *100%

(2) Specificity = TN/ (TN+FP) * 100%

(3) Accuracy= (TP+ TN)/(TP+ TN+FP+FN)*100 %

(4) F1-score=(2*TP)/(2*TP+ FP+ FN)*100%

4. RESULT AND DISCUSSION

The images were obtained from www.kaggle.com. As input, a count of 500 images was used. Kernel fuzzy c-means with CNN is utilised to segment and classify brain MRI images in this work. Appropriate preprocessing is done to achieve better performance. The tumour region is segmented from MRIs using kernel fuzzy c-means, and features are extracted using grey level co-occurrence matrix. The CNN classifier is used to divide brain images into benign, malignant, and tumor-free categories. We compared our results of proposed approach with existing approaches that are Otsu-SVM (Gurbina *et al.*, 2019), FCM-SVM (Praveen and Singh 2015), CNN (Hemnath *et al*., 2019).

The proposed methodology achieved an accuracy of 93.6% , 93.33% specificity and sensitivity of 96.6%. When compared to other widely used methodologies, the proposed methodology seems to be extremely effective. The comparisons are shown in table1.

Table 1: Table representing accuracy, sensitivity, sensitivity and f1 score of proposed and other state of art techniques

Techniques	Accuracy	Specificity	Sensitivity	F1 score
Otsu-SVM	81.56	85.49	71.12	74.02
CNN	88.3	85.3	92.7	87.82
FCM-SVM	90.3	88.74	94.96	88.76
Proposed	93.6	93.33	96.6	92.8

.

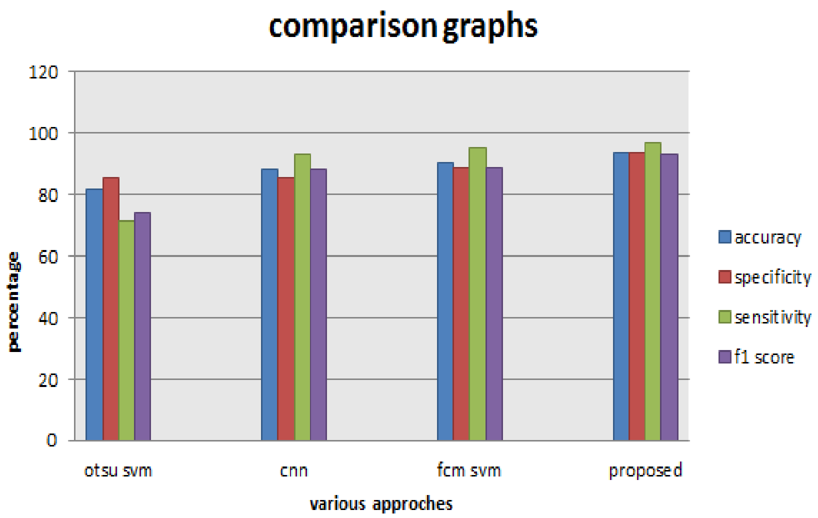


Figure 4: Comparison graph of proposed methodology with other state of art techniques.

5. CONCLUSIONS

This proposed technique for brain MRI images proved to be an effective method for detecting brain tumours. The hybrid technology of integrating kernel fuzzy c-means clustering and CNN for classification yields accurate results for brain tumour detection. The results reveal that with the right training data, CNN can distinguish between abnormal and normal tumour regions and accurately classify them as a benign tumour, malignant tumour, or healthy brain.

In future, more non-linear classifiers, such as the kernel PCA, which have proven to be very effective in classification, could be used in the future. Texture and shape feature filters, as well as wavelet-based image fusion methods, can be used to improve tumour classification accuracy.

References

Ameta , A., and Jain, K. (2017). Classification of HRD using SVM. *Global Journal of Computer Science and Technology.*7(1).

Divyamary, D., Gopika, S. and Pradeeba, S. 2020. Brain Tumor Detection from MRI Images using Naive Classifier. *6th International Conference on Advanced Computing and Communication Systems* held at Coimbatore, India. pp. 620-622.

Gurbină, M., Lascu, M. and Lascu, D. 2019. Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines. *42nd International Conference on Telecommunications and Signal Processing (TSP)*, 2019, pp. 505-508.

Hemanth, G., Janardhan, M. and Sujihelen, L. 2019. Design And Implementing Brain Tumor Detection Using Machine Learning Approach. *Proceedings of the Third International Conference on Trends in Electronics and Informatics*, pp. 1289-1294.

Jain, K., (2017) “A Survey on Feature Selection Technique” *IJIERT 4(5)*.

Jain, S. and Jain, K., 2016. Estimation of Missing Attribute Value in Time Series Database in Data Mining, *GJCST-C, 16(5): 73-76.*

Kanade, P.B., and Gumaste, P.P. 2015. Brain Tumor Detection Using MRI Images. *International Journal of Innovative Research In Electrical, Electronics, Instrumentation and Control Engineering.* **3**: 146-150.

Pant, S.,and Jain, K. (2017). Sentiment Analysis using feature selection and classification Algorithms – A SURVEY. *IJIERT.*4(3),109-113.

Parveen and Singh, A. 2015. Detection of brain tumor in MRI images, using combination of fuzzy c-means and SVM. *2nd International Conference on Signal Processing and Integrated Networks,* 2015, pp. 98-102.

Raju, A., Ratna, P., Suresh and Rao, R. R. 2018. Bayesian HCS-based multi-SVNN: A classification approach for brain tumour segmentation and classification using Bayesian fuzzy clustering. *Biocybernetics and Biomedical Engineering*. **38**: 646- 660.

Sachdeva, J., Kumar, V.,Gupta, I., Khandelwal, N. and Ahuja, C. K. 2013. Segmentation,feature extraction, and multiclass brain tumor classification. *Journal of Digital Imaging*, **26**, 1141-1150.

Shahriar Sazzad, T.M., Tanzibul Ahmmed, K.M., Hoque, M.U. and Rahman, M. 2019. Development of Automated Brain Tumor Identification Using MRI Images. *International Conference on Electrical, Computer and Communication Engineering* held at Bangladesh, 2019. pp. 1-4.

Sujan, Md., Alam, N., Noman, S.A. and Jahirul Islam, M. 2016. A Segmentation based Automated System for Brain Tumor Detection. *International Journal of Computer Applications.* **153**: 41-49.

Tyagi, V. 2019. A Review on Image Classification Techniques to classify Neurological Disorders of brain MRI. *International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)*, held at Ghaziabad, India. pp. 1-4.

Usman, K. and Rajpoot, K. 2017. Brain tumour classification from multi-modality MRI using wavelets and machine learning. *Pattern Analysis and Applications*. **20**: 871-881.

ViswaPriya, V. , and Shobarani. 2016. An Efficient Segmentation Approach for Brain Tumor Detection in MRI. *Indian Journal of Science and Technology*. **9**: 1-6.

Zhong-dong, Wu, Wei-xin, Xie and Jian-ping, Yu. 2003. Fuzzy C-means clustering algorithm based on kernel method. *Fifth International Conference on Computational Intelligence and Multimedia Applications. ICCIMA* held at Xi'an, China in 2003. pp. 49-54.