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Brain tumor classification and detection using a hybrid deep learning model

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Abstract

Dignosis of brain tumor is an important topic in medical area. It involves a combination of medical imaging techniques, clinical assessments and sometimes molecular analysis. However, classification of brain tumor can be accomplished by deep learning methods easily and accurately. Therefore, automatized medical systems integrated with deep learning are highly demanded nowadays. Deep learning is a subset of machine learning, which itself is a branch of artificial intelligence (AI). It's based on the idea of artificial neural networks which is inspired by the structure and function of the human brain. They are designed to learn and make decisions in a similar way to humans. Brain tumor classification with deep learning includes using neural networks to analyze medical images such as MRI scans and classify them into different categories based on the presence or type of tumor. In this study, a hybrid deep learning model was designed and examined by combining pretrained VGG16 model with Random Forest machine learning classification algorithm. While deep features were extracted with pretrained model, classification with these features was handled by machine learning algorithm. A brain tumor dataset was trained and tested with proposed hybrid deep learning model. At the end of the experiments, it was seen that hybrid model approach has given promising accuracies of 92.31% and 90.48% in training and validation parts respectively.

Keywords: Brain Tumor Classification, Brain Tumor Diagnosis, Convolutional Neural Network, Deep Learning, VGG16, Random Forest, Hybrid Deep Learning.

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1. INTRODUCTION

Diagnosis of brain tumor is an important topic in medical area. It involves a combination of medical imaging techniques and clinical assessments. Computer aided systems can provide an automation process involving clinical data such as tumor type and location in the brain. Detection and classification of tumor in terms of size, shape, volume and type van be described as a hard task since the tumor can be differ between individuals. Generally magnetic resonance imaging method (MRI) is used while representing brain tumor images in diagnosis processes since it supplies superior image contrast [1]. Brain tumor develops from two sources. The first is the uncontrolled growth of own cells of the brain's (primary brain tumors) and the second appears in brain tissues which are formed through cancers developing in other organ systems in the body, especially the lung and prostate. In both cases, tumor masses that develop in a limited area of the skull put pressure on the brain tissue and increase intracranial pressure. Neurological and epileptic problems may occur in individuals with brain tumors [2]. An accurate and quick diagnosis of brain tumor results in an effective treatment leading improvement of the patient in a positive way. Accurate diagnosis can be challenging with human visual investigation due to the complex structure of brain tumor images [3]. However, classification of brain tumor can be accomplished by deep learning methods easily and accurately. Artificial intelligence plays a vital role in precise detection of boundaries, types and size of brain tumor via segmentation. At this deep learning has become a critical tool in the detection and diagnosis of brain tumors due to its ability to handle complex medical imaging data with high accuracy. Especially convolutional neural networks (CNNs) have demonstrated superior performance in identifying and classifying brain tumors from medical images like MRI scans. These models can often detect subtle abnormalities that may be missed by the human eye or traditional image analysis methods [4], [5]. As a result, an automatized medical system integrated with deep learning are highly demanded nowadays. In this study, a hybrid deep learning model was designed and examined by combining pretrained VGG16 model with Random Forest machine learning classification algorithm. While deep features were extracted with pretrained model, classification with these features was handled by machine learning algorithm. A brain tumor dataset was trained and tested with proposed hybrid deep learning model. At the end of the experiments, it was seen that hybrid model approach has given promising results at classifying tumors accurately and reached an accuracy of 92.31% and 90.48% in training and validation sets respectively.

2. METHODS AND MATERIALS

In this study, a hybrid deep learning model was utilized to classification and detection of brain tumor cells. At this context, brain tumor dataset was taken from Kaggle platform [6]. This dataset has images grouped in “yes” and “no” folders for image classification and object detection purposes. The dataset containing 253 images was split into training and validation parts in the ratio of 70:30. Therefore, 169 images which constitute 70% of the dataset were used for training, whereas 84 images which make up 30% of the total images were selected for validation. Label encoder was used for labelling images and after preprocessing stage, feature extraction was achieved with VGG16 deep learning model and obtained features became input for Random Forest algorithm. Random Forest and VGG16 will be explained in detail in further subsections.

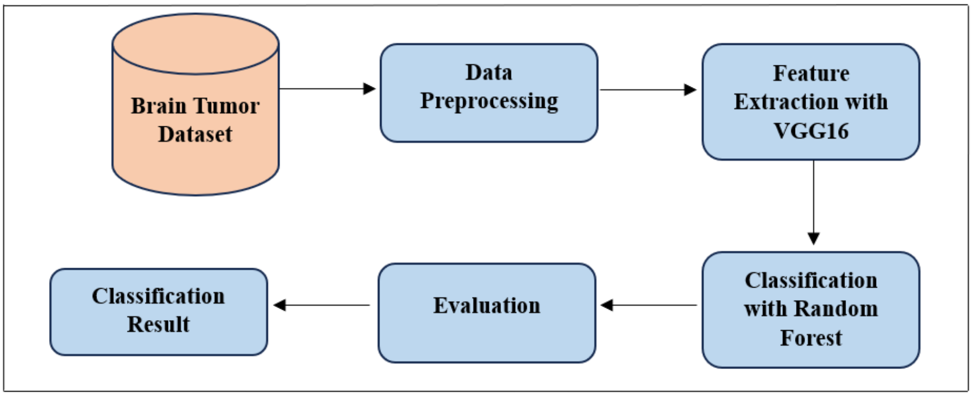

Fig. 1.
Architecture of Hybrid Deep Model

2.1. Random Forest

Random Forest is a popular machine learning algorithm used for both classification and regression tasks. Ensemble learning method combines the predictions of multiple individual models to improve accuracy. Random Forest is built upon the concept of decision trees. A decision tree is a structure where each leaf node represents a class label in classification process. However, decision trees tend to overfit the training data and it means that they capture noise or random fluctuations in the data. Random Forest randomly selects a subset of the training data (with replacement) to train each decision tree and this process is called bagging. Random Sampling stage includes training each tree on a different subset of data and this process introduce diversity among the trees.

Instead of considering all features to determine the best split, Random Forest randomly selects a subset of features. This further adds randomness and diversity to the trees (Random Subset of Features). Random Forest builds a forest of decision trees. The number of trees in the forest is a parameter that can be specified by the user. Each tree is trained independently using the above random sampling and feature selection process (Building the Forest).

Once all trees are built, each tree in the forest predicts the output class (in classification). In classification tasks, the mode (most frequent class) of all the predictions is taken as the final prediction [7], [8].

2.2. VGG16 (Visual Geometric Group-16)

VGG16 is a convolutional neural network (CNN) architecture that was developed by the Visual Geometry Group (VGG) at the University of Oxford. It was introduced by Karen Simonyan and Andrew Zisserman [9].

VGG16 is known for its simplicity and effectiveness, and it has become a foundational model in the field of computer vision. VGG16 consists of 16 weight layers: 13 convolutional layers and 3 fully connected layers. The model also includes 5 max-pooling layers. Each convolutional layer uses small receptive fields (3x3 filters) with a stride of 1 and padding of 1 to preserve spatial resolution. The number of filters increases progressively from 64 in the first two layers to 128, 256, and finally 512 in the deeper layers. Rectified Linear Unit (ReLU) is used as the activation function after each convolutional and fully connected layer.

Five max-pooling layers, each with a 2x2 filter and a stride of 2, are used to reduce the spatial dimensions. After the convolutional layers, there are three fully connected layers, with the first two having 4096 units each and the last one having 1000 units for the 1000 classes in the ImageNet dataset. Dropout is applied to the fully connected layers to prevent overfitting.

VGG16's pre-trained weights on ImageNet are widely used for transfer learning in various computer vision tasks, such as object detection, image segmentation, and fine-grained image classification. By using the pre-trained model, users can leverage the learned features and adapt them to specific tasks with limited data. Furthermore, transfer learning offers numerous advantages including reduced training time, improved performance with limited data, better generalization, and resource efficiency.

3. RESULTS

Dataset was trained with VGG16 model on Google Colab environment which is a cloud-based platform provided by Google that allows users to write, execute and share codes in a Jupyter notebook platform. Keras library and NVIDIA Tesla T4 GPU were used for the training process. Experiments were carried out with hyperparameters shown in Table 1. Total number of epoch and learning rate were selected as 5 and 0.001 respectively. Batch size was chosen as 32 and Adam was preferred as optimization algorithm. Epoch can be described as the total number of iterations of a learning task. Learning rate decides the change level of the model based on predicted error during updating model weights. Batch size defines the number of samples in an epoch and optimization algorithm is responsible for the weights minimizing the prediction error. In addition, momentum helps optimizing the convergence and was fixed to the value of 0.937 in the study.

TABLE I

Hyperparameters of VGG16 Model

Parameter	Value
Epoch	5
Learning Rate	0.001
Batch Size	32
Optimization Algorithm	Adam
Momentum	0.937

At the end of the training, deep features were obtained from VGG16 model and then features were used as an input to Random Forest machine learning algorithm. After classification process, accuracies and loss values of training and validation datasets were analyzed. In the light of the results, it was noticed that accuracies of training and validation parts were observed as 92.31% and 90.48%, respectively (Table 2). On the other hand, losses were recorded for training and validation sets as 18.03% and 39.41%, respectively. It can be said that training accuracy increased more steadily than validation accuracy which behaves in a fluctuating way seen in Figure 2. In contrary to that, validation loss was monitored more stable than training loss depicted in Figure 3.

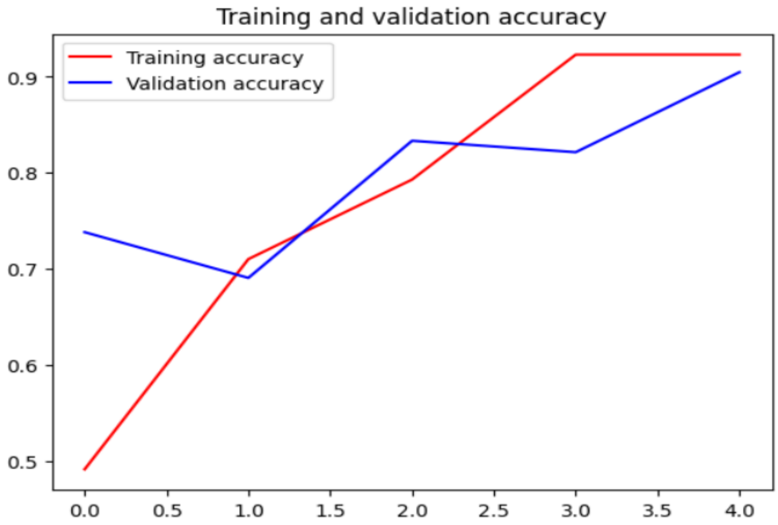

Fig. 2.
Training and Validation Accuracy

Fig. 3.
Training and Validation Loss

TABLE II
Accuracy and Loss Results of Each Data Subset

Data Subset	Accuracy	Loss
Training	92.31%	18.03%
Validation	90.48%	39.41%

4. CONCLUSION

Artificial intelligence (AI) has become increasingly important in the field of medical imaging, particularly in the detection and diagnosis of brain tumors. The integration of AI in this domain brings numerous advantages that significantly enhance clinical outcomes. Also, AI can process and analyze medical images much faster than humans. This rapid processing capability can reduce the time required to diagnose brain tumors, leading to quicker treatment decisions and potentially better patient outcomes. Moreover, it can help in the early detection of brain tumors by identifying minute changes in imaging data that might indicate the presence of a tumor. Early detection is critical for improving prognosis and expanding treatment options. In summary, the application of AI in detecting brain tumors brings significant benefits, including enhanced diagnostic accuracy, speed, and consistency. AI supports early detection, precise tumor localization, personalized treatment planning, and reduces the burden on radiologists, all of which contribute to better patient outcomes and more efficient healthcare delivery. With the help of deep learning and machine learning models, in this study, a hybrid deep learning model was built by combining VGG16 and Random Forest models. Features of the images were received from VGG16 and given as an input to Random Forest machine learning architecture for classification. It can be concluded hybrid model has given outstanding performance with an accuracy of 92.31% and 90.48% in training and validation subsets respectively. For the future study, comparison of other machine learning models combined with deep learning algorithms will be analyzed to find better results.

Conflict of Interest: The authors declare no conflict of interest.

Ethical Approval: The study adheres to the ethical guidelines for conducting research.

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