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BRAIN NET: HYBRID TRANSFER MACHINE LEARNING MODEL FOR BRAIN HEMORRHAGE DETECTION

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ABSTRACT

This research delves into the critical realm of early detection for Alzheimer's disease and brain tumors, two debilitating neurological conditions affecting millions worldwide. The conventional diagnostic methods, reliant on visual inspection and expert interpretation, are time-consuming, subjective, and potentially error prone. To address this challenge, this research explores the application of transfer learning models, specifically deep learning algorithms, to automate and enhance the detection process. In addition, the need for accurate and swift diagnosis has fuelled the development of machine learning models capable of processing extensive medical image data, particularly MRI scans. Transfer learning, a technique leveraging pre-trained deep learning models, offers a promising avenue to overcome the complexities of these diseases. By harnessing the knowledge encoded in large datasets, these models can efficiently identify intricate patterns and abnormalities indicative of Alzheimer's disease and various types of brain tumors. In essence, this research underscores the transformative impact of transfer learning models on Alzheimer's disease and brain tumor detection. By amalgamating advanced machine learning techniques with medical imaging, this approach holds the promise to revolutionize healthcare delivery, offering new horizons for early intervention, improved patient care, and a more efficient healthcare system.

Keywords: Early Detection, Transfer Learning Models, Deep Learning, Medical Image Data, Healthcare, VGG16, VGG19

1. INTRODUCTION

Historically, the diagnosis of neurological conditions such as Alzheimer's disease and brain tumors has heavily relied on conventional methods, including visual inspection of medical imaging scans and expert interpretation. However, these approaches are often time-consuming, subjective, and prone to errors, leading to delays in diagnosis and potentially inadequate treatment. The advent of advanced imaging technologies, such as magnetic resonance imaging (MRI), has revolutionized the field by providing detailed insights into the brain's structure and function. Nevertheless, the analysis of MRI scans remains a complex task, requiring specialized expertise and significant time investment. As a result, there has been a growing recognition of the need for automated and efficient diagnostic tools to improve patient outcomes and streamline healthcare delivery.

The motivation behind this research stems from the urgent need for accurate and timely detection of Alzheimer's disease and brain tumors, given their significant impact on patient health and well-being. Conventional diagnostic methods are often inadequate in detecting subtle abnormalities in medical imaging data, leading to delays in treatment initiation and potential exacerbation of the conditions. Moreover, the increasing prevalence of these neurological disorders highlights the pressing need for scalable and cost-effective diagnostic solutions to meet the growing healthcare demands. Transfer learning, a technique that leverages pre-trained deep learning models, presents a compelling approach to address these challenges by capitalizing on the wealth of knowledge encoded in large datasets. By applying transfer learning models to medical imaging data, researchers aim to automate and enhance the detection of Alzheimer's disease and brain tumors, thereby facilitating early intervention and improving patient outcomes.

2. LITERATURE SURVEY

Hon and Khan [1] proposed a transfer learning approach. It was introduced by using the two most famous deep CNN architectures (Inception and VGG16) with the already trained and fine-tuned weights of ImageNet data. Using a pre-trained model on ImageNet, the researchers trained the last fully connected layer with a small number of training MRI scans. To overcome the over-fitting of the small training dataset, image entropy was applied to MRI images, to extract the most informative portions. An OASIS cross-sectional dataset with 416 subjects was used in an experiment aimed at the binary classification of AD. Five-fold cross-validation was applied with an 80 percent and 20 percent split between training and testing in the fully connected layer retraining. To compare the results VGG16 was also trained from scratch, as well as with transfer learning. Due to the small training set, the VGG16 trained from scratch performed less well in terms of accuracy, 74.12%, while the VGG16 with transfer learning provided 92.3% accuracy. Finally, Inception V4 was used with transfer learning that provided promising results with 96.25% accuracy.

Sarraf and Tofighi [2] utilized CNN with LeNet-5 was utilized for the classification of the brain with AD and the normal brain, by using functional MRI 4D data. In the first step, the 4D data was transformed into 2D by using the neuroimaging packages Nibabel and OpenCV. Then, 2D images were labeled as AD vs NC. The LeNet model, based on CNN, was then used for the binary classification of the images. The results were compared with the famous support vector machine model and, in contrast to it, the proposed model provided better results, with 96.86% accuracy.

Liu et al. [3] proposed a framework with the combination of sparse auto-encoders (SAEs) and a softmax logistic regression was used, along with autoencoders, to use unlabeled data. Two data sets, MR and positron emission tomography (PET) from the ADNI database, were used. The main target of this research was to use SAE for high-level feature selection in the unsupervised pre-training stage. As a result of two different neuroimaging modalities, a zero-masking technique was used for the extraction of complimentary details from these different datasets. Features extracted from SAE, using unsupervised data, were then manipulated with a softmax regression. The performance of the model was tested on the classification of AD. In comparison with other advanced models, like SVM and other deep learning methods, the proposed model performed very well with 91.4 percent accuracy just because of its capability to extract features in one setting and its requiring of less labeled data.

In another study by Liu et al. [4] customized 2D-CNN model, with 9 depth-wise separable convolutional and normalization layers, was used, along with Inception V3 and Xception models for transfer learning. In this research, the classification of AD patients, class imbalance, and data leakage issues were discussed. The second fully connected layer used the sigmoid function as an activation function to categorize the data into two classes. An OASIS dataset, with T1-weighted structural MRI images, was used and the dataset was divided into 3 portions: set 1, set 2, and set 3. Cross-validations with 2-folds, 5-folds, and 9-folds were applied to the partitioned datasets, respectively. Dataset 1 was used for the prediction of AD, dataset 2 was used for class imbalance and dataset 3 was used for data leakage problems. For the AD classification on dataset 1, 45 subjects were used for training and validation purposes. Stochastic gradient descent (SGD) was used as an optimization algorithm. For loss function, binary cross entropy was used. In comparison with other deep learning models, the proposed model, which was based on transfer learning, provided promising results.

Tufail et al. [5] developed a deep learning framework with a softmax output layer and stacked autoencoders are used for the detection of Alzheimer's disease and its initial stage MCI. MRI data of 311 patients available on the ADNI database was used. Gray matter (GM) was extracted from the MRI images, which made the baseline for the detection of MCI and the CMRGlc patterns using PET. Elastic Net is then used to extract the high-level features. In individual cross-fold, 90 percent of subjects are used for training and the rest of the 10 percent for testing. SK-SVM and MK-SVM are considered for comparison with the proposed model. The model gives 87.76 % accuracy in the binary classification of AD patients.

Liu et al. [6] employed AlexNet, a fine-tuned pre-trained CNN, was used for the binary and multi-class classification of 3D MRI images. The proposed model was trained on the already pre-processed data in which WM, GM, and CSF were segmented and, then, the testing of the model was conducted on the unsegmented 3D MRI scans of the human brain. An OASIS dataset, consisting of 382 subjects, was used for training and testing. After the training of the proposed model on the segmented dataset, the retrained convolutional neural network was then used for the validation over the unsegmented 3D MRI images. For multi-class classification, the proposed model outperformed the binary classification, with 92.8% accuracy versus 89.6%.

Maqsood et al. [7] proposed a modified Siamese CNN model, inspired by Oxford Net (VGG16), was used for the classification of AD stages. The basic idea behind the proposed model was to use the augmentation technique, with an extra convolutional layer in VGG16. Augmentation was applied to an OASIS dataset after the pre-processing phase. Two parallel layers of modified VGG16 worked for the extraction of the most important features. Batch normalization was applied to increase the learning rate, which gradually decreased, due to changing the parameter in individual layers of the CNN model. In comparison with the other state-of-the-art models, the proposed model provided 99.05 % accuracy, and it also reduced the problems of over-fitting and regularization. In [7], a layer-wise transfer learning approach and tissue segmentation were used for the classification of AD. The dataset used in this research was collected from the ADNI database. In the pre-processing step, the skull stripping, and extraction of GM, WM, and CSF were conducted using SPM12. The VGG-19 network was customized by modifying the last two fully connected and classification layers. Instead of freezing the trained fully connected layers, the researchers divided the model into two groups and then they gradually fixed CNN layers in different blocks. The training of the proposed model was done on both augmented and non-augmented datasets. In the first group, 8 CNN layers with 3 max-pooling layers were kept fixed, and in the second group 12 CNN layers along with 4 max-pooling layers were kept fixed. In experiments after the augmentation, the classification results of the proposed model were 98.73%, 83.72%, and 80% on AD vs NC, EMCI vs LMCI, and other classes, respectively.

Mehmood et al. [8], a cross-model technique, using the transfer learning technique, was used to reduce the over-fitting problem, while the training was done on a small set of MRI images. The proposed model was trained on the structural MRI data collected from the ADNI database and then tested on the DTI dataset. The outcome of the model on the two different cross-modalities was outstanding, with 92 percent accuracy on NC vs AD, 80 percent on NC vs MCI, and 85 percent on MCI vs AD.

Mehmood et al. [9] employed the deep learning models, GoogLeNet and ResNet, were trained from scratch on structural MRI data sets available on the ADNI database. The main target of this research was to segment the gray matter (GM) and then train the CNN networks on these segmented GM images. The addition of the augmentation layer proved to be a useful step in the classification of the four stages of AD.

3. PROPOSED SYSTEM

The description of the implementation steps for the project:

- Uploading Dataset: Upon clicking the "Upload Dicom Alzheimer Brain Dataset" button, the user is prompted to select a directory containing DICOM images related to Alzheimer's disease and brain tumors. This dataset typically includes images labeled as 'Normal' or 'Alzheimer Brain Tumor'.
- Image Preprocessing: After uploading the dataset, the program preprocesses the images. This involves reading each DICOM image, resizing it to a standard size (e.g., 32x32 pixels), converting it into a numerical array format, and associating each image with its corresponding label ('Normal' or 'Alzheimer Brain Tumor'). These preprocessed images and their labels are then stored for further use.
- Training and Testing VGG16 Model: The program trains and tests a pre-existing VGG16 convolutional neural network (CNN) model using the preprocessed image data. The VGG16 model is trained to classify images into the two categories: 'Normal' or 'Alzheimer Brain Tumor'. The training process involves optimizing the model's parameters to minimize classification errors, while the testing process evaluates the model's performance on unseen data.
- Training and Testing VGG19 Model: Similarly, the program trains and tests a proposed VGG19 CNN model using the same preprocessed image data. The VGG19 model architecture is similar to VGG16 but with deeper layers, potentially leading to improved performance in image classification tasks. The training and testing procedures for the VGG19 model are similar to those for the VGG16 model.
- Test Image Prediction using VGG19 Model: Finally, the program allows users to upload a test DICOM image for tumor detection using the trained VGG19 model. The model predicts whether the uploaded image contains a brain tumor associated with Alzheimer's disease. The prediction is displayed along with the uploaded image, providing a quick assessment of the model's performance on unseen data.

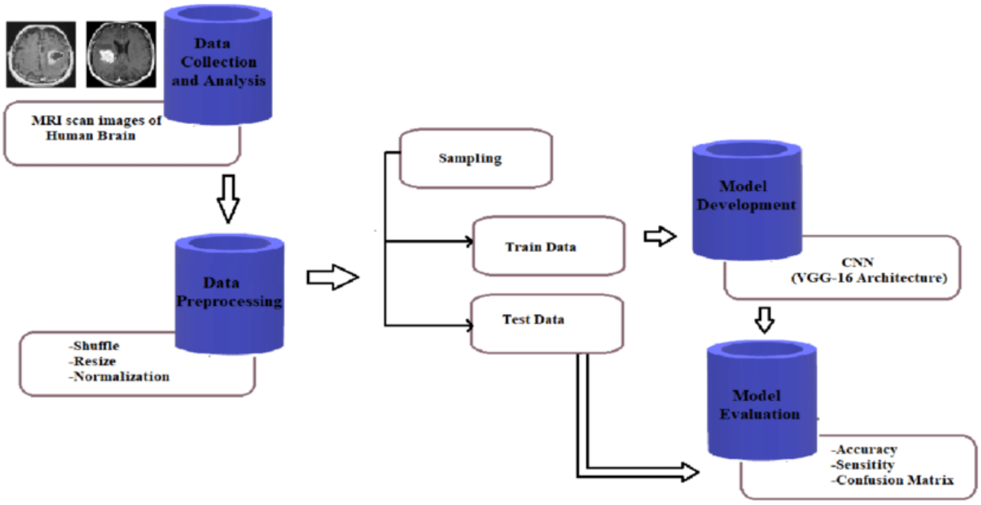

Figure 1 Block Diagram of Proposed System.

The VGG19 model, short for Visual Geometry Group 19-layer model, is a convolutional neural network (CNN) architecture proposed by the Visual Geometry Group at the University of Oxford. It gained prominence for its simplicity and effectiveness in image classification tasks. VGG19 is an extension of the earlier VGG16 model, with deeper layers resulting in improved performance on various visual recognition tasks.

The architecture of VGG19 can be visualized as a sequence of convolutional layers followed by max-pooling layers, culminating in fully connected layers for classification.

Here is a simplified block diagram illustrating the key components of VGG19:

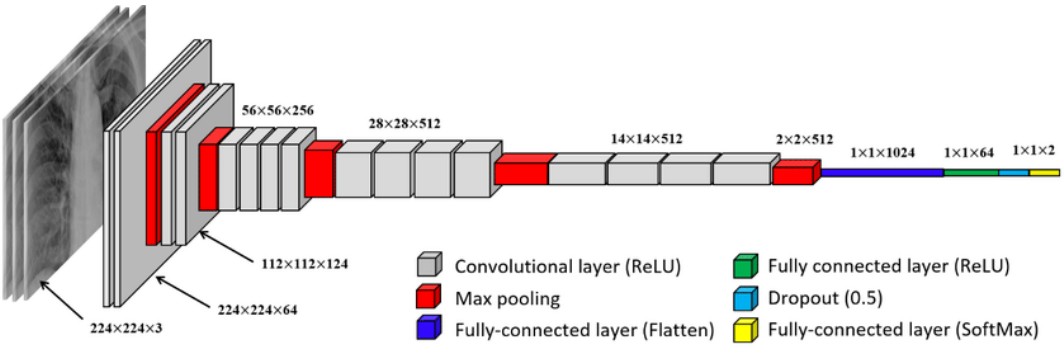

Figure 2: Architecture diagram of VGG19 model.

VGG19 operates by passing the input image through a series of convolutional layers interspersed with max-pooling layers. These convolutional layers are responsible for extracting features at different levels of abstraction. Each convolutional layer applies a set of filters to the input image, detecting various patterns such as edges, textures, and shapes.

The max-pooling layers serve to downsample the feature maps, reducing their spatial dimensions while retaining the most salient information. This downsampling helps in reducing computational complexity and mitigating overfitting.

As the input image progresses through the network, the feature maps become increasingly abstract and complex, capturing higher-level representations of the input image.

After passing through several convolutional and max-pooling layers, the output is flattened and fed into a series of fully connected layers. These fully connected layers perform high-level reasoning and decision-making based on the extracted features, ultimately producing a probability distribution over the possible classes.

The final layer typically employs a softmax activation function to convert the raw output into a probability distribution, indicating the likelihood of the input image belonging to each class in the dataset.

4. RESULTS

Figure 3 displays the confusion matrix of the VGG16 model. The confusion matrix is a table that describes the performance of a classification model, showing the counts of true positive, true negative, false positive, and false negative predictions.

Figure 4 Shows the confusion matrix of the VGG19 model., this matrix provides insights into the classification performance of the VGG19 model on a specific dataset.

Figure 5 Illustrates an accuracy comparison graph between the VGG16 and VGG19 models. This graph likely compares the accuracy scores of the two models across different evaluation metrics or datasets.

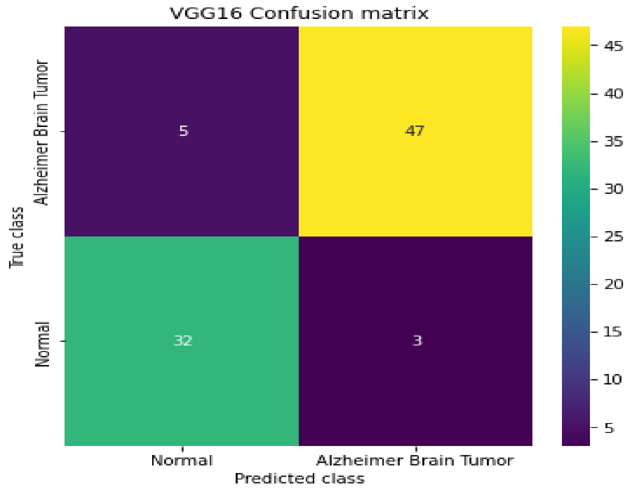

Figure 3: Shows the confusion matrix of VGG16 model.

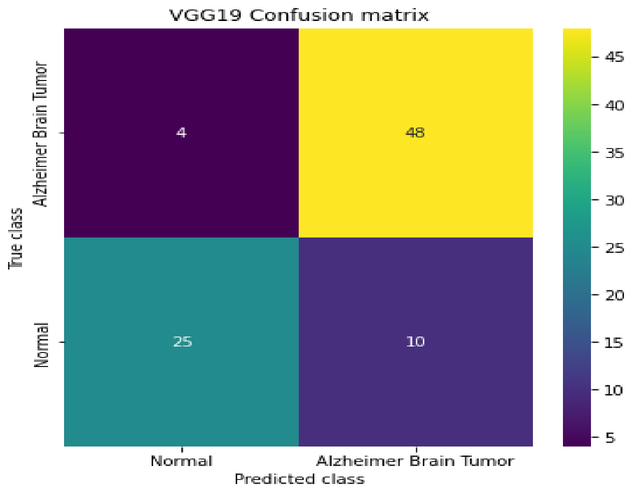

Figure 4: Shows the confusion matrix of VGG19 model.

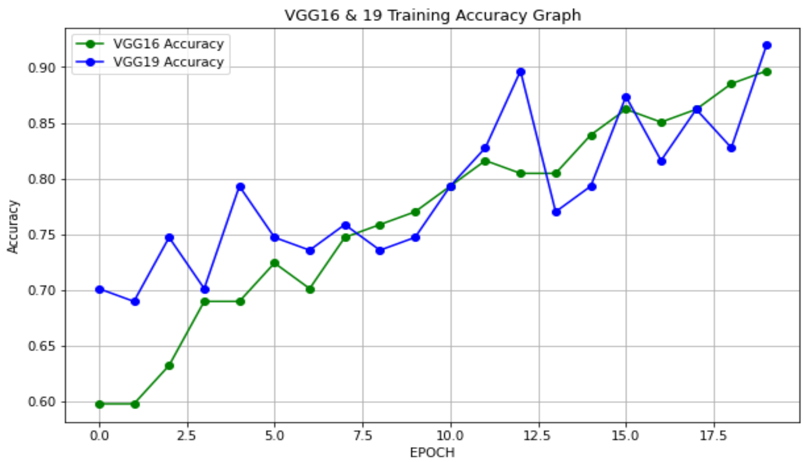

Figure 5: Shows the Accuracy Comparison graph of VGG16 and VGG19 models.

Table 1: Performance comparison of quality metrics obtained using VGG16 And VGG19 model.

Model	VGG19	VGG16
Accuracy (%)	90.8	83.9
Precision (%)	90.2	84.4
Recall (%)	90.8	81.8
F1-score (%)	90.5	82.6

For the VGG19 model:

- The Accuracy is 90.8, indicating the accuracy between the actual and predicted values
- The Precision is 90.2, suggesting that, on average Precision between the actual and predicted values.
- The Recall is 90.8, suggesting that, on average Recall between the actual and predicted values.
- The F1-score is 90.5, representing the average F1-score between the actual and predicted values.

5. CONCLUSION

In conclusion, this research delves into the transformative potential of transfer learning models in the early detection of Alzheimer's disease and brain tumors, presenting a paradigm shift from traditional diagnostic methods. The limitations of time-consuming and subjective visual inspection are addressed through the application of deep learning algorithms, leveraging transfer learning techniques. By harnessing the knowledge embedded in pre-trained models, these algorithms demonstrate remarkable efficiency in processing extensive medical image data, particularly MRI scans. The research highlights the significant strides made in automating and enhancing the detection process for these debilitating neurological conditions. The amalgamation of advanced machine learning techniques with medical imaging not only promises early intervention but also holds the key to improving patient care and overall healthcare system efficiency.

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