Prediction of Stage of Alzheimer from MRI Segmentation Images of Patients Using Deep Learning Algorithm (CNN)

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***Abstract*—Alzheimer's disease is a neuro-degenerative disorder associated with unusual accumulation of protein in the brain which leads to cognitive impairment. The disease is more responsive towards medical treatment in its early stages; therefore, early identification helps in essential for treatments. To diagnose the disease in the patients, the doctors analyze MRI Segmentation of the human brain to visualize the internal structures and identify abnormalities. In recent times, deep learning has been booming in the field of medical imaging and thus deep learning algorithms has potential to classify patients with Alzheimer into Mild Demented, Moderate Demented, Non-Demented and Very mild Demented. In this study, the Alzheimer's Dataset (4 class of images) is used which contains images of MRI segmentation of patients.**

***Index Terms*—Deep Learning, CNN, Alzheimer**

I. INTRODUCTION

Alzheimer's disease is a degenerative neurological condition that results in the death and degeneration of brain cells. A person's capacity to operate independently is affected by a persistent deterioration in mental, behavioral, and social abilities, which is the most prevalent cause of dementia. Globally, there are more than 10 million new cases of dementia annually, or one new case every 3.2 seconds[1].

Because Alzheimer's disease is a progressive illness, symptoms appear gradually over many years and then intensify. It has an impact on several brain processes. Severe symptoms include memory loss interfering with day-to-day activities, difficulties with problem-solving or planning, having trouble doing routine chores, error about the time or location, trouble comprehending spatial relationships and pictures, losing track of things and incapable of taking back steps, Reduced or subpar discernment, heightened agitation, anxiety, and disruptions in sleep, etc [2].

The degree of alterations in various brain regions varies depending on the stage at which the disease advances. The stages in that the research are concerned about in increasing order of Alzheimer effect is as follows:

- Non-Demented
- Very Mild Demented
- Mild Demented
- Moderate Demented

Recently, the possibility of detection of several biomedical diseases such as brain tumor detection, breast cancer detection etc., are being tackled using AI-based systems. Among the Deep Learning models, the CNNs have shown great performances in image classification and are widely being used by researchers.
The research aims to build a prototype automatic Alzheimer detection system for patients by analyzing Magnetic Resonance Imaging using Deep Learning. To reach the aim the Alzheimer's Dataset (4 class of images) is used as it contains MRI segmentation images of patients with different stages of Alzheimer. A CNN model is trained on the dataset and performance has been evaluated.

II. DATASET DESCRIPTION AND ANALYSIS

The Alzheimer's Dataset (4 class of images) is used for this project which is publicly accessible from Kaggle.[3] The dataset contains 5121 train images and 1279 test images separated into folders of each stage – NonDemented, VeryMildDemented, MildDemented and ModerateDemented. The images are then separated into a train, test and validation set. Thus, the training set has 4608 samples, validation set has 513 and test set contains 1279 samples.

The following figures show some samples of X-Ray images. This dataset perfectly aligns with the research aim of predicting Pneumonia in children as it contains images of pediatric patients. Also, the dataset contains classes which means that it is possible to solve the classification problem using Deep Learning. For this task, the CNN models are found to be ideal as this is later discussed. Figure 1, Figure 2, Figure 3 and Figure 4 shows samples of Non-Demented, Very Mild Demented, Mild Demented and Moderate Demented MRI samples respectively. Furthermore, Figure 5 shows distribution of all the stages in the dataset.

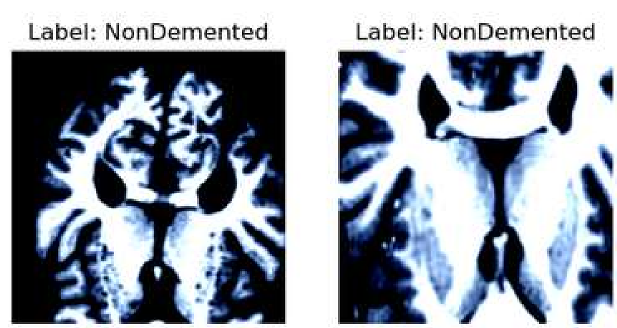

Figure 1: Sample of Non-Demented Images

Github Link - https://github.com/sakshi172015/Azheimer-Stage-Detection-Using-Deep-Learning

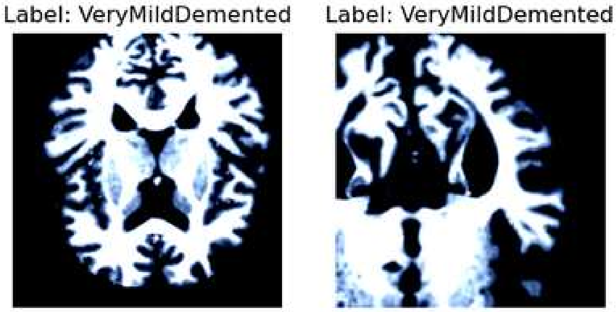

Figure 2: Sample of Very Mild Demented Images

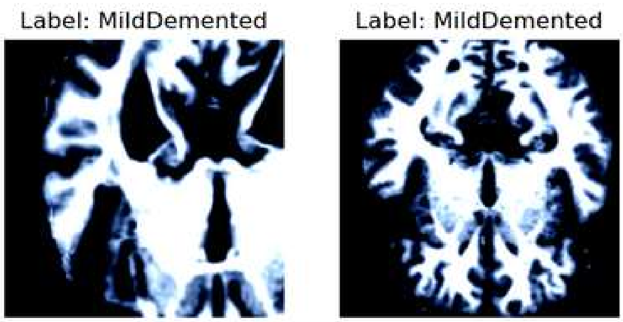

Figure 3: Sample of Mild Demented Images

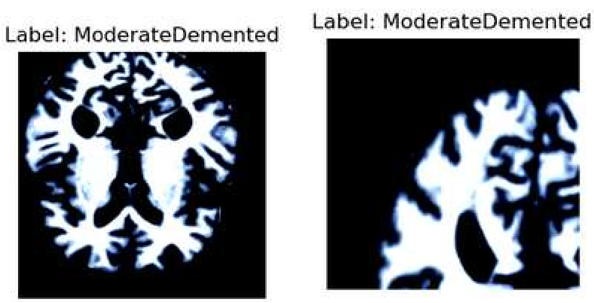

Figure 4: Sample of Moderate Demented Images

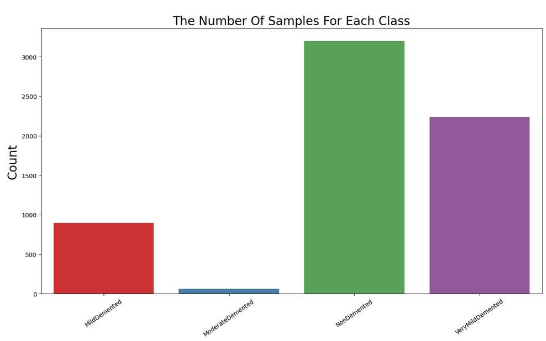

Figure 5: Distribution of all stages of Alzheimer in the database

III. RELATED WORK

A machine learning approach was presented by R. Ben Ammar and Y. Ben Ayed that utilized speech processing to extract different language variables to diagnose AD early. Different feature selection strategies were used to further process the retrieved language characteristics (syntactic, semantic, and pragmatic) from 242 participants who were impacted and 242 subjects who were not affected. The ML classifier then receives the chosen features. When separating AD patients from NC, the suggested machine learning model uses KNN feature selection with SVM classifier to achieve the highest precision of 79% [3].

Moreover, the suggested approach by K. Vaithinathan and L. Parthiban extracts 2D textures from T1 weighted MRI scans of 189 patients, 165 convert to MCI, 231 MCI-non converters, and 227 NC participants in order to differentiate between AD, MCI, and NC. The Rough ROI (RROI) technique was used to extract features from the designated ROIs. These characteristics were then generalized using high dimensional feature selection techniques, and patients were categorized into several groups using machine learning techniques. It was found that Fisher performs better than the other feature selection methods[4].

Su and others [26] Combining machine learning methods with magnetoencephalography (MEG) has made it possible to identify Alzheimer's disease (AD), which is one of the most prevalent types of dementia. An enhanced score-level fusion technique is the foundation of a bimodal recognition system that is suggested to support the interpretation of the brain activity recorded by gradiometers and magnetometers. According to this early investigation, markers produced from the gradiometer generally work better than markers based on magnetometers. It is noteworthy that, among the ten areas of interest, the left-frontal lobe has a mean recognition rate that is approximately 8% higher than that of the left temporal lobe, which is the second-best performing region for AD/MCI/HC categorization[5].

IV. METHODOLOGY

1. Convolutional Neural Network (CNN)

CNN is a type of Neural motivated by the human visual cortex's multilayered design. A basic CNN consists of several layers. CNN is made of four main parts. They help the CNNs mimic how the human brain operates to recognize patterns and features in images:

- Convolutional layers – It extracts features from an input image by applying a mathematical calculation called Convolution that takes two inputs like an image matrix and a filter or a kernel.
- Rectified Linear Unit (ReLU for short) – It is an activation function commonly used in neural networks, particularly deep learning. It is a mathematical operation that is performed on every neuron's output before it is sent to the following layer. It is defined as:
  ReLU (x) = max (0, x)
- Pooling layers - A neural network layer that down samples the input feature maps is called a pooling layer. It preserves the most crucial data while reducing the feature maps' spatial dimensions (width and height).
- Fully connected layers - Layers in which every neuron is coupled to every other neuron in the layer above are also referred to as dense layers. To merge the characteristics retrieved by the convolutional and pooling layers and provide final predictions, they are usually employed at the conclusion of the CNN design. Based on the patterns that have been learnt, these layers evaluate the features and carry out the final classification or regression tasks.

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The below image shows the convolutions of an image.

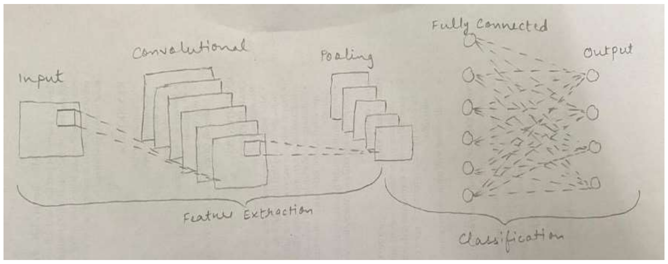

Fig. 4. Illustration of Convolution on an image [21]

2. Data Preparation and Pre-Processing

The dataset preparation involves several crucial steps to ensure the images are properly pre-processed and ready for training the CNN model. Firstly, transformation is applied to the images to augment and standardize them. The transformer randomly crops a part of the image and then resizes the cropped part to a specified size of 224x224 pixels, then randomly flips the image horizontally with a default probability of 0.5, then it into a tensor of shape (C X H X W) which is later normalized. This aids in expanding the dataset by producing different picture versions, which can strengthen the model's resilience. improves the model's ability to generalize by teaching it to detect objects in a variety of orientations and prevent overfitting.

Moreover, the data is loaded into test and train using separate folders. These are subsequently split into training set, validation set and test set.

3. Model Architecture and Training

The outline of CNN network used in this paper is described below:

- Input Image: 128x128x3
- Conv Layer 1: 128x128x16
  [3x3 conv, 16 filters, stride 1, padding 1]
- ReLU Activation
- Max Pooling: 64x64x16
  [2x2 kernel, stride 2]
- Conv Layer 2: 64x64x32
  [3x3 conv, 32 filters, stride 1, padding 1]
- ReLU Activation
- Max Pooling: 32x32x32
  [2x2 kernel, stride 2]
- Conv Layer 3: 32x32x128
  [3x3 conv, 128 filters, stride 1, padding 1]
- ReLU Activation
- Max Pooling: 16x16x128
  [2x2 kernel, stride 2]
- Flatten: 32768
  [16x16x128]
- Fully Connected Layer 1: 32
- ReLU Activation
- Fully Connected Layer 2: 64
- ReLU Activation
- Fully Connected Layer 3: 4

The training process begins with defining the loss function and optimizer. For multi-class classification problems, the Cross-Entropy Loss function is appropriate as it penalizes inaccurate classifications by measuring the discrepancy between the true class labels and the predicted class probabilities. Considering its effectiveness and adjustable learning rate capabilities, which aid in quicker convergence and the management of sparse gradients, the Adam optimizer is used to update the model weights. Over 50 epochs are used to train the model. The training photos are handled in batches during each epoch. Based on the labels and the model's predictions, the loss is calculated for every batch. In order to minimize this loss, the optimizer then modifies the model weights, thus learning from the data. The model's performance is assessed on the validation set at the end of each epoch in order to check for overfitting and enable hyperparameter adjustment. By assessing the model's accuracy and loss on the validation set, adjustments can be made to improve generalization to unseen data. The thorough design and training procedure guarantee that the model acquires the ability to accurately categorize MRI pictures according to various phases of Alzheimer's disease.

4. Model Evaluation

The trained PyTorch model is evaluated on a test dataset. The optimal model weights are loaded from a saved file named 'best_model.pth' encapsulating the learned parameters of the model. This guarantees that the evaluation uses the most effective model configuration. Additionally, the model is set to evaluation mode to ensure layers work in inference mode rather than training mode. The test dataset is looped through, and each batch is unpacked into images and its corresponding labels, computing and recording the accuracy for each batch. Within each iteration, the model performs a forward pass on the image data, generating predictions for each image and calculates the overall test accuracy. This accuracy value is recorded for further analysis. After processing all batches in the test set, the recorded accuracy values are averaged to derive the overall accuracy of the model on the test data.

V. RESULTS AND DISCUSSION

Figure 6 shows the training and validation loss and accuracy over 50 epochs. The x-axis represents the number of epochs whereas y-axis represents loss value. The blue line is for training loss and orange is for validation loss. The training loss and validation loss curves converge over the epochs, indicating the model's progressive learning and performance improvement throughout the training process. The graph depicts that training loss shows a general decreasing trend, which is expected as the model learns and improves over epochs. Similarly, the training loss starts around 1.0 and gradually decreases to around 0.8, indicating the model is fitting better to the training data over time.

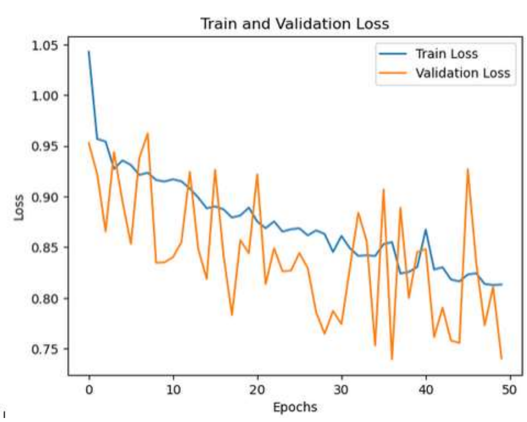

Figure 6: Train and Validation Loss trend

The following figure 7 illustrates train and validation accuracy. The x-axis represents the number of epochs whereas y-axis represents

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accuracy value. The blue line is for training accuracy and orange is for validation accuracy. It can be observed that training accuracy demonstrates an overall upward trend, suggesting better training data performance. It steadily rises from around 50% to roughly 60–63%, indicating that the model is acquiring new skills and improving its ability to make accurate predictions based on the training set.

On the other hand, validation accuracy has significant fluctuations, much like the validation loss. Despite the fluctuations, there is an overall increasing trend, similar to training accuracy.

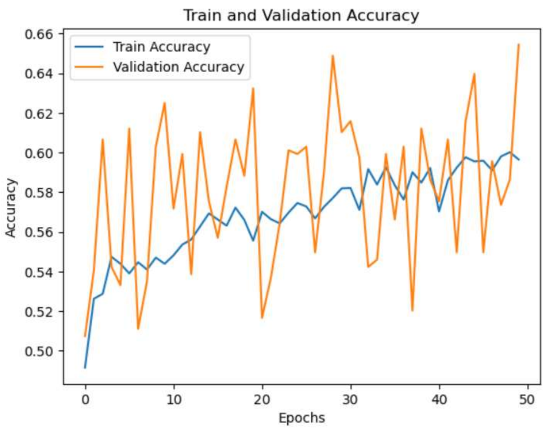

Figure 7: Train and Validation accuracy trend

At the end, the model can predict Alzheimer stages based on MRI segmentation images in the test data with an accuracy of approximately 60%.

Figure 8 exhibits confusion matrix between predicted and true stages of the Alzheimer, to visualize the performance of classification model. The color intensity represents the count of instances for that cell. Following are the inferences that can be made from the plot:

- High Accuracy for Class 2: The model performs best with class 2, with many correct predictions.
- Confusion between Classes: There is significant confusion between classes 0 and 3, as well as between classes 2 and 3.
- Poor Performance for Class 1: The model struggles significantly with class 1, with most instances being misclassified.

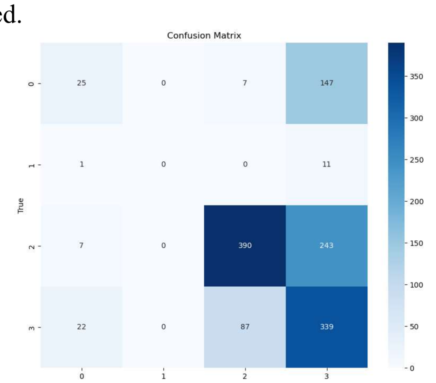

Figure 8: Confusion Matrix

VI. CONCLUSION AND FUTURE WORK

This study provided a prototype prediction system for stages of Alzheimer. A CNN architecture was trained on a pertinent dataset for this study to evaluate the effectiveness of the model's numerous evaluation matrices. Following construction and training, the CNN model's accuracy score was determined to roughly 60%. It is evident from the training and validation accuracy as well as the loss plots that the model is learning and generalizing successfully since it demonstrates that both the validation and training accuracies increase and stabilize across the epochs, reaching high values.

To bolster the performance of the model, the following steps could be considered:

- Number of epochs – Increase the number of epochs to better train the model.
- Class Imbalance – Techniques for data augmentation or resampling can be used if a class has fewer samples.
- Model tuning – To increase classification accuracy, experiment with various topologies, modify model parameters, or apply ensemble techniques.

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