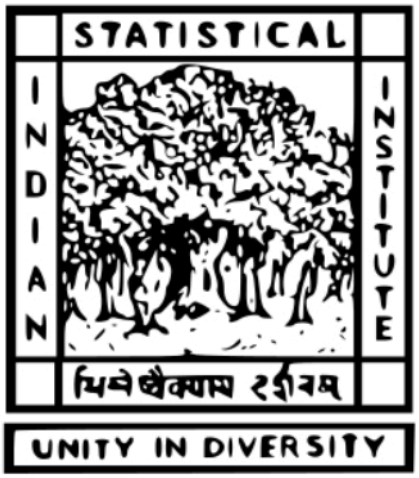

Indian Statistical Institute

CLASSIFICTION OF ALZHEIMER'S DISEASE BY MACHINE LEARNING METHODS USING MRI AND fMRI DATA

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Abstract

Alzheimer's disease is a progressive illness that gradually damages the brain, making it tough to remember stuff and do regular tasks. We're working on creating a computer tool that can analyze brain scans like MRI and fMRI. This tool will determine whether an individual has Alzheimer's, mild cognitive impairment, or falls within the normal control category. The idea is that it'll help doctors decide the best treatment for each person.Many studies have been developed for classification using the degree of deformation of the brain region which includes methods using spatial and temporal features. We are using MRI and fMRI data for our model building. While appropriate processing of MRI scans may yield noticeable abnormalities, if present, the fMRI provides real-time information about which areas of the brain are active during different tasks or at rest. This functional mapping helps identify regions associated with memory, cognition, and other cognitive functions affected by AD. Using fMRI in addition to MRI, we are having two methodologies for the sake of looking for an appropriate diagnostic tool for Alzheimer's disease. For MRI Model, We used 3D volume of MRI image as features and we use Correlation matrix obtained from fMRI and 3D Volumes of fMRI as temporal feature. Different Classical ML and Deep Learning models have been used for this purpose which includes Multi Layer Perceptron, 2D and 3D convolutional Neural Networks and EIDETIC 3D LSTM. We compare our proposed method to the existing methods of classification and find that it gives comparable results with other methods.

Keywords: EIDETIC 3D LSTM, 3D CNN

This is to certify that the dissertation entitled "Classification Of Alzheimer's Disease by Machine Learning methods using both MRI and fMRI data" submitted by Madhurendra Kumar to Indian Statistical Institute, Kolkata, in partial fulfillment for the award of the degree of Master of Technology in Computer Science is a bonafide record of work carried out by him under my supervision and guidance. The dissertation has fulfilled all the requirements as per the regulations of this institute and, in my opinion, has reached the standard needed for submission.

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Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

Medical image analysis involves carefully examining the images used in healthcare to solve complex problems. Alzheimer's disease is a progressive brain condition that worsens over time, impacting memory and thinking abilities. This condition leads to forgetfulness, the loss of crucial brain functions, and challenges in independent living. Special scans like MRI [1] and fMRI [2] reveal changes in the brain associated with Alzheimer's. The anticipated increase in Alzheimer's cases in the future will have significant effects on society, the economy, and healthcare.

Individuals with Alzheimer's can be categorized into three groups: those without noticeable problems (normal controls), those with minor cognitive impairment (at a higher risk of developing Alzheimer's), and those currently facing challenges due to Alzheimer's. There is a need for a tool that can automatically predict the disease's progression for personalized treatment.

In the healthcare landscape, new methods involving artificial intelligence and advanced technologies are gaining importance in diagnosing and treating illnesses.

This study aims to enhance tools for classifying Alzheimer's, normal cases, and minor cognitive impairment using advanced machine learning and deep learning. Alzheimer's is a brain condition causing forgetfulness, paranoia, and false beliefs. Early detection is challenging, but automated systems show promise in being more accurate than humans, resulting in fewer mistakes.

Previous research utilized images (MRI and fMRI) and biomarkers to better understand Alzheimer's. Automating the detection process makes it faster and more cost-effective, providing more precise results. Tools using classification techniques on scans can identify people with dementia, particularly in the early stages.

In early Alzheimer's, people handle tasks but struggle with memory. As it progresses, support becomes vital for communication, adaptation, and movement due to cognitive decline. Older individuals facing similar challenges may risk infections like pneumonia, with changing abilities making communication harder.

1.2 Motivation

Matching human instincts with standard measurements is challenging in today's circumstances. To overcome this challenge, we can use advanced methods like machine learning and deep learning. These techniques are increasingly being applied in categorizing diseases. This automated approach is helpful for testing and providing accurate and personalized prescriptions. It not only improves the lives of patients but also assists doctors in deciding on treatment. The main aim is to classify the level of impairment into AD, NC, and MCI. This helps in providing the necessary precautions and treatments based on individual needs.

While appropriate processing of MRI scans may yield noticeable abnormalities, if present, the fMRI provides real-time information about which areas of the brain are active during different tasks or at rest. This functional mapping helps identify regions associated with memory, cognition, and other cognitive functions affected by AD. Using fMRI in addition to MRI, we are having two methodologies for the sake of looking for an appropriate diagnostic tool for Alzheimer's disease.

Chapter 2

Related Works

Sophisticated ML models have been studied to detect dementia based on MRI and fMRI data features. Popular ML models Naive Bayes(NB), Support Vector Machine(SVM), XGBoost and KNN are tried on the MRI dataset. In [1], The framework comprises a range of machine learning algorithms, including Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), and K-Nearest Neighbor (K-NN). It also incorporates variations of Support Vector Machine (SVM), such as SVM with RBF kernel, Polynomial Kernel, and Sigmoid kernel, along with Gradient Boost (GB), Extreme Gradient Boosting (XGB), and Multi-layer Perceptron Neural Network (MLP-NN).

Additionally, the framework introduces an Ensemble-Based Generic Kernel where a Master-Slave architecture is integrated to enhance performance. Specifically, the proposed model combines Extreme Gradient Boosting, Decision Tree, and SVM with a Polynomial kernel (XGB + DT + SVM) to form the ensemble. This ensemble model (XGB + DT + SVM) has demonstrated superior performance compared to existing state-of-the-art algorithms, achieving an accuracy of 76.77%.

LSTMs are really good at understanding long patterns in data because they have memory cells, which are like a special storage space as shown in figure 2.1. This helps them remember things for a long time, making their predictions better. LSTMs have three gates: an input gate, a forget gate, and an output gate. The input gate brings in new information, the forget gate decides what to forget, and the output gate chooses what information to use.

In CNN-LSTM[2], a 3D-CNN is used to understand the shape and details of the data. Then, an LSTM model is used to understand how things change over time. U-Net is used To analyze the shape of the data. The timing of the data is adjusted to three different sizes

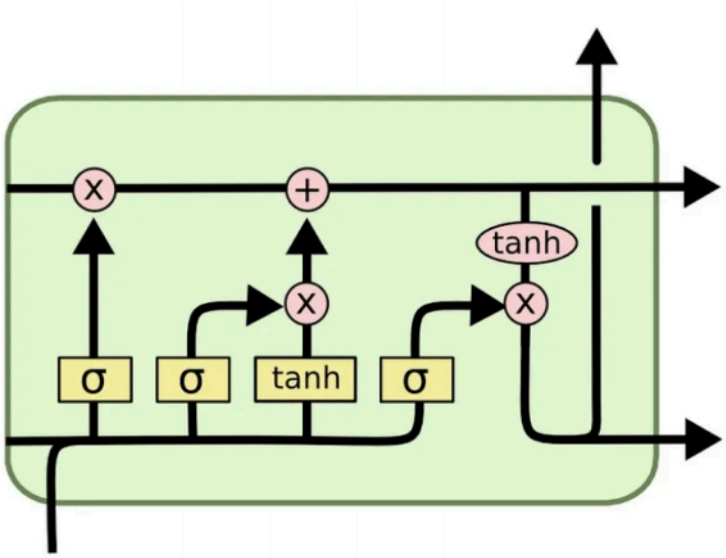


Figure 2.1: Long Short Term Memory(LSTM)

based on the dataset's size. Initially, the time duration was 140, and we changed it to 70 and 35 using a specific method. After figuring out the shape details, then LSTM is used to understand the changes over the 140, 70, and 35 time points. Finally, a fully connected layer is used to make sense of the information and used the softmax function for the last step.

CNN architecture employed in the study utilized a 2D convolutional approach[3], presumably processing 2D slices from volumetric MRI scans. there are six consecutive Convolution and Max pooling layers are used, followed by five Dense layers. The CNN model achieves an accuracy of approximately 84% on the ADNI dataset.

While in paper[4], Instead of training the model from scratch, a pre-trained deep learning model, Densenet-169, was used as a base model. Gradually, transfer learning was applied to this base model for Alzheimer's detection. A novel model has been developed for multi-class classification of a disease using a brain MRI dataset. It incorporates three pre-trained convolutional neural network architectures, namely DenseNet196, VGG16, and ResNet50, for

feature extraction. The model utilizes a stacking ensemble approach and has demonstrated an impressive accuracy of 89% when evaluated on the Kaggle-published dataset.

Chapter 3

Dataset and Preprocessing Tasks

MRI and fMRI are widely used and valuable medical imaging method. It involves using a magnetic field and computer-generated radio waves to produce a detailed picture of the brain and other organs. This technique provides a non-invasive means to examine organs, tissues, and the skeletal system.

We use the Alzheimer's Disease Neuroimaging Initiative (ADNI) test datasets as our main reference for the disease classification task. The collection includes a total of 650 3D MRI scans and 150 fMRI scans. The training set specifically contains 500 MRI scans and 120 fMRI scans. Before feeding the data into the model, several preprocessing steps have been performed, such as resampling the MRI scans, skull stripping, registration, intensity normalization, and histogram matching. The outcomes of these data preprocessing steps are presented below.

3.1 Dataset Preprocessing

To attain our objective, we need to transform our data before inputting it into the model. However, the raw data we acquire is not suitable for direct input into the model. Therefore, we must undergo various preprocessing steps to prepare the data for implementation in the model. Specifically, in our case, we are working with MRI and fMRI data, each requiring distinct preprocessing steps, although some steps are common between them.

3.1.1 Data Visualisation

We use data visualization to gain insights into its features, aiding us in subsequent preprocessing steps to extract additional information.

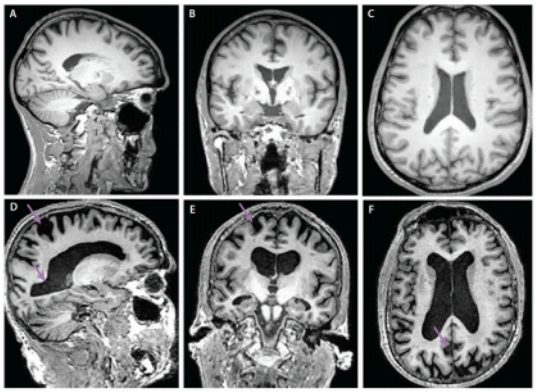


Figure 3.1: a)AD image(A-C) b)NC image(D-F)

MRI Data Visualization

In Alzheimer's disease (AD), MRI images frequently show noticeable abnormalities, like atrophy in brain regions linked to memory and cognitive functions. This can involve the reduction in size of crucial areas such as the hippocampus, affecting learning and memory. On the other hand, Healthy brain structure has no pronounced atrophy or abnormalities found in AD cases.

In the figure 3.1, two sets of MRI scans are presented. The first row displays brain images depicting individuals with Alzheimer's disease (AD), while the second row showcases images of individuals without cognitive impairment (NC). These images are captured from all three dimensions.

fMRI Data Visualization

Alzheimer's disease is known to impact various functional brain networks. Connectivity measures can highlight disruptions in the default mode network (DMN), which is often affected early in AD. We are looking at how connections between different parts of the brain change in fMRI data might show that the communication between brain areas involved in memory, thinking, and other functions affected by Alzheimer's disease is not working well. We have

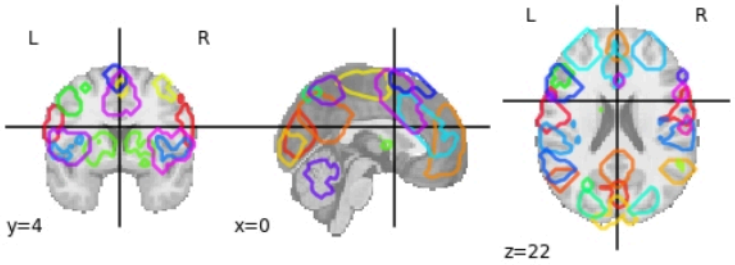


Figure 3.2: Brain regions

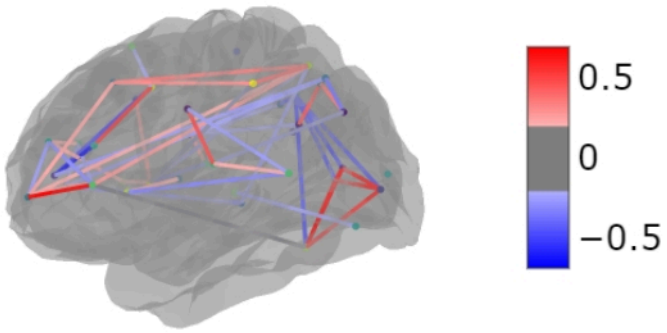


Figure 3.3: Connectivity

shown Brain ROIs, Connectivity and Voxel intensity change with time in figures 3.2, 3.3 and 3.4.

3.1.2 Resampling

Resampling involves altering a digital image to convert it into a different form, which can include changes in resolution, orientation, rotation, and sampling points. In figure 3.5 and 3.6 the images before and after skull stripping with the help of fsl.bet() [6] [7] function are given.

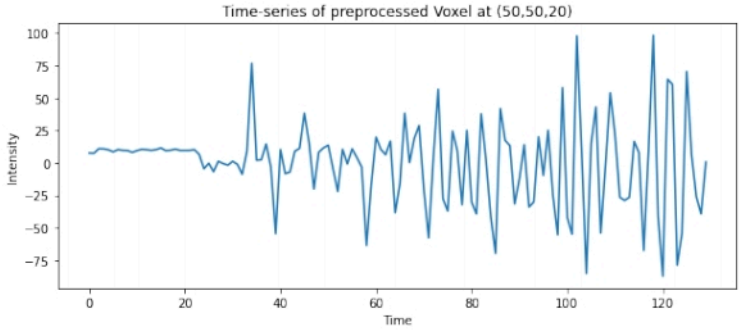


Figure 3.4: Voxel intensity with time

3.1.3 Skull Stripping

Removing the skull is a vital step before registration and segmentation. It gets rid of non-brain tissues that have varying contrasts and shapes, like the scalp and marrow. This process is also resilient to bias fields and works well with a variety of scans.

3.1.4 Segmentation

Segmentation is a critical aspect of this work where the original brain image is split into three main parts using SPM12: Cerebrospinal Fluids, White Matter, and Gray Matter. Our focus is solely on Gray Matter images due to reported associations with certain brain disorders like Alzheimer's disease.

3.1.5 Image Registration

Aligns multiple MRI images to ensure they are in the same coordinate system. This is crucial when combining images from different modalities or time points.

3.1.6 Intensity Normalization

Normalization of intensity in brain scans are performed due to variations in scanners and acquisition parameters used during image capture.

3.1.7 Spatial Smoothening

Techniques such as filtering are applied to reduce noise and improve the signal-to-noise ratio.

3.1.8 Temporal Pre-processing

Remove or filter out noise from the time series data and low-frequency trends to focus on the more rapid changes related to neural activity.

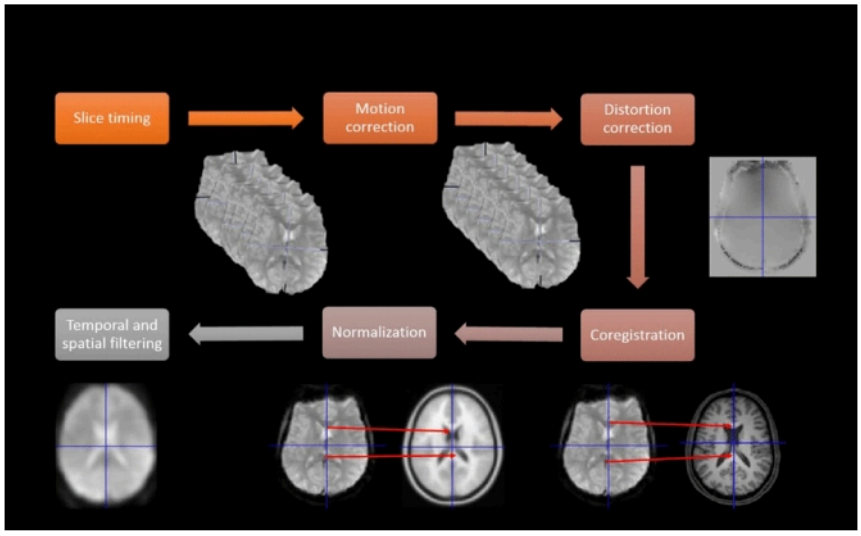


Figure 3.5: Preprocessing steps(fMRI)

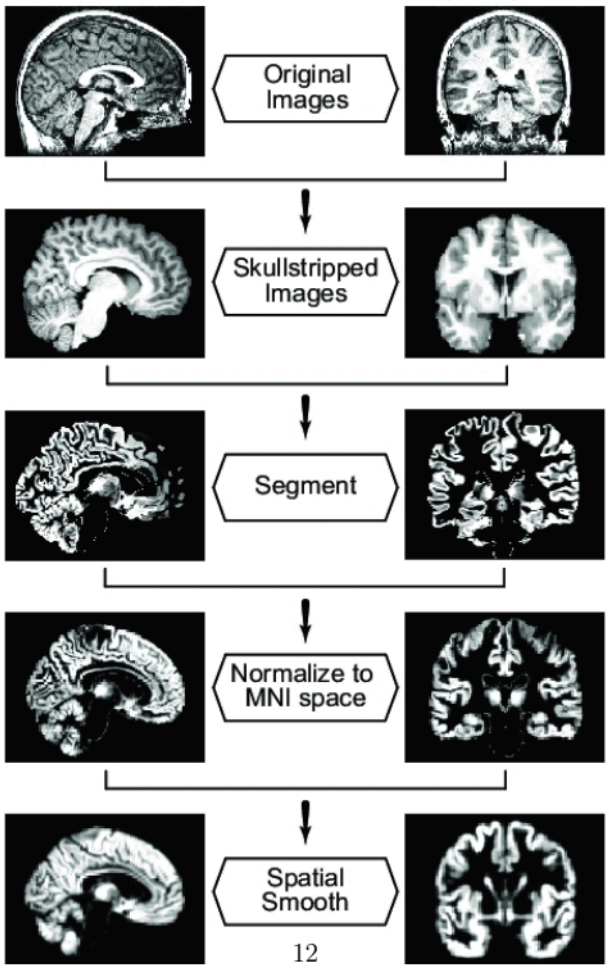


Figure 3.6: Preprocessing steps(MRI)

Chapter 4

Methodology

As already stated, our investigation in Alzheimer's disease classification involves two different datasets. While appropriate processing of MRI scans may yield noticeable abnormalities, if present, the fMRI provides real-time information about which areas of the brain are active during different tasks or at rest. This functional mapping helps identify regions associated with memory, cognition, and other cognitive functions affected by AD. Using fMRI in addition to MRI, we are having two methodologies for the sake of looking for an appropriate diagonistic tool for Alzheimer's disease. Overview of work is shown in figure 4.1.

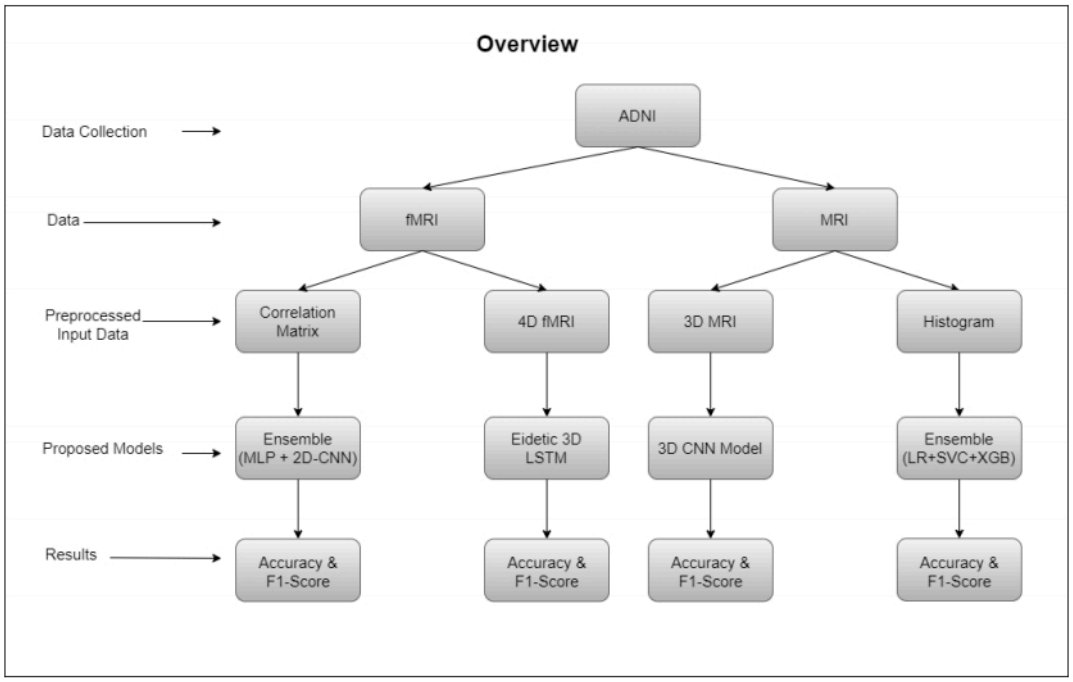


Figure 4.1: Overview

4.1 Ensemble Model using 1D Flattened 3D MRI

We flattened 3D MRI to make it a vector of single dimension which is of length 1048576. Then we applied Principal Componenent Analysis(PCA) to retain 99% of variance the dimension of an entry became of length 532. We applied different ML models and try to ensemble for better results and we got ensemble of Logistic regression, SVC and XGB as most accurate model, shown in figure 4.2. In addition to the previously mentioned model, we experimented with other ensembles involving Support Vector Classifier (SVC), Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest, XGBoost (XGB), and Decision Tree. However, ensembles containing Decision Tree and Random Forest did not yield satisfactory performance. On the other hand, the ensemble including MLP showed promising results, comparable to our primary model. We limited the ensemble to three models to prevent overfitting.

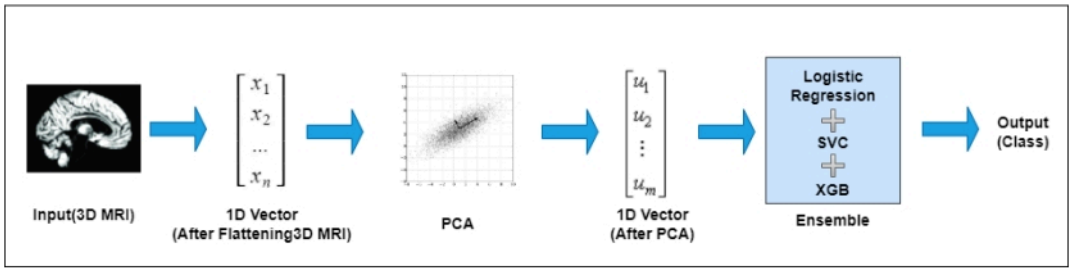


Figure 4.2: Ensemble

4.2 Autoencoder

We have to classify AD and NC using MRI using 3D CNN model. For this purpose An autoencoder was used. It consists of an encoder and a decoder, both of which are neural networks as shown in figure 4.3. The main objective of an autoencoder is to learn a compressed, low-dimensional representation of input data.

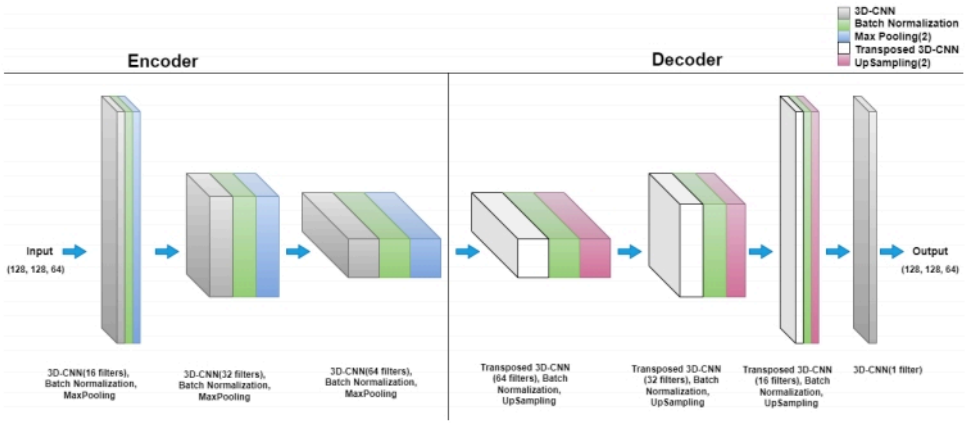


Figure 4.3: Autoencoder Architecture

4.2.1 Key Components

Encoder: The encoder function, denoted as f(x), maps the high-dimensional input data x to a lower-dimensional latent space representation h:h = f(x). Mathematically, the encoder consists of a series of transformations and non-linear activations.

Decoder:The decoder function, denoted as g(h), reconstructs the input data from the learned representation: x'=g(h). The decoder aims to generate an output that approximates the original input x.

Feature Extraction: The encoder learns a set of features in the latent space that captures essential characteristics of the input data. In the context of Alzheimer's classification, these features may correspond to patterns indicative of disease-related changes in brain imaging data.

Dimensionality Reduction: By mapping the input to a lower-dimensional space, the autoencoder inherently performs dimensionality reduction. This reduction focuses on the most salient features, simplifying the representation while retaining critical information related to Alzheimer's disease.

Anomaly Detection: The autoencoder is trained to minimize the reconstruction error, making it sensitive to deviations from the learned normal patterns. Anomalies in the reconstruction may signal potential signs of Alzheimer's disease, as the model is adapt at capturing normal variations.

Mathematical Foundation: Training involves minimizing a loss function, often the mean squared error (MSE), which quantifies the difference between the input x and the reconstructed output x'. The training process employs optimization techniques like gradient descent to update the network parameters.

The encoder, which has been trained to capture meaningful features from the input data during the autoencoder training, can serve as a powerful feature extractor for other tasks, such as classification. So, For model building we are extracting encoder from autoencoder and use it for classification.

In the Autoencoder architecture, the Encoder consists of three layer blocks comprising CNN, Batch Normalization, and MaxPooling with 16, 32, and 64 filters and a kernel size of 3, respectively. Each MaxPooling operation uses a kernel size of 2. In contrast, the Decoder employs Transposed CNN, Batch Normalization, and Upsampling with 64, 32, and 16 filters

and a kernel size of 3, respectively. Each Upsampling operation uses a kernel size of 2. The final layer in the Decoder utilizes a CNN layer with 1 filter to match the output size to the input size. We use mean squared error as loss function and ADAM optimizer.

4.3 Ensemble(Multi Layer Perceptron + 2D CNN)

Connectivity measures provides insights into the functional interactions and communication between different regions of the brain [10]. These measures are typically derived from neuroimaging data, such as functional magnetic resonance imaging (fMRI), and help capture the complex network patterns associated with Alzheimer's disease.

Functional Brain Networks: Connectivity measures analyze activity correlation between different brain regions, forming functional networks. Alzheimer's disrupts these networks, affecting communication between brain areas. Connectivity measures identify these altered patterns, with anomalous connections becoming indicative features for classification.

Graph Theory Analysis: Using graph theory, connectivity measures represent brain regions as nodes and connections as edges. Metrics like degree and betweenness centrality quantify network organization, serving as features for classification.

Machine Learning Features: Connectivity measures pinpoint potential Alzheimer's biomarkers, capturing Alzheimer's-specific communication alterations for differentiation. These Biomarker Identification helps in early detection and progression monitoring for diagnostic tool development.

The Common measures for Connectivity measures include correlation matrix is a square grid of numbers, where each number represents the strength and direction of the correlation between two specific brain regions. Connectivity Measure, extracted from fMRI data which is of (39, 39) dimension for each fMRI data can be used as input in a CNN model. Then the matrix is flattened which can be used in an MLP model.

We applied a CNN model to a correlation matrix, employing 2D CNN layers, MaxPooling, Batch Normalization, and Dense Layers with the ADAM optimizer is used with

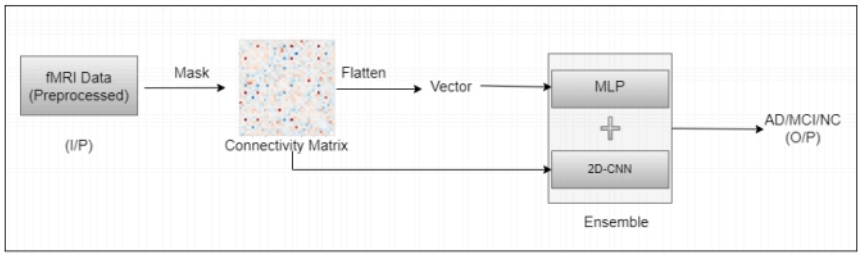


Figure 4.4: Ensemble(MLP+CNN)

the learning rate of 0.0015 with a batch size of 5 and categorical cross-entropy loss. Our architecture included 32, 64, 128, and 256 filters with a kernel size of 3, interspersed with MaxPooling layers of size 2 and Batch Normalization. Following these layers, we flattened the data and added a Dense layer of size 32 before the output layer. after that we flatten the correlation matrix and took only upper triangular matrix part as correlation matrices are symmetric and also excluded diagonal information too. We used this as feature data for model building using Logistic Regression, SVC, XGB, Random Forest and Decision tree. We try to build an ensemble model with one of the model as 2D CNN model and other model mentioned above. We found that MLP and CNN(in Figure 4.4) was able to classify better than other combinations. After extracting Encoder after training autoencoder and add Flatten and Dense layers to make a classification model.

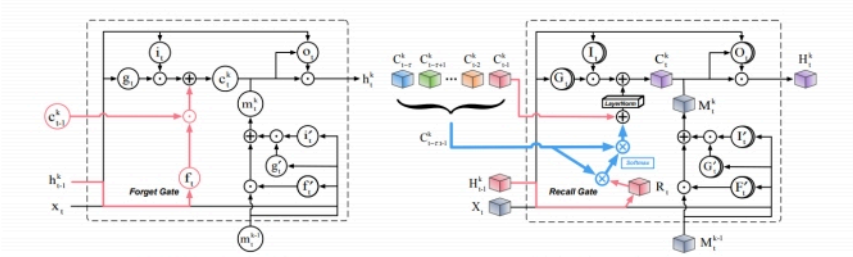
4.4 Eidetic 3D LSTM

Temporal feature of fMRI is used in the method below where we are using Eidetic 3D LSTM which is designed for spatiotemporal modeling, particularly suited for processing 3D volumetric data across temporal sequences.

4.4.1 Architecture

The Eidetic 3DLSTM model architecture[5], leverages a combination of 3D convolution operations, Eidetic 3DLSTM cells, self-attention mechanisms, and convolution-deconvolution layers to capture and retain spatial and temporal dependencies in the input data as shown in Figure 4.5. This is like an upgraded version of Spatiotemporal LSTM for 3D data, but with

some tweaks. In E3LSTM, we've added special memory gates, like the input modulation gate (g) and the recall gate (r), along with the usual gates. These extra gates help the model better control memory and pay attention to important spatial and temporal features.E3LSTM builds on the ST-LSTM design by using convolutional operations to adjust memory. This means the model gets better at understanding patterns and connections in 3D data.



(a) Spatiotemporal LSTM (b) Eidetic 3D LSTM

Figure 4.5: Spatiotemporal Models

The aforementioned function is employed for performing Convolution-Deconvolution operations on both the input and hidden states which extracts information from a volume before it proceeds to subsequent operations to calculate I_t,G_t, R_t etc.

Algorithm 1 Pseudo-code for `e3dlstm_cell`

function E3DLSTM_CELL(input_shape, hidden_size, kernel_size, x, c_history, m, h)

$in\_channels \leftarrow input\_shape[0]$

Define gates

$W_{xi} \leftarrow$ conv_deconv_3d$(in_channels, hidden_size, kernel_size)$

Similarly, we get $W_{xr}, W_{xg}, W'_{xi}, W'_{xg}, W'_{xf}, W'_{xo}$ with same arguments.

$W_{hi} \leftarrow$ conv_deconv_3d$(hidden_size, hidden_size, kernel_size, \text{bias} = False)$

Similarly we get $W_{hr}, W_{hg}, W'_{mi}, W'_{mg}, W'_{mf}, W_{ho}, W_{mo}, W_{co}$ with same arguments.

$R_t \leftarrow \sigma(W_{xr} * X_t + W_{hr} * H_{k,t-1} + b_r)$

$I_t \leftarrow \sigma(W_{xi} * X_t + W_{hi} * H_{k,t-1} + b_i)$

$G_t \leftarrow \tanh(W_{xg} * X_t + W_{hg} * H_{k,t-1} + b_g)$

Self-attention

$\text{RECALL}(R_t, C_k^{t-\tau:t-1}) \leftarrow \text{softmax}(R_t \cdot (C_k^{t-\tau:t-1})^T) \cdot C_k^{t-\tau:t-1}$

$C_k^t \leftarrow I_t \odot G_t + \text{LayerNorm}(C_k^{t-1} + \text{RECALL}(R_t, C_k^{t-\tau:t-1}))$

$I_0^t \leftarrow \sigma(W_{0xi} * X_t + W_{mi} * M_{k-1}^t + b_{0i})$

$G_0^t \leftarrow \tanh(W_{0xg} * X_t + W_{mg} * M_{k-1}^t + b_{0g})$

$F_0^t \leftarrow \sigma(W_{0xf} * X_t + W_{mf} * M_{k-1}^t + b_{0f})$

$M_k^t \leftarrow I_0^t \odot G_0^t + F_0^t \cdot M_{k-1}^t$

$O_t \leftarrow \sigma(W_{xo} * X_t + W_{ho} * H_{k,t-1} + W_{co} * C_k^t + W_{mo} * M_k^t + b_o)$

$H_k^t \leftarrow O_t \odot \tanh(W_{1\times1\times1} * [C_k^t, M_k^t])$

c_history = concatenate(c_history, C_k^t)

return c_history, m

The Current cell state C_t is obtained through the Recall Gate, incorporating past cell states as depicted in Figure 4.3.

To calculate spatiotemporal memory states M_t^k, Output Gate O_t and hidden State H_t^k at time t, we have calculations similar to ST-LSTM architecture shown below in Figure 4.4. The whole structure so far makes a E3LSTM Block. During the forward propagation of our model, input is sequentially processed through multiple E3LSTM Blocks. The final hidden block obtained from the last time step of the last E3LSTM Block is then fed into a series of layers, including 3D CNN, Maxpooling, Batch-normalization, dropout, Flatten, and Dense layers. We utilize Categorical Cross-Entropy as the loss function and apply softmax activation at the final layer for classification in building our model.

Chapter 5

Experiment and Results

We utilized MRI and fMRI data to create two separate models for each dataset. To evaluate the performance of the model F1 score and accuracy is used. Performance of the models are presented in tabluar form in Figure 5.1. For the MRI data, we constructed various models including Logistic Regression, Support Vector Classifier (SVC), XGBoost (XGB), Random Forest, Decision Tree, and Multi-Layer Perceptron (MLP) using histogram information. Upon applying PCA, our feature count reduced from 1,048,576 to 532. Notably, Decision Tree and Random Forest models exhibited less effectiveness, with accuracies below 70%. On the other hand, MLP, XGB, SVC, and Logistic Regression models showed improved accuracies at 81%, 70%, 80%, and 84%, respectively.

When we attempted to create an ensemble model using all three top-performing individual models, the accuracy slightly dropped to 83%. However, by selecting XGB, SVC, and Logistic Regression for the ensemble model, we achieved a slightly higher accuracy and F1 score.

Attempting to create a CNN model with 3D MRI data as input, we initially began with a few layers and gradually augmented complexity. Despite adjusting parameters such as the number of filters, pooling, dropout, dense layers, learning rate, and decay rate, we were only able to achieve an accuracy of 62%. Subsequently, we employed an autoencoder model and utilized its encoder for classification, resulting in an accuracy of 68.67% and an associated F1 score of 0.66.

We constructed a 2D CNN model using the correlation matrix derived from fMRI data. Initially, we incorporated a few layers of CNN along with pooling layers and batch normalization. However, attempts to increase complexity were counterproductive due to the limited

data and the small size of the correlation matrix (39x39). Additionally, Dropout did not yield significant improvements.

Following the Flattening step, we applied MLP, Logistic Regression, XGB, SVC, and Random Forest models. Upon ensembling these models with the CNN model, we observed that MLP produced the best results. While XGB showed better performance compared to others individually, the ensemble of CNN and MLP demonstrated superior accuracy.

We employed 4D fMRI data as input for our custom-built Eidetic 3D LSTM model, which was developed from scratch based on the theoretical model's procedures. Due to the model's complexity, we incorporated additional layer normalization to improve training effectiveness. Following the E3DLSTM layers, we integrated CNN, Pooling, and dense layers, with a stride value set to two. For the final layer, we utilized softmax activation, the ADAM optimizer, and Categorical Cross Entropy as the loss function.

The Eidetic 3D LSTM model yielded an accuracy of 61.21% and an F1 score of 0.56. Meanwhile, the CNN and MLP Ensemble model demonstrated an accuracy of 59.12% with an accompanying F1 score of 0.51.

Due to the high dimensionality of MRI and fMRI data and the limited dataset available for all three models, our proposed methods, E3DLSTM and CNN models, exhibit average performance.

But 3D CNN, 2D Deep CNN and XGB+DT+SVM ensemble models using MRI data, produces similar results in terms of accuracy, even though their input data is 3D, 2D and 1D. similarly, For input as 4D fMRI data CNN-LSTM and CNN-RNN performs similar in terms of accuracy.

Table 5.1: Relative Performances of Proposed Algorithms for Disease Progression

Data	Training Data	Method	Accuracy(%)	F1-Score
MRI	2D image slices	2D Deep CNN	55.89	0.43
MRI	3D MRI	Autoencoder	68.67	0.66
MRI	1D-Vector(Flattened from 3D MRI)	Ensemble(XGB + DT + SVM)	74.61	0.76
MRI	1D-Vector(Flattened from 3D MRI)	Ensemble(LR + XGB + SVM)*	84.6	0.85
MRI	1D-Vector(Flattened from 3D MRI)	Logistic Regression	84.6	0.84
fMRI	Connectivity Matrix	MLP	56.7	0.55
fMRI	Connectivity Matrix	Ensemble(CNN+MLP)*	59.12	0.53
fMRI	4D fMRI	3D-CNN-LSTM	60.4	0.57
fMRI	4D fMRI	E3DLSTM*	58.2	0.51

* Models built while dissertation.

Chapter 6

Conclusion and Future Works

This study aims to investigate CNN, MLP, model ensemble and spatio-temporal algorithms in a supervised way of Alzheimer's disease classification. Although it achieves average results and there were still pre-existing algorithms which work better than this but the methods still can be promising for Alzheimer's disease classification. We utilized MRI and fMRI data in various models and obtained results; however, we were unable to determine which dataset yielded superior performance.

Our study used cross-entropy for classification, but MRI and fMRI data often has imbalanced classes. Exploring a "focal loss" technique in future research could improve handling this imbalance and potentially lead to better predictions. We tested our models on fMRI dataset from ADNI, but in the future, we should see how well they work on datasets from other repositories like MIRIAD(Minimal Interval Resonance Imaging in Alzheimer's Disease)[1] and OASIS(Open Access Series of Imaging Studies)[2]. More diverse testing will make our findings more relevant to a variety of patient populations and imaging technologies. We should investigate novel spatio-temporal modeling approaches to evaluate their performance on fMRI datasets from established repositories. Dimensionality reduction techniques like PCA or t-SNE could be employed to extract the most informative features from MRI and fMRI data. This would allow us to build complex models with improved efficiency by focusing on the most relevant information.

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[2] https://www.oasis-brains.org

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