Hybrid model for brain tumor detection using convolution neural networks

Bhagyalaxmi Kuntiyellannagari[1], Bhoopalan Dwarakanath[2], Panuganti VijayaPal Reddy[3]
[1]Department of Computer Science and Engineering, School of Computing, SRM IST, Kattankulathur, India
[2]Department of Information Technology, SRM IST, Ramapuram, India
[3]Department of Computer Science and Engineering, Matrusri Engineering College, Hyderabad, India

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ABSTRACT

The development of abnormal cells in the brain, some of which may turn out to be cancerous, is known as a brain tumor. Magnetic resonance imaging (MRI) is the most common technique for detecting brain tumors. Information about the abnormal tissue growth in the brain is visible from the MRI scans. In most research papers, machine learning (ML) and deep learning (DL) algorithms are applied to detect brain tumors. The radiologist can make speedy decisions because of this prediction. The proposed work creates a hybrid convolution neural networks (CNN) model and logistic regression (LR). The visual geometry group16 (VGG16) which was pre-trained model is used for the extraction of features. To reduce the complexity, we eliminated the last eight layers of VGG16. From this transformed model, the features are extracted in the form of a vector array. These features fed into different ML classifiers like support vector machine (SVM), and Naïve Bayes (NB), LR, extreme gradient boosting (XGBoost), AdaBoost, and random forest for training and testing. The performance of different classifiers is compared. The CNN-LR hybrid combination outperformed the remaining classifiers. The evaluation measures such as Recall, precision, F1-score, and accuracy of the proposed CNN-LR model are 94%, 94%, 94%, and 91% respectively.

Corresponding Author:

Bhagyalaxmi Kuntiyellannagari
Department of Computer Science and Engineering, School of Computing, SRM IST
Kattankulathur, India
Email: bk8019@srmist.edu.in

1. INTRODUCTION

The brain is anessential organ of the human body responsible for decision-making and control. As the control center of the nervous system, this part is very important to protect against injury and disease. One of the conditions that directly endanger a person's life is brain tumors. Delineating the cranial layers surrounding the brain makes its behavior difficult to study and also increases the complexity of disease detection [1]. Brain diseases are not the same as other parts of the body, but they can be caused by abnormal growth of cells that eventually destroy the structure of the brain and cause brain tumors.

On the other hand, according to the world health organization (WHO), 9.6 million cancer-related deaths occurred globally in 2018 and between 30% and 50% of those with initial cancer diagnoses [2]. Brain tumors are among the many types of cancer that are fatal. As a result, data indicate that 17,760 adult deaths from brain tumors occurred in the previous year. Due to the disastrous location and abnormal growth of cancer, as well as the complexity of brain structures, timely diagnosis is necessary. Many medical imaging methods have been developed to acquire images for the diagnosis of different diseases. Ultrasonic imaging

(UI), computed tomography (CT), X-ray, single-photon emission computed tomography (SPECT), magnetic resonance spectroscopy (MRS), positron emission tomography (PET), and magnetic resonance imaging (MRI) are commonly employed technologies [3]. When combined with high-quality brain imaging, MRI is particularly helpful for tumor analysis. The use of MRI technologies in brain imaging has increased [4]. Because maximal spatial and contrast determination can be visualized in the best way possible thanks to MRI technology, which presents a special opportunity.

Accurate knowledge of brain tumor staging is crucial for both disease prevention and therapy. For this reason, radiologists frequently utilize MRI to examine braintumors [5]. The analysis's findings show whether the brain is normal or deviant. Conversely, when an anomaly materializes, it pinpoints the kind of tumor. The processing of MR images is becoming more and more crucial with the introduction of machine learning (ML) in order to detect brain tumors quickly and accurately [6]. Initially, the study consisted of three parts: (i) Pre-processing of MR images. (ii) creation and extraction of features; (iii) classification. In recent years, a number of automated or semi-automatic techniques for the identification and categorization of brain tumors have been put forth [7].

For low-level feature extraction, gray-level co-occurrence matrices (GLCM) are frequently utilized [8]. Neural networks, on the other hand, are used for classification problems dealing with the complex textures of brain tumors. Deep learning (DL) emerged as a method to capture intricate and nonlinear connections between input and output layers [9]. DL structures are an extension of traditional neural networks (NNs). It is formed by adding an additional hidden layer to the network model. In ML, we use DL as subfields to describe feature hierarchies [10] in this subfield, the concept revolves around incorporating multiple tiers of learning, where the higher levels are intricately connected to and explained by the lower levels. Functionality remains consistent across both higher and lower levels.

Researchers are drawn to DL because of its outstanding capabilities, making it the optimal choice for various challenges in medical image analysis, including tasks like image denoising, segmentation, and classification [11]. It has been proven that various DL architectures currently exist, but in recent years, convolutional neural networks (CNN) have been used as an architecture that uses convolutional filters to perform complex operations [12]. To classify images, CNN is a network architecture commonly used along with some of the ML classifiers.

Ural [13] proposed a method that leverages a probabilistic neural network (PNN) approach for the detection and localization of brain tumors. Notably, their proposed method achieves a low computational time while maintaining a reasonably high level of accuracy. Classification involved the utilization of two neural network architectures: fully connected networks and convolutional neural networks. Within these two architectural categories, additional experiments were conducted by augmenting the original 512×512 axial images [14]. The experimental outcomes indicated by Kang *et al.* [15] states that combining deep features in an ensemble leads to a significant performance improvement in most instances, the support vector machine (SVM) employing a radial basis function (RBF) kernel demonstrates superior performance compared to other ML classifiers. Rammurthy and Mahesh [16] proposed a BT detection method, called "whale harris hawks optimization" (WHHO), which combines the whale optimization algorithm (WOA) and harris hawks optimization (HHO) within a DL framework. It begins with image tumor segmentation using cellular automata and features such as size, variance, mean, and kurtosis are extracted. These features are then used for enhanced brain tumor detection through the WHHO approach [16]. Sharif introduced a dynamic DLsystem for the segmentation and classification of brain tumors. The process involved contrast enhancement, followed by the saliency-based deep learning (SbDL) method to create a saliency map. Thresholding was applied, and the resulting images fine-tuned a pre-trained CNN model, Inception V3. Additionally, DRLBP features were extracted and combined with CNN features. Anuse and Vyas [17] evaluated the performance of tumor classification methods for categorizing MR brain image features into distinct classes, including no tumor, multifocal, multicentric, and gliomas.

This classification process involved the analysis of statistical properties within the input images and the systematic categorization of the data into different groups [18]. Ge *et al.* [19] proposed an approach involved generative adversarial networks (GAN)-based augmentation of brain MR images to enhance the training dataset. It used post-processing to combine glioma subtype classifications at the slice level via majority voting. A two-stage training strategy was employed, starting with GAN-augmented MRIs and transitioning to real MRIs for learning glioma features. Summary of few proposed methods listed in the Table 1.

These methods use a variety of techniques and algorithms to enhance the accuracy of brain tumor detection and classification, combining DL, feature extraction, ensemble methods, and data augmentation to improve the performance of the systems. The choice of methods and techniques may vary depending on the specific objectives and available data. Each method mentioned has its own limitations. For example, the performance of SVM with RBF kernels can be sensitive to hyperparameter tuning, and the effectiveness of optimization algorithms like WOA and HHO can depend on the specific problem and dataset. Addressing these weaknesses often requires careful consideration of the specific application, data, and clinical context, as well as ongoing research and development to improve the robustness and reliability of these methods in clinical practice.

Table 1. summary of related work

Author	Classification method	Dataset	Accuracy
Ural, 2018	PNN	25 MR images	90%
Saed *et al.*, 2017	CNN	587 MR images	91.16%
Paul *et al.*, 2017	Fully connected and CNN	3,064 MR images	91.43%
Kang *et al.*, 2021	SVM, RBF	253, 2364	89%
Rammurthy and Mahesh	WHHO	BraTS	81.6%
Sharif *et al.*	SbDL	BraTS17	83.73%
Cinarer and Emiroglu	SVM, KNN	Kaggle	90%
Ge *et al.*	U-Net architecture, GANs	BraTS	88.82%

In this paper, gigantic non-handcrafted highlights are extricated utilizing CNN to demonstrate at that point different classifiers are choosen to classify the course of the given MRI brain pictures. The CNN-logistic regression (LR) demonstrates employment points of interest in both strategies. CNN focuses on sparse networks between neurons in progressive layers and weight distribution between layers.

The LR classifies the information tests based on the subordinate highlights we have given. This CNN-LR demonstrates extricated the notable highlights consequently and diminishes the difficulty and time utilization. Consequently, this proposed demonstration has way better execution compared to other models CNN-SVM [20], CNN-XBOOST, CNN-ADABOOST, CNN-decision tree, CNN-voting classifiers, CNN-K nearest neighbor (KNN), CNN-random timberland, CNN-Naive Bayes (NB). Performance metrics: the proposed CNN-LR is assessed based on execution measurementssuch as precision, F1-score, accuracy, and recall. These execution measurements are characterized as takes after.

– Accuracy=correctpreds/all_preds
– Recall=true positive/(true positive+false negative)
– Precision=true positive/(true positive+false positive)
– F1=2 X (precision X recall)/(precision+recall)

2. METHOD

2.1. Transfer learning

Transfer learning empowers us to use the data learned by a pre-trained demonstrate to improve execution on a modern, related assignment, as opposed to starting from zero and preparing an unused demonstrate from scratch on an unused dataset. This regularly produces prevalent comes about whereas sparing a critical sum of time and computational assets [21]. For occasion, a pre-trained picture acknowledgment show that was created on a sizable dataset like ImageNet can be moved forward on a smaller dataset for a specific work, like identifying different sorts of objects.

By beginning with a pre-trained show. In this paper we utilized a pre-trained demonstration visual geometry group 16 (VGG16) for include extraction [22], we will not make utilize of the completely associated range of VGG16 since, in this work, classification is done utilizing ML algorithms such as SVM [23], Naïve Bayes, extreme gradient boosting (XGBoost), AdaBoost, and random forest. The layers of VGG16 are reduced to decrease m the complexity. The layers in the reduced model consist of 3 blocks.

In the first block, there will input layer in which the size of the image is (32, 32, 3), it is followed by two convolutional layers and max-pooling layers of the following size (conv1 (32, 32, 64), conv2 (32, 32, 64), Max (16, 16, 64)). the block2 the input size goes through the following changes, the layers will be the same as Block1 (conv1 (16, 16, 128), conv1 (16, 16, 128), Max (8, 8, 128)) as given in the Figure 1. In the last block, we have three convolutional layers and one max pooling layers in which image size goes through changes (conv1 (8, 8, 256) conv2 (8, 8, 256), conv3 (8, 8, 256), Max (4, 4, 256).At last, we have added the flattened layer.

2.2. Logistic regression as classifier

CNN performance as a classifier is affected by the overfitting phenomenon. Due to the complexity of the CNN model, excessive assembly will become apparent when there is a shortage of training data [24]. We propose using LR on CNN features to improve performance. LR could be a factual strategy commonly utilized in ML for binary classification issues, where the objective is to predict one of two conceivable results, such as true/false or yes/no. Here are a few reasons why LR is widely used in classification assignments. LR may be a moderately basic calculation that's simple to get it and translate [25]. It can give insights into the relationship between the independent factors and the likelihood of a specific result. LR can perform well indeed when there's constrained information accessible, making it a valuable calculation when managing with little datasets. In general, LR may be a well-known and compelling strategy for twofold classification issues. Be that as it may, it may not be reasonable for more complex classification issues where there are different classes or nonlinear connections between the input factors and the result.

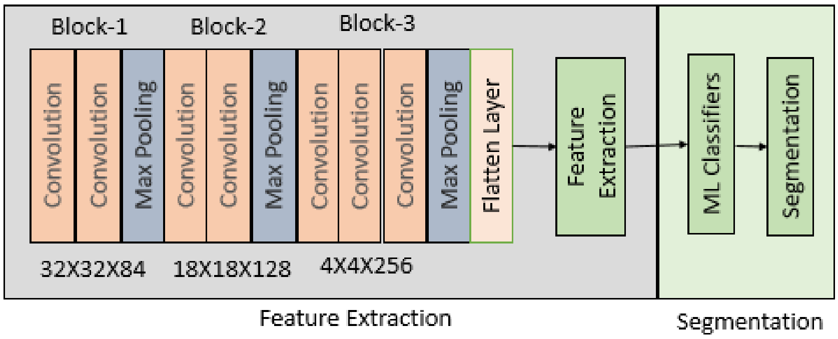

Figure 1. Block diagram of the model

3. EXPERIMENTAL SETUP

The MRI in the dataset is of distinctive measure so these pictures are resized to the size (32×32). These pictures are put away in an array and there comparing labels in another array. The indexes are utilized to coordinate the picture with the comparing label. The part proportion of 9:1 is utilized, which implies 90% of information is utilized in the training phase and 10 % is utilized in the testing phase.

The first thing we import here is the VGG16 model in tensorflow keras. The preprocess input module is imported to properly scale pixel values for the VGG16 model. Image modules are imported to preprocess image objects. The numpy module is imported for array processing. Then the pre-trained weights of the imagenet dataset are loaded into his VGG16 model. A VGG16 model consists of convolutional layers followed by one or several fully connected dense layers [26]. We can choose if required the final dense layer using include top. A value of false indicates that the final dense layer has not been loaded into the model. Since the feature extraction component of the model extends from the input layer to the final max pooling layer, We used three convolutional layer blocks, followed by max pooling. Finally, a flattened layer to collect the features in an array format as given in the Figure 2. Different ML classifiers are applied and chosen LR based on its performance, so the softmax layer of the fully connected layer is removed in VGG16.

4. RESULTS AND DISCUSSION

The proposed model was built using Kaggle's image database of brain tumors and executed on a Dell laptop stocked with an Intel i5, 12th generation processor, 16 GB DDR4 RAM, and a 4 GB NVIDIA graphics card. The dataset consists of 253 images total of which 98 images are of no class and 155 images are of yes class as given in Table 2. The authors of the dataset are Aeyong Kang, Zahid Ullah, and Jeonghw. The training and testing samples are both processed in the required format while pre-processing, and image augmentation is applied before being used in the training and testing phases. Each image measures 32×32×3. The CNN model is trained on a training data set of 253 images, 98 of which are tumor images and 155 of which are not.

CNN model architecture is described in CNN model architecture and illustrated in Figure 1. The complete training process is shown in Figure 2. The CNN will extract the features of every image, these features and corresponding labels are given to the ML classifiers for testing and training. The accuracy of all ML classifiers tested is given in Figure 3, and the confusion matrix for every algorithm is obtained and compared to the algorithm with the most accuracy is considered as our model, i.e. CNN-LR. The performance metrics of different algorithms are listed in Table 3.

Along with the accuracy recall, precision, and F1-scores are also calculated for all the ML classifiers. while accuracy is a straightforward metric, the F1 score, and other metrics are often preferred when dealing with imbalanced datasets or when certain classes are of greater importance, especially in medical imaging. It's essential to consider the specific problem and data distribution to choose the most appropriate evaluation metric. In our implementation, precision-recall and F1 scores metrics of CNN-LR are outperformed when compared with the remaining classifiers.

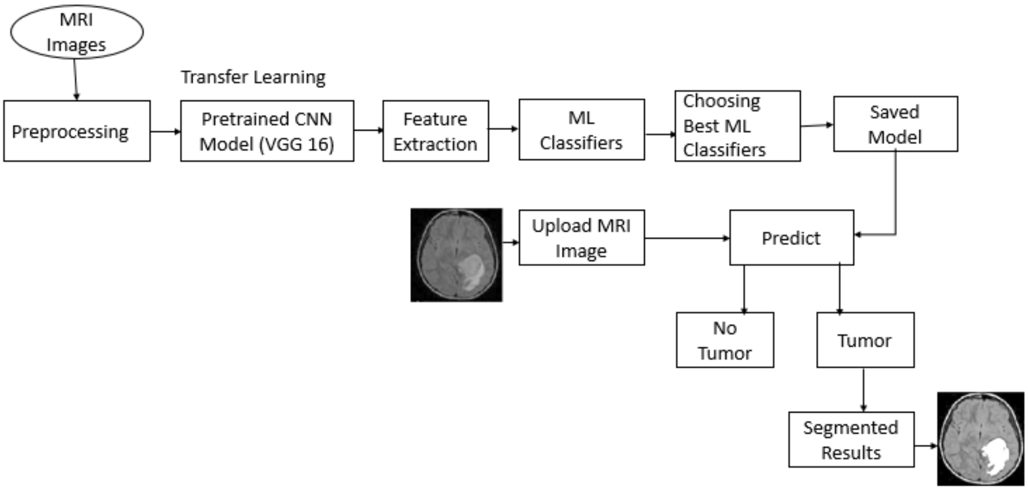

Figure 2. Testing and training phases

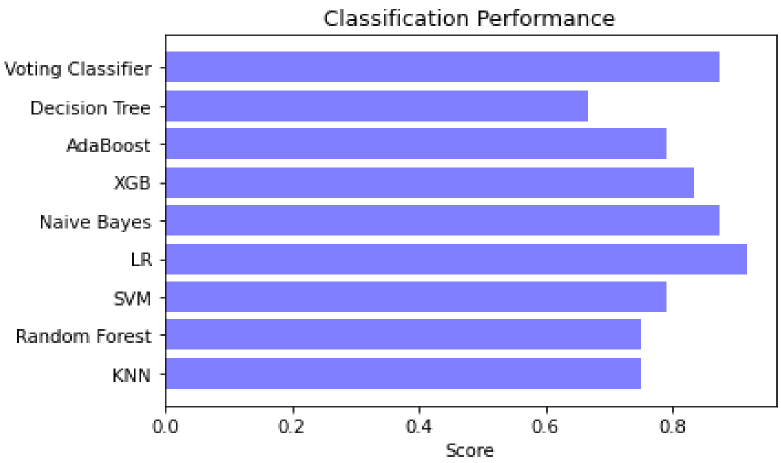

Figure 3. Accuracy comparison

Table 2. Dataset

S. no.	Tumor class	No. of images
1	Tumor	155
2	No-Tumor	98

Table 3. The performance metrics of different algorithms

S. no.	Method	Recall	Precision	F1 score	Accuracy
1	CNN-KNN	81	81	81	75
2	CNN-random forest	78	88	82	75
3	CNN-LR	94	94	94	91.66
4	CNN-SVM	82	88	85	79.16
5	CNN-NB	88	94	91	87.5
6	CNN-XGBOOST	83	94	88	83.33
7	CNN-ADABOOST	79	94	86	79.16
8	CNN-decision tree	75	75	75	66.66
9	Voting classifier	88	94	91	87.5

5. CONCLUSION

In this study, a hybrid CNN-LR model is employed to address the MRI brain tumor classification problem, and the model is trained using the brain tumor dataset. Non-handcrafted features are retrieved by CNN and utilized as input to a variety of classifiers, including KNN, CNN, SVM, LR, NB, voting classifiers, XGBoost, Adaboost, and decision tree, to forecast the output class. Performance criteria including accuracy, F1 score, precision, and recall are used to assess the effectiveness and viability of the proposed hybrid CNN-LR model. The findings demonstrate the benefits of this model combination. This hybrid CNN-LR model, according to the findings, is a viable model for classifying MRI brain tumors. In contrast to previous traditional classifiers, which took more time to extract the appropriate hand-crafted features, the model automatically extracted the relevant characteristics, reducing the tedious and time-consuming process. Second, this hybrid CNN-LR model integrated the best aspects of the two most effective and widely used classifiers for image recognition and classification, CNN and LR. Finally, the decision-making process slightly increases the complexity of the hybrid model. With an accuracy of 91.66%, the proposed CNN-LR model outperformed all other models, including CNN-XGBoost, CNN-SVM, CNN-NB, CNN-voting classifier, and CNN-decision tree. The main limitation of the work is dataset class imbalances and limited dataset size. These issues need to be addressed in future work along with state of art CNN architecture-based transfer learning needs to adopt to enhance the model's performance.

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BIOGRAPHIES OF AUTHORS

Bhagyalaxmi Kuntiyellannagari M.Tech. is a research scholar at SRMIST Chennai. She is M.Tech. (CSE) from JNTU having 20 years teaching experience. Published around 15 papers in international journals and conferences. Her interest areas are deep learning, image processing. She is a member of CSI and ISTE. She can be contacted at email: bk8019@srmist.edu.in.

Dr. Bhoopalan Dwarakanath M. Tech., Ph.D. is Assistant Professor in the IT Department of SRMIST, Ramapuram, Chennai, Tamil Nadu. Ph.D., in Machine Learning-Information Technology in 2019 from Hindustan Institute of Technology and Science, Chennai, Tamilnadu. He has done his M.Tech., CSE from Vellore Institute of Technology, Vellore in the year 2004. He has 19 years of teaching experience and has 27 publications in International Journals and Conferences. His research interests include machine learning, image processing, and network programming. He is an active member of ACM, IET, ISTE, CSI, and IEANG. He can be contacted at email: dwarakab@srmist.edu.in.

Dr. Panuganti VijayaPal Reddy M. Tech., Ph.D. is Professor in the Department of Computer Science and Engineering, Matrusri Engineering College, Hyderabad. He did Ph.D. in Computer Science and Engineering from JNT University, Hyderabad. He Published 52 research articles in reputed journals and conferences, authored 5 text books. He has executed funded projects worth 9 lakhs. He is currently supervising 8 Ph.D. scholars. He can be contacted at email: drpvijayapalreddy@gmail.com.