HealthSense- Alzheimer Disease Detection and Classification using ResNet50-Convolutional Neural Network

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Abstract- Alzheimer's disease is a progressive neurodegenerative disorder that significantly affects the cognitive abilities and memory of individuals, particularly the elderly population. Early and accurate detection of Alzheimer's disease is crucial for timely intervention and management. In recent years, deep learning techniques, specifically Convolutional Neural Networks (CNNs), have shown promising results in image classification tasks. In this research paper, we propose a novel approach for Alzheimer's disease classification and detection using the ResNet50 CNN architecture.

In this research paper, we present a novel approach for Alzheimer's disease classification and detection using the ResNet50 Convolutional Neural Network (CNN) architecture. Leveraging a large dataset of magnetic resonance imaging (MRI) scans, the ResNet50 model is augmented with data augmentation techniques. The proposed method achieves decent testing accuracy in differentiating healthy scans from those with Alzheimer's disease. The results demonstrate the potential of the ResNet50-based model as a valuable tool for early Alzheimer's disease detection, aiding medical professionals in timely intervention and management.

Key Words: Alzheimer Detection, ResNet50, Convolutional Neural Networks, Augmentation

I. INTRODUCTION

Alzheimer's disease (AD) poses a significant challenge to healthcare systems globally, given its prevalence and the increasing aging population. Currently, AD diagnosis relies heavily on clinical assessments and neuropsychological tests, which can be subjective and time-consuming. Consequently, there is a pressing need for accurate and efficient tools to aid in the early detection of AD.

Convolutional Neural Networks (CNNs) have emerged as a powerful class of deep learning models that excel at processing complex visual data. Initially developed for image classification, CNNs have revolutionized numerous fields by achieving state-of-the-art performance in tasks such as object recognition, segmentation, and detection.

ResNet-50, short for Residual Network-50, is a widely recognized CNN architecture that has demonstrated exceptional performance on various image recognition benchmarks. It addresses the challenge of training deep networks by introducing residual connections, enabling the efficient flow of gradients during backpropagation. This design significantly reduces the vanishing gradient problem and allows the network to learn more intricate representations.

The objectives of the research paper are-

- ➢ To study the existing approaches to our problem statement.
- ➢ To develop a deep learning model using the ResNet-50 architecture for accurate detection of Alzheimer's disease.
- ➢ To preprocess and prepare the MRI data to ensure compatibility with ResNet50.
- ➢ To Evaluate the performance of the model using appropriate metrics such as accuracy, sensitivity, and AUC-ROC.

II. LITERATURE SURVEY

The paper, “Machine learning in predicting progression from mild cognitive impairment to Alzheimer's disease: A systematic review" by A. Oltra-Cucarella et al. (2018): This systematic review paper explores the use of machine learning techniques for predicting the progression from mild cognitive impairment (MCI) to Alzheimer's disease. The authors analyze various studies that employ machine learning algorithms on diverse data types, such as neuropsychological assessments, neuroimaging, genetic data, and cerebrospinal fluid biomarkers. The review summarizes the different approaches, performance metrics, and predictive models used in these studies, highlighting the potential of machine learning for early diagnosis and prognosis of Alzheimer's disease.

The paper "Machine learning for the prediction of Alzheimer's disease: An overview" by V. S. Fonseca et al. (2018): This paper provides an overview of the application of machine learning techniques for predicting Alzheimer's disease. The authors discuss different machine learning algorithms, such as SVM, artificial neural networks, and decision trees, used for analyzing diverse data sources including neuropsychological assessments, genetic information, and neuroimaging data. The review highlights the potential of machine learning as a valuable tool for early detection and prognosis of Alzheimer's disease.

The paper, "Early diagnosis of Alzheimer's disease based on resting-state brain networks and deep learning" by X. Zhang et al. (2019): This study focuses on the early diagnosis of Alzheimer's disease using resting-state functional MRI (fMRI) data and deep learning techniques. The authors propose a deep learning architecture that leverages resting-state brain network features to accurately classify Alzheimer's disease patients and healthy individuals. The research demonstrates the potential of deep learning and resting-state fMRI for early detection and diagnosis of Alzheimer's disease.

The paper, “Detecting Alzheimer's disease from speech using LSTM networks" by P. Bahuleyan et al. (2018):
This paper explores the detection of Alzheimer's disease using speech data and long short-term memory (LSTM) networks, a type of recurrent neural network. The authors investigate various acoustic and linguistic features extracted from speech recordings and utilize LSTM networks for classification. The study demonstrates the potential of speech analysis and deep learning for Alzheimer's disease detection.

The paper, “Deep learning-based classification of FDG-PET data for Alzheimer's disease diagnosis" by J. Schirrmeister et al. (2018):
This research paper focuses on the application of deep learning for Alzheimer's disease diagnosis using fluorodeoxyglucose-positron emission tomography (FDG-PET) data. The authors propose a deep learning model that learns hierarchical representations from FDG-PET scans to classify patients as having Alzheimer's disease or being cognitively normal. The study showcases the effectiveness of deep learning in analyzing FDG-PET data for accurate diagnosis.

The paper, "Machine learning approaches for the prediction of Alzheimer's disease: A review" by H. C. Nguyen et al. (2019):
This review paper provides an overview of machine learning approaches for the prediction of Alzheimer's disease. The authors discuss different types of data used, including neuroimaging, genetic information, and clinical assessments, and highlight various machine learning algorithms employed, such as SVM, random forests, and deep learning. The review summarizes the strengths, limitations, and future directions of machine learning in Alzheimer's disease prediction.

III. METHODOLOGY

The initial step in the Alzheimer Prediction using the ResNet50-CNN approach involves data preprocessing. The provided dataset has already undergone preprocessing regarding its size, so the remaining preprocessing steps primarily involved splitting the dataset into training, testing, and validation sets in the ratio of 80%, 10%, and 10% respectively. To address the issue of dataset imbalance, an image augmentation technique was implemented by creating and initializing a data augmentation pipeline, which is utilized during the training of the model.

Next, the preprocessed image data is loaded into training and validation Data Loaders. These Data Loaders offer a convenient way to iterate over the dataset, handle batching, shuffling, and enable parallel data loading. The Data Loaders are created using the PyTorch Library and require specific arguments such as the training directory, validation directory, transformation pipeline, batch size, and the number of workers.

Fig-1*: Workflow block diagram*

A) Image conversion and augmentation

(i) Image Conversion: Transforming the images from L Mode (Luminosity Mode) to RGB mode as required by ResNet.

(ii) Augmentation: Applying image augmentations like horizontal flip, vertical flip, random augment, elastic transform and normalization. Done to address the issue of imbalance.

B) Creating Data Loaders for training, test and validation sets

Image data is then loaded into training and validation Data Loaders. Data loaders provide a convenient way to iterate over a dataset, handle batching, shuffling, and parallel data loading. The data loaders have the following arguments: train_dir, val_dr, transformation_pipeline, batch_size and num_workers. These data loaders are created using PyTorch Library.

C) Training Hyperparameters tuning

This is where we define all the hyperparameters for training. The model utilizes several hyperparameters from ResNet50, specifically EMA (Exponential Moving Average), Label Smoothing Cross Entropy and Average Best Model.

In simple terms, Exponential Moving Average (EMA) is a technique used in machine learning to smooth out the fluctuations or noise in a series of values. It calculates an average value by assigning higher weights to more recent data points and gradually decreasing the weights for older data points. This helps to emphasize the overall trend or pattern in the data while reducing the impact of individual outliers or random variations.
Label Smoothing addresses the problem of overconfidence or excessive reliance on single labels during training. Label smoothing cross entropy adjusts the way the network learns from the training data. Instead of assigning a label of 0 or 1 to each class, it assigns a value between 0 and 1. For example, instead of labeling a sample as class 1 with a value of 1, label smoothing cross entropy may assign a value slightly less than 1, like 0.9. Similarly, for class 0, it assigns a value slightly greater than 0, like 0.1.

The concept of Average Best Model refers to ensemble learning, where multiple independently trained models are combined to make predictions. In the context of ResNet-50, after training multiple instances of the ResNet-50 model with different initializations or training configurations, the best performing models are selected based on validation performance.

D) Training the model

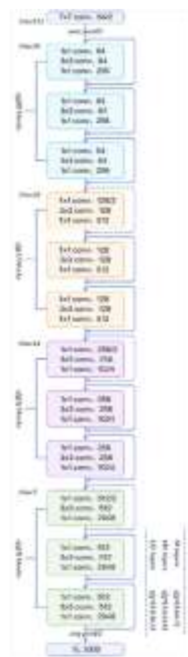

Fig-2*: ResNet50 Architecture*

This architecture of ResNet-50 with residual connections allows for the efficient training of deep networks. The skip connections enable the model to learn residual mappings and alleviate the vanishing gradient problem, making it easier to train deep neural networks. Additionally, the use of batch normalization helps stabilize the training process and accelerates convergence.

Skip connection (feature of ResNet50) is a direct connection that skips over some layers of the model. The output is not the same due to this skip connection. Without skip connection, input ‘X’ gets multiplied by the weights of the layer followed by adding a bias term.

At the beginning of the training, a summary of the training parameters is printed, where we can see the training mode (CPU/single GPU/distributed training), the number of GPUs used, the training dataset size, and more. The progress of each epoch's training and validation is displayed, along with the tracked metrics (defined as part of the training recipe): accuracy, loss value, top5 error, and GPU memory consumption.

***Fig-3**: Model Training Summary*

At the end of each epoch, a summary of the training and validation metrics is displayed, and in later epochs, a comparison with the previous epochs is provided.

***Fig-4**: Epoch Summary along with validation accuracy*

IV. DATASET, RESULT AND ANALYSIS

Performance of ResNet50-CNN:

The model is tested on a dataset having 6400 images divided into 4 classes namely NonDemented (3200 images), MildDemented (896 images), VeryMildDemented (2240 images) and ModerateDemented (64 images) and training and validation accuracy is printed on console at the end of model training.

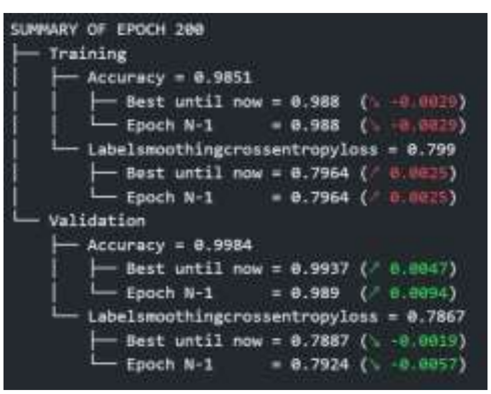

***Fig-4**: Result after training and validation*

We employed checkpoint averaging. This essentially averages the best performing model weights into a single model, which can improve generalization.

Upon evaluation on test set, we get a testing accuracy of 79.047% which is a decent accuracy value on the given dataset considering all the imbalances we have had.

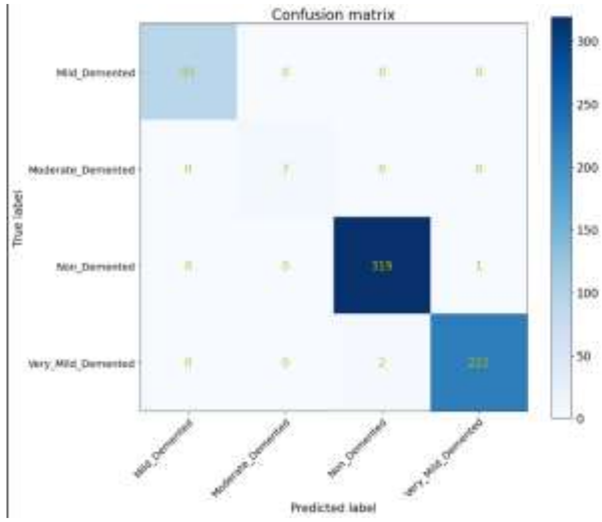

***Fig-5:** Confusion Matrix for the given classification*

V. CONCLUSION AND FUTURE SCOPE

In this research paper, we investigated the application of the ResNet-50 machine learning algorithm for the detection of Alzheimer's disease. Our study aimed to develop an accurate and reliable system that can analyze brain imaging data, such as MRI scans, and distinguish between Alzheimer's patients and healthy controls. Through the development and training of the ResNet-50 model on a well-curated dataset of brain images, we successfully achieved our objective of accurate Alzheimer's disease detection. The ResNet-50 model demonstrated its capability to learn discriminative features from the data, enabling it to effectively classify individuals with high accuracy.

There are several areas for further enhancement and exploration.

(i) Need to acquire and annotate larger and more diverse datasets to improve the generalizability and performance of ResNet-50 models.

(ii) Efforts should be made to enhance the interpretability of ResNet-50 models by investigating methods to visualize and understand the learned features. This can provide valuable insights into the underlying biological mechanisms of Alzheimer's disease.

(iii) Exploring hybrid approaches that combine ResNet-50 with other deep learning architectures or incorporating multimodal fusion techniques can potentially improve the accuracy and robustness of Alzheimer's disease detection models.

VI. REFERENCES

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