An Enhanced Approach for Alzheimer's Disease Classification by Data Balancing and Data Augmentation

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Abstract—. ***Alzheimer's disease (AD) is one of the most common neurodegenerative diseases that results in the central nervous systems stop working. Over the past decades, the area of AD is attaining more attention due to the large number of AD cases around the world. Researchers are studying to improve the existing conventional diagnosis techniques to detect AD at its early phase. Various deep learning and machine learning approaches are being applied to predict and classify AD. In this work, we have implemented Support Vector Machine (SVM), Visual Geometry Group-16 (VGG-16), Residual Neural Network-50 (Resnet50), and Convolutional Neural Network (CNN) to detect AD using Magnetic Resonance Imaging (MRI) scans in order to classify AD. After comparing the approaches, we found that our proposed method performed better with a F1 score of 0.83.***

Keywords: Alzheimer's disease, CNN, Machine learning, Deep Learning, Medical Images and Data Balancing.

I. Introduction

Alzheimer's disease is a type of brain disorder which is a slowly progressive disease that begins many years ahead of symptoms. Difficulty remembering names, events and recent conversations are early clinical symptoms of this disease. Later the patients suffer from speaking difficulty, swallowing and walking ("Alzheimer's Disease Facts and Figures", 2021).

Alzheimer disease (AD) is the most common form of dementia that affects remembrance power, thinking capabilities and other mental capacities. Mostly people over the age of 65 suffer from AD ("Alzheimer's disease", 2021). According to ("Alzheimer's Disease Statistics", 2021), 44 million people around the world are living with AD or related forms of dementia. Moreover, this is the sixth-leading cause of death in the US.

According to Alzheimer's Association ("Stages of Alzheimer's", 2021), Ad can be categorised into three stages: Mild (early stage), Moderate (middle-stage) and Severe (late-stage). Patients usually function individualistically without any help and the symptoms may not be ostensible at this stage. They might have difficulty remembering names, organizing any task etc. Middle-stage Alzheimer is the longest period when a patient needs support in terms of daily activities due to greater memory loss and cognitive difficulties. At this stage, patients forget personal history, their moods swing a lot. Sometimes they are unable to remember their addresses, contact numbers. Their sleeping patterns, personalities and behaviours change with the time being. Restlessness, anger, and tearfulness is also a very common sign at this stage. At the final stage of Alzheimer, dementia syndromes become severe. They face complications with reading, writing and working with numbers. In the worst scenario, they forget their family and friends. Apart from that, inability to communicate, loss of bladder and bowel control is a very common occurrence among AD patients at late phase ("Stages of Alzheimer's", 2021; "What Are the Signs of Alzheimer's Disease?", 2021).

Regardless of experimenting several treatments to prevent or control AD, the progress rate is very low, specifically at the last stage of this disease (Ebrahimi et al., 2010). Early diagnosis of this disease can give the patient a longer period to survive. This diagnosis process is based on clinical assessment, investigating brain scans and inquiring about a patient and his/her close family members (Lerch et al., 2008 ; Gerardin et al., 2009). This procedure is difficult because of the inadequate knowledge to find out the affected part of the brain. A wide range of analyses has been conducted to detect Alzheimer at middle stage using artificial intelligence (Ebrahimi, & Luo. 2021). With the progression of Magnetic Resonance Imaging (MRI) technology (Lohrke et al. 2016) and the development different computer vision based approaches where deep learning and machine learning techniques have been implemented have contributed to the detection systems of AD at middle phases using MRI brain scans (Altay et al. 2020). However, to identify Alzheimer at the early stage is still very challenging and these studies do not contribute to this phase. Recent studies show that compared to machine learning techniques, deep learning methods perform better to detect AD. Instead of extracting features from classifiers, deep learning techniques can learn the parameters of neural networks straightforwardly from images without any human intervention (Liu, Z., Yan, W. Q., & Yang, M. L. 2018).

Though many machine learning and deep learning methods have been applied in recent many research works, the outcomes indicate that deep learning outperforms machine learning methods. In this research paper, we have implemented both deep learning and machine learning techniques and have conducted a comparative analysis in order to detect Alzheimer disease. The methods we have applied are: SVM, VGG16, ResNet-50, Custom CNN.

II. Literature review

In recent couple of years, many researchers have made tremendous contributions in order to identify Alzheimer using artificial intelligence. (Ebrahimi, & Luo, 2021) compared several deep models and configurations which includes 2D CNN, 3D CNN and RNN (recurrent neural network) and they found that voxel-based technique with transfer learning from ImageNet to MRI datasets using 3D CNNs significantly improved the results compared with the others.

(Valliani, & Soni, 2017) proposed a framework that applies deep residual CNNs which has been pre-trained on large, non-biomedical image datasets. Moreover, they have shown that pre-trained ResNet with data augmentation gives more accuracy compared to data without augmentation. A method consisting of two attention model networks has been initiated in (Altay et al. 2020) in order to help AD detection from MRI images at preclinical stages. Also, they compared these two network models with a 3D CNN based baseline model and came to a conclusion that the transformer model provides better accuracy level which is 91.18%.

(Bari Antor et al., 2021) analysed various machine learning models: Support Vector Machine (SVM), Logistic Regression, Decision Tree and Random Forest for detecting dementia. Comparing the results, it is found that SVM performs better (accuracy: 92.0%) than the other models. (Ji, Liu, Yan & Klette, 2019) presented an ensemble learning method for the early diagnosis of AD by using deep learning and the authors claimed that the performance of this model is superior to the traditional machine learning approaches. Temporal convolutional network (TCN) has been employed as a sequence-based model in (Ebrahimi, Luo and Chiong, 2021) and the accuracy is 91.78%. It also shows that it is possible to improve the classification of 2D and 3D CNNs up to 10% by applying sequence-based models. (Ju, Hu, Zhou, and Li, 2019) has put forward a new approach, a combination of brain network and deep learning model and achieved about 20 percent of improvement on the classification accuracy. A thorough investigation has been conducted by (Jiang, 2020) to compare the pros and cons of applying deep learning models in the field of Alzheimer's disease.

III. Proposed Methodology

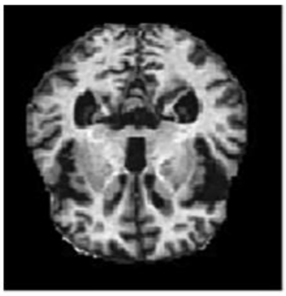
A. *Dataset and Preprocessing*

The Alzheimer's dataset has been collected from the Kaggle machine learning repository ("Alzheimer's Dataset- 4 class of Images", 2021).

This dataset contains 4 different classes which are mainly categorized as:

1. MildDemented
2. VeryMildDemented
3. NonDemented
4. ModerateDemeneted

based on the severity of Alzheimer's. This complete dataset is segregated into the Train dataset and Test dataset where we have considered 80% of data for training and 20 % for testing the accuracy. Figure 1 and 4 represent the categories mentioned. In this dataset standard MRI scan images are used. Alzheimer's detection using MRI Scanning is an ever continuing study of clinical, imaging and genetic dataset developers for the quick detection of Alzheimer's. There are ~6400 Images altogether in which the categories MildDemented contains only 717 and ModerateDemented only 52 images. For that reason, we have balanced the dataset by using a combination of oversampling and undersampling methods which in turn improved our results.



(a)

Figure 1 Mild demented.

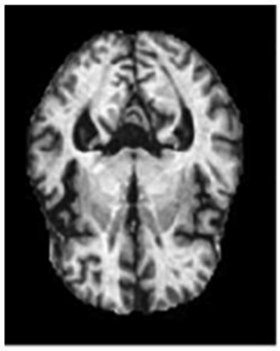


Figure 2 Moderate demented.

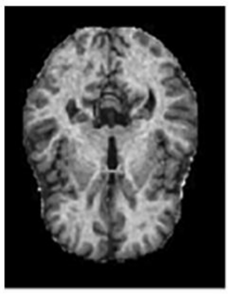


Figure 3 Very mild demented

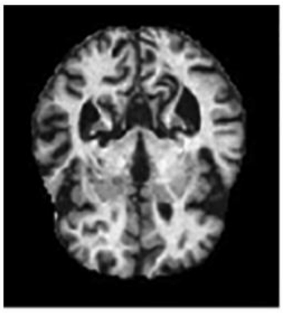


Figure 4 Not demented

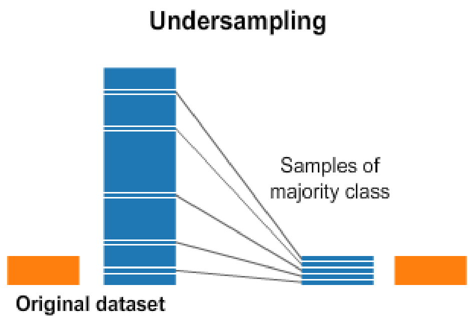


Figure 5: Undersampling method.

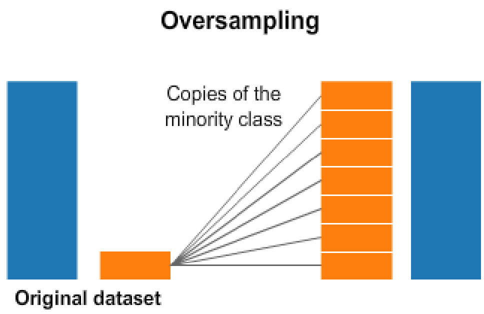


Figure 6: Oversampling method.

B. *Data Augmentation:*

1) *Image Augmentation:*

It is a part of image preprocessing which assists in altering the existing data by different factors to increase the total number data for model training. It also helps to reduce bias by creating a variety of data within a preferred range which gives the model new information to learn. To augment our images we applied zoom, altered brightness and flipped the images within a given range.

2) *Undersampling and Oversampling (SMOTE):*

Oversampling and undersampling is a form of data augmentation. As we have an imbalanced dataset we have passed our dataset through these methods. Incorporating only one of these methods also works, however, their combination has a better performance (Chawla, 2002). One of the simplest ways oversampling of the minority class can be done is by duplicating the minority class instances. However, it will just increase the number of instances and will not. This is the reason we have selected the "Synthetic minority over-sampling technique" in short SMOTE for our oversampling. Rather than just duplicating it synthesizes minority class instances to create new data points. It selects the nearby instances of the feature space and connects them by drawing a line. And, new instances are generated along the line. Using this makes our minority class reach the same numbers as the larger classes. After that we performed undersampling using Random Undersampling method which basically removes random data points from the majority classes and by implementing this along with SMOTE our dataset gets balanced which in turn removes our underfitting issue.

C. *SVM*

In supervised learning Support Vector Machine (SVM) is one of the classic machine learning methods that perform really well both in terms of speed and accuracy. It creates an Optimal Separating Hyperplane (OSH) between classes for classification. It uses a function called support vector that focuses on the maximum distance between classes to classify and because of this reason SVM generalizes better than other algorithms. For the svm the training dataset with m instances it can be defined as $\{x_i, y_i\}$ where i = 1.2.....m; y = {0,1,2,3}. The hyperplane in the SVM can be defined as,

$$w*x + b = 0 \text{ --------(1)}$$

Where w is the weight or normal of the hyperplane, x is the point lying on the hyperplane and b is the bias. Also, in some space H, the optimal values for both w and b can be calculated using Lagrange multipliers α_i (i=1,….m) by solving a constrained minimization equation (Schuldt, Laptev, & Caputo, 2004).

$$f(\boldsymbol{x}) = \operatorname{sgn}\left(\sum_{i=1}^{m} \alpha_i y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b\right) \quad \text{---(2)}$$

Here, the α_i is Lagrange multiplier and $K(x_i, x)$ is the radial basis function. And, for multiclass classification,

$$(w_i)^T * \phi^*(x) + b_j \text{ --------(3)}$$

Where ϕ is the mapping function in the high dimensional space H.

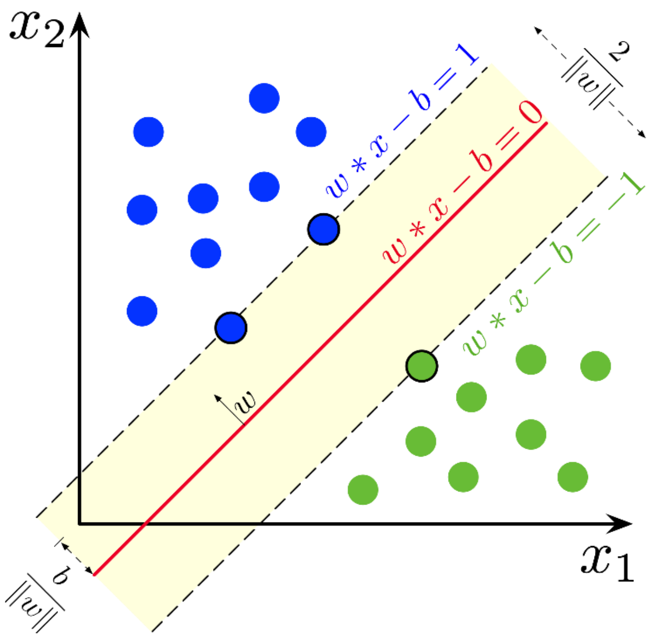


Figure 7: SVM classifier

D. CNN:

Convolutional Neural Network has become famous for image classification tasks due to its groundbreaking layer containing a collection of kernels. It is a black box classifier which has five major components: structure, kernel, receptive field, number of layers and feature maps (Pavel, 2020). The feature extractor of CNN extracts different information of the images which depends upon the layers. Lower level layers extracts information like edges, corners, etc. and higher the layer more complex features are extracted from the images. These features are then passed through the fully connected layers and flattened into a single dimensional array which afterwards are fed into the classifiers. The classifier outputs the probability score of the image of which class it belongs to (Chang, & Sha, 2016). Below is a sample CNN structure:

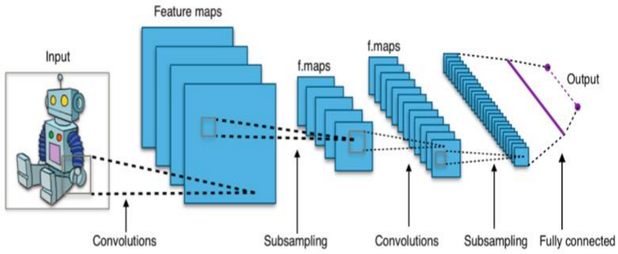


Figure 8: Basic CNN architecture.

Using this CNN structure above we have built a custom CNN, below Image shows the schematic view of the custom CNN:

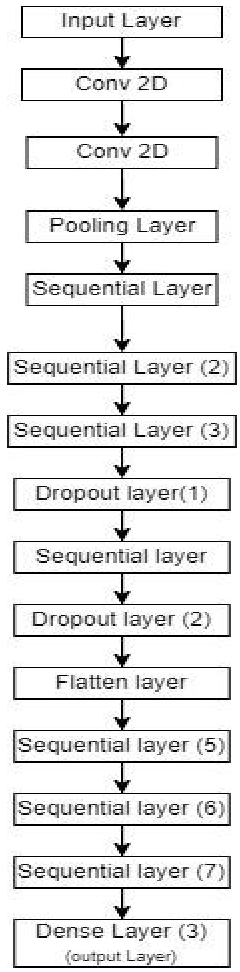


Figure 9: Custom CNN architecture.

1) VGG16:

VGG is a CNN which is a light weight deep neural network that made records in Imagenet classification, reaching more than 90% accuracy and it was considered as a state of the art at that time. It is also known as an extended version of AlexNet. VGG became famous for its approach by deepening its layers by using smaller convolutional blocks of 3X3 filters, 2X2 pooling layers etc. for feature learning (

(Jiang, Liu, Shao, & Huang, 2021). Following is the structure of the VGG16:

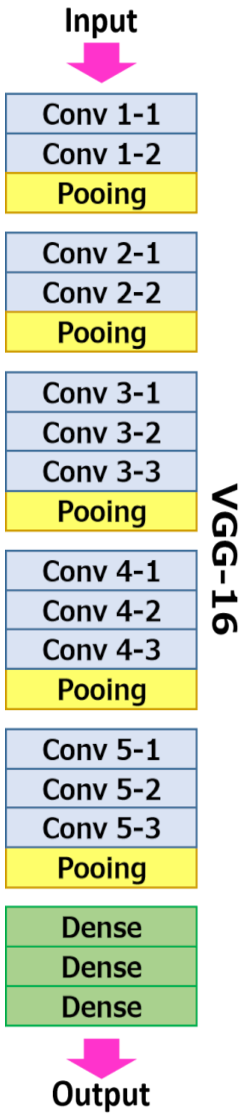


Figure 10: VGG16 Architecture

E. RESNET50:

Deep Neural Networks are heavily dependent upon data and depth of the architecture. However, deeper networks come with their own demerits. Due to vanishing gradients after some depth deeper networks face performance issues and to tackle that one of the solutions was brought forth by residual networks. Where the gradients can skip layers in the middle and flow from the initial layer to some later layers that helped the ResNet to outperform many other architectures (He, Zhang, Ren and Sun, 2016). There are different variants of ResNets and we used the variant ResNet-50.

Below is the residual block of ResNet-50 which skips three layers at a time

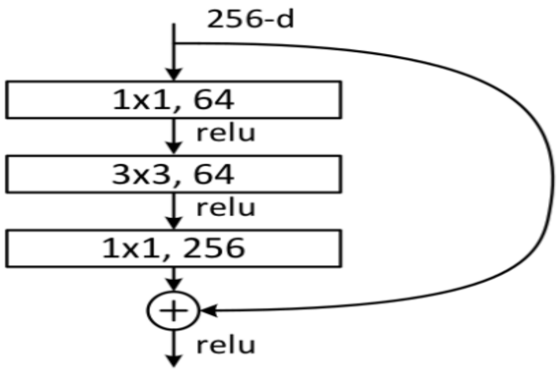


Figure 11: Residual Block of ResNet-50

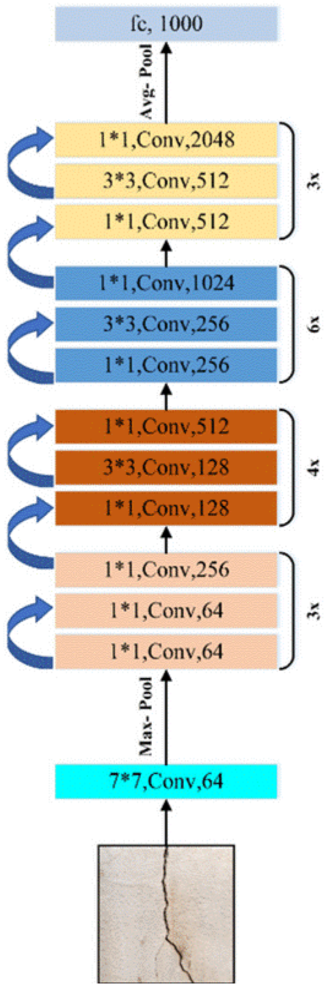


Figure 12 : Architecture of ResNet-50

We have followed two different approaches to validate and analyze the data, In the first approach we have performed only Image augmentation and fed the images to the Machine learning models. Figure 13 denotes the initial architecture of our solution where the performance of Custom CNN Model outperformed (SVM, VGG16, CNN and RESNET 50). Our second approach is to improve the results by augmenting Images along with balancing the dataset with the help of oversampling and undersampling the data. Second approach has shown better results though we have limited number of training data for two categories as we have done data balancing before passing it to machine learning algorithms. Figure 14 represents the second approach of our solution where the performance of Custom Model outperformed (SVM, VGG16, CNN and RESNET 50. Based on both the approaches we conclude that the Custom CNN Model performed very well with accuracy as me

IV. EXPERIMENTAL RESULTS

In the experimental setup, the results obtained after running the CNN Machine learning techniques for Alzheimer's data set which consists of 12800 images of size 224 x 224. To construct the algorithms, we use Python3 IDE in Anaconda – Jupyter Notebook, Scikit Learn Libraries as Knowledge sources. This experiment is performed on the 11th Gen Intel® Core Processor with 2.80 GHz CPU and 16GB RAM running on Windows Platform.

In the first approach, for Alzheimer's classification, we validate our proposed system by randomly taking 20% (1280 images) of the Alzheimer's dataset as a testing dataset and 80% (5120 images) as training data. We fine-tune the training options like mini-batch size, learning rate, and number of epochs for the training. We set the mini-batch size to 64 for faster processing and the number of epochs were set to 20. We have performed some data augmentation operations on the

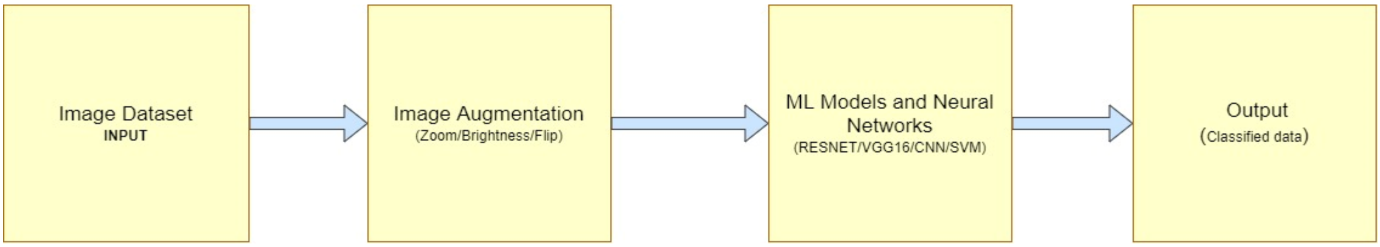


Figure 13 : The schematic diagram of the Initial system for Alzheimer's classification (approach 1)

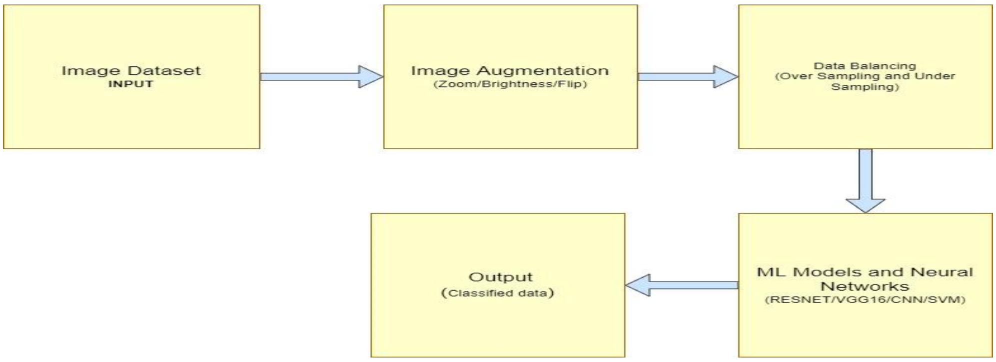


Figure 14 : The schematic diagram of the Proposed system for Alzheimer's classification (approach 2)

training images to prevent the network from overfitting and underfitting. The operations include image resizing according to network input where the image sizes are varying in the dataset to make distinct image channels, randomly flipping in the y-direction.

Below Table 1 shown represents different Metrics analyzed while running the networks:

	Approach 1 -Before Data Balancing					
	Precision	Training a	F1 score	Recall	AUC	TestAccuracy
CNN(CUSTOM)	0.78	0.995	0.73	0.717	0.886	0.738
SVM	0.83	0.741	0.5	0.47	0.67	0.68
VGG16	NIL	0.772	NIL	NIL	NIL	0.742
RESNET50	0.583	0.775	0.16	0.098	0.8	0.75

Table 1: Comparing models with Metrics – Before Data Balancing

As per the Table when data augmentation is used there is Custom CNN model that has high performance in terms of accuracy.

Below graphs show the results after performing augmentation alone using Custom CNN.

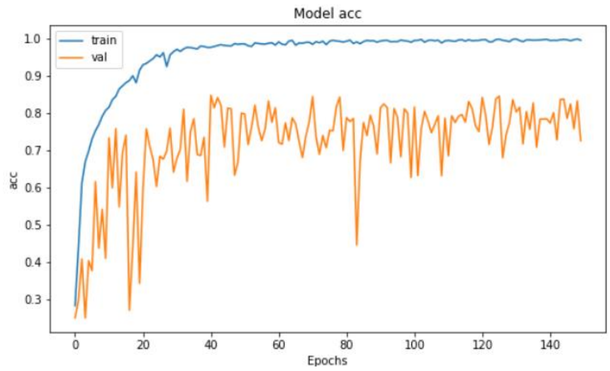


Figure 15: Graph show Accuracy metrics for 150 Epochs

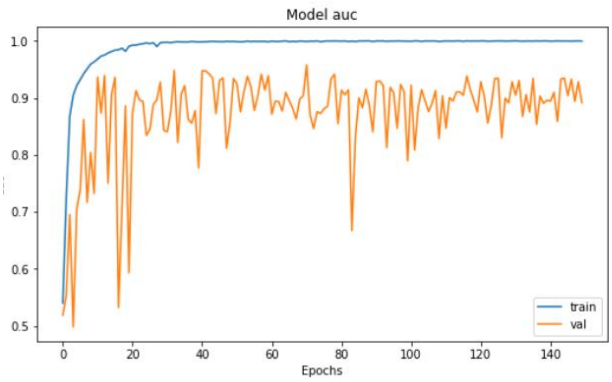


Figure 16: Graph show AUC Metric for 150 Epochs

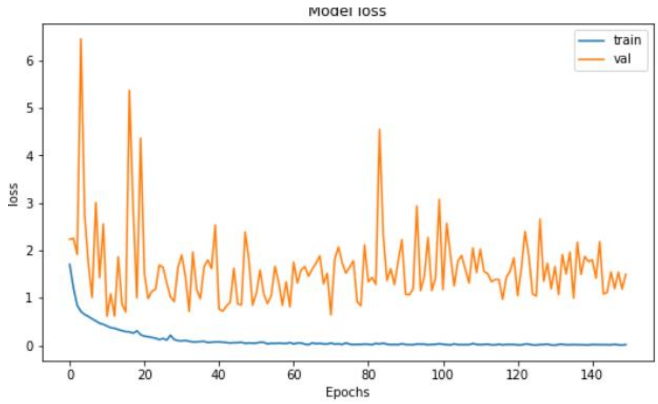


Figure 17: Graph show Loss metrics for 150 Epochs

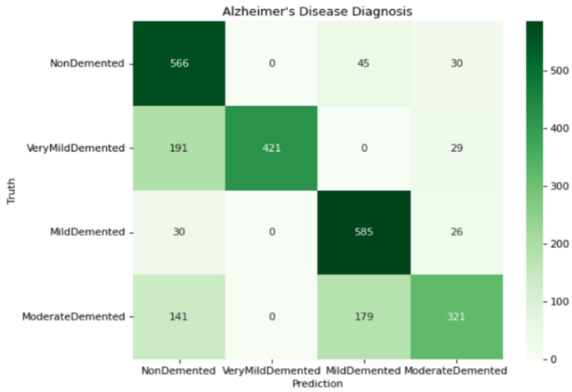


Figure 18: Confusion matrix for Approach 1 result set

In the second approach, for Alzheimer's classification, we validate our proposed system by randomly taking 20% (2560 images) of the Alzheimer's dataset as a testing dataset and 80% (~10000 images) as training data. We fine-tune the training options like mini-batch size, learning rate, and number of epoch for the training. We set mini-batch size to 64 for faster processing. We have performed some data augmentation operation on the training images to prevent the network from overfitting and underfitting. The operations include image resizing according to network input where the image sizes are varying in the dataset, color preprocessing to make distinct image channels, randomly flipping in the y-direction, translate up to 30 pixels, and 10% scaling in both directions. Followed by augmentation we have done data balancing by oversampling the samples first and then by under sampling the dataset. Below Table 2 shown represents different Metrics analyzed while running the networks using the second approach:

	Approach 2 -After Data Balancing					
	Precision	Training a	F1 score	Recall	AUC	TestAccuracy
CNN	0.85	0.99	0.83	0.82	0.89	0.86
SVM	0.841	0.762	0.69	0.59	0.772	0.797
VGG16	NIL	0.772	NIL	NIL	NIL	0.778
RESNET50	0.72	0.82	0.26	0.083	0. 791	0.85

Table 2: Comparing models with Metrics – After Data Balancing

As per the Table 2 above when data augmentation is used there is Custom CNN model that has high performance in terms of accuracy.

Below graphs shows the Training accuracy statistics shows the results after performing augmentation and data balancing using Custom CNN.

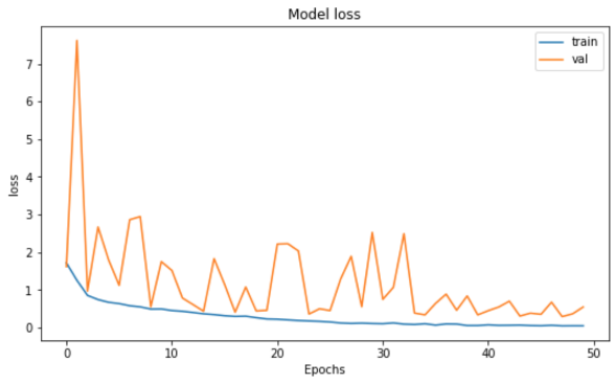


Figure 19: Graph show loss metrics for 150 Epochs

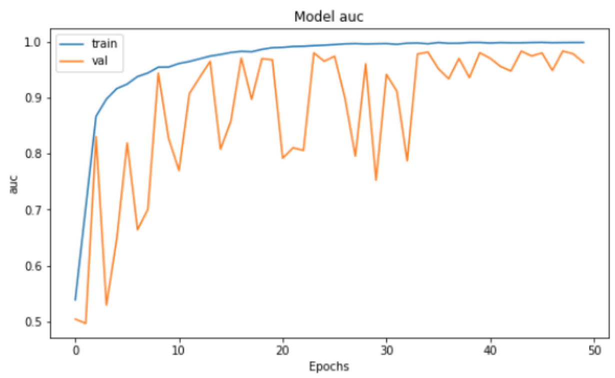


Figure 20: Graph show auc metrics for 50 Epochs

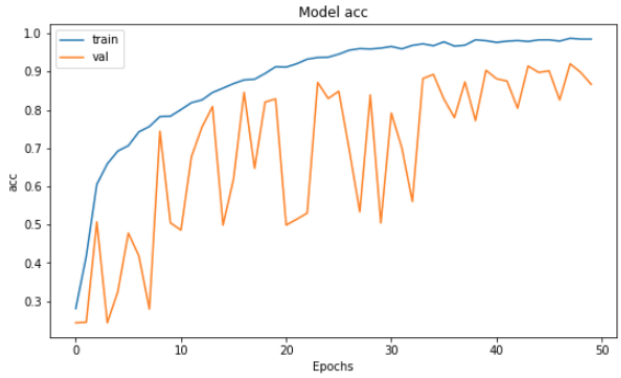


Figure 21: Graph show Accuracy metrics for 50 Epochs

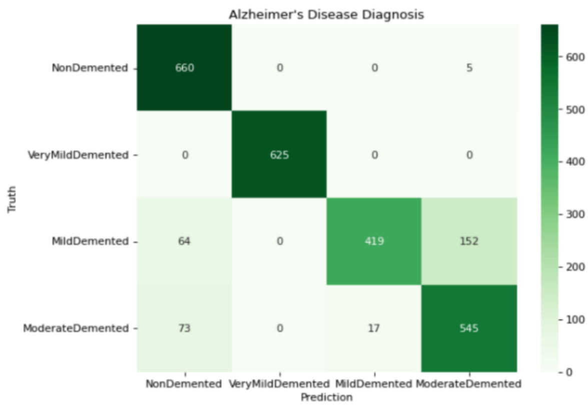


Figure 22: Confusion matrix for Approach 2 result set

Figure 15 - Figure 18 shows the graphical representation of the Accuracy, Loss and AUC metrics when ran for 150 Epochs in Custom CNN, based of approach 1 discussed in methodology section.

Figure 18 - Figure 21 shows the graphical representation of the Accuracy, Loss and AUC metrics when ran for 50 Epochs in Custom CNN based of approach 2 discussed in methodology section.

We can see from these result set that using approach one without balancing the dataset though the training accuracy is nearly ~98%, Accuracy of validation dataset remains at 7we run the epochs the accuracy remained at 73%. After Data balancing the validation Accuracy of the Custom CNN has drastically increased to 85%

After comparing the results between the initial approach and the Proposed approach with Accuracy as metric we can see there is a lot of improvement in terms of accuracy by comparing the two tables, though there are some categories that were underfitting in the initial dataset considered.

V. FUTURE WORK

Our proposed solution will assist in the early detection of Alzheimer's patients. In the future, we want to work on complete MRI scans rather than the 2D splices. We believe we will be able to extract more information that way. However, as the medical images are quite difficult to get it will be challenging for us too. Also, we want to incorporate more raw image pre-processing techniques. Our target is to get better ROIs as well as enhance those ROIs so that the models can learn useful information fast. Successful implementation of that will both reduce our training time and improve our accuracy.

VI. CONCLUSION

We have demonstrated two approaches to classify among the four classes of AD. Our primary dataset had imbalanced data on which we conducted our tests. We also fed the images to our custom CNN. However, in our first approach it can be seen that our model didn't outperform the other models. After we incorporated data balancing techniques which in general improved all the model's performance but our model outperformed in this second approach. From this it can be clearly understood that the importance of both image augmentation and balancing the data are significant.

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