Comparative analysis of glioma tumor in brain using machine learning and deep learning techniques

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Abstract. Brain tumour is one of the major causes of the increasing mortality rate. There is an emerging need for precise diagnosis from the pathology, as human prediction is prone to errors. Brain pathology is captured using Magnetic Resonance Imaging (MRI) which gives high quality images of the blood vessels. These MRI images can be used to extract features and predict the tumor. The extracted features can be classified using Machine learning (ML) algorithms. In this advanced and emerging deep learning era, images can be fed directly to the prediction system and the system itself extracts features at higher level of abstraction and classifies the images. This article presents a comparative analysis for classifying the MRI images of Glioma (a type of brain tumor) and healthy brain using convolutional neural networks (CNN) and ML algorithms like support vector machines (SVM), random forests, and bagging. CNN and the ML algorithms were implemented on BRATS 2013 challenge dataset and it is found that CNN has achieved highest accuracy of 95%.

1. Introduction
As per the survey quoted in [1], “Brain tumor pathology is one of the mortality issues in the medical field where the evaluation rate is 25 per 1,00,000 grownups in which 33% of the tumors are yet to be confirmed as benign or border-line malignant.” Any tumor is like a swelling and it is connected with a neoplasm caused by cell multiplication. Risk factors of tumor are dimension of tumor, tumor type, position, and mode of tumor. Glioma is the most widely occurring brain tumor for the people above the age group of 50. It originates from glial cells and it has four grades of classification: Grade I and II are called poor quality glioma tumors; Grade III & IV are high grade gliomas [2]. Nowadays, many imaging modalities are developed for examining the human body. These modalities are ultrasonography, Magneto Encephalon Graphy (MEG), X-ray imaging, computer tomography (CT), Positron Emission Tomography (PET), Electroencephalogram (EEG), Magnetic Resonance Imaging (MRI), etc. MRI is used to capture the images of tumor for diagnosis [3]. With the MRI images, internal structures of the human body can be examined. MRI procedure includes, T1 weighted MRI, T1c, and T2flair. Weighted T1c (contrast enhancement) images will provide images with clear
descriptions of the brain vessels, necrotic, and active tumor regions. Edema area around the tumor is visible clearly in T2 weighted MRI images. T2flair images helps to isolate the edema and cerebrospinal fluid. To extract the tumor area, brain images of T1, T1c, T2, and T2Flair are used as multi-quality MRI images. Axial, sagittal, and coronal planes of MRI are shown in figure 1.

![MRI Planes](image)

(a) Axial plane  (b) Sagittal plane  (c) coronal plane

Figure 1. Planes of brain MRI.

2. Related work

Few significant contributions in the field of brain tumor segmentation and classification are listed in this section. Liu et al. survey of brain tumor segmentation techniques was proposed [6]. Different types of segmentation methods such as a threshold-based method, Region based method, Markov random filed, fuzzy C Means, geometric deformable model. This model has good performance in segmentation, but it has low accuracy and high robustness rate. Huda et al. presented a hybrid feature selection of ensemble classification is applied for brain tumor detection system [7]. Some of the ensemble classifiers are bagging, decision tree, and random forest are used to classify the tumor by constructing multiple classes at training time and outfitting the class label to predict the class label.

Mohsen et al., proposed fuzzy c- means segmentation technique to segment the tumor regions from flair images. Discrete wavelet transform applied to extract the wavelet features of the given image [8]. At the last deep neural network is constructed for classifying the tumor with high precision rate. These techniques are compared with KNN and sequential minimal optimization classification system and the accuracy rate is 90% in the detection of DNN algorithm but high complication and poor performance. Menze et al, in recent days, many classification and segmentation methods used for brain tumor detection have been proposed [9]. Great developments have been made in the field of deep Learning techniques. Pixel classification is one of the main methods in Deep Learning techniques for multi-modality properties (T1, T1c, T2, T2-FLAIR) depicted in figure 2 each voxels divided into supervised, semi-supervised and unsupervised. Most of the unsupervised methods based on clustering concepts by justifying the similarity of pixel classification. Gering et al, MRF (Markov Random Fields) is a class of semi-supervised technique, it could reduce the overlapping problem in the previous model. This method takes a long time for processing and complexity is very high [10].
Fig 1. Typical diagnostic MR scanning modalities: (a) T2Flair (b) T1c (c) T1 (d) T2.

Janani et al. proposed the combination of two different algorithms used to segment the tumor area such algorithm are fully connected conditional random fields and fully connected convolution neural network [11]. Automatic tumor segmentation has been followed some steps such as pre-processing, segmentation, and post processing. During preprocessing, images are pre-processed by subtracting the grayscale value with histogram normalization. In segmentation, FCNN and CRF used to isolate the tumor region. After segmentation, enhance the performance of the result in post-processing. The output of the post processing has five classes such as edema, enhancing core, non-enhancing core, necrosis and healthy tissues. This method primarily used for tumor segmentation, but the computation time is high. Zhao et al. presented multimodal brain tumor segmentation technique to overcome the existing segmentation methods. The different segmentation algorithm is to get good computational speed and performance time than previous techniques. These algorithms are complexity in isolating tumor regions [12].

Menze et al. to predict brain tumor, the author applied Adaboost machine learning approach to magnetic resonance images [13]. This method contained three elements such as preprocessing, feature extraction, classification. Median filter is used to remove noisy data and it’s used to convert RGB to gray-scale images. After segmentation, GLCM is used as learning features. 22 vary features are obtained from GLCM algorithm. On the last stage, AdaBoost is adaptive boosting technique gives 89% accuracy and it could predict result as a malignant tumor or benign tumor. The accuracy of the Adaboost algorithm gives Low accuracy and false statement. Kharat et al. proposed an architecture in which adaptive histogram equalization is applied to improve the image contrast, fuzzy c means segmentation algorithm used to isolate the tumor area from background regions [14]. After segmentation, Gabor filter is applied to extract the features of segmented images. Finally, K Nearest neighbor classification algorithm used to find the normal region and the abnormal region of the brain. This method has high complexity and low accuracy rate.

In the development of Deep learning network, image vision systems can separates two fundamental sorts, such as (1) traditional technique, for example, textons, SIFT, SURF furthermore, Local Binary Pattern (LBP) and the combination of machine learning and (2) Deep learning based systems [15]. In customary methods, Computer-Aided Diagnosis (CAD) and regularized non-negative matrix factorization (NMF) frameworks with calculation techniques like k-means grouping [16]. Furthermore, Principal Component Analysis (PCA) and Support Vector Machines (SVM) are utilized for cerebrum tumor recognition [17]. In this calculation, it is mandatory to hand-tune the highlights speaking to mind tumors, which is a difficult and time-consuming assignment. This dreary hand-create highlight age can be overwhelmed by applying profound learning systems, principally, convolutional neural networks.

Zeng et al. deep learning based procedures are decent prospects for Image division; particularly convolutional neural systems (CNN) are customized for image pattern recognition [18]. Neural
systems gain features frankly from the basic information on a various leveled style, as opposed to the measurement procedures, for example, SVM, which depend available made highlights. Deep neural systems have been effectively connected for medicinal picture investigation undertakings, for example, image segmentation, recovery, and tissue prediction. In medical related state, examination of gold immunochromatographic strips is effectively executed by utilizing the deep belief network. Liu et al., an ongoing review on deep neural system architectures and their function, to restorative picture examination is displayed in [19]. Newly, pixel-based order is picked up prominence and is relied upon to give most extreme precision if each pixel is properly characterized.

One of the supervised image classification techniques is CNN, it used for classifying the labels by grouping similar data into one cluster. Krizhevsky et al., presented a deep neural network system, it extracts more abstract data (other than linear data) [20]. The author developed an image Net pattern, analyze technique tested by deep CNN, which also make improvement in image and segmentation fields.

3. Proposed methodology
In this proposed research work, MRI images of brain tumor are classified using convolutional neural networks (CNN), support vector machines (SVM), and random forests (RF). The workflow of the proposed research work is shown in figure. 3. Each phase in the Figure. 3 is discussed in the following sections:

3.1. Image acquisition
First phase in this research work is to get the input MRI images of Glioma tumor lesions and healthy lesions. Images used in this research work are acquired from BRATS challenge which is a publicly available dataset [21].

3.2. Preprocessing
In this phase, quality of the images are enhanced and to extract the features with precision. The images acquired from the dataset are affected with salt and pepper noise and it is filtered using median filter. It is a non-linear filter that is used to remove the noise and preserve the edges. Median filter with 3 x 3 masks is used in this research work.
3.3. Segmentation
Segmentation is the process of extracting the tumor from the background. Morphological operations like dilation and erosion are used in this research work to segment the tumor. For dilation and erosion, 5 x 5 disk shaped structural element is used. Small connected regions are removed using the erosion process and the tumor region is located using dilation process.

3.4. Feature extraction
Feature extraction is the process of extraction meaningful features from the segmented lesion. In this research work, texture features of the tumor are extracted with gray level co-occurrence matrix (GLCM) [22]. GLCM is constructed for the segmented region and from the matrix features contrast, homogeneity, correlation and entropy are extracted from four directions with the distance of 1.

3.5. Classification
In this research work, the brain tumor lesions are classified using i) SVM, ii) RFs, and iii) CNN. For SVM and RFs, GLCM features are used; for CNN, enhanced brain tumor regions are given as input.

3.5.1. SVM
In the field of speech recognition and audio recognition many supervised learning algorithms have proved to be accurate. Support Vector Machines (SVM) is promising classification algorithm with a wide range of customizable parameters to obtain necessary results. The basic principle of SVMs include choosing samples from various classes that are termed as support vectors and further structuring a linear function to split them accordingly. SVMs are, on a grass root level, a classifier which performs classification tasks through utilizing hyperplanes in multidimensional space. This classifier utilizes parameters to identify decision planes and data planes and compute distance between them to find the most probable class fitting in a hyperplane as shown in figure 4 [23].

In this research work, SVM’s classifies the healthy and tumor lesions with the GLCM features. Hyperplane with maximum are then categorized into normal and abnormal classes.

3.5.2. Random forests
Random Forests [24] aims to shrink the variance of a set of decision trees. It is an expansion over Bootstrap Aggregation (Bagging). From the training sample, data subsets are created by randomly chosen with substitution. To train the decision tree, each subset data is used. Random assortment of features takes place rather than utilizing all features to develop trees. Finally, we come up with an ensemble of various models. Predictions averages from different trees are utilized instead of a single decision tree which is more robust. The following Figure 5 shows the random forest’s pictorial representation.
3.5.3. *Convolution neural network*

Convolutional neural networks are providing convincing results in the field of medicine [25]. It is a multi layered feed forward neural network which processes the input images and learns the pattern from its candidate features of the images. The first layer of CNN is the input layer where the brain tumour images are given as input to the network. Then, the consecutive layers extract edges as the candidate features. In feature map, input images are represented by small blocks by extracting pixel values. Next, feature maps are given as input to the max pooling layer and this layer preserves significant features. Output of the max pooling layer is a vector. Fully connected network combines the output of previous layers for predicting the output. FCN combines the previous layers to predict the output. Architecture of CNN is shown in Figure 6. Before classification process; the MRI images are enhanced using noise removal. Layers of the CNN are explained as follows:

![Figure 6. Architecture of CNN](image)

3.5.3.1. *Convolutional Layer*

Convolutional layer considers the relationship between the pixels and performs convolution operation. This layer uses functional properties like weights and kernels of varying size depending upon size of the image and its complexity. The weight parameter extracts information from the input images and this parameter act like a filter. In the example given below, the input size of the image is initialized as 6 x 6 matrix and the filter size is 3. After applying filter to the 6 x 6 images, it is converted into 4 x 4 images to extract features such as edges, borders of images. Advantages of this layer are:

1) Weight-sharing mechanism help both 2-D and 3-D data, hence it provides high dimensional information.
2) Input topology connectivity has been exploited using various kernels (2D or 3D)
3) Shift invariance is accomplished in pooling layer

\[
\text{Process of convolution is given in equation (1) and}
\text{Input Image} \ast \text{weight} = \text{Convolved Output}
\] (1)

3.5.3.2. Feature Map
Feature maps are obtained by applying conventional filters which can take around region image pixel value in forming accuracy and to predict class labels in the concept of pixel wise classification [22]. Multiple kernels generate multiple maps at every layer. The \( n^{th} \) feature map in the Convolutional layers follows

\[
O_{m}^{n} = f(b_{m}^{n} + \sum W_{m}^{l,n} \ast O_{m-1}^{l})
\] (2)

In this equation, \( f \) represents the nonlinear activation function, \( l^{th} \) represents an input channel, \( W \) represents the weight of the image.

3.5.3.3. Non-linear activation function
After convolutions, ReLu Layers are used to detect the edges and the border of the input images. The Layer applied activation function \( \max(0, A) \) which turns negative values to zeros (by thresholding concepts). ReLu layer avoids the vanishing gradient problem it caused by constant values zero [23] and increasing the training speed. The layer does not change the volume of image and no hyper-parameters.

\[
\text{ReLu}(a) = \begin{cases} 
af & \text{if } a \geq 0 \\
0 & \text{if } a < 0
\end{cases}
\] (3)

3.5.3.4. Pooling layer
Pooling is used to reduce the dimensionality of the image when the image size is huge and it should enhance the image pixels by compressing the data [24]. The primary goal of the pooling layer is to trim down the spatial size of the image. In pooling, the stride is used to boost up the complex prediction process when the sizes of the feature maps are reduced. The layer helps to reduce the computational load for next process. And it’s also overcome the fitting problem. Pooling layer has three sorts of pooling, Max-pooling, Sum pooling and average pooling. The most commonly used and applied layer is max pooling.

3.5.3.5. Fully connected layer
After applied multiple layers and padding, Fully Connected (FC) form fully connected with previous layers. Primarily the principal work of the weight kernel and pooling layer would able to extract features of the input images. In output layer it would connect all layers together to generate the output class. This layer changed the 2-Dimensional features into one-dimensional vector in the form of a binary vector. The output of the layer either predicts tumor or non-tumor (class labels). Fully-connected layer using a soft-max activation function it used to classify the feature vector of the given image into a variety of classes based upon on the training data set.

4. Results and discussions

4.1. System implementation
The proposed work was executed in MATLAB R2018b. In proposed method I, Radial basis function is applied as kernel function. In proposed method II, the networks are trained in the Stochastic
Gradient Decent Momentum (SGDM) optimization techniques with initial parameters. We set each of the parameters as (Maximum Number of iteration: 5, Mini Batch Size: 4, Initial Learning rate: 0.0001, and the verbose Frequency 1) Rectified Linear Unit Activation Function and Batch Normalization Layer has been added after each of the Convolution layers which makes the training progress faster even for a large amount of data. The CNN architecture performs better with these training parameters compared with the other architecture.

4.2. Dataset
The experimental result carried out from BRATS 2013 database, which has three subparts, such as training, leader board and testing. Each patient class divided into four MRI modalities: T1-weighted, T1-weighted with contrast enhancing, T2 weighed and FLAIR images. In this experiment, testing data set and training data set is used to assess the results. There are two categories of data set: HG and LG. 20 HG and 10 LG samples and patient labels are used as the classification process. Brain tumor classified into four divisions, such as necrosis, non-enhancing tumor, enhancing tumor and edema.

4.3. Performance metrics
In these each class, two performance metrics are calculated: accuracy and precision. They are defined as follows:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{5}
\]

where,

- TP represents True Positive; classification result is positive in the presence of malignant
- TN represents True Negative; classification result is negative in being of benign
- FN represents False Negative; classification result is negative in the presence of malignant
- FP represents False Positive, classification result is positive in being of benign

| S.No | Classification Algorithm | Precision |
|------|--------------------------|-----------|
| 1    | SVM                      | 0.85      |
| 2    | RF                       | 0.82      |
| 3    | CNN                      | 0.95      |

4.4. Discussion
The result of the SVM and CNN classifier evaluated using BRATS 2013. The proposed results indicate better performance than existing methods. In table 1 the output value of the future technique (Deep learning network) evaluated with SVM (machine learning). The results of the CNN and SVM
classifiers were compared using BRATS 2013 and it is furnished in table 1. It clearly portrays that the proposed work using CNN is performing better than the proposed work using SVM.

Moreover, proposed work is compared with existing methods and their results are tabulated in table 2. According to the results, in high-grade glioma the planned method present enhanced results in the comparison of Machine learning methods. CNN provides the pixel relationship of input images with training, weight describes the high discriminate information. The layers in the proposed method extract precision feature and local information together. FCN layers provide classification result it depends on feature extraction values and this feature vector will speed up the program to run. The proposed Deep learning network algorithm has yielded significantly better results compared with the machine learning techniques of existing methods.

5. Conclusion
In proposed algorithm 1, SVM has been employed and algorithm 2, CNN has been constructed to classify the class label as a tumor or non-tumor. In algorithm 1, statistical features are calculated by calculating the GLCM after pre-processing and those are fed into SVM to identify tumor and non-tumor classes. It has yielded a precision of 8.5. In proposed algorithm 2, after pre-processed, the input images are passed through CN architecture; it facilitates to predict class labels. Axial, Sagittal and coronal planes play an important role when training the images it could help to recognize the different

| Authors      | Methodology                                     | Accuracy (%) |
|--------------|------------------------------------------------|--------------|
| Huda, S [7]  | Hybrid feature selection of ensemble classifiers| 88           |
| Mohsen, H [8]| Fuzzy C- Means Segmentation                    | 90           |
| Menze, B [9] | Pixel Classification                            | 89           |
| Gering, D [10]| Markov Random Field                        | 91           |
| Janani, V [11]| FCNN and CRF segmentation                  | 91           |
| Zhao, X [12]| Multi-modal segmentation                       | 86           |
| Jakab [13]   | Adaboost classification                        | 89           |
| Kharat, K [14]| K-Nearest Neighbor                           | 90           |
| Minz, A [15]| Feature extraction of Local binary pattern    | 88           |
| Sauwen, N [17]| Support Vector Machine                      | 89           |
| Zeng, N [18]| 2D Convolutional Neural Network               | 92           |
| Krizhevsky [20]| Image Net classification                   | 91           |
patterns. In the optimization stage different parameters tuning are performed for increasing accuracy and precision. It has obtained a precision performance of 9.5. Our experimental results of proposed algorithm using CNN indicate significantly better performance and improved results in detecting tumor region with less time complexity. This study can be extended further by executing this algorithm on different data sets.

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