A Novel Technique for Brain Cancer Image Classification and Segmentation

Kumud Sachdeva[1]
Department of Computer Science and Engineering, Chandigarh University, Gharuan, Punjab, 140413, India

Corresponding author: kumud.cse@cumail.in

Amandeep Kaur[2]
Department of Computer Science and Engineering, Chandigarh University, Gharuan, Punjab, 140413, India

Corresponding author: amandeep.e11367@cumail.in

Rajan Sachdeva[3]
Department of Computer Science and Engineering, Chandigarh University, Gharuan, Punjab, 140413, India

Corresponding author: rajan.e12441@cumail.in

Abstract

The primary causes of brain lesions are abnormalities in brain cells. Tumor develops in the brain as a result of these aberrant lesions. MRI and CT scans are two examples of medical imaging (CT) are the two different techniques for brain imaging scanning. The interior regions of the brain are scanned using MR imaging in this research project. There are two types of aberrant lesions in the brain: benign and malignant. Benign lesions can be treated with radiation therapy, whereas malignant lesions require adequate surgery performed by a radiologist with expertise. Uncontrolled cell proliferation in any area of the body is referred to as a tumor. Tumor come in a variety of forms, has unique traits, and call for a range of therapies. Brain tumors are a current problem. Malignant or metastatic brain tumors and primary brain tumors are two different categories. The metastatic or malignant tumors start as a cancer somewhere else in the body before spreading into the brain region, but the primary tumors start in the brain and have a tendency to stay there. The automatic tumor detection and segmentation method has therefore. In order to accurately classify and identify the tumor sections, three brain tumor segmentation methods are proposed in this study. First, a powerful brain tumor segmentation method is used by merging Convolution Neural Networks (CNN) and Multi Kernel K Means Clustering and Network (MKKMC). The proposed CNN-MKKMC technique uses the CNN algorithm to classify MR images into normal, IV, and abnormal categories. The next step is to separate the brain tumor from the aberrant brain imaging using the MKKMC algorithm. The accuracy, sensitivity, and specificity of the proposed CNN-MKKMC algorithm are assessed visually as well as objectively in comparison to the currently used segmentation techniques. The experimental findings show that the suggested CNNMKKMC technique produces greater segmentation accuracy for brain tumours while requiring less time. Both clinical datasets and publically accessible open access datasets are used to test the meningioma brain tumour detection approach.

Keywords: Neural Network, Deep Learning Neural Network, Convolution Neural Network, Multi Kernel K Means Clustering and Network, Multi Kernel K Means Clustering and Network.

1 INTRODUCTION

For most people and many doctors alike, the idea of a brain tumour is one of the most dramatic types of human illness. Almost every family has encountered someone who has a tumor of some kind, either inside the family unit as a whole or within a group of friends, family, and acquaintances. The second most frequent type of paediatric cancer is brain tumor, which have a significant impact on the affected family. The prevalence of primary brain tumor in adult's ranges from sixth to eighth among all neoplasms, and as primary cancer control techniques improve, more and more people are affected by brain tumours that have spread there. Although they are only to blame for 7% of the years of life lost to cancer before the age of 70, primary brain tumor are accountable for roughly 2% of cancer fatalities.20% of malignant tumours seen in people under the age of 15 have their involvement. In western civilization, 30% of deaths are attributable to cancer, and at autopsy, cerebral metastatic deposits are found in one in five of these cases. The diagnosis of brain tumor has undergone a revolutionary change, and as a result, there has been a significant improvement in surgical management effectiveness and detection rates. Based on the fine anatomical detail made possible by contemporary imaging technology, this is claimed.

1.1 TUMOR IMAGING AND TREATMENT

In order to diagnose and cure cancer, multi-modality imaging is crucial. The "tumor burden" is found, located, and described during the diagnostic process. Imaging is utilised to direct radiation therapy planning (RTP), surgical resection, and treatment evaluation when a tumour has been identified. To better understand the shape and function of the tumor and surrounding organs, many imaging modalities, including radiography, CT, SPECT, MRI, PET, and others, can each be used. The development of imaging technology has made it possible to collect volumetric data sets that can be used to portray a tumor in an acceptable way. By injecting a tracer material into the circulatory system, dynamic imaging can obtain functional information from the kinetics of the tracer distribution. In order to be detected by the imaging modality, the tracer or contrast material is given as a bolus and circulates through the body. For specific imaging modalities, several tracer compounds have been produced. It is crucial to be able to distinguish between benign and malignant tumours, and you may do this by looking at the microcirculation and/or oxygenation level. Increased blood flow to the tumour is a sign of elevated blood.

1.2 TYPES AND CLASSIFICATION OF BRAIN TUMOR

A brain tumor is often detected in the human brain as a mass or a collection of abnormal or anomalous cells. The stiff substance that houses our human brain is called the skull. Serious issues could be caused by the confined area or the growth of unwelcome cells inside the skull. Generally speaking, there are two basic categories for brain tumors. One is a malignant cancerous tumor, and the other is a benign cancerous tumor. Malignant and benign cancerous tumors that are growing may take up more room and put pressure on the skull. As a result, it causes certain major issues and causes human deaths. Human brain tumors are divided as primary tumors and secondary tumors, in accordance with (Danaei 2005).Typically, the human brain is where the first brain tumor develops. Most people think of primary brain tumors as either malignant or benign tumors. The metastatic brain tumor, also known as a secondary brain tumor, is typically made up of cancer cells that have moved from other regions of the body, such as the breast or the lung, to the brain. The tumor region is highlighted in the MR brain image in Figure 1.1

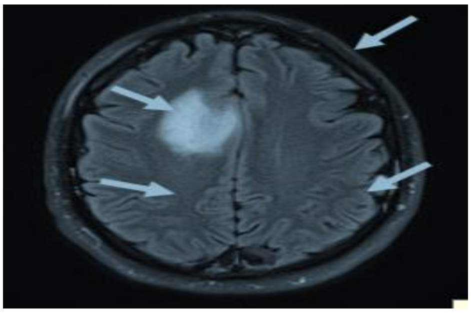

Figure 1.1: Brain tumor in MR image

The majority of people have secondary brain tumors. This tumor may have started in one area of the body and then spread to other areas, where it may create serious issues. Our body may be affected by this tumor if it spreads, including the following:

- Breast
- Kidney
- Skin

Secondary brain tumors are more specifically categorized as being of the malignant variety.

1.3 MENINGIOMA

As seen in Figure 1.2, the meningeal coverings of the brain are where this typical benign tumor develops. The convexity (A), falx (B), olfactory groove (C), sphenoidridge (D), **tuberculum** sell(E), tentorium (F), and cerebellopontine angle (F) are typical locations where it may be found (G). Ameningioma should always be suspected when a mass appears in such a site.

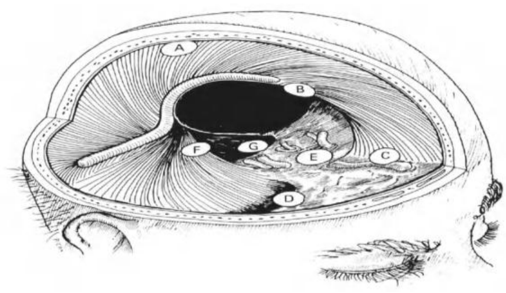

Figure 1.2 Representation of Meningioma tumor in human brain

They could be found inside the ventricles as well. The slow-growin**g** tumor known as a meningioma may be present for many years before a diagnosis is made. Depending on where the tumor is, headaches and a wide range of additional symptoms may develop. However, this lesion may be treatable with surgical removal, thus a precise diagnosis is crucial.

Although most meningiomas have a homogeneous consistency, some may develop cysts or calcify (visible on plain films). Arteriography will reveal hypertrophied meningeal arteries and a consistent tumor blush because these tumors receive the majority of their blood supply from meningeal vasculature. When a surgeon needs to know more about the vascular supply before doing surgery or when there is a question about the diagnosis made by a CT scan, arteriography can be very beneficial. Meningiomas could be hard to spot on MRI, however with more advancements in pulse sequences and enhancement, this issue should be resolved.

2. LITERATURE SURVEY

A tumor is essentially an uncontrolled proliferation of cancerous cells in any part of the body, but a brain tumor is mainly an uncontrolled growth of malignant cells in the brain. Both benign and malignant brain tumors are possible. Whereas benign brain tumors are uniform in structure and lack active cells, malignant brain tumors are variable in structure. While high-grade tumors like glioblastoma and astrocytomas are classified as malignant tumors, low-grade tumors like gliomas and meningiomas are examples of benign tumors. In clinical decision support systems, the segmentation, detection, and extraction of tumour in MR brain images becomes a very time-consuming and crucial operation.

2.1 MEDICAL IMAGE PREPROCESSING

Enhancement is the process of enhancing each pixel's contrast in a poor resolution brain image (Celik et al. 2012). The improvement of image contrast relies heavily on histogram equalization (Gonzalez et al. 2002) because Implementation is simple and clear. The fundamental disadvantage of this approach is that not all portions of the image's contrast can be enhanced. In equalised images, however, over sharpening, noise, and artefacts will appear. The quality and contrast of the photos are improved using several HE-based techniques. Brightness Conserving Bi-Histogram Equalization (BBHE) was first introduced by Kim et al. (1997). By employing the mean intensity or brightness to divide an input image into two sub-images, this technique allows for the independent processing of each sub-image using histogram equalisation. Nevertheless, the brightness of the input and output photographs cannot be exactly matched by this method. The Contrast Limited Adaptive Histogram Equalization (CLAHE) method was introduced by Pizer et al. in 1990. To minimise error, the local histogram mapping function is used.

2.2 MEDICAL IMAGE SEGMENTATION

Automated analysis begins with segmentation, which separates structures of interest from background tissue and requires a large commitment (Aparna 2012). In algorithm development, this separation, which is typically simple and quick for the human visual system, can provide significant difficulties. Since measurements and other processing steps are based on segmented regions, the segmentation approach frequently determines the outcome of the entire analysis. Using techniques like thresholding, region expanding, deformable templates, and pattern recognition methods like neural networks, fuzzy clustering, machine learning, and deep learning, segmentation algorithms act on the intensity or texture variations of the image (Hamamci et al. 2012).The primary goal of this research is to identify brain tumors in MR images.

2.3 MACHINE LEARNING ALGORITHMS FOR BRAIN TUMOR SEGMENTATION

Using an ensemble method, Cabria et al. (2017) have introduced a new algorithm for segmenting MR brain tumors. The potential field for the MRI pixels was derived using a clustering method. The determined pixel is a tumor zone if the calculated pixel was smaller than the adaptive potential threshold. For the purpose of identifying aberrant objects in brain MRI images, Vidya Dhanve et al. (2017) adopted the labelling method. The segmented regions of the segmented pictures were classed as either normal or abnormal based on the calculated labelling on the image regions by the authors using the k-means segmentation algorithm. For real-time oncology detection in clinical settings, the labelling counts for various aberrant locations were high and required a lot of computational effort.

An unsupervised machine learning approach was used by Rundo et al. (2018) to extract necrosis in MR brain tumor picture. The extraction of the necrosis in the MR brain picture is greatly aided by the segmentation of the gross tumor volume. The CANFIS classification algorithm was employed by Jasmine Hephzipah Johnpeter et al. (2019) to locate and locate malignancies in brain MRI data. Using the histogram equalisation method, the tumour regions are boosted without the detection of edges in brain pictures. When this proposed method was used on brain pictures from an open access dataset, it achieved sensitivity of approximately 96.5%, specificity of about 97.7%, segmentation accuracy of about 98.8%, and DCI parameter of around 96.1%.

2.4 DEEP LEARNING ALGORITHM FOR BRAIN TUMOR SEGMENTATION

The brain tumor segmentation method was created by Dong et al. (2017) using the deep convolutional network via U-Net. The proposed technique is tested using multimodal datasets of brain tumor images. This method can produce outcomes that are nearly comparable for the entire tumor, and better for the primary tumor sites. A unique method for locating and segmenting aberrant tissue connected to brain fluid was developed by Soltaninejad et al. (2017). Their plan of attack relied on the super pixel system. The support vector machine (SVM) was used to build an extremely classed randomised tree that divided each super pixel into tumour and non-tumor categories. A deep learning-based brain tumor segmentation method was proposed by Mamta Mittal et al. in 2019. To segment the brain tumor, our technique uses a developing CNN and a stationary wavelet transform. A deep CNN (DCNN) approach-based glioma brain tumour detection method was put forth by Saddam Hussain et al. (2018). MR brain images are normalised and corrected for bias during the pre-processing stage, after which the extracted patches are sent into the DCNN. The morphological procedure segments the region of interest using the DCNN output. To segregate the tumour in MR brain images, Shubhangi Nema et al. (2020) used a RescueNet-based deep learning technique. The fundamental areas of the brain pictures are improved through RescueNet-based training. A CNN model based on a dilated convolutional feature pyramid was proposed by Wang et al. in 2021 for segmenting the brain tumour in multimodal MR brain tumour images. This model's dilated feature pyramid is employed to increase the neural network's effectiveness for better classification.

3 DEEP CNN AND MKKMC LEARNING MODEL

The two main elements of the technique being explained are segmentation and classification. In the classification step, the input photographs are classified as normal or abnormal, and in the segmentation phase, the afflicted region is split separately. Pre-processing is done first to the provided photographs. After pre-processing, the output of our suggested method is given to the classifier convolution neural network. In this case, the input image is classified as either normal or abnormal. The second element of the system we are describing is segmentation. The abnormal regions of MR images are separated using a multi-kernel k-means clustering (MKKMC) method. The suggested CNN-MKKMC method has the following phases, which are illustrated below: segmentation based on MKKKC and classification based on CNN pre-processing.

3.1 Pre-processing

The input MR pictures of the brain are improved during pre-processing. Image enhancement is a process used to increase or improve contrast ratio, brightness, reduce noise from images, and make it simpler to recognise anomalous parts efficiently. The contrast of a poor contrast brain MR image is enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE) pre-processing algorithm.

3.2 Classification using CNN

The suggested technique makes use of a three-layer Convolutional Neural Network (CNN) that can recognise and classify images into one of the two specified classes. The convolution layer, the subsampling layer, and the output layer are the three layers that make up this network. A*a*c, where a stands for the picture's length and width and c for the number of channels, is the input format for the convolutional layer. The convolutional layer will have filters of size b*b*c in cases where "b" is less than the size of the picture. Convolution is computed using the filter on a portion of the image that fits the filter's size. The output, which consists only of single numbers, is given a bias. Convolution is achieved in this scenario by multiplying a component of the image with a b*b*c-sized filter in a matrix. All of these outputs are combined to produce a feature or activation map.

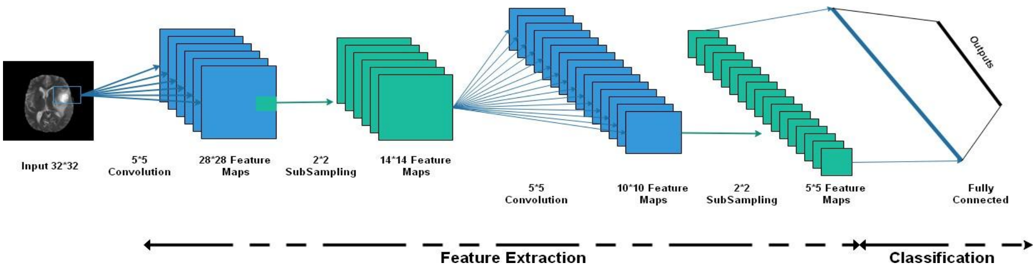

Figure 3.1: Architecture of the proposed convolutional neural network

Each convolution results in a reduced image size. The proposed architecture uses 32 maps in the first convolutional layer, producing good accuracy at a cheaper cost. Using deep convolution layers with many units allows for a small increase in precision with a small increase in processing cost.

3.3 Segmentation using MKKMC

The suggested method uses a clustering algorithm after classification to separate the tumour section from the aberrant image. MKKMC, or multi-kernel K means clustering, is the segmentation process algorithm. Here, a multiple kernel learning technique is added to the conventional k-means clustering algorithm. The multi-kernel technique used by the proposed method uses two hybrid linear and quadratic kernels. New hybridized kernel functions are used in hybrid work, and the segmentation process is carried out using these hybridized kernel functions.

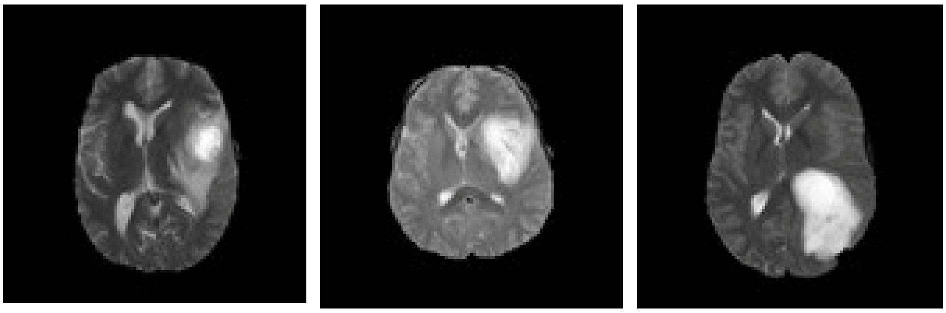

Figure3.2: Sample test MR brain tumor images

3.4 Evaluation Metrics

The effectiveness of the suggested CNN-MKKMC approach is evaluated using parameters such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), coupled with the selection of pixel differences. The efficacy of this strategy is assessed using the False Positive Rate (FPR), False Negative Rate (FNR), and Sensitivity, Specificity, and Accuracy metrics. Moreover, distance-based metrics like Hausdorff Distance (HD), Local Distance (LD), and Global Distance (GD) are taken into account by looking at the ground truth images in order to judge how well the suggested technique segments tumours. Evaluation metric result is defined in table 3.1 and 3.2.Graphical representation for objective measures of the proposed method in figure 3.3 and 3.4.

Table 3.1: Evaluation metric results for the proposed CNN-MKKMC

Measures/ Images	PPV	NPV	FPR	FNR	Sensitivity	Specificity	Accuracy
MRI 1	0.602	0.997	0.0182	0.0386	0.9613	0.9818	0.9812
MRI 2	0.875	0.998	0.0067	0.0047	0.9954	0.9932	0.9933
MRI 3	0.889	0.995	0.0057	0.1128	0.8873	0.9944	0.9892
MRI 4	0.965	0.9968	0.0015	0.0696	0.9305	0.9986	0.9953
MRI 5	0.798	0.9973	0.0064	0.0962	0.9037	0.9937	0.9912

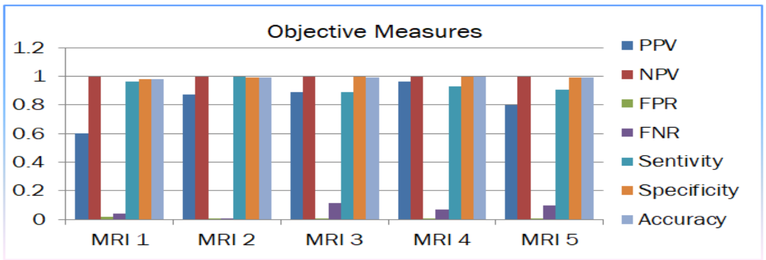

Figure3.3: Graphical representation for objective measures of the proposed method

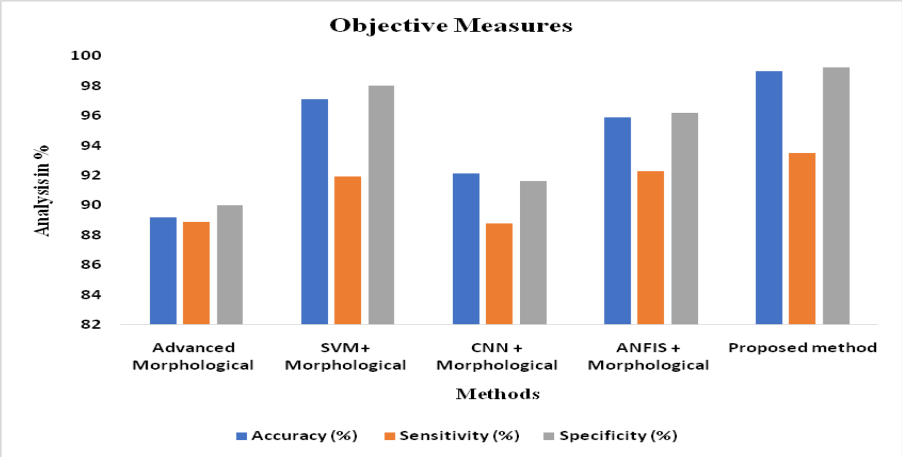

Figure 3.4: Comparative plot for different objective measures of various segmentation methods

Table 3.2: Experiment Results of various segmentation methods.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Advanced Morphological	89.20	88.9	90
SVM+ Morphological	97.1	91.9	98
CNN + Morphological	92.1	88.8	91.6
ANFIS + Morphological	95.9	92.3	96.2
Proposed method	**99**	**93.5**	**99.22**

4. CONCLUSION

The study makes recommendations for segmenting and identifying brain tumors. Performance measures used to evaluate our proposed technique include PPV, NPV, FPR, FNR, Sensitivity, Specificity, and accuracy. The segmentation and tumor identification technology achieves the highest levels of sensitivity, specificity, and accuracy when compared to the present approach.To evaluates the effectiveness of the proposed strategy (CNN+MKKMC) versus the existing technique (CNN+KC). Our suggested method has sensitivity, specificity, and accuracy for brain MR images that are 0.93, 0.99, and 0.99, respectively, when compared to other existing methods. The experimental results make it evident that the provided method outperforms other methods in terms of performance.

5. FUTURE WORK

The suggested method can be improved in recent studies to include epilepsy detection. The proposed technology mentioned in this research will be used in the future to detect and diagnose brain cancers utilizing thermal brain imaging. Additionally, the new U-Net approach can be expanded to introduce existing brain cancers including glioblastoma and glioma.

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