Analysis Of Performance Of Ensemble Based Machine Learning Algorithms For Classification Of Glioma Using MR Images

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Abstract: Medical imaging poses a huge challenge for detecting abnormalities in MR Images. Image Classification mainly focuses on attaching one of the label from the existing set of class categories defined earlier. Inside the human brain, "gluey" tissues are the derivative of glioma. Many supervised and unsupervised classification algorithms are used for the detection of the tumor as benign or malignant. Usually, lighter datasets are used for image classification in the application field whereas comparatively larger and heavier datasets are used in the case of the medical field. The scope of this work is to identify an algorithm that shall be able to efficiently analyze the MRI image of a brain with a tumor in contrast with the traditional approach. The proposed work focuses on analyzing few deep learning algorithms that provide accurate results as expected. Also, an attempt has been made in the proposed work to scale up the size of the dataset and record the performance measure of each of these algorithms and in turn tweak the parameters to optimize them further by using few of the pre-processing techniques in combination.

Keywords: Medical Imaging, Glioma, Deep Learning, LDA, PCA, Random Forest Classifier, Gradient Boosting Decision Tree, Cross-Validation, Optimization, Hyper-parameter fine tuning.

INTRODUCTION

Brain tumor in recent past has become one of the deadly diseases commonly seen in human beings. The medical image when inspected by radiologist manually needs a lot of time since experience of the radiologist makes a difference in finding the accuracy. Brain tumor, is considered as a common disease that attacks brain claiming most of the lives often. According to the International Agency for Research on Cancer (IARC) approximately, more than 126000 people are diagnosed with brain tumors per year around the world, with more than 97000 mortality rates [1]. Although there has been a sincere effort to rise above the problems of brain tumor, it is observed that the survival rate of these patients has been continually low. Image Classification holds a vital role to play in the field of computer vision through labeling these images into any of the already defined categories. Although lots of machine learning and deep learning algorithms [6] have been used for analysis, algorithms such as Random Forest Classifier, Gradient Boosting Decision Tree and dimensionality reduction techniques such as Linear Discriminant Analysis and Principal Component Analysis are experimented in the current work. The performance of the proposed algorithms has been extensively monitored and care has been taken to introduce pre-processing technique such as PCA and LDA for enhancing the performance of these classifiers by fine tuning the parameters chosen for the analysis. Usually lighter datasets are used for image classification in application field where as comparatively larger and heavier datasets are used in case of medical field. Thus the above said algorithms have been extensively experimented with the best possible parameters to achieve better performance than the other.

1.1 Overview

Normally, experts capture the images of the soft tissues to analyze the condition of the organs in human body to replace the surgical procedures often [2].The word tumor is a synonym for a word neoplasm which is formed by an atypical growth of cells [3]. A tissue which has an abnormal mass that multiply without any control on their growth that never can be controlled by any mechanism as that of normal cells within human brain is called tumor. The tumor as it enlarges obstructs the normal functioning of the brain thereby calling for an early detection of tumor. Various techniques [4] were developed for the detection of tumors in the brain. Three types of tumor are commonly observed viz. Benign, Pre-Malignant, Malignant [5].Glioma" is an acronym for the type of tumor that is caused by ("gluey") tissue located in the brain. The functioning of this tissue is to keep intact the neurons and manage their activity. Although it has been observed from previous work carried out extensively by other authors that data augmentation enhances the performance of the classifier in image classification task, but in case of medical images it could possibly have a negative impact if used. Thus standard dimensionality reduction techniques such as LDA and PCA has been used in this work in combination with various classifiers to diagnose the parameters that actively contribute in classification task and hence cater to the improvement in performance of the classifiers.

Thus many parameters chosen during training play a very important role in measuring the performance and accuracy of the system. Thus an attempt shall be made to suggest the need for pre-processing technique to enhance the performance of the proposed system.

1.2 Linear Discriminant Analysis

We know that for any deep learning architecture like CNN, the limitation lies in passing the larger data set as input. Fortunately, this obstacle can be dealt with by applying one of the intuitive techniques to increase the size of the data set i.e. using data augmentation. Most state-of-art architectures in neural networks suffer from performance issues due to millions of parameters being generated for training. Unfortunately, the starvation of data leads to loss and low performance of the model. Thus to improvise these small data sets that are available under a variety of conditions, augmentation or synthetic modification of data can be a boon. Often we leave it to the machine to perform this image augmentation and pass on this input to the classifier to perform the classification. There have been tremendous data augmentation technique contributions made towards natural image tasks but not many on medical imaging. Although it has experimented with techniques like flip, rotation, scaling, random cropping, and translation, very little improvement in the performance is seen with medical image statistics.

Each augmentation technique is applied as shown below:

- **Flips:** A vertical and horizontal upside-down movement is carried out for each image J in the training set to capture the unique property of the medical image.
- **Gaussian Noise:** Generation of an array M, with each element in the array being a sample from the Gaussian distribution with μ = 0 and with σ2 in the range of [0.1,0.9]. Then, for each image J, we obtain a noisy image,

$$J' = J + M \quad (1)$$

- **Jittering:** it is all about adding or subtracting the intensity values by a factor of 1-4 for each J.
- **Scaling:** Here for every image J, an affine transformation is applied using the formula.

$$A = \begin{pmatrix} s_x & 0 \\ 0 & s_y \end{pmatrix}. \quad (2)$$

- **Powers:** the power P is calculated using the equation P = n.r+1, where n is a random value of Gaussian distribution having variance as 1 and mean as 0.r is a number less than the variance. Thus the formula used to generate this augmented image is :

$$Ia = \text{sign}(I) * (|I|p). \quad (3)$$

- **Rotations:** This affine transformation is carried out using the formula :

$$A = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \quad (4)$$

- **Shears:** For every image J that is sheared, s defines the by what amount it was sheared using the following affine transformation formula:

$$A = \begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}. \quad (5)$$

In any aspect, again augmentation is completely carried out only on training samples and as per the survey, a considerably improved accuracy ranging from 60% to 80% is seen.

1.3 CNN Architecture

Of all the architectures in neural networks Convolution Neural Networks (CNNs) are considered as an efficient classifier for tasks that are a part of image classification. Convolution Neural Networks is an extension of traditional Multi-layer Perceptrons, based on Local receives fields, Shared weights, Spatial / temporal sub-sampling.

Convolution, in the field of mathematics is termed as an operation which accepts two functions (f and h) as input and produces as a result another function that refers to the shape that is eligible for modification by others. Convolution depends on both the method involved in computing it and its result function. The convolution of f and h is written f*h, using an asterisk. It is formulated as an product of the two functions under the integral which is reversed and shifted.

$$\boxed{g(x) = \int_{-\infty}^{\infty} f(\tau) h(x-\tau) d\tau \qquad g = f * h}$$

(6)

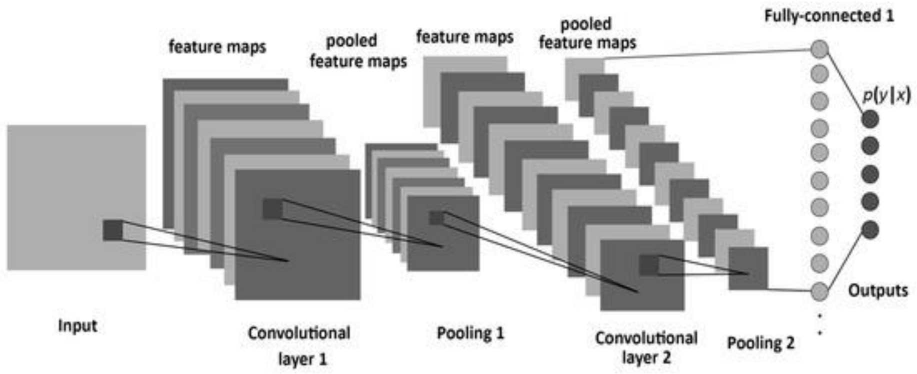


Fig 1: CNN Architecture

The general architecture of CNN is made up of Data Input, Convolution Layer, Non-linear unit, Pooling Layer, Flattened, Fully connected network as depicted in Fig 1:

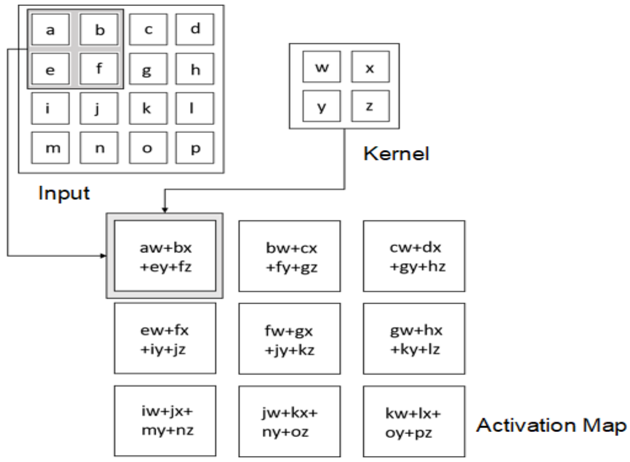


Fig 2: Convolution Operation in CNN

Convolution is the most important layer in the architecture of CNN. The entire load of computation is carried over the network there-by owning the evaluation of dot product between two matrices. Kernel, which otherwise holds the parameter set is one of the learnable matrices, whereas the second matrix is responsible for holding the receptive field that belongs to restricted portion. The kernel moves sideward across the images' height and width in the forward pass on the input image and generates a new representation of the receptive region as shown in Fig 2. A 2D activation map, representing the image is produced that clearly identifies the spatial position of the image stored in the kernel.

The advantage of Deep architectures over traditional hand-engineered representations is they should be able to capture salient aspects of a given domain thereby perform better and thus make it possible to apply for large-scale visual recognition tasks. Note that the performance entirely depends on the training data set size. If the size of the training data set is limited then fully-supervised deep architectures generally overfit.

2. LITERATURE REVIEW

In the detailed survey work [7] carried out on CNN deep learning model, it has been observed that much importance has not been given to the pre-processing technique rather more contributions have been made in developing an efficient algorithm. Thus in the proposed work, we shall concentrate on the importance of the pre-processing technique that shall extract the exact location of the existence of the tumor automatically and not randomly as suggested in the data augmentation technique. This extracted image is fed to the CNN model for analysis and classification where an enhanced accuracy value of the classifier is observed and recorded.

It has also been observed that various CNN architectures viz., VGG, IBCa, ResNet34 have been experimented by various authors as discussed in [7] and an accuracy of about 68% to 96.9% is recorded. In all the cases, the drop in performance was observed due to the lack of preprocessing against the training data.

3. METHODOLOGY

The tools that can automate the working principle of diagnosis could prove to be of great help during prognosis and pre/post surgery in subjects who are diagnosed for brain disorder. In this regard, an attempt has been made to list the issues in the existing system and develop a methodology to overcome this through the proposed system.

3.1 Existing System

To meet the above-specified objective some of the issues to be addressed in the existing system are:

1. Quality assessment of the images
2. Basic and Advanced pre-processing issues
3. Region of Interest coding issues

3.2 Proposed Methodology

In the process of making any decision, the pathologists are completely unaware about the precision of conceptual data considered. In the field of medical diagnosis, major concern should be towards interoperability whereas in case of clinical practice transparency is of highest priority in making decisions. In our approach we would like to attempt to demonstrate the importance of image pre-processing techniques to give an accurate estimate of the features of the tumor in the human brain, then classify them based on the non-parametric parameters using deep learning approach for the classification. Although we are aware that in deep learning techniques, the user has no control over feature engineering, it becomes equally important to note that a proper pre-processing technique can ensure better performance than applying just data augmentation on the given data sets.

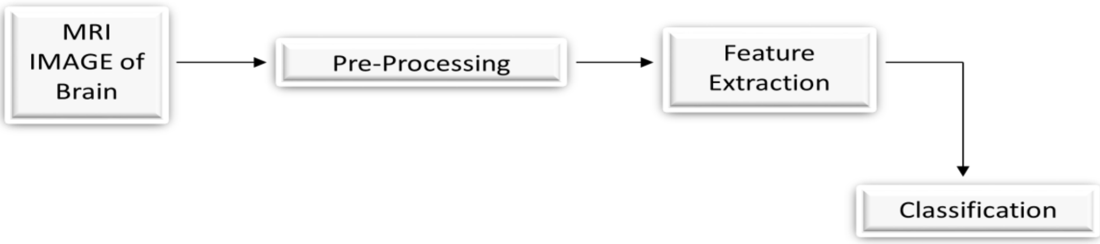


Fig 3: Proposed Methodology for Deep Learning Architecture

The proposed methodology represented in Fig 3 focuses on the preprocessing technique against the synthetic data duplication using the data augmentation techniques. Although GANs and other neural network architectures perform image augmentation, the importance here is on pre-processing.

Proposed Algorithm for pre-processing:

Step 1: Crop and locate exactly the location by marking the extreme top, bottom, left, and right points of the brain find the acute points by extracting contours using OpenCV.

Step 2: Once the boundaries are known, reduce the size of the image variants to (240, 240, 3) dimensions such that equi-shape property in a neural network before being fed as an input.

Step 3: Perform normalization to produce the pixel values in the range 0–1.

4. Implementation Details

The work carried out here shows the improvement in the accuracy of the classifier significantly when pre-processing is primarily done manually and then given to the CNN model rather than providing an augmented image data set to the CNN model. The proposed work aims at preprocessing as its main step as it is one of the most important steps as a part of data preparation. A preprocessing algorithm has been developed to improve the efficiency of the CNN classifier for a standard brain tumor data set that is obtained from kaggle.com.

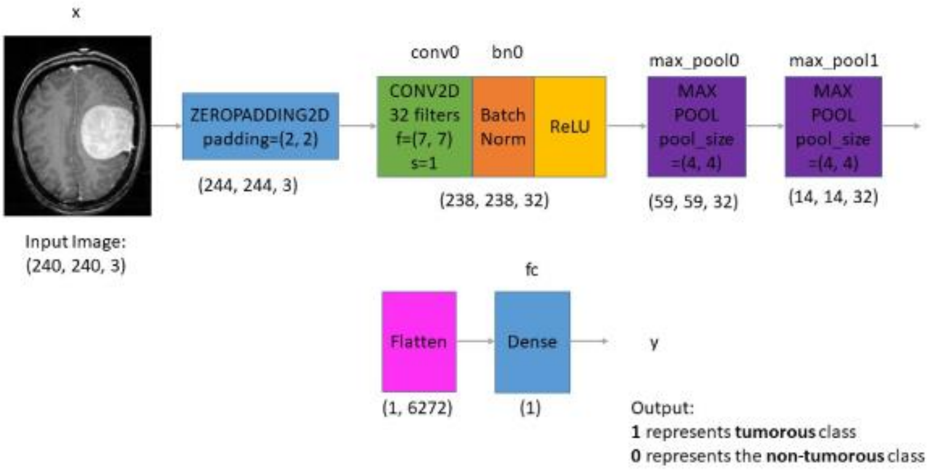


Fig 4: Architecture of CNN used for experimentation

The image data used for Brain Tumor Detection is divided into two classes NO and YES which is encoded as ‘0’ and ‘1’ respectively which detects the presence or absence of tumor. For the experimentation purpose, about 70% of the samples are used for training and in remaining 30%, about 15% is used for validation and other 15% of data is used for testing.

The work was carried out using python as the base language, with tensor-flow as backend. A CNN model with 7 dense layers is used for experimentation as shown in fig 4. In the work carried out, Relu is used as an activation function. Each cropped sample considered is of the dimension 240x240. Around 2315 samples for experiment 1 were considered. For experiment 2 about 5008 samples were considered.

In both cases, the CNN architecture was not altered. A total of about 11,137 parameters were chosen of which 11073 were trainable.

5. Results and Discussion:

Fig 5.1: Accuracy of CNN using data augmentation

The work is carried out in two phases. In the first phase, the input data is augmented and directly given to the CNN model for classification. Care was taken to generate pose invariant data before feeding the input images to the CNN model. A total of 253 images data set was considered before performing data augmentation of which 155 were positive and 98 were negative samples. A total of 2315 images were available post data augmentation of which about 1239 were positive and about1076 were negative examples. The classification results of the CNN model after image augmentation was recorded as 60.3% as shown in Fig 5.1 which is considerably low on CNN architecture.

```
In [22]: print (f"Test Loss = {loss}")
         print (f"Test Accuracy = {acc}")

Test Loss = 0.3411943523444085
Test Accuracy = 0.8357348442077637
```

Fig 5.2: Accuracy of CNN without data augmentation for 2315 samples

In the second phase, the input data set is scanned through the manual pre-processing algorithm developed where the region of existence of tumor is only considered for analysis, and the unnecessary regions are left out even before they are fed into the CNN classifier. Here observe that the user has no control over the features being extracted but the role of pre-processing considerably improved the performance of the classifier. The performance of the classifier obtained was 83.57% as shown in Fig 5.2.

```
In [22]: print (f"Test Loss = {loss}")
         print (f"Test Accuracy = {acc}")

Test Loss = 0.06225690221570224
Test Accuracy = 0.9826897382736206
```

Fig 5.3: Accuracy of CNN without data augmentation for 5008 samples

The same procedure was repeated for another larger data set of 5008 samples and the model outperformed all the results that had been recorded earlier. The CNN model without data augmentation and with the same CNN architecture outperformed the combination models that were used and recorded an accuracy of 98.26% as shown in figure 5.3.

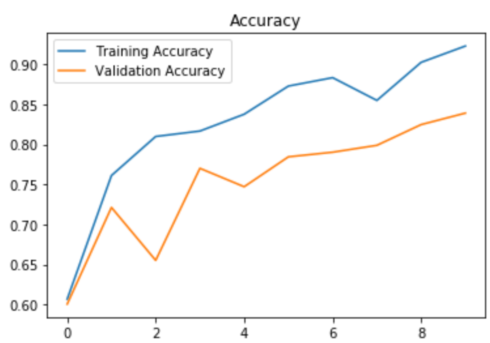


Fig 5.4: Accuracy of CNN for 2315 samples

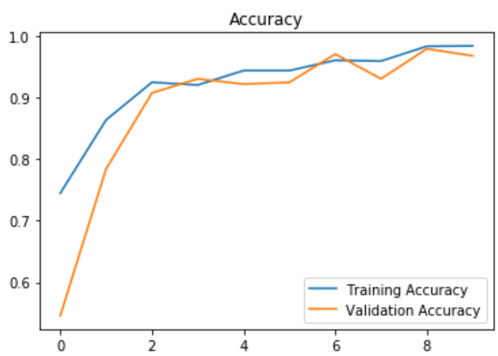


Fig 5.5: Accuracy of CNN for 5008 samples

Fig 5.4 and fig 5.5 depict the graphical representation of the performance of the CNN model without data augmentation with 7 dense layers has been evaluated with a batch size of 32 for 2315 and 5008 samples respectively. The model chosen for evaluation is a bidirectional model and the accuracy measure is plotted with the x-axis being the epoch and y-axis being the percentage of training and validation measures.

In the proposed work, the F score evaluation method has been used to calculate the accuracy of the model which is given by the formula

$$F\ Score = 2*(Recall * Precision) / (Recall + Precision) \qquad (7)$$

Where precision is defined as the ratio of correctly predicted positive observations to the total predicted positive observations which are given by the formula

$$Precision = TP/TP+FP$$

(8)

And recall is defined as the ratio of correctly predicted positive observations to all observations in actual class – yes which is given by the formula

$$Recall = TP/TP+FN \qquad (9)$$

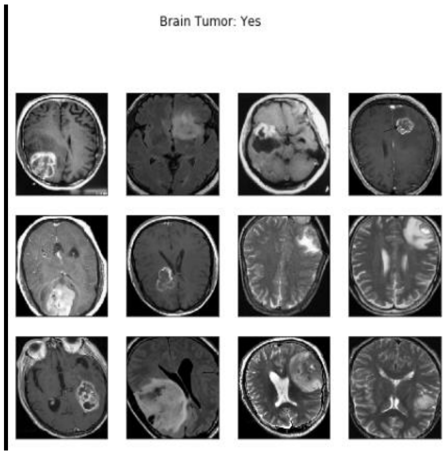
Where

True Positives (TP) is defined as correctly predicted positive values.

True Negatives (TN) is defined as the correctly predicted negative values.

False Positives (FP) is calculated when the actual class is no and predicted class is yes

False Negatives (FN) is calculated when the actual class is yes but predicted class in no.



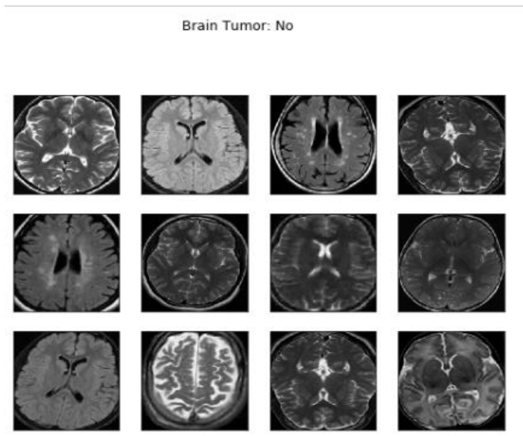


Fig 5.6: Detection of Malignant tumors **Fig 5.7: Detection of Benign tumors**

Finally, Fig 5.6 and Fig 5.7 depict the output snapshot of the CNN classifier clearly distinguishing between the malignant and the benign tumors. In the figures below you can visualize that the malignant and benign tumors are marked under YES and NO category respectively.

Conclusions and Future Work

In the proposed work, from the results, it is very evident that even deep learning architectures like CNN also suffer from low accuracy if preprocessing is not taken care of. Thus we can conclude from this research work that data or image augmentation can be a bane for classifying the MRI images as malignant or benign as they hinder the accuracy of the CNN classifier. Also, we can conclude from the above findings that data preprocessing shall be a boon for classifying the MRI images more accurately than using data augmentation technique especially for medical data Also, we propose that image augmentation may not always yield positive results as they are just the duplication of the data under certain environmental restricted conditions. Finally, we conclude with the remark that automated pre-processing entrusted better accuracy than the data augmentation technique even on the robust CNN architecture for MRI images.

Hence the results obtained through the proposed work motivate to further investigate this proposed pre-processing technique on a variety of data sets and ensure that the model performs consistently without degrading the performance of the CNN model.

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