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Non-Invasive Pre-Diagnosis Implementation of Psychiatric Mental Disorders from EEG Bio-Signal Data Using Ensemble Deep Learning: A Comparative Analysis

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ABSTRACT

Studies about detection of psychiatric diseases area have gained higher importance among science, engineering and medical areas. There have been a lot of different and unique types of mental problems/diseases and some of them could be seen very common among people worldwide. There were some ways to analyze and interpretate the mental disorders such as from neuroimages, EEGs and other outputs of radiological types of imaging systems. This research aims analyzing and pre-diagnosis of Alzheimer's disease (AD) and Attention Deficit Hyperactivity Disorder (ADHD) from an open source and publicly available EEG dataset by performing specific ensemble deep learning models to create an automated medical image analysis Computer Aided Diagnosis (CAD) system in detail. In medical area, fundamentally, the current diagnostic methods were time-consuming, subjective and needed detailed knowledge. To address and overcome these limitations, improving the diagnostic procedure in a fast way, we proposed a developed version of pre-diagnosis with using the development of a deep neural network system capable of accurately and efficiently analyzing biological signal data. Moreover, three different deep learning models of ResNet50, VGG19 and InceptionV3 were applied to the three separate mental disease groups and for this phase EEG signals were converted to the spectrogram images and used in detail. The models were extensively trained on the pre-processed image dataset and evaluated using multiple accuracy metrics. To improve diagnostic accuracy and efficiency, the trained models were combined using an ensemble approach and incorporated into an intuitive MATLAB software version. The most remarkable accomplishment of this study was the InceptionV3 model, which attained an impressive 99.47% for AD and ADHD discrimination via bio-medical signal processing. These findings highlight the significant potential for making the models sufficient to pre-diagnose during the clinical progress for neurologists, brain surgery area and other related doctors/clinicians.

1. INTRODUCTION

Especially in the medical area, the change rate of Computer Aided Diagnosis (CAD) Systems has become higher and spread over worldwide in human life. Analyzing and investigating psychological diseases has become more popular and become on medical/biomedical methodologies such as EEGs and some types of radiological imaging systems f [1, 2].

Alzheimer's disease (AD) is a degenerative neurological disorder impacting millions globally, making early detection crucial for effective treatment [3]. Conventional diagnostic techniques can be slow, prone to errors, and dependent on specialized expertise. Utilizing deep learning for automated medical image analysis provides a more accurate, efficient, and scalable solution for detecting and diagnosing Alzheimer's through imaging data [4].

A key challenge in diagnosing AD is the lack of reliable biomarkers for predicting its onset and progression. Existing methods, including cognitive testing, imaging, and neurological exams, are often subjective and susceptible to misdiagnosis, especially in the early stages when symptoms are minimal or absent [5]. Deep learning and ensemble techniques offer objective and precise evaluations of brain function and structure, helping to overcome these limitations. Additionally, automating medical image analysis can aid in Alzheimer's treatment by identifying disease-related biomarkers, which support the development of new therapies [6]. Deep learning models trained on extensive MRI datasets can detect intricate brain patterns, significantly improving early Alzheimer's detection [7].

Attention-deficit/hyperactivity disorder (ADHD) is among the most common neuropsychiatric disorders in childhood. Globally, approximately 5% of school-aged children are affected, and around 60% of preteens continue to exhibit symptoms into adulthood [8]. ADHD is marked by developmentally inappropriate inattention, hyperactivity, and impulsiveness. Indeed, because the diagnostic process can be both time-consuming and subjective, numerous studies have employed various neuroimaging methods, such as electroencephalography (EEG), to identify the neural correlates of ADHD.

Research utilizing EEG to study AD and ADHD began approximately long years ago. Since then, EEG has evolved into one of the most widely employed neuroimaging techniques due to its accessibility, informativeness, and affordability [9, 10, 11]. A variety of signal processing methods have been developed to identify electrophysiological abnormalities in children with ADHD, including power estimation techniques [12, 13], complexity analyses [14, 15, 16], and synchronization measures [17, 18]. Furthermore, by leveraging meticulously handcrafted AD-related features, several machine learning algorithms [19, 20], linear discriminant analysis (LDA) [21, 22], and support vector machines (SVM) [23, 24]—have been applied to create classification models that serve as complementary diagnostic tools for ADHD.

Generally, automating medical image analysis with deep learning offers significant advantages, such as improved diagnostic accuracy and efficiency, early disease detection, and better disease management. This technology also reduces the burden on healthcare professionals, enabling them to concentrate on more critical responsibilities on patients who have suffered from mental diseases.

The primary goal of leveraging deep learning for automating diagnosis of specific mental diseases through medical image analysis is to improve diagnostic accuracy, efficiency, and accessibility, ultimately leading to better patient outcomes [25]. This study aims to integrate results from multiple deep learning models to develop a robust approach for detecting and diagnosing AD and ADHD diseases using medical imaging data (EEG signals). The research focuses on training ensemble deep learning models, including ResNet50, VGG19 and InceptionV3, on large open source brain EEG datasets to identify subtle brain changes associated with these mental diseases.

To accomplish this, the project is structured around several critical phases. First, a comprehensive collection of images—encompassing both AD and ADHD patients and healthy individuals—would be assembled. This dataset could be used to train the selected popular ensemble deep learning models, with their performance primarily assessed based on accuracy. Next, the performance of these models could be compared against traditional diagnostic methods to evaluate their effectiveness. The main goal of using deep learning and ensemble methods to automate medical image analysis for AD and ADHD diagnosis was to provide healthcare professionals with a more precise and efficient diagnostic tool.

2. MATERIAL AND METHODS

The process of automating medical image analysis for Alzheimer's diagnosis through a deep learning-based ensemble approach consisted of multiple stages. These included data collection and pre-processing, selecting appropriate models, extracting relevant features, training and validating the models, testing and saving the results, implementing the ensemble method, and integrating the system, as illustrated in Figure 1 in detail.

2.1 Data preparation and preprocessing procedures

In this study, an open-access publicly available EEG dataset from Kaggle was chosen and used in detail [26]; so no ethical permission was needed for this study in detail. For this study, 50 subjects for AD and 50 subjects for ADHD were randomly chosen from the Excel open-access data list, and EEG numerical data of the studies were plotted, and the EEGs were used via MATLAB 2024a version indeed. According to the detailed information. In this study, a Kaggle dataset was used and the EEG data was first plotted according to the numerical values in the Excel file, and then, after Preprocessing, Spectrogram images were converted, obtained and used for Deep Learning models.

For the EEG preprocessing part; 3×3 sized Median filtering and artefact reduction (via Independent Component Analysis-ICA) processed were mainly achieved and the signals were become ready for the processing.

The dataset is divided into two folders: Training and Testing, and it includes brain EEG signals categorized into four distinct classes. The dataset's labels have been verified, ensuring its reliability for building machine learning models [27]. The inclusion of various dementia types enables the development of a more comprehensive model for AD and ADHD diagnosis. Its substantial size provides ample data for training and testing, contributing to more precise and robust results. In Figure 2, a flowchart of the experimental part of the study is represented in detail.

The dataset was initially uploaded to Google Drive as a zip file, then imported and extracted. The original images in the dataset were raw signals with 45 min. duration, which were segmented and only 45 min parts were chosen regularly and used. Then these signals were converted to the Spectrogram image versions and then they resized to 255×255 um to reduce computational complexity during training. After resizing, a preprocessing function was implemented to prepare the data for the algorithm. This function assigned labels to the images and applied one-hot encoding to convert the data into a format suitable for processing. The labels enabled the algorithm to distinguish between different classes, while one-hot encoding optimized data handling [28]. To train the model effectively, the training data was split into two subsets: a validation set and a training set. The validation set was created by randomly selecting 30% of the training data, while the remaining 70% was used for actual training part.

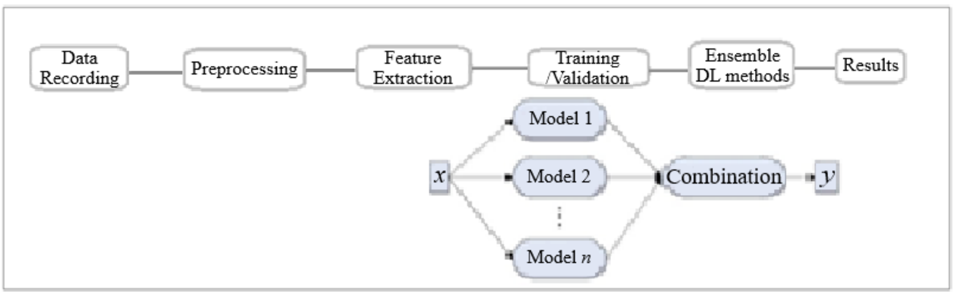

Figure 1. The methodology flowchart of the study

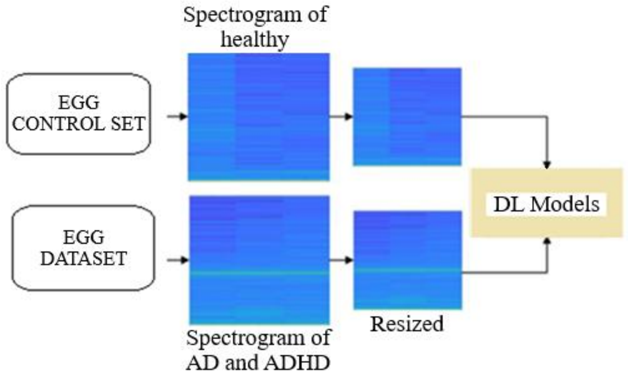

Figure 2. Flowchart of the experimental part of the study

2.2 DL model selection procedure

For this study, the experimental part was achieved via ResNet50, VGG19 and InceptionV3 in detail. These models were chosen for the task of analyzing and identifying AD and ADHD mental diseases from brain EEGs and their Spectrogram versions because of the capacity to learn complex features from datasets. The ResNet50 was defined and considered as an effective candidate model for image feature extraction and classification processes for the publicly open source datasets of 50 EEGs for AD and 50 EEGs for ADHD diseases. Generally, ResNet50 could handle small and large datasets with complicated features and characteristics. ResNet50 is a pretrained model and the pretraining could be used to extract features of the datasets [29].

VGG19 was also chosen for the task of analyzing AD and ADHD diseases from brain EEGs and because of 19-layer architecture, this model could learn all levels of the features from the signal dataset [30]. For this project, we considered utilizing VGG19 with its pre-trained weights from MATLAB software, a vast dataset of general EEG signals. VGG19's deep architecture and high accuracy make it a strong candidate for feature extraction and classification tasks, with its pre-trained weights significantly reducing training time. Additionally, VGG19, with its more complex structure, was also considered suitable for feature extraction. VGG19 has 19 layers compared to VGG16 model, enabling it to capture more intricate details from images. This makes it a strong candidate for diagnosing these specific mental diseases, as the condition leads to significant structural and complexity changes in the brain EEGs. However, VGG19 was also found to be computationally demanding, requiring substantial memory and processing power [31].

InceptionV3 was also selected as a suitable option for feature extraction from brain EEG signals in AD and ADHD diseases diagnosis [32]. The model's dense connectivity structure could allow efficient information flow throughout the network, enabling it to learn complex features. This capability could be particularly beneficial for identifying subtle patterns and variations in brain signals that may indicate the mental diseases [33].

2.3 Feature extraction process

For feature extraction in ResNet50 involved utilizing a pre-trained model with the top layer removed. The image was first loaded and pre-processed to match the required input size of ResNet50. Once pre-processed, the image was passed through the model, which extracted the features. These extracted features were then used as input for a new model, either for classification or further processing [34].

The feature extraction process in VGG19, feature extraction involved loading the pre-trained model, removing the fully connected layers at the top, and utilizing the remaining convolutional layers to extract image features [35]. Pre-processed input images were passed through the network, and the output from the final convolutional layer served as the feature representation for each image. These extracted features could then be used for various tasks such as classification, clustering, and image retrieval [36].

The feature extraction process in InceptionV3 followed a similar approach to other convolutional neural networks. The pre-trained model was loaded, and the final fully connected layer was removed, retaining only the convolutional layers. The input image was then processed through the model, and the output from the last convolutional layer was obtained, representing the image's high-level features [37]. These extracted features could then be used for training another machine learning model or any other required task.

2.4 Training and validation evaluation progresses

When the models of ResNet50, VGG19 and InceptionV3 were analyzed, several key factors provided insights into their architecture and performance. The first consideration factor was the overall network structure. While VGG19 could share a similar design with sequential convolutional layers followed by fully connected layers, InceptionV3 incorporated inception modules with multiple parallel paths, and ResNet50 utilized residual connections to support more deeper networks [38].

Another critical factor was the number of parameters, which influenced model complexity and the risk of overfitting. VGG19 could have the highest parameter count among these models, whereas ResNet50 had relatively fewer parameters. Additionally, training time was an important consideration, particularly for large datasets [39]. Indeed, VGG19 generally required more time to train compared to ResNet50.

Model accuracy was another crucial metric for performance evaluation. ResNet50 had demonstrated state-of-the-art accuracy on various image recognition tasks, including classification and object detection, while InceptionV3 had also shown competitive results. Regularization techniques, such as dropout and batch normalization, played a vital role in improving generalization and preventing overfitting. All these models incorporated some form of regularization, with ResNet50 leveraging residual connections. Additionally, the depth and width of the networks significantly impacted their effectiveness. Indeed, ResNet50 were deeper compared to VGG19, while InceptionV3 maintained an intermediate depth but a wider architecture [40].

After understanding these models, training was totally performed. Deep learning algorithms required extensive data to effectively learn patterns and generalized to unseen samples. In the context of medical image analysis, training and validation were crucial for building models capable of accurately detecting and diagnosing diseases. In this study; VGG19, ResNet50 and InceptionV3 were trained on a dataset containing totally 100 brain EEG spectrogram version images. A batch size of 16 was used, and the number of epochs ranged from 12 to 20, depending on model performance on the validation set.

During training, the models learned to identify key patterns in the input data and associate them with diagnosis of these mental diseases. The choice of hyperparameters, such as the learning rate and optimizer, significantly influenced model performance. To prevent overfitting, early stopping was implemented across all models. This technique helped regulate training by halting the process before the model began memorizing the training data. Early stopping involved monitoring validation loss and stopping training if no improvement was observed after a predefined number of epochs [41].

Following training, model performance was evaluated using a separate validation set. This assessment helped determine the accuracy of the models. Monitoring both training and validation loss was essential in detecting overfitting, which occurs when a model performs well on training data but poorly on validation data.

2.5 Testing evaluation progress

The final stage in developing deep learning models for Spectrogram image analysis of EEGs was testing. In this study; VGG19, ResNet50 and InceptionV3 were evaluated for their ability to detect AD and ADHD diseases using a dataset of 100 Spectrogram of EEGs. A batch size of 20 was used for all models, and the number of epochs ranged from 10 to 20, depending on validation performance. During testing, the trained models were presented with previously unseen data, and their classification accuracy was assessed.

Several performance metrics were used, including accuracy, precision, recall, and the F1 score [42]. Accuracy represents the percentage of correctly classified images, while precision measures the proportion of true positives among all positive predictions. The F1 score, which is the harmonic mean of precision and recall, indicates the proportion of actual positive cases correctly identified. However, for this study, only accuracy was compared across models.

2.6. Ensemble deep learning methods

Generally, three pre-trained models—ResNet50, VGG19, InceptionV3— were employed to demonstrate an ensemble approach for image classification. The objective of ensemble methods was to combine predictions from multiple models to enhance overall accuracy and robustness.

In this implementation, each model independently predicted the class label of an input image. The final class label was determined using a voting mechanism, where the class receiving the majority of votes became the final prediction.

The preprocessed image was then passed through each of the three models, and the predicted class label was determined by identifying the index of the highest value in the output vector. Finally, the function aggregated the predicted labels from all models using a voting system, providing both the final predicted label and the preprocessed images for each model. To sum up, this approach presents a straightforward yet effective way to integrate multiple models' predictions for image classification tasks.

3. RESULTS AND DISCUSSION

Confusion matrices were generated for all three DL models for two specific mental diseases to assess their classification performance by comparing the predicted labels with the actual labels and a confusion matrix was given in Figure 3.

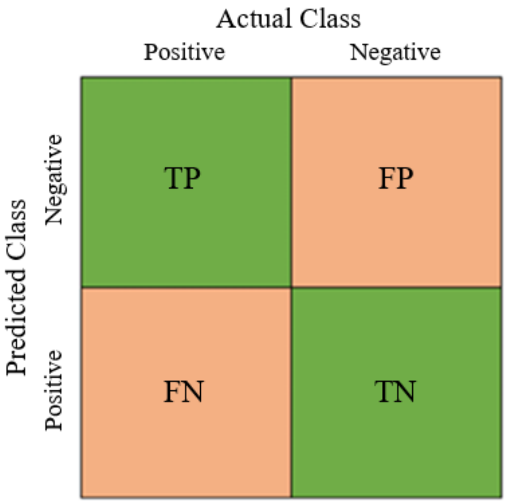

Figure 3. Confusion matrix for binary classification

In each confusion matrix, the y-axis represented the true labels or ground truth of the EEG-Spectrogram images, while the x-axis denotes the labels predicted by the ensembled DL model. Each cell in the matrix indicated the number of images classified into a particular category.

If the model correctly predicted the stage of the disease, it was recorded as a true positive (TP) in the corresponding cell. An incorrect prediction of the disease stage was classified as a false positive (FP). Conversely, if the model failed to detect the mental disease when it was actually present, it was categorized as a false negative (FN). If the model correctly identified the absence of the disease, it was marked as a true negative (TN).

In the confusion matrix for InceptionV3, the model correctly classified 98 out of 2 AD and ADHD images. However, it misclassified 1 image, 49 as NonAD. The model demonstrated perfect accuracy in predicting all AD and ADHD images discrimination. In the confusion matrix for VGG19, the model correctly classified 82 out of 18 AD and ADHD images. However, it misclassified 12 images, 38 as NonAD. In the confusion matrix for ResNet50, the model correctly classified 80 out of 20 AD and ADHD images. However, it misclassified 20 images, 30 as NonAD.

The accuracy plot is an essential tool for evaluating a deep learning model's performance, providing insights into how well the model performs during training on both the training and validation datasets.

This plot offers a clear indication of the model's behavior. A significant gap between the training and validation accuracy may signal overfitting, where the model learns the training data too well but fails to generalize. On the other hand, low validation accuracy suggests underfitting, where the model is unable to capture the underlying patterns in the data. Ideally, a well-generalized model will show similar accuracy values for both training and validation datasets.

In conclusion, the accuracy plot is an important resource for assessing model performance and helping guide decisions on further training, parameter tuning, or model selection. The x-axis typically represents the number of epochs, while the y-axis displays the accuracy metric.

The VGG19 model demonstrates exceptional performance in image classification, achieving an impressive test accuracy of 79.06% and validation accuracy of 78.03% after just 10 training epochs. This highlights its ability to recognize key class features and accurately classify new images. With a low loss value of 0.78%, the model effectively predicts outputs for most inputs. Despite its complexity and large number of trainable parameters, VGG19 avoids overfitting, as reflected by its high test accuracy. However, it's important to remember that test accuracy alone doesn't offer a full assessment, as it only measures the test set's performance. Therefore, it should be complemented with other metrics for a more thorough evaluation. The accuracy plot for VGG16 is shown in Figure 4.

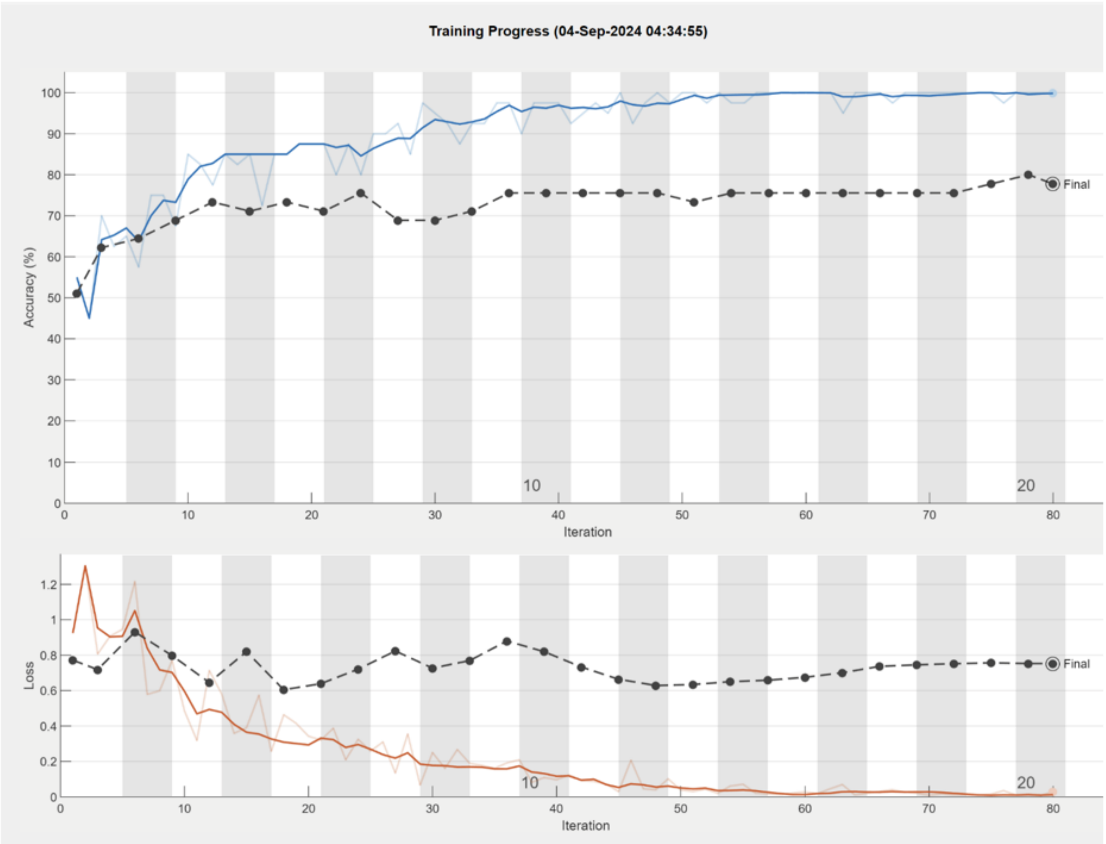

Figure 4. Model accuracy result for VGG19

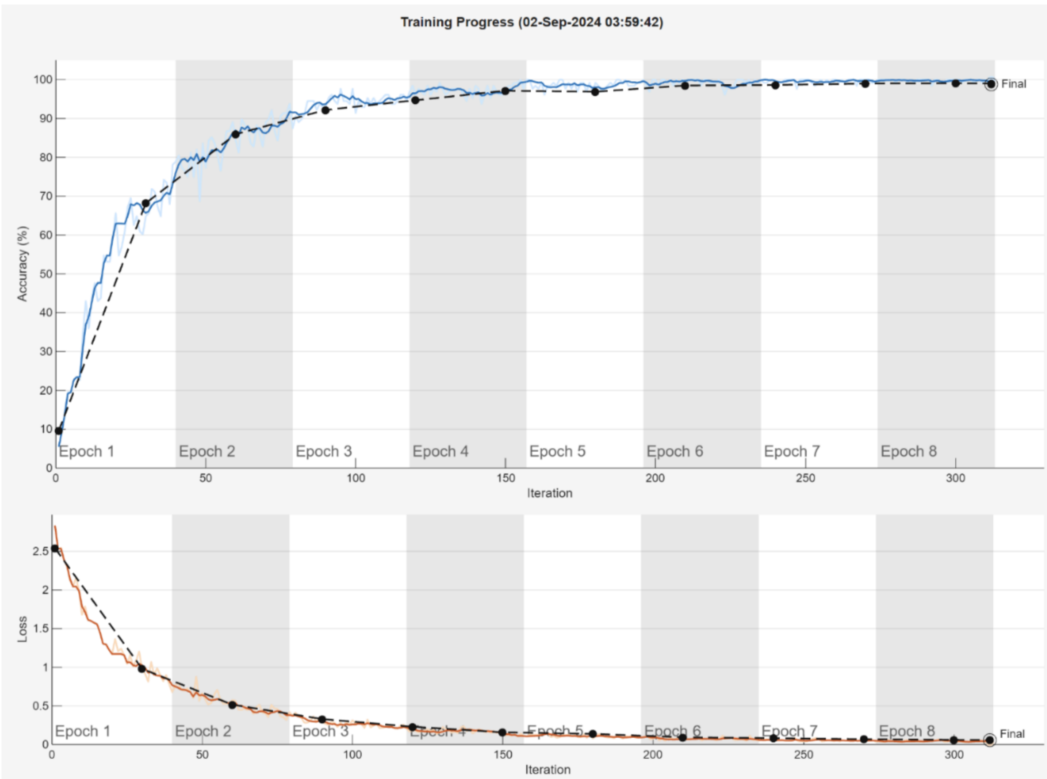

Figure 5. Model accuracy result for InceptionV3

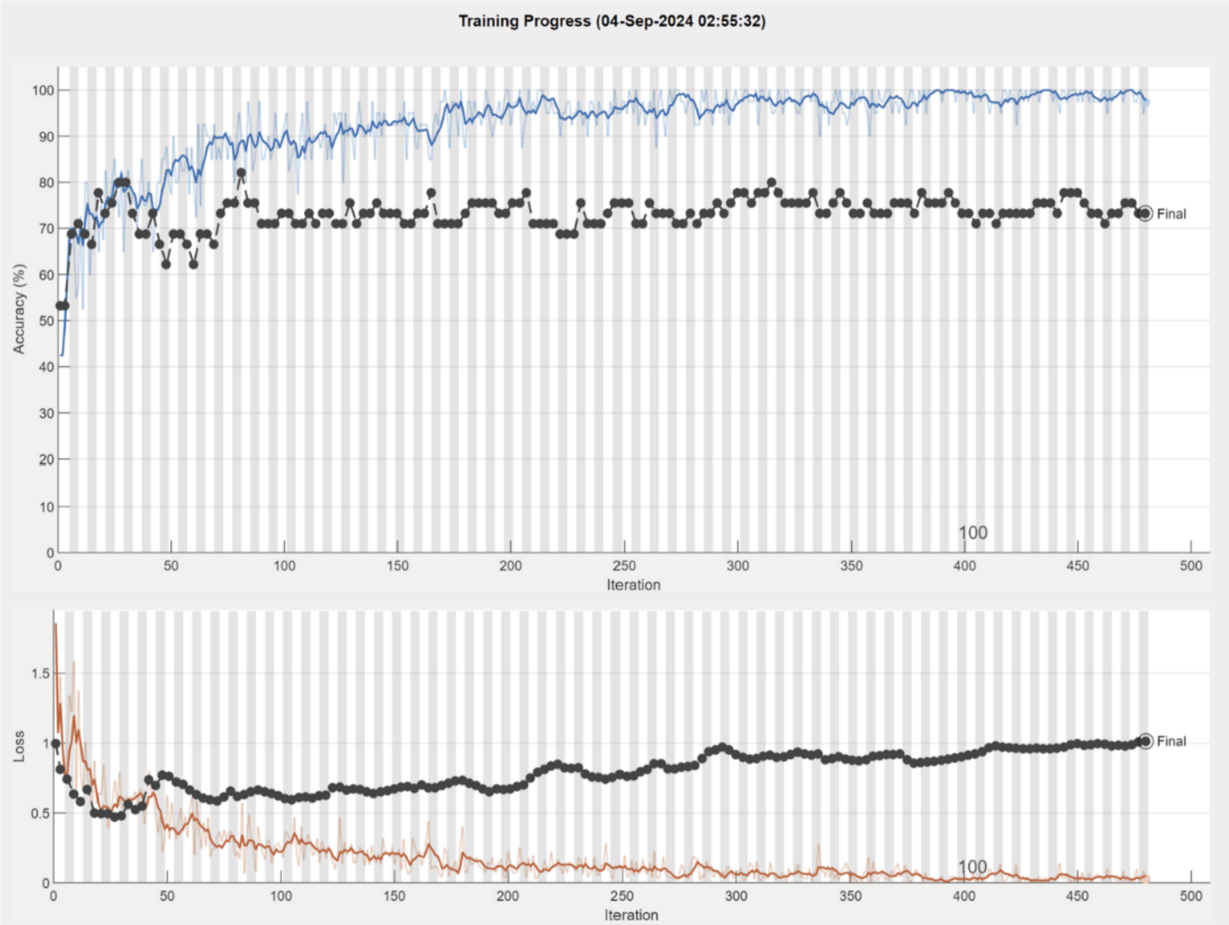

Figure 6. Model accuracy result for ResNet50

The InceptionV3 model demonstrates strong performance after 20 epochs of training. It achieves an impressive test accuracy of 99.47%, highlighting its ability to perform accurate image classification, a critical feature for such models. Additionally, the model's 98.1% validation accuracy emphasizes its skill in generalizing to new data, which is vital for real-world applications. A loss value around 3% indicates that the model effectively learns the data's patterns and makes accurate predictions. Low loss values are desirable, suggesting the model generally provides accurate predictions for most inputs. Overall, InceptionV3 shows promising results, making it a viable option for image classification tasks. However, it's important to note that performance may vary depending on the specific dataset and problem, so a thorough evaluation on the target dataset is recommended. The accuracy and loss value graphs for InceptionV3 are shown in Figure 5.

The ResNet50 model was trained to classify AD and ADHD disease Spectrogram images. The model's performance was assessed using key metrics, such as test accuracy and validation accuracy, which are essential for evaluating deep learning models. After training, ResNet50 achieved commendable results, with a test accuracy of 73.2% and a validation accuracy of 71.3%, as shown in Figure 6. These results highlight the model's effectiveness in accurately categorizing the images, which is particularly important in mental disease image classification. The accuracy and loss value graphs for ResNet50 are shown in Figure 6.

To sum up, the tabular description of all the modules in terms of test accuracy, validation accuracy and loss value has shown in Table 1.

Table 1. Test accuracy, validation accuracy, and loss values for models used in the study

Models	Test Accuracy	Validation Accuracy	Loss Value
ResNet50	73.2	71.3	1.0
VGG19	79.06	78.3	0.78
InceptionV3	99.47	98.1	0.1

4. CONCLUSION

The progress of deep learning and ensemble techniques in medical image analysis brings new hope to the complex field of AD and ADHD disease diagnosis. These approaches have shown significant potential in identifying subtle structural and functional changes in the brain that indicate the presence of the disease. By combining convolutional neural networks with ensemble methods, the accuracy of these models has significantly improved, enhancing confidence in their ability to diagnose mental diseases with greater precision.

However, implementing deep learning and ensemble techniques in medical image analysis comes with its own set of challenges. One of the biggest hurdles is obtaining large volumes of high-quality data for model training. Acquiring such data can be both difficult and costly, and data quality plays a crucial role in determining model accuracy. Additionally, these methods require extensive computational resources, leading to high costs and time-consuming processes. Another major challenge is the interpretability of these models, which remains a critical concern in their practical application.

These methods provide healthcare professionals with a powerful tool for precise disease detection and prediction, enabling early intervention and better patient outcomes. Deep learning and ensemble techniques excel at identifying complex patterns and features that might be overlooked by the human eye. Furthermore, these approaches are highly adaptable and capable of continuous improvement. As more data becomes available, models can be retrained to enhance their accuracy and reliability. Additionally, transfer learning allows models to be trained on larger and more diverse datasets, further improving their accuracy and generalizability.

In conclusion, the future of automating medical image analysis through deep learning and ensemble techniques for other mental diseases is vast and promising. With ongoing technological advancements, we can expect greater accuracy and efficiency in medical image processing, ultimately leading to better patient outcomes. The integration of deep learning with diagnostic tools, wearable technologies, personalized medicine, interpretable algorithms, and telemedicine has the potential to transform the landscape of other diseases diagnosis and treatment. Moreover, this study was first achieved and performed on the medical data, and spectrogram images were fed into the DL models. In the near future, clinical version validation will be achieved, and this study will only defined as an experimental comparative study.

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