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Research Article

Feature Extraction Using Hybrid Approach of VGG19 and GLCM For Optimized Brain Tumor Classification

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Abstract:

A brain tumor is among the illnesses that are fatal. This is the rationale behin significance of early disease detection. Intelligent techniques are always needed to researchers and medical professionals in diagnosing tumors. Today's doctors empl variety of approaches to identify the illness. The most popular technique involves gettir MRI of the brain and analyzing it to look for specific diseases. However, man evaluating the MRI pictures is quite complex and time-consuming. As a result, attempt made to discover novel methods for cutting down on the prediction time. Deep lea algorithms assist researchers in spotting brain tumor. Many deep learning method employed, including CNN, RNN, LSTM, and others. There are benefits and drawb related to these methods. One of the most widely utilized methods for categorization is C It's critical to identify the best features while classifying the tumor. Resnet, Ale VGGNet, and DenseNet are some of the feature extraction methods employed. In research, we proposed a method that extracts unique and high-quality features using a h approach of VGG19 and GLCM. CNN is then used to classify the resulting images. suggested method's performance evaluation metrics—specificity, sensitivity, ROC, accu and loss—are examined. The method yields a 0.98 accuracy. The algorithm's sensitivity specificity are 0.97 and 0.99, respectively. The performance of the suggested moc examined by contrasting it with the methods currently in use.

1. Introduction

There are many diseases that can be fatal in today's world. A brain tumor is one of these deadly diseases. Data and statistics show that a number of people are diagnosed with tumors each year. It is the second most common cause of mortality, according to World Health Organization (WHO) research [1]. Brain tumors are frequently referred to as intracranial carcinoma (IC) and are caused because of the unregulated proliferation of cells in the human brain [2]. There are two categories of brain tumors: Primary BT and Secondary BT [3]. Primary BT can be benign or malignant. [4]. The primary distinction between the two is that a benign tumor grows more slowly than a malignant tumor. While both are harmful, benign tumors typically impair the ability of bodily parts to function, whereas malignant tumors pose a threat to life. The World Health Organization (WHO) further divides these into subgroups according to the degree of aggressiveness, such as Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG). Tumors classified as Grade I and II belong to the LGG category, while those classified as Grade III and IV belong to the HGG category[5]. The classes of brain tumors are depicted in the figure 1. Timely diagnosis and treatment of the tumor are essential for improving the life expectancy of the patient. Nowadays, there are numerous manual techniques available for tumor detection. However, putting these techniques to use requires a lot of labor, time, and complexity. Delaying the detection of tumor can result in the death of the patient. Treatment options for tumors are often determined by the type of tumor,its size, location, and a few other factors [6]. One of the safest techniques used by medical professionals is medical image analysis.

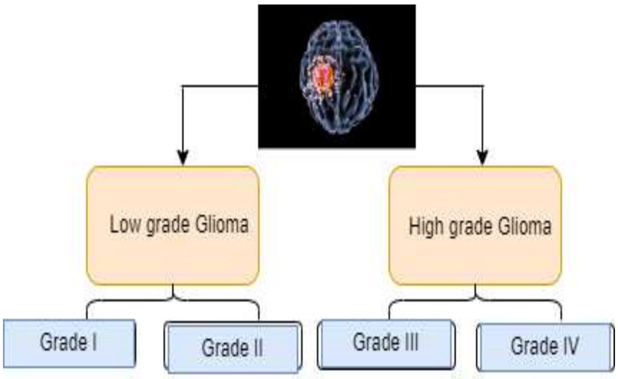

Figure1. *Categorization of Brain Tumor*

These images play a key role for on-time treatment of the disease. Computed tomography (CT), Positron Emission Tomography (PET), Positron Magnetic Imaging Resonance (PET-MRI), and Magnetic Imaging Resonance (MRI) are a few of the frequently utilized imaging techniques [7,8].MRI is regarded as the most practical approach among these. Manual MRI image analysis is very expensive and time-consuming and it can impact the life expectancy of the survivor.Since it is not good to waste time on manual inspection, as the treatment's decision impacts the treatment's effectiveness, there is a need for such methods that can save time and help medical practitioners treat patients. Machine Learning and Deep Learning techniques help to categorize the tumor. [9] Many methods are available under Artificial Intelligence, which can be categorized as ML methods or DL methods. In deep learning (DL), multiple invisible layers exist between the input and output layers. It is a subfield of artificial intelligence that maps the functioning of the human brain to facilitate better decision making [10]. When it comes to detection, DL techniques outperform conventional methods. Using the idea of transfer learning, various DL techniques are applied to interpret the MRI images [11]. Typically, a convolutional neural network is utilized to segment, classify, and classify the tumor. Using MRI scans, CNN is utilized to identify several brain cancers [12]. When training for many echos, the smaller size dataset typically notices the issue of overfitting. [13]. One of the main issues with the classification process is also the segmentation of the brain images. The research offers a solution to these issues by classifying brain tumors using a pre-trained VGG-19 model in conjunction with GLCM. The rest of our paper is organized as follows: the previous research in this field is reviewed in part 2, the materials and techniques utilized in the suggested method are covered in section 3, and a comparison of the suggested technique and the current techniques is covered in section 4.

2. Literature Review

CNN is one of the easily adopted methods to classify the tumor. Sultan et al. [14] gave a CNN based method for tumor classification and reported accuracies of 96.13% and 98.7% for the two different datasets. A classification method on the basis of CNN was proposed by Zhou et al. The proposed model achieved WT 0.83, TC 0.68, and ET 0.60 on the BRATS2013 dataset; WT 0.82, TC 0.68, and ET 0.60 on the BRATS2015 dataset; and WT 0.8658, TC 0.7688, and ET 0.74434 on the BRATS2018 dataset.[15]. A GLCM based approach was given to extract the features T-test approach to classify the tumor proposed by the Indra et al. [16]. A selective attention technique was incorporated by Akil et al. which improved the form of the features taken from an MRI image. [17]. Wahlang et al. proposed a DL based on LeNet to classify an image as normal or pathological. They reported an accuracy of 88% [18,19]. Maqsood et al. proposed a 17-layer DNN for segmentation, MobileNetV2 CNN to extract the feature and to classify images they used M-SVM. Their technique achieved an classification accuracy of 97.47% on BraTS 2018 and 98.92% on Figshare. A CNN+SVM method was given by Latif et al. [20] using CNN to extract the important features and SVM for the classification. Their proposed method classified 96.19% of images accurately for HGG gliomas and 95.46% for the LGG glioma. An evolutionary method with a deep learning to identify brain tumor images was proposed by Ahmed et al. [21]. To extract the features, Xception model was used by the author after applying bilateral filtering (BF) based noise removal and skull stripping. Attention based long short-term memory (ALSTM) technique was used for the classification and the accuracy obtained for the proposed model was 99.06%. Kazemi et al. proposed a parallel CNN model that consists of AlexNet and VGGNet [22]. For Binary classification, accuracy was up to 99.14%, and for multiclass classification, it was 98.78%. Kumar et al. used ResNet152 [23]. They used the optimization technique CoV-19 OA and modified the weight parameters and reported an accuracy of 99.57%. Shahzadi et al. [24] proposed a hybrid model that combines VGGNet, ResNet, and LSTM models for tumor classification. They reported the accuracy of the model as 71% for the AlexNet and ResNet and 84 % for VGG16 and LSTM.

3. Materials and Methods

In the paper, a brain tumor dataset has been used for the experiment. The dataset is taken from [25].

The dataset is pre-processed before carrying out further steps. After pre-processing, dataset is augmented as the original size of dataset is small. After the augmentation step, features are extracted using the Vgg19 model. After feature extraction the images are given to CNN for classification. A confusion matrix has been designed to analyze the performance. The metrics used for the performance evaluation are Accuracy, sensitivity, specificity, recall, and ROC.

Experimental Setup: The experiment was carried out using the PyCharm notebook using Python language, which uses the AMD Ryzen 5 7520U with a Radeon Graphics processor.

Dataset Collection: A dataset of MRI images of brain tumors is used for the experiment [25]. The dataset comprises 3060 images. The dataset is pre-processed and divided for training and validation.

Figure 2 gives the basic flow of the process which is done for the classification of tumor.

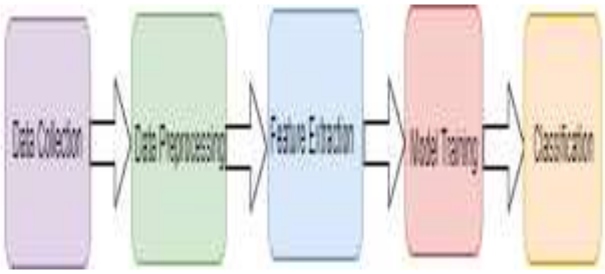

Figure 2. *Basic Flow Diagram of the Classification*

Data Pre-processing: Raw data is not adequate for the classification tasks. Many types of irregularities are there i.e. noise, data irregularities, missing values, etc. If the data is provided to the classifier without pre-processing for classification purposes, it may produce incorrect and false results making it necessary to clean it and process it to make it fit for the classification. In figure 3 sample images of the data set are represented.

Data Augmentation: A large dataset is required for the classification for better results. However, the dataset used in this paper is relatively smaller. To make this dataset adequate and large data augmentation is required. Several data augmentation techniques are used i.e. scaling, rotating, flipping, etc. to name a few.

Feature Extraction: To select the best features from the dataset, feature extraction is performed on the processed data. These extracted features are then divided into the training and testing ratio for the classification. Several techniques are there which can be used to extract the features. These are VGG 16, HOG, SIFT, GLCM, VGG 19. VGG19 and GLCM have been used to extract the features in the proposed model.

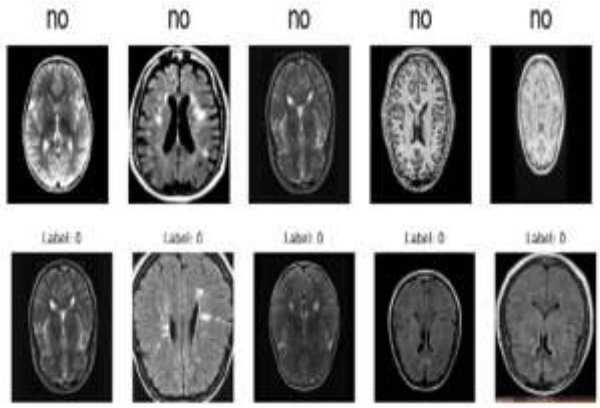

Figure3*. Sample Images of Brain Tumor Dataset*

Training and Testing: After the feature extraction, the dataset is divided into train and validate in a ratio of 80:20.

Architecture Design of the VGG19 and GLCM:

Architecture of VGG19: Figure 4 gives the basic architecture of VGG19.

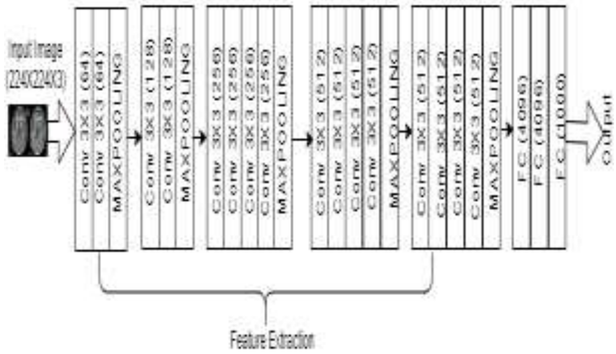

Figure4.*Basic Architecture of VGG 19*

Here the feature extraction process is explained. It has 19 Layers. from these 19 layers, 16 layers are convolutional layers and 3 layers are fully connected layers. A 224 x 224 size image is passed into the model for the extraction. The Maxpooling layer is implemented in between and it uses the ReLu function.

Architecture of GLCM: The GLCM stands for grey co-level matrix. It is a method used to examine an image's spatial relationship between pixels. This matrix is used to extract various texture features that describe the image. Figure 5 represents the basic working of GLCM.

Working Flow of Proposed Model:

Figure 6 represents a working of the proposed approach. Here first the input images are processed before passing them to the next layer. Then this

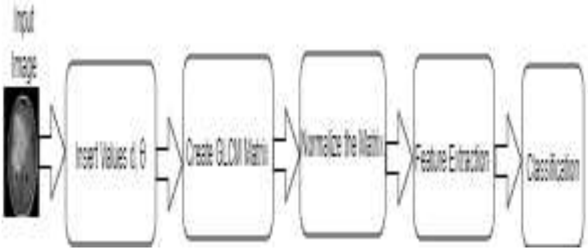

Figure5. *Working Flow of GLCM*

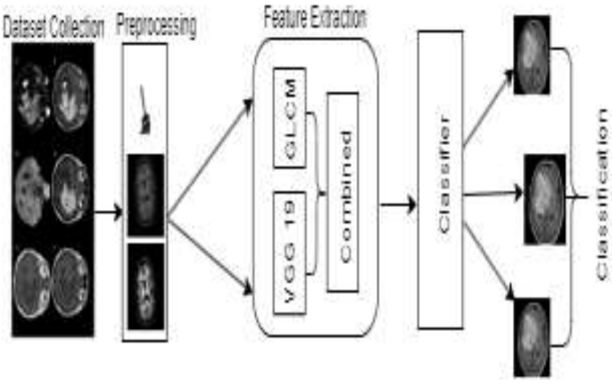

Figure6.*Working Diagram of Proposed Model*

image set is fed for the feature extraction to the VGG19 and then to the GLCM after that, the extracted features are combined. The features are then passed to the classifier for classification purposes.

Performance Metrics

It is necessary to evaluate a model after its completion whether it is accurate and efficient enough to apply it to real-world problems and whether it can be used to classify the disease promptly. The performance metrics used are Accuracy, sensitivity, specificity, and ROC. In this section, we will discuss every performance metric in brief.

Accuracy: Accuracy is an elementary and straightforward evaluation of the performance of a model. Accuracy is defined as the proportion of correctly classifications to the total number of cases.

$$\text{Accuracy} = (\text{TN} + \text{TP})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (1)$$

Precision: It is obtained by dividing the true positive by the total positive predictions made by the model.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})(2)$$

Sensitivity: Sensitivity is the proportion of true negative instances present among all the actual negative instances.

$$\text{Sensitivity} = \text{TN}/(\text{TN} + \text{FP}) \qquad (3)$$

Specificity: It is also known as recall. It is the ratio of the actual positive instances out of all the present instances

$$\text{Specificity} = \text{TP}/(\text{TP} + \text{FN})(4)$$

ROC:The Receiver Operating Characteristic (ROC) curve is used to measure the efficiency of the classifier in terms of its accuracy. It is used to show the ability of a classifier system.

4. Results and Discussion

The performance is measured to determine how accurately the model classified the images. The performance is measured on accuracy, loss, ROC, sensitivity, and specificity.

The table 1 summarizes the performance achieved by the proposed model

Table 1.*Performance of proposed model*

Performance Matrix	Results
Accuracy	0.98
Specificity	0.99
Sensitivity	0.97
Loss Function	0.14

Confusion Matrix: Figure 7 shows the confusion matrix. It represents the True positive, True negative, False Positive, and false negative.

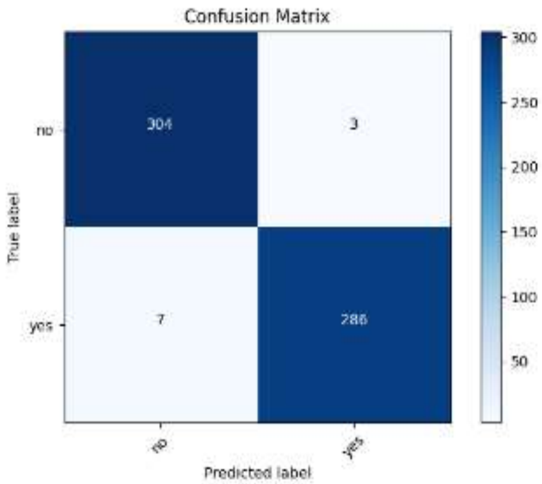

Figure7. *Confusion Matrix*

Accuracy: The model has obtained an accuracy of 0.98 as shown in figure 8. The figure represents both the training as well as the validation accuracy of the model. Loss: Figure 9 represents the loss of the model. As the model has a loss value of 0.14. 1.6.3. ROC: Figure 10 shows the ROC curve of the proposed model.

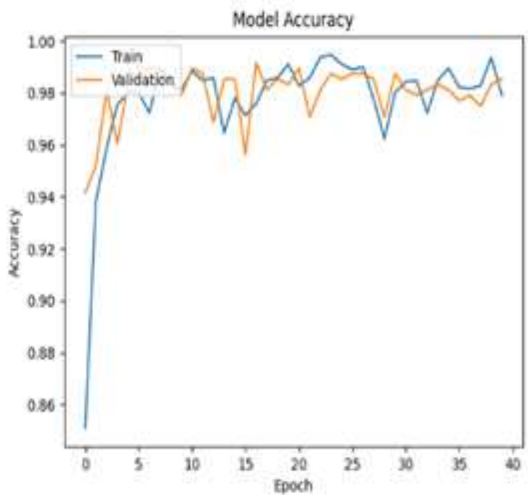

Figure8.*Accuracy of the Proposed Model*

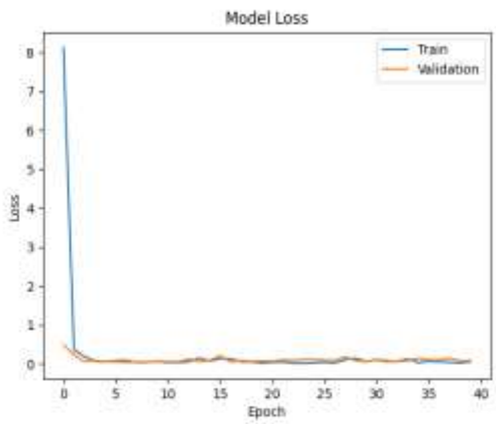

Figure 9.*Loss of the Proposed Model*

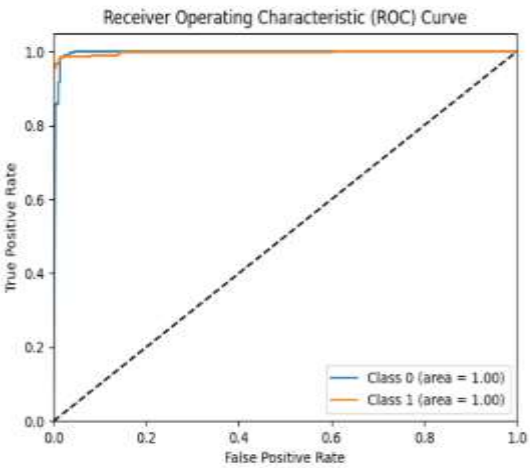

Figure 10.*ROC curve for the proposed technique*

Comparative Analysis of the Proposed Model

The performance of the model is compared with the Densenet121 and AlexNet,. Table 2 represents the comparison of the model with the rest of the two models.It is evident from the table that the proposed model is the more accurate.

Table 2. *Comparison of other modelswith the proposed Model*

Model	Accu	Sensit	Specif	L
AlexNet	0.51	0.72	0.31	0.
DenseNet 121	0.59	0.44	0.72	0.
Proposed(VGG+GL(	0.98	0.97	0.99	0.

5. Conclusion

Brain tumor very fataldiseases and it became crucial to detect them on time. The paper has proposed a model of VGG and GLCM techniques for feature extraction. After extracting the features the model has classified the brain tumor and can achieve an accuracy of 0.98. Still, there are regions of the brain that are not inspected automatically even though using the most advance techniques. In the future, efforts will be made to find a technique that can detect and analyze these regions which are the main epicentre of tumor, and to detect the brain tumor more accurately and years before the actual occurrence. Brain tumor is studied in literature and reported [26-30].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:**The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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