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Brain MR Image Classification for Glioma Tumor detection using Deep Convolutional Neural Network Features

Ghazanfar Latif [a, b*], D.N.F. Awang Iskandar [a], Jaafar Alghazo [b], M. Mohsin Butt [c]

[a] *Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak, Malaysia.*
[b] *College of Computer Engineering and Sciences, Prince Mohammad bin Fahd University, Khobar, Saudi Arabia.*
[c] *College of Applied and Supporting Studies, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.*
Email: glatif@pmu.edu.sa, dnfaiz@unimas.my, jghazo@pmu.edu.sa, mohsinbutt@kfupm.edu.sa
*Corresponding Author *: Ghazanfar Latif, Deanship of Research, Prince Mohammad bin Fahd University, Al-Khobar, 31952, Saudi Arabia, Tel: +966-501057422, Email: glatif@pmu.edu.sa*

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Abstract:

Background: Detection of brain tumor is a complicated task which requires specialized skills and interpretation techniques. Accurate brain tumor classification and segmentation from MR images provide an essential choice for medical treatments. The different objects within an MR image have similar size, shape, and density which makes the tumor classification and segmentation even more complex.

Objective: Classification of the brain MR images into tumorous and non-tumorous using deep features and different classifiers to get higher accuracy.

Method: In this study, a novel four-step process is proposed; pre-processing for image enhancement and compression, feature extraction using convolutional neural networks (CNN), classification using the multilayer perceptron and finally, tumor segmentation using enhanced fuzzy c-means method.

Results: The system is tested on 65 cases in four modalities consisting of 40,300 MR Images obtained from the BRATS-2015 dataset. These include images of 26 Low-Grade Glioma (LGG) tumor cases and 39 High-Grade Glioma (HGG) tumor cases. The proposed CNN features-based classification technique outperforms the existing methods by achieving an average accuracy of 98.77% and a noticeable improvement in the segmentation results are measured.

Conclusion: The proposed method for brain MR image classification to detect Glioma Tumor detection can be adopted as it gives better results with high accuracies.

Keywords: Tumor Detection, MR Image Classification, CNN Features, Glioma Tumor, Tumor Segmentation, Brain MRI.

1. INTRODUCTION

A tumor inside the brain is formed due to a collection of abnormal cells. Brain tumor can be classified into noncancerous (benign) and cancerous (malignant) brain tumor [1]. The glial cells encircling the neurons are the primary cause of brain tumor. Oligodendrocytes, astrocytes, and ependymal cells are the three types of glial cells that are responsible for tumor growth [2].

Identification of brain tumor is a complicated task which requires specialized skills and interpretation techniques to pinpoint the location of the tumor. Capturing the internal structure of the brain in high resolution with all features is of the utmost importance in this process. MRI machine use powerful magnets, radio waves, and computing machines to capture a detailed image of the internal brain structure [3]. The MRI scans provide better picture details, contrast and brightness compared to other methods due to the tissue relaxation properties (T1 and T2) and are preferred by doctors for diagnosis [4]. Manual diagnosis of brain tumor is still a slow and lengthy process. The MRI machine can produce different types of scans (T1, T2, T1c, and flair) based on the contrast and brightness value, repetition time, and time to echo [5]. The captured MR Images are also used for automatic tumor diagnosis and classification using image processing techniques.

Machine learning systems are being integrated into various aspect of modern life. They can be used to identify different objects from input images, convert speech to text, matching posts and searches according to user relevance, etc. [6]. Machine-learning techniques can be categorized into supervised and unsupervised learning. In supervised learning,

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a training data set is utilized for the learning of the internal parameters. The internal parameters are adjusted to minimize an objective function. The objective function calculates the error between the preferred and the observed output from the machine. Conventional machine learning methods require careful expertise and engineering design to adjust the internal parameters for a suitable feature extraction from which a classifier can detect or classify image patterns. However, an alternative is to use the deep learning based methods. The feature extraction in deep learning can be done by the machine that extracts the patterns with high appearance frequency.

Deep learning uses backpropagation algorithm to learn the data representation in multiple abstraction layers. The raw input is transformed using non-linear module into a high-level representation at each level. The function used most frequently in Neural Networks design is the Rectified Linear Unit (ReLU) [7]. Gradient vector of an objective function is calculated along with non-linear weights of the multilayer stack using backpropagation algorithm.

Convolutional Neural Networks (CNN) can process various image and signal data using multi-dimensional arrays [8]. Two layers make up the first few stages of CNN namely the convolutional layer and the pooling layer. Units of the convolutional layer makeup what is referred as feature maps. The feature maps units of one layer is linked to the feature map unit of the previous layer through filter banks. Filter banks can be considered as weights connecting these feature maps units in consecutive layers. Local weighted sums are passed through non-linear functions such as ReLU with the result passed to the next layer. The pooling is then used to combine similar features. The unit in this layer calculates the maximum within a feature map. Neighboring pooling units use the shifts in rows and columns to reduce the dimension of the design which helps in creating invariance to distortions and changes. Multiple convolution and pooling layers are stacked to form the CNN and backpropagation gradients are calculated to train the filter banks. The computation complexity of these CNN requires high processing power. However, if the input is compressed to contain only the relevant information, the time to calculate the weights of the filter banks can be reduced. All these various computer aided methods are intended to assist medical doctors and radiologists in the diagnosis based on MR images and various imaging technologies which is usually a time consuming and expensive task when done manually. In addition, it is susceptible human error, however, when it is automated human error becomes an irrelevant factor in the diagnosis process.

In this paper, the input MR images are enhanced in the preprocessing stage and features are extracted using CNN. Multilayer perceptron is used to classify the tumorous and non-tumorous images and results are compared with other classifiers. The proposed methods provide better performance when evaluated on the BraTS 2015 databases [9]. This research study is organized as follows; in section 2 current studies related to brain MRI classification are presented. In section 3, the proposed architecture is presented. Experimental results is presented in section 4. Section 5 presents the discussion related to the results obtained and section 6 concludes the paper.

2. RECENT STUDIES

MR Image classification and segmentation plays a significant part in identifying the location, size and shape of the tumor which can assist radiologists in brain tumor diagnosis [10]. Computer Aided Design (CAD) is utilized in evaluating the malignancy of the diffused gliomas in [11]. The image is converted into grayscale, and the similarities between nearby pixels are assessed based on histogram moment and textual image features. Prediction of the tumor is achieved using a logistic regression model, and the system comparison is made using the global features of the MRI scans. The system provides a better classification of the glioblastomas compared to low-grade gliomas.

The authors in [12] used machine learning methods to perform brain tumor segmentation and increase the intensity features of the image using a semi-automatic method that incorporates the spatial features of the image into consideration. It uses minimum user interaction to segment the brain tumor by training and generalization within the brain images. The method is tested by using the MIICCAI-BraTS 2013 dataset and achieved 86% accuracy for core tumor.

Deep learning methods are gaining popularity in many fields of computer vision specifically image processing and speech analysis [13]. A Deep learning method CNN and Deep Belief Networks (DBN) is used in [14-15] for handwritten recognition and Synthetic Aperture Radar (SAR) image classification respectively. Decision forests classifier based brain tumor tissues identification using context-aware spatial features is presented in [16]. The results calculated achieved average 85.33% accuracy for gross tumor.

The effect of CNN depth on the accuracy for large-scale image recognition is analyzed in [17]. The authors show significance improvements using 3×3 convolution layers with 16-19 weight layers. The ReLU function is used for the non-linear analysis. The work secured top accolades in the classification of ImageNet Large-Scale Visual Recognition Challenge in 2014. Besides this, deep learning methodologies also have been used for various character recognition systems in the recent years [18][19].

Deep Neural Networks (DNN) for classification of low and high-grade tumor in MRI scans is used in [20]. The authors present a two-path architecture that takes into account the local features and the global contextual features at the same time. The local features are modelled using two CNN and training is performed in two phases which help in providing better network efficiency and performance. The authors indicate that the time needed to segment the whole brain using their proposed architectures varies from 25 seconds to three minutes. The system outperforms most current methods in accuracy and speed based on BraTS 2013 data set. Automatic brain tumor segmentation using CNN is proposed in [21]. The authors use small 3 x 3 kernels to a deep network having fewer weights. Image intensity is normalized at the start which enhances the accuracy of the system.

Kernel weights are adopted using backpropagation algorithm and are shared between all the units inside a feature map. Due to this method, the system is less prone to overfitting because the convolution layers have fewer weights to train. The authors use leaky rectifier linear unit (LReLU) [22] as the function that creates a small slope in the negative region of the original ReLU function that avoids the gradient overflow.

In [23], the authors present a cross section study of tumors utilizing biomedical image modalities. Magnetic Resonance image (MRI) modalities are chosen among the rest for their study. The image processing technique presented in the paper detects solid cum cystic tumors from MR images. The paper presents the importance of image processing in automating the tumor detection process. In [24], the authors present various feature based machine learning methods for detecting brain tumors from MR images. Features such as Scale Invariant Feature Transform (SIFT), texture, entropy based, Elliptic Fourier Descriptors (EFDs), and morphological are extracted from MR brain images. Support Vector Machines (SVM) with kernels, Radial Base Function (RBF), Polynomial, Decision Tree (DT), Gaussian, and Naïve Bayes were used for detecting the tumor. Jack-knife 10-fold cross validation was used for testing and validation of the database. Naïve Bayes achieved the highest detection accuracy based on morphological, entropy, texture, and SIFT features. In [25], the authors proposed a novel automatic detection and recognition for skin lesion using deep convolutional neural networks (DCNN). The method is tested using the ISIC 2017 and PH2 datasets. 95.1% is achieved on the ISBI dataset, 94.8% on the ISBI 2017 dataset and 98.4% on the PH2 dataset. In [26], the authors propose an enhanced algorithm for glioma MR image classification utilizing hybrid statistical and wavelet features. 52 features were extracted using 1st and 2nd order statistical features in addition to discrete wavelet transform (DWT) giving 152 features in total. Multilayer perceptron (MLP) classifier is then applied using the MICCAI BraTS 2015 dataset and an accuracy of 96.72% was obtained for high grade glioma and 96.04% accuracy for low grade glioma. In [27], the authors propose to improve the automatic classification and segmentation of brain MR image utilizing phase congruency. They remove the skull portion from the image using converging square and phase congruency based edge detection and then they extract features from the segmented part of the brain used DWT. Principle component analysis is applied to reduce extracted features. 99.43% classification accuracy was achieved. In [28], the authors proposed the use of CNN for the classification of Alzheimer's disease (AD), normal Control (NC) and mild cognitive impairment (MCI) individuals based on MR images of the brain in the hippocampus region. The method achieved an accuracy of 92.3% for AD/NC, 78.1% for MCI/NC and 85.6% for AD/MCI. The proposed method showed that using only a small part of the hippocampus image can produce reasonable classification results. In [29], the authors propose a fuzzy membership function for the classification and automatic diagnosis of liver cancer from low contract CT scan images. Images are enhanced using fuzzy linguistic constant (FLC). They achieved a 98.3% classification accuracy using SVM. In [30], the authors propose a brain tumor classification method based on MR images. Wavelet features are extracted from the images and random forest classifier is used to classify the images to benign and malignant. 94.33% classification accuracy is achieved in this case. Then the region growing image segmentation is performed to extract the tumorous portion of the image. Further wavelet features are extracted from the portion that was segmented and classification is done to determine the tumor type. 96.08% classification accuracy is achieved for tumor type classification. In [31], the authors present a review study of automatic methods for segmentation of meniscal structures from the knee joints based on MR images to detect tears. They analyze the methods and results obtained from the various method along with the advantages and disadvantages of each method.

3. ROPOSED METHODOLOGY

3.1. Preprocessing

The Pre-processing phase is essential for the end quality of the medical MR images. Image denoising and compression is performed on the MR images by maintaining special features in the images.

Although, with the advent of high-tech imaging technologies, still noise and spackles are an issue in the medical imaging modalities. The noise is removed from MR images by performing image registration and using anisotropic diffusion filter [32]. It reduces noise and increases the homogeneity in image regions by preserving the edges. A diffusion based Non-Linear anisotropic filter is exerted on the input image to improve the edges and make the image smooth [33]. A diffusion function is also applied on the image to decrease the gradient monotonically. Every pixel in the image is updated based on the surrounding four pixels.

Anisotropic diffusion process is formulated in [34]. The authors strengthen the process by inhabiting integration smoothing.

$$\frac{\partial}{\partial t} I\left(a', i\right) = \nabla\left(c\left(a', i\right) \nabla I\left(a', i\right)\right) \qquad (1)$$

Where $I\ (a', t)$ is the brain image and a' stands for the image axes, i describes the number of iterations and $c\ (a', i)$ represents the diffusion function which is shown in Equation 2.

$$c\,(a', i) = \exp\left(-\left(\frac{\nabla I\,(a, i)}{\sqrt{2}\,K}\right)^2\right) \qquad (2)$$

Where K represents the diffusion constant, whose value affects the filter's behaviour and further improve the results. CNN usually handle noises in images very well but for segmentation of images, noise reduction is an important step. Fig. 1 shows the input image and pre-processed diffused image.

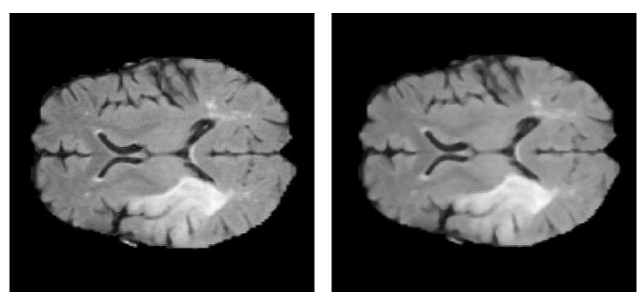

Figure 1. Sample of input MR Image (left) and pre-processed MR Image (right)

3.2. CNN Architecture for Feature Extraction

Deep Learning uses Convolutional Neural Networks (CNN) in order to extract features of images automatically outperforming other feature extraction methods. The key element is filters that slide over the input images producing a feature map. The type of filter used affects the types of feature maps produced. The number of filters also affects the number of image features which in turn affects the recognition process. Parameters controlling the size of the feature map include depth (number of filters), Stride (number of pixels the filter covers) and zero padding (Bordering the image with zeros).

Data is the real world is non-linear and thus it is imperative to introduce data as such. Therefore, the ReLU function is used as non-linear operation. ReLU replaces all negative pixel values by zero and thus has to be implemented on each pixel of the image. The resulting feature map is called the rectified feature map [35].

A normalization layer is needed to speed the training process and minimize the sensitivity to network initialization. The mechanics of the normalization layer involves subtracting the mini-batch mean and dividing the result by the standard deviation of the mini-batch. This is followed by shifting the input by a learnable offset β and then scaling it by a factor γ. For input of mini batch $B = \{x_{1,\ldots\ldots,m}\}$ with parameters, β and γ which produce output layer $\{y_i = BN_{\gamma,\beta}(x_i)\}$ based on Equation 3-6.

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \tag{3}$$

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2 \tag{4}$$

$$x_i' = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{5}$$

$$y_i \leftarrow \gamma x_i' + \beta \equiv BN_{\gamma,\beta}(x_i) \tag{6}$$

Computation complexity and special dimensions are reduced using a pooling layer. The layer also takes care of the overfitting problem. Different pooling functions can be used in this layer with max pooling being the most used. Commonly the pooling layer with filter size of 2x2 is used.

Every neuron in consecutive layers are connected in what is referred to as a Fully Connected Layer (FCL). Softmax activation functions is used with FCL for classification of the features of the input image based on the training dataset. The FCL has an added benefit of learning non-linear combinations of the extracted features.

In this paper, 17 layer CNN architecture is used for MR Image feature extraction. The Layers of the proposed CNN is organized in Table 1. The first layers of the CNN capture primitive features which are combined in later layers to form high level image features that are more appropriate for the recognition phase that will follow. FCL extracts the final 4096 features to be used for the recognition process [8].

3.3. Classification

Extracted CNN Features are tested using different well-known classifiers like Support Vector Machines (SVM), K Nearest Neighbors (KNN) and Multilayer Perceptron (MLP). Based on the experimental results, MLP outperformed so it has been chosen as standard classifier in the purposed methodology.

MLP is the most basic type of Deep Learning architecture in which each element of a hidden layer of the network is connected to the elements of the next layer. This type network is widely used in image denoising and classification. In brain MR images, tumorous and non-tumorous data is not linearly separable. In this supervised learning, all the nodes in the hidden layers act as neurons having a nonlinear activation function. In MLP network, the matrices W encodes the conversion from one layer of the network to another using matrix multiplication. If you have m neurons in one layer connected to n neurons in the next layer, then the transformation matrix can map an input X to an output Y according to the following Equation 7.

$$Y = X^T W \quad (W \epsilon R^{m*n}, X \epsilon R^{m*1}, Y \epsilon R^{1*n}) \tag{7}$$

Each column in the transformation matrix W converts the edges moving from one layer to next. The major problem, however, with MLP is that the deep connection between the hidden layers make this deep learning network difficult to scale. This results in training the MLP a difficult and long process. This, in turns affect the sensitivity of the network if the features of the image that keep changing because the MLP will need to re-learn and training becomes harder.

Table 1. Proposed CNN Architecture for MRI Features Extractions

#	Layer Name	Description
L1	Input MR Image	Pre-processed MR Images of size (240 × 240 × 3)
L2	Convolution	Filters (96, 11 × 11 × 3), Stride Size (4 × 4)
L3	ReLU	ReLU
L4	Normalization	Using 5 channels in each element
L5	Pooling	SoftMax pooling (3 × 3), Stride Size(2 × 2)
L6	Convolution	Filters (256, 5 × 5 × 48), Stride Size (1 × 1), padding(2 × 2)
L7	ReLU	ReLU
L8	Normalization	Using 5 channels in each element
L9	Pooling	SoftMax pooling(3 × 3), Stride Size (2 × 2)
L10	Convolution	Filters (384, 3 × 3 × 256), Stride Size (1 × 1) and zero padding(1 × 1)
L11	ReLU	ReLU
L12	Convolution	Filters (384, 3 × 3 × 192), Stride Size (1 × 1) and zero padding(1 × 1)
L13	ReLU	ReLU
L14	Convolution	Filters (256, 3 × 3 × 192), Stride Size (1 × 1) and zero padding(1 × 1)
L15	ReLU	ReLU
L16	Pooling	SoftMax Pooling(3 × 3), Stride Size (2 × 2)
L17	FCL	Fully Connected Layer with 4096 Features

3.4. Experimental Data

MICCAI BraTS 2015 MRI dataset which contains Low Grade Glioma (LGG) tumor and High Grade Glioma (HGG) tumor [9] was used to obtain the experimental results of the proposed architecture. The dataset contains training samples with annotated data and testing cases without annotated data. Each sample case contains T1, Flair, T1c and T2 weighted sequence types of MR images, and each sequence type has 155 scans.

The proposed architecture was tested using 26 LGG tumor cases and 39 HGG tumor cases with a total 40,300 MR images of all MRI sequence types as shown in Table II. In LGG, each sequence type has 1,684 tumorous MR images and 2,346 non-tumorous MR images. For HGG, each sequence type has 2,594 tumorous and 3,451 non-tumorous MR images. Each MR image has pixel size of 240×240 with 1 to 6 mm slice thickness.

In this particular study, out of the total 40,300 MR images, 80% was employed for training of which 20% was used for validation and 80% training. The rest of the 20% of the total images was used for testing.

Table 2. Summary of used BraTS Dataset

	HGG	LGG	Total
Number of Patients MRI Data	39 Patients	26 Patients	65 Patients
Number of MRI Modalities	4	4	4
Total MR Images	24,180	16,120	4,0300
Tumorous MR Images for each Modality	2,594	1,684	4,278
Non-tumorous MR Images for each Modality	3,451	2,346	5,797

The three channels used for the input of the MR image are only replicated channels of the single channel of MR image.

4. RESULTS

The proposed architecture was tested on the BRATS-2015 dataset. As shown in Table 2 the average accuracy, using CNN features and MLP classifier on four different modalities of MR images for the recognition of LGG was 98.42% which is comparatively better than the SVM and KNN classifiers. The average accuracy for the recognition of the HGG was 98.59% using MLP classifier with the CNN feature set. Fig. 2 shows the classification accuracy rates of tumorous and non-tumorous MR images for the selected classifiers against each MRI modality. The average MLP based accuracy for the Flair MR Images was 98.89%, T1 was 98.49%, T1c was 98.19%, and finally for T2 was 98.79%.

Table 3. Comparison of Brain MRI Classification Accuracies for LGG and HGG Glioma Tumor for different modalities with different CNN Feature based Classifiers

Glioma Tumor Type	Imaging Modality	Classifier Type		
		SVM	KNN	MLP
HGG	Flair	95.09%	98.75%	98.89%
	T1	89.70%	98.27%	98.49%
	T1c	84.78%	97.50%	98.19%
	T2	89.79%	97.40%	98.79%
	HGG Average	89.84%	97.98%	98.59%
LGG	Flair	87.69%	98.22%	98.52%
	T1	91.99%	97.77%	98.66%
	T1c	90.51%	97.48%	98.65%
	T2	90.81%	98.37%	97.84%
	LGG Average	90.25%	97.96%	98.42%
Overall Average		90.04%	97.96%	98.50%

The use of Deep learning architecture as feature extraction for brain tumor classification is a new concept and as previously mentioned in the introduction. The feature extraction is an automated process in deep learning that is based on the defined layers.

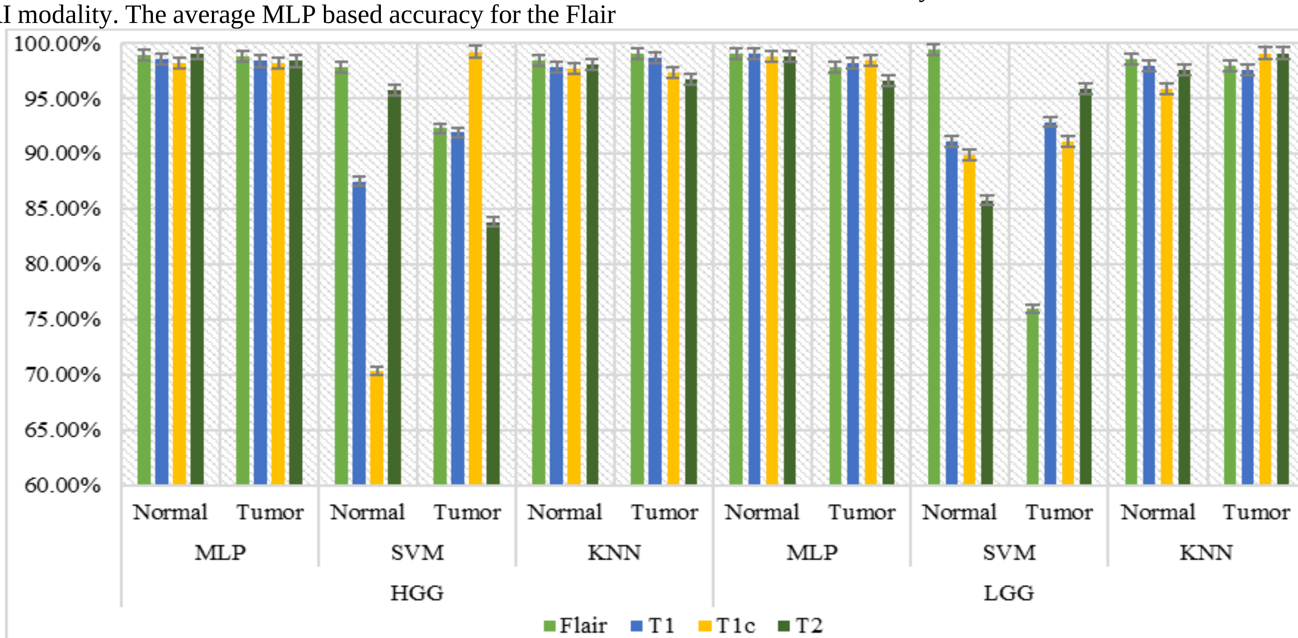

Figure 2. Accuracy comparison for correctly classified tumorous and non-tumorous images for corresponding LGG and HGG Glioma Tumor types with different classifiers with ±0.5% error margins.

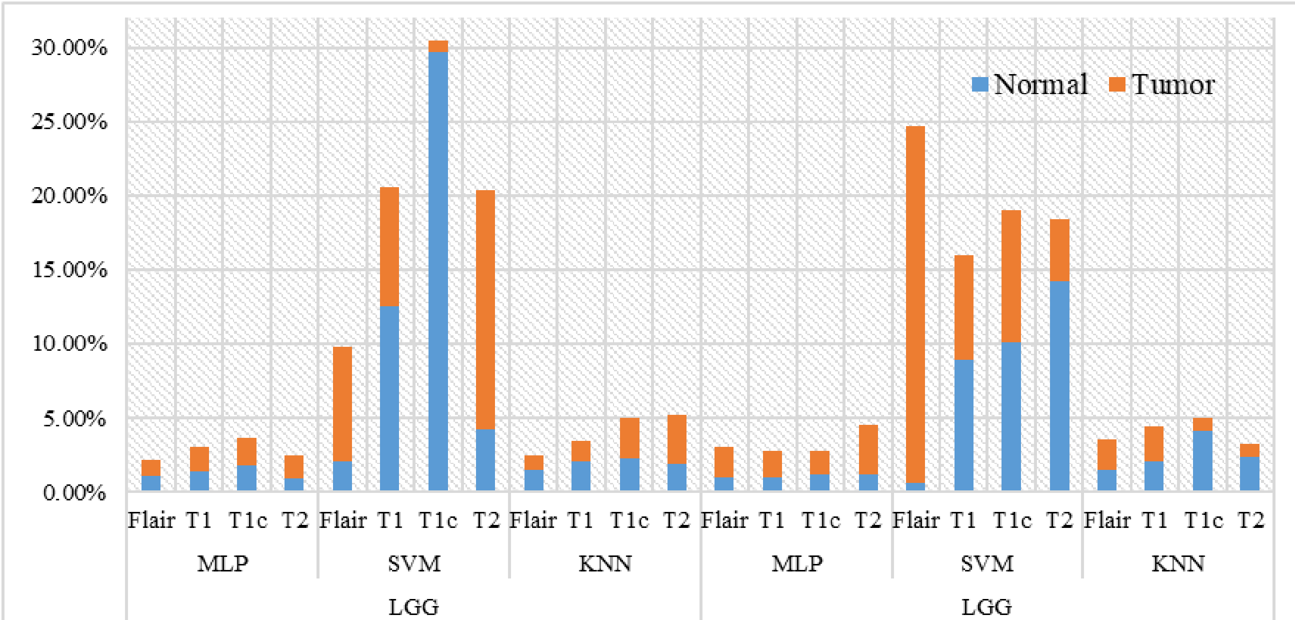

Figure 3. Comparison of error rates for tumorous and non-tumorous image classification for LGG and HGG Glioma Tumor using different classifiers.

Fig. 3 shows the error rate for the tumorous and non-tumorous image classifications for LGG and HGG Glioma tumor against selected classifiers. As shown, the average error rate is very low 2.175% for tumorous LGG and 1.1% for non-tumorous LGG using MLP classifiers with the CNN Features set. Similarly, the error rate is 1.555% for tumorous HGG and 1.3% for non-tumorous HGG with the MLP which is better in comparison with SVM and KNN classifiers.

5. DISCUSSION

The results reported in this work indicate that the proposed technique outperforms similar methods reported in previous literature. The reason for this improvement in results is the use of the deep CNN architecture which has been proven to achieve better results than the feature based Artificial Neural Networks (ANNs). In addition, the architecture was carefully designed with number of hidden layers and coefficients taking into account the balance between performance and accuracy. Many of the already proven concepts regarding Deep CNN were taken into consideration in designing the Deep CNN architecture proposed in this paper including but not limited to number of hidden layers and its impact on accuracy and computational time.

There are various limitation that apply to this study and various similar studies that explore the automatic detection of cancer using imaging technologies. One limitation is that different methods are being applied to different datasets. The research community have not reached a consensus in order to regulate the datasets for research purposes and thus would show clearly the improvements in proposed methods. Interpretability of AI in medical applications is a limitation for studies such the one proposed in this paper. Lack of government regulation, lack of accountability laws for AI systems, and lack of clinical trials are all considered limitation to the AI based medical research. In particular, the state of the art computing equipment can be considered a limitation as more computing power would allow faster performance and faster yield of results.

Overall, the proposed Deep CNN architecture proposed and developed in this paper showed excellent results for the binary classification of Glioma Tumor using MR images.

6. CONCLUSION

Brain tumor is one of the fatal and painful diseases. It can lead to the cause of death if not diagnosed in its early stages. In this article, a new deep learning architecture is proposed for feature extraction which classifies brain MR images into tumorous and non-tumorous images. Deep learning-based features are used for producing accuracy level superior to other techniques on the same database. Experiments are performed by using 56 cases of HGG and LGG Glioma tumor with total 34,720 MR Images. The result shows that an average accuracy of 98.42% and 98.59% was achieved for LGG and HGG classification respectively. It is the intention of the authors to continue the focus in future works to further improve the segmentation of tumor part from the MR images.

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