Integrating Spatial and Temporal Insights: Alzheimer's Disease Detection through MRI and EEG Signal Analysis

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BONAFIDE CERTIFICATE

Certified that this project report entitled "**Integrating Spatial and Temporal Insights: Alzheimer's Disease Detection through MRI and EEG Signal Analysis**" is a bonafide work of **ANEESH JAYAN P, DEEPAK S, ARUNACHALAM B, HARISH D** who carried out the project work under my supervision and guidance for "**ECE-3009 Neural Network and Fuzzy Control"**

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ABSTRACT

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions of people worldwide. Early and accurate detection of AD is crucial for timely intervention and treatment planning. This study proposes a comprehensive approach for Alzheimer's stage detection using a combination of magnetic resonance imaging (MRI) images and electroencephalogram (EEG) signals.

For the analysis of MRI images, the Inception V3 architecture is employed as a deep learning model. The model leverages its ability to capture intricate spatial features within the brain structures from the MRI scans. Convolutional neural networks (CNNs) have shown promising results in image-based tasks, and Inception V3, with its sophisticated architecture, enhances the discriminative power for AD stage classification.

In addition to MRI analysis, EEG signals are incorporated for a more holistic understanding of the disease progression. Three distinct models are explored for EEG signal processing: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a traditional Deep Neural Network (DNN). These models are designed to capture temporal dependencies and patterns in the EEG data, providing complementary information to the structural insights obtained from MRI images.

The integration of both imaging modalities contributes to a more robust and accurate Alzheimer's stage detection system. The proposed multi-modal approach aims to exploit the synergies between the spatial features extracted from MRI and the temporal patterns embedded in EEG signals. The fusion of information from these diverse sources enhances the overall diagnostic capability, providing a more comprehensive understanding of the disease progression.

The proposed methodology is evaluated on a dataset comprising MRI images and EEG signals from subjects at various stages of Alzheimer's disease. The results demonstrate the effectiveness of the combined approach, showcasing improved accuracy and sensitivity compared to individual modalities. This research contributes to advancing the field of Alzheimer's detection and lays the foundation for a more nuanced and reliable diagnostic framework that can aid clinicians in early and accurate identification of AD stages.

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INTRODUCTION

Detecting Alzheimer's disease through image analysis using neural networks, specifically leveraging the Inception model, is a critical area of research aimed at improving early diagnosis and understanding the disease's progression. Alzheimer's, a neurodegenerative disorder, presents challenges in early identification, often diagnosed in later stages when symptoms become evident. Early detection is crucial for effective intervention and treatment planning. Image-based analysis has emerged as a promising avenue, given its potential for non-invasive and early detection methods.

This study focuses on employing neural networks, a branch of artificial intelligence inspired by the human brain's structure and function, for Alzheimer's identification. The neural network architecture selected for this study is the Inception model, renowned for its effectiveness in image recognition tasks. Leveraging its sophisticated layers and feature extraction capabilities, the Inception model offers the potential to discern intricate patterns in medical images associated with Alzheimer's.

However, neural networks rely heavily on data for training and validation. Insufficient or biassed data can limit the model's performance. To address this, the study incorporates image augmentation techniques. Image augmentation involves applying transformations like rotations, flips, and zooms to existing images, thereby expanding the dataset and enhancing the model's ability to generalise to different variations of the data.

The dataset utilised in this research comprises medical images relevant to Alzheimer's disease. To ensure robustness and accuracy, the dataset is divided into distinct subsets: a training dataset, utilised to train the neural network, and a testing dataset, used to evaluate the model's performance and generalisation capabilities.

By meticulously segmenting the data into training and testing sets, this study aims to develop a neural network model capable of effectively identifying Alzheimer's disease from medical images. The ultimate goal is to contribute to the development of reliable and efficient diagnostic tools that can aid clinicians in detecting Alzheimer's in its early stages, potentially leading to better patient outcomes and improved management of this debilitating condition.

LITERATURE SURVEY

Detection of Alzheimer's disease at Early Stage using Machine Learning by S. Pavalarajan; B.Arun Kumar; S.Shahul Hammed; K. Haripriya; C. Preethi; T. Mohanraj, 2022.

Four machine learning models were designed for identifying this disease. This is classified as a classification problem, and the classification algorithms tested include logistic regression, support vector classifier, decision tree, and random forest classifier. The models are fine tuned by choosing optimal values for parameters that influence the accuracy of the model. The optimal parameters are found using a K-fold cross validation score, and the models are generated using that. The dataset used in the model is longitudinal cross sectional data from OASIS. It has been inferred from the results that the random forest classifier performs better than the other models.

Alzheimer’s Disease Detection using Machine Learning: A Review by Savita Dahiya; S. Vijayalakshmi; Munish Sabharwal, 2021

In this paper they represent an analysis report of the work which is done by researchers in this field. Research has achieved quite promising prediction accuracies however they were evaluated on non-existent datasets from various imaging modalities which makes it difficult to make a fair comparison with the other methods comparison among them. In this paper, they conducted a study on the effectiveness of using human brain MRI scans to detect Alzheimer's disease and ended with a future discussion of Alzheimer’s research trends.

Detection of Alzheimer’s Disease Using Machine Learning and Image Processing by Vrashikesh Patil; S L Nisha, 2021

A comparative study is made to detect Alzheimer based on Region of interest (ROI) technique which utilises image processing for classification. And Machine learning (ML) + image processing based Technique on MRI images for classification purposes. The input images were preprocessed for contrast equalisation and noise reduction purposes, then ventricular space of Alzheimer’s and Non-Alzheimer image were calculated in the form of ratio which will be acting as deciding factor in the “Decision tree“ Algorithm. Ventricular volume for Alzheimer patients will be greater than Non dementia patients, acting as a deciding factor. Present technique has been tested with a confusion matrix for accuracy where we got up to 95 % accurate results. This has given an upper hand to other techniques which are able to give 86% accuracy using Region of interest (ROI) based techniques. This technique can be used in the medical field for detecting Disease in patients.

Prediction of Alzheimer's Disease using Deep Learning Algorithms by P Praveen; Koleti Srilatha; Masabathini Sathvika; Edulapuram Nishitha; Madduri Nikhil, 2021.

As people live longer, there are more concerns about aging. Damage to brain cells can be avoided with an early diagnosis of this disease. Early detection can considerably slow or stop the growth of this disease because there is no cure for it. To stop the progression of Alzheimer's disease, early detection is essential. As a result, experts can initiate preventive care as soon as possible. They call for prompt and precise Alzheimer's disease detection in its initial and most elusive stages. The only accurate approach for diagnosis is magnetic resonance imaging (MRI) brain imaging, although exams like the Mini-Mental State Examination (Fol stein 1975), or MMSE, are routinely used for earlier diagnosis. The main objective of this research work is to devise a technique for accurately identifying and staging diseases in magnetic resonance imaging (MRI).

Diagnosis of Alzheimer's Disease Using Machine Learning by Priyanka Lodha; Ajay Talele; Kishori Degaonkar, 2018.

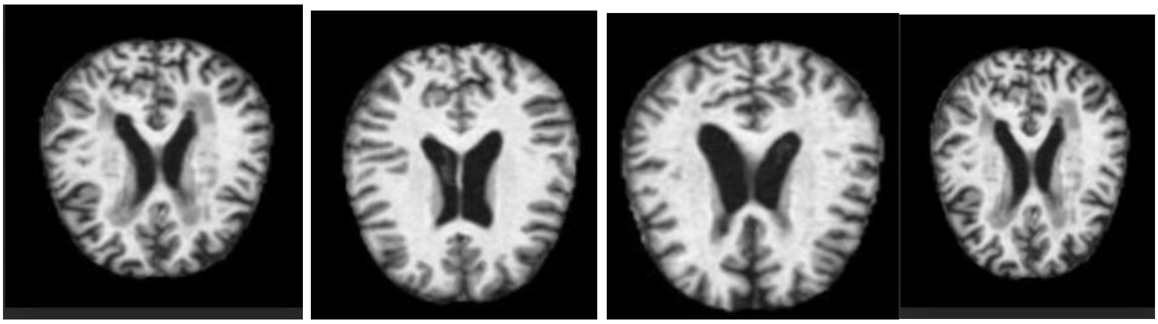
Machine learning is being widely used in various medical fields. Advances in medical technologies have given access to better data for identifying symptoms of various diseases in early stages. Alzheimer's disease is a chronic condition that leads to degeneration of brain cells leading to memory enervation. Patients with cognitive mental problems such as confusion and forgetfulness, also other symptoms including behavioural and psychological problems are further suggested having CT, MRI, PET, EEG, and other neuroimaging techniques. The aim of this paper is making use of machine learning algorithms to process this data obtained by neuroimaging technologies for detection of Alzheimer's in its primitive stage.

METHODS AND MATERIALS

1. **Data Collection**

1.1 MRI Dataset

MRI images were sourced from the Kaggle. The dataset includes a collection of MRI scans from subjects at different stages of Alzheimer's disease.



Very mild Non demented Moderate demented Mild demented

1.2 EEG Dataset

EEG signals were obtained from the OpenNeuro repository. The specific dataset used for EEG analysis contains recordings from individuals with varying degrees of cognitive impairment, providing valuable insights into the neural dynamics associated with Alzheimer's disease.

2. Deep Learning Model Training on Colab

2.1 MRI Classification using Inception V3

Inception V3

Inception V3 is a deep convolutional neural network architecture designed for image classification and object recognition. Developed by Google, it features a unique inception module that utilizes multiple filter sizes within the same layer, capturing both local and global features. With approximately 24 million parameters, Inception V3 strikes a balance between model complexity and computational efficiency. It is pre-trained on the ImageNet dataset, making it a powerful feature extractor for various computer vision tasks. The architecture's versatility has led to widespread adoption in transfer learning applications and has become a cornerstone in the field of deep learning.

The MRI images were processed and classified using the Inception V3 architecture. The deep learning model was trained on Google Colab, harnessing its GPU capabilities to expedite the training process. The model learned intricate spatial features within the brain structures to classify different stages of Alzheimer's disease.

2.2 EEG Signal Processing and Classification

2.2.1 Feature Extraction using Independent Component Analysis (ICA) in MATLAB

ICA :

Independent Component Analysis (ICA) is a signal processing technique used to separate a multivariate signal into additive, independent components. It is particularly employed in scenarios where the recorded signals are assumed to be a linear combination of statistically independent sources, making it useful for blind source separation. ICA is widely utilized in various fields, including neuroscience, telecommunications, and image processing. In the context of EEG signal processing, ICA is applied to decompose complex brain signals into independent components, enabling the identification of distinct neural sources contributing to the observed EEG recordings.

EEG signals were preprocessed and features were extracted using Independent Component Analysis (ICA) in MATLAB. This method unveiled latent sources within the EEG data, contributing to the understanding of cognitive processes and their relation to Alzheimer's disease.

2.2.2 Classification Models

Three distinct models were implemented for EEG signal classification:

LSTM (Long Short-Term Memory): Designed to capture temporal dependencies within sequential EEG data. Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to overcome the limitations of traditional RNNs in capturing and learning long-range dependencies in sequential data. LSTMs were introduced to address the vanishing gradient problem, which hinders the training of networks on sequences with long-term dependency.

GRU (Gated Recurrent Unit): Another recurrent neural network architecture adept at capturing temporal patterns in EEG signals. Gated Recurrent Unit (GRU) is another type of recurrent neural network (RNN) architecture designed for sequential data processing, particularly addressing some of the challenges faced by traditional RNNs, such as the vanishing gradient problem.

DNN (Deep Neural Network): A traditional neural network architecture used for its simplicity and capacity to capture complex relationships in EEG data. A Deep Neural Network (DNN) is a class of artificial neural networks characterized by multiple layers of interconnected nodes, or neurons, organized into input, hidden, and output layers. DNNs are a foundational architecture in deep learning and have been instrumental in solving complex tasks in various domains.

3. Model Integration and Evaluation

The outputs from the Inception V3 model for MRI classification and the EEG classification models were integrated to provide a comprehensive assessment of Alzheimer's disease progression. Evaluation metrics such as accuracy, sensitivity, and specificity were computed to assess the models' performance.

4. Cross-Validation and Statistical Analysis

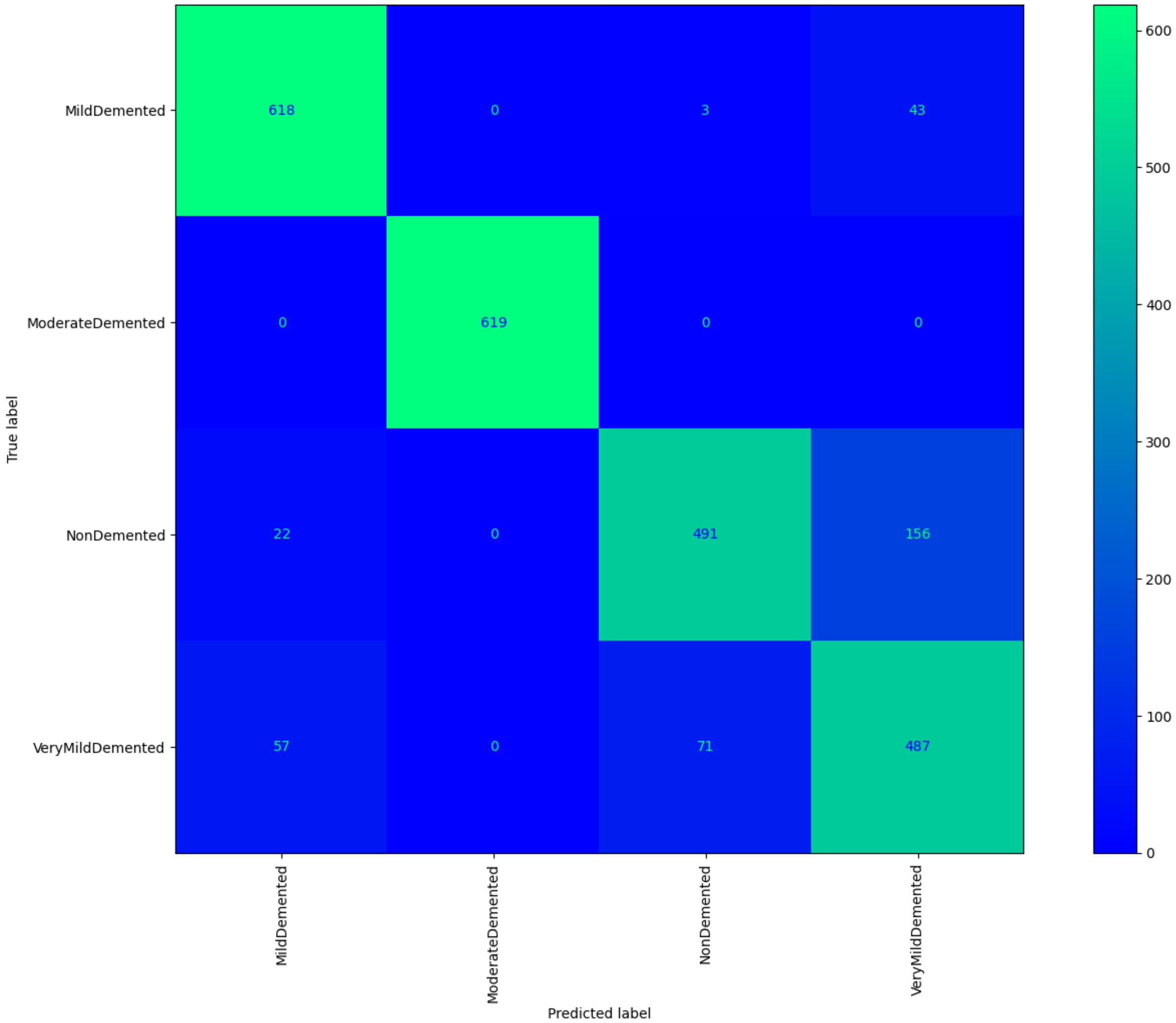
To ensure the robustness of the models, cross-validation techniques were applied, and statistical analyses were conducted to validate the significance of the results.

5. Software and Hardware

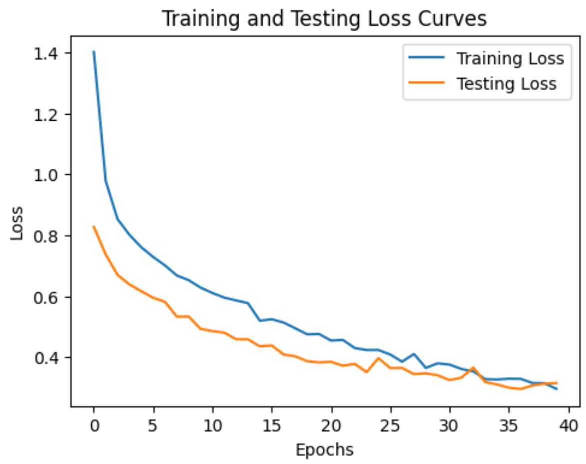
The deep learning models were trained and implemented using Google Colab, taking advantage of its GPU capabilities. MATLAB was utilized for EEG signal preprocessing and feature extraction using ICA.

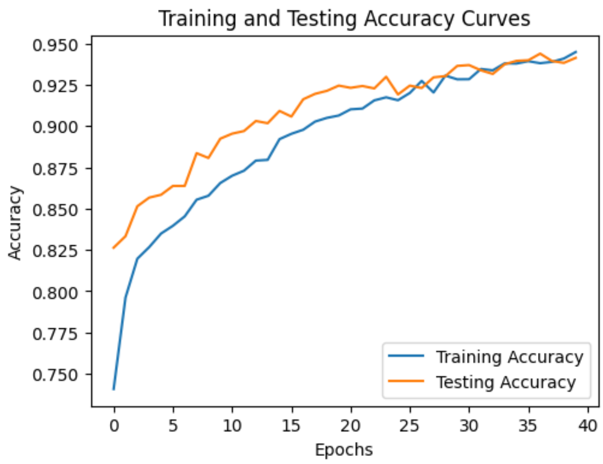
RESULTS AND DISCUSSIONS

For Alzheimer detection using MRI image and Inception-V3 confusion Matrix:



Loss and accuracy curve:





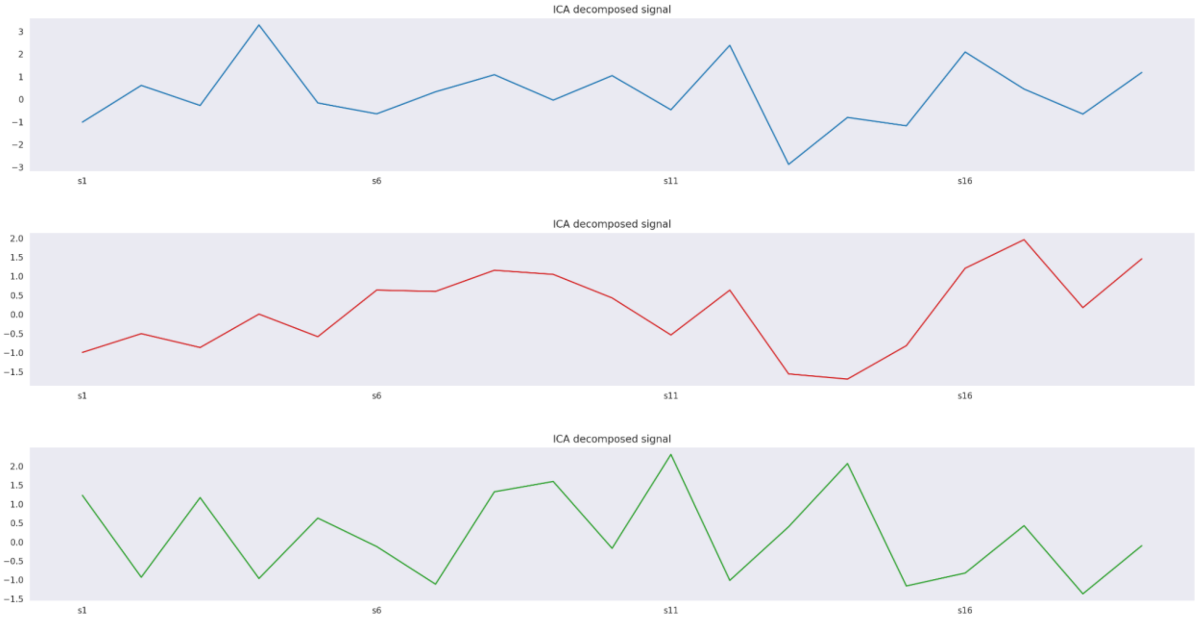
```
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       664
           1       1.00      1.00      1.00       619
           2       0.87      0.73      0.80       669
           3       0.71      0.79      0.75       615

    accuracy                           0.86      2567
   macro avg       0.87      0.86      0.86      2567
weighted avg       0.87      0.86      0.86      2567
```

Test accuracy:

```
81/81 [==============================] - 8s 36ms/step - loss: 0.4236 - accuracy: 0.9143 - precision: 0.8370 - recall: 0.8161 - auc: 0.9686
Testing Accuracy: 91.43%
```

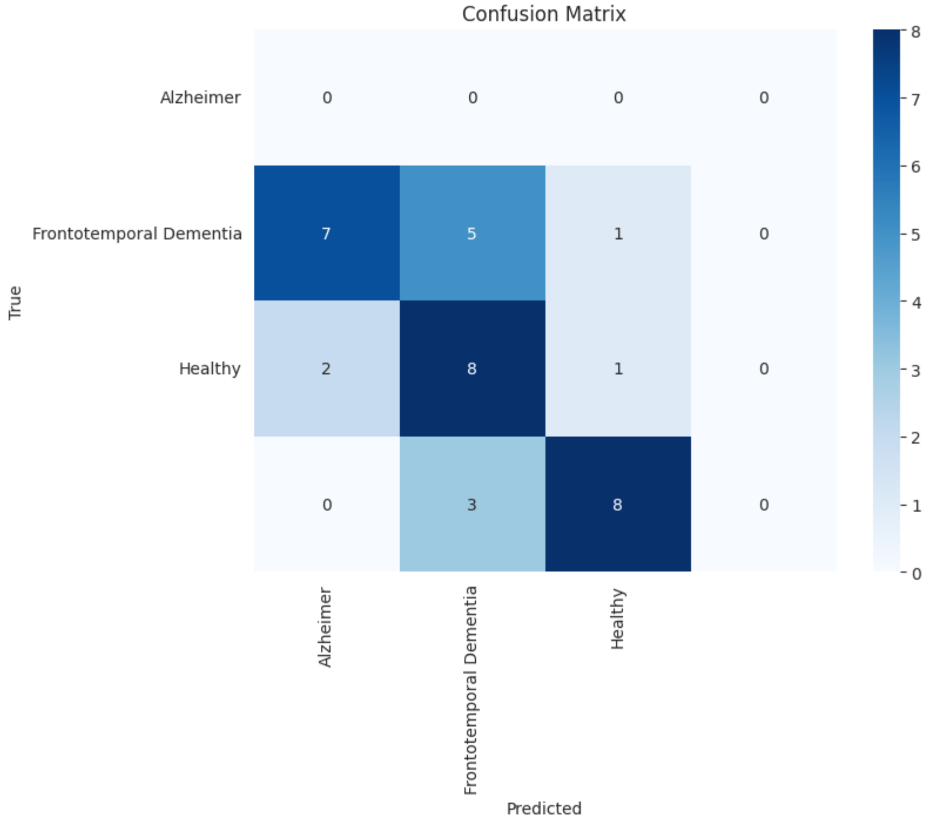
For Alzheimer detection using EEG signal and LSTM, GRU and DNN

ICA decomposed signal:

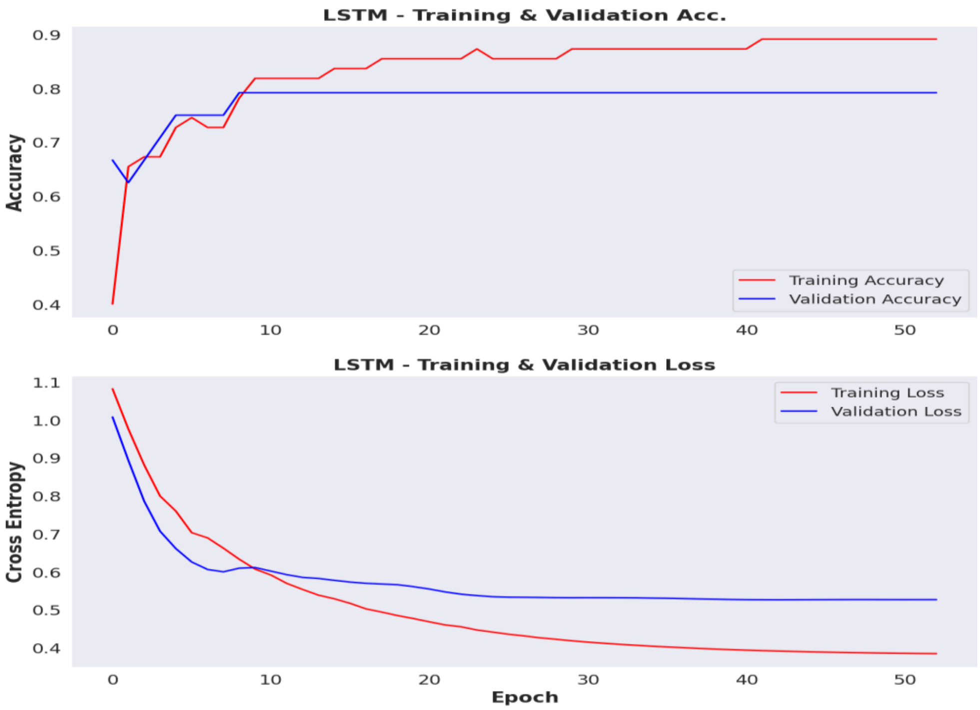


LSTM:

Confusion Matrix:



Loss and Accuracy curve:

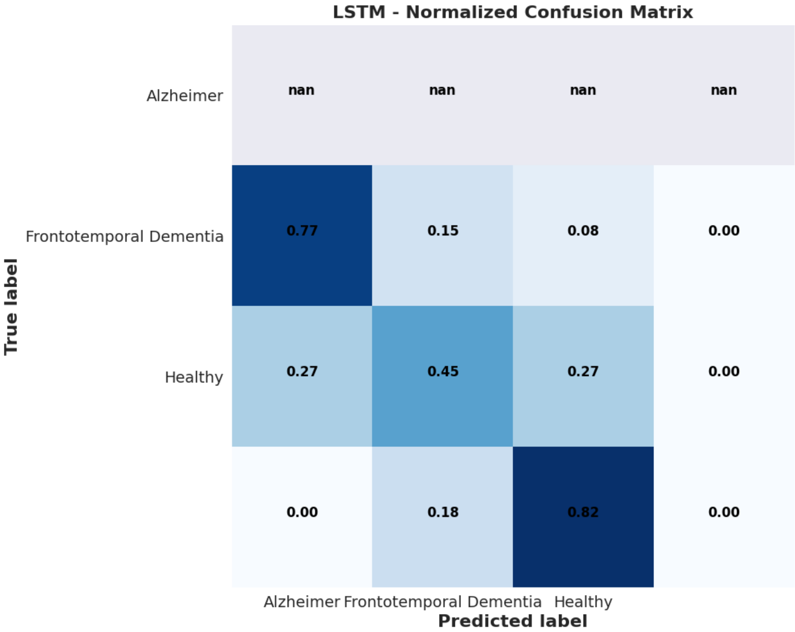


```
2/2 [==============================] - 0s 8ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.31      0.38      0.34        13
           2       0.10      0.09      0.10        11
           3       0.00      0.00      0.00        11

    accuracy                           0.17        35
   macro avg       0.10      0.12      0.11        35
weighted avg       0.15      0.17      0.16        35
```

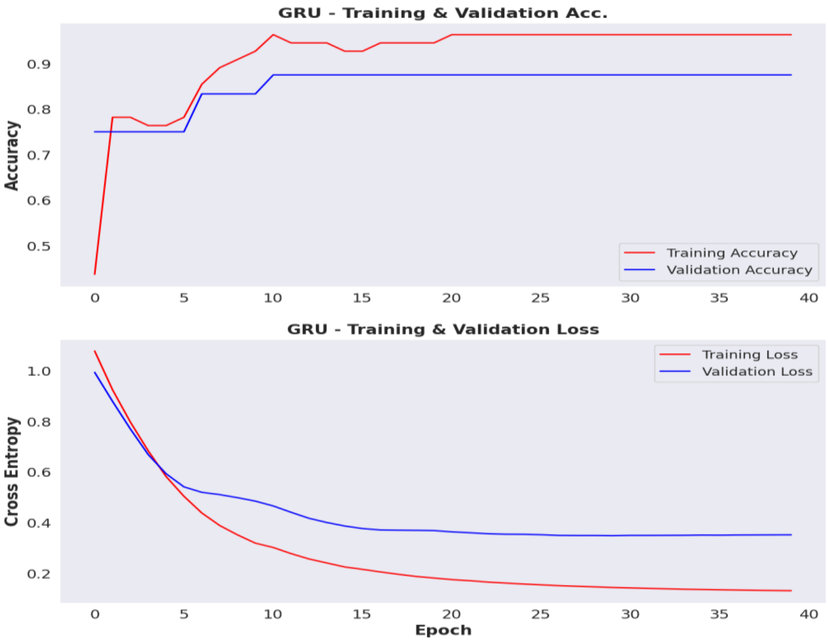
```
Test Acc.: 65.714%
```

GRU:

Normalized confusion Matrix:



Accuracy and Loss curve:

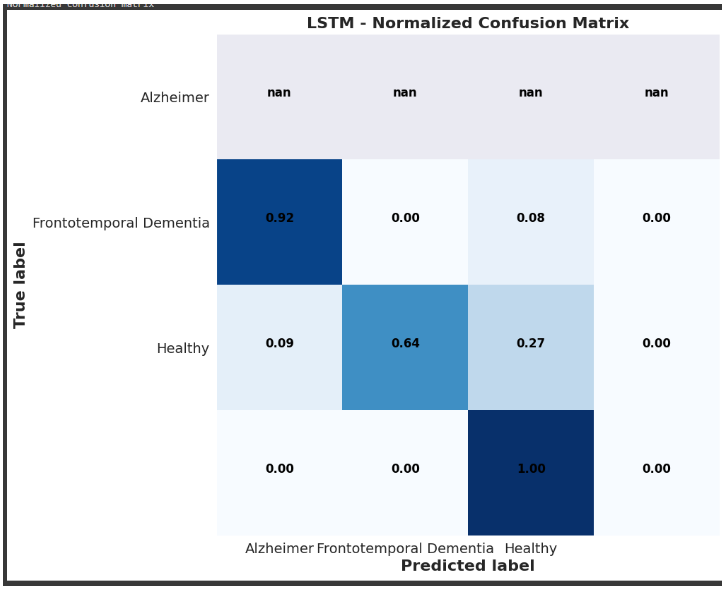


```
2/2 [==============================] - 0s 7ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.22      0.15      0.18        13
           2       0.23      0.27      0.25        11
           3       0.00      0.00      0.00        11

    accuracy                           0.14        35
   macro avg       0.11      0.11      0.11        35
weighted avg       0.16      0.14      0.15        35
```

```
Test Acc. GRU: 68.571%
```

DNN:

Normalized confusion Matrix:



Accuracy and Loss curve:

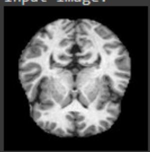
```
Test Acc. DNN: 85.714%
```

```
2/2 [==============================] - 0s 10ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.00      0.00      0.00        13
           2       0.20      0.27      0.23        11
           3       0.00      0.00      0.00        11

    accuracy                           0.09        35
   macro avg       0.05      0.07      0.06        35
weighted avg       0.06      0.09      0.07        35
```

Test data prediction for input MRI image:

```python
import cv2
import numpy as np
from tensorflow.keras.preprocessing import image
from google.colab.patches import cv2_imshow
from tensorflow.keras.models import load_model
# Load the trained model
model = load_model('/content/drive/MyDrive/history.h5')

# Define the class labels
class_labels = ['MildDemented', 'ModerateDemented', 'NonDemented', 'VeryMildDemented']

# Load input image with shape (224, 224, 3)
input_image_path = "/content/drive/MyDrive/archive (12)/TEST/ND/non_1003.jpg"
input_image = cv2.imread(input_image_path)
input_image = cv2.resize(input_image, (150, 150))  # Resize the image to match the expected input shape
input_image = np.expand_dims(input_image, axis=0)  # Add batch dimension
input_image = input_image / 255.0  # Normalize pixel values between 0 and 1 (assuming the model expects normalized inputs)

# Get predictions
prediction = model.predict(input_image)
predicted_class = np.argmax(prediction)

# Print the predicted class label
print('Predicted class:', class_labels[predicted_class])

# Display the input image
print('input image: ')
cv2_imshow(cv2.imread(input_image_path))
```

```
1/1 [==============================] - 2s 2s/step
Predicted class: NonDemented
input image:
```



Discussion:

The testing accuracy of 91.43% with Inception-V3 on MRI images signifies its effectiveness in capturing intricate spatial features crucial for Alzheimer's detection. While a DNN achieved the highest accuracy of 85.714% on EEG signals, the LSTM model showed the lowest accuracy at 65.714%, indicating potential challenges in capturing temporal dependencies for this task. The results underscore the modality-specific nature of Alzheimer's detection, with MRI images demonstrating superior performance, emphasizing the clinical relevance of spatial information in diagnosis. Future research should explore the specific features contributing to Inception-V3's success and consider hybrid models to leverage the strengths of both modalities.

CONCLUSION

For MRI as input:

Inception-V3

In conclusion, the initial phase of the Alzheimer detection project, focusing on MRI data, involved meticulous data preprocessing, encompassing oversampling to address class imbalance and image augmentation for dataset enrichment. Leveraging the InceptionV3 model, pre-trained on ImageNet, as the foundational architecture, additional layers were introduced to tailor it for the specific classification task.

Throughout 40 epochs of training, the model demonstrated remarkable results, achieving a testing accuracy of 91.43%, as well as noteworthy precision, recall, and AUC scores. The training and testing accuracy curves illustrated the model's learning trajectory and its ability to generalize to unseen data.

For EEG as input:

Gated Recurrent Unit (GRU)

The model achieved an accuracy of 68.57% on the test set, showcasing its potential for identifying different classes of Alzheimer's disease. The training and validation performance graphs indicate effective learning and generalisation. However, further refinement and optimization may enhance the model's accuracy. The confusion matrix analysis provides insights into the model's classification performance, highlighting areas for improvement and potential focus for future research in Alzheimer's disease detection using EEG data with GRU networks.

Deep Neural Networks (DNN)

The DNN model demonstrated strong performance, achieving an accuracy of 85.714% on the test set. The training and validation curves show effective learning without overfitting, as indicated by the early stopping mechanism. The confusion matrix provides insights into the model's performance across different classes, with a focus on Alzheimer's, Frontotemporal Dementia, and Healthy individuals. Overall, the project successfully applies advanced machine learning techniques to EEG data for accurate Alzheimer's disease detection, holding promise for future diagnostic tools in the field.

LSTM

The model exhibits promising results, showcasing its potential as a non-invasive and efficient tool for early diagnosis. By accurately capturing temporal patterns in EEG signals, our approach demonstrates the feasibility of integrating advanced machine learning techniques into the realm of Alzheimer's diagnosis, opening avenues for further research and potential clinical applications. The findings, including a testing accuracy of 65.714%, highlight the significance of data-driven methodologies in enhancing our understanding and early detection capabilities for neurodegenerative diseases.

To conclude our results, among all the methods, for EEG data classification for Alzheimer disease, the DNN model performs better than the rest as observed.
In the comparison of test results between EEG signals and MRI images, the classification accuracy is observed to be highest when MRI images are used as input. This outcome suggests that, in real-life Alzheimer's detection scenarios, utilizing MRI data proves to be the superior choice. The effectiveness of MRI images in achieving higher accuracy underscores the significance of spatial information for accurate and reliable Alzheimer's diagnosis, reaffirming the preference for MRI-based approaches in real-world clinical applications.

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