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DEMNET: A Deep Learning Model for Early Diagnosis of Alzheimer Diseases and Dementia From MR Images

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ABSTRACT Alzheimer's Disease (AD) is the most common cause of dementia globally. It steadily worsens from mild to severe, impairing one's ability to complete any work without assistance. It begins to outstrip due to the population ages and diagnosis timeline. For classifying cases, existing approaches incorporate medical history, neuropsychological testing, and Magnetic Resonance Imaging (MRI), but efficient procedures remain inconsistent due to lack of sensitivity and precision. The Convolutional Neural Network (CNN) is utilized to create a framework that can be used to detect specific Alzheimer's disease characteristics from MRI images. By considering four stages of dementia and conducting a particular diagnosis, the proposed model generates high-resolution disease probability maps from the local brain structure to a multilayer perceptron and provides accurate, intuitive visualizations of individual Alzheimer's disease risk. To avoid the problem of class imbalance, the samples should be evenly distributed among the classes. The obtained MRI image dataset from Kaggle has a major class imbalance problem. A DEMentia NETwork (DEMNET) is proposed to detect the dementia stages from MRI. The DEMNET achieves an accuracy of 95.23%, Area Under Curve (AUC) of 97% and Cohen's Kappa value of 0.93 from the Kaggle dataset, which is superior to existing methods. We also used the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset to predict AD classes in order to assess the efficacy of the proposed model.

INDEX TERMS Deep learning, Alzheimer's Disease, MRI image, convolutional neural network, Cohen's kappa.

I. INTRODUCTION

AD is the most common stages of dementia that requires extensive medical care. For initiation of clinical progress and efficient patient treatment, early and precise analysis of AD prediction is necessary [1]. AD is a chronic, neurobiological brain disorder that steadily kills brain cells induces memory and thinking capacity deficits, and eventually accelerates the loss of ability to perform even the most basic tasks [2]. In the early stages of AD, doctors use neuroimaging and computer-aided diagnostic approaches to classify the disease. A summary of the most recent census by the World Alzheimer's Association reports that over 4.7 million individuals aged over 65 years have survived this disease in the United States [3]. In the next fifty years, they estimated 60 million people may be affected by AD. Of all forms of dementia globally, Alzheimer's disease accounts for around 60-80%. Every three seconds, one person affected by dementia out of it, 60% is due to AD [4].

Dementia with Alzheimer's is approximately divided into the following:

- *Mild Cognitive Impairment:* Commonly affected by lack of memory to many individuals as they become older, whereas, for others, it leads to the problem of dementia.
- *Mild Dementia:* Cognitive impairments that sometimes affect their daily lives are encountered by people with

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moderate dementia. Symptoms include lack of memory, uncertainty, changes in personality, being lost, and difficulties in executing routine tasks.

- *Moderate Dementia:* The everyday lifestyle becomes much complex, where the patient requires extra care and support. Symptoms are equivalent to mild yet elevated dementia. People may need more help even to comb their hair. They can also exhibit significant personality changes; for example, they become paranoid or irritated for no reason. Sleep disorders are likely to occur as well.
- *Severe Dementia:* The symptoms may become deteriorated during this stage. These patients may lack the capacity to communicate, and full-time treatment may be required for the person. One's bladder control may be lost, and even small activities are impossible for them to perform actions like keeping their head up in a normal position and sitting in a chair.

Early detection of this disorder is being researched to slow down the abnormal degeneration of the brain, reduce medical care cost reduction, and ensure improved treatment. The recent failures in Alzheimer's disease research studies may suggest that early intervention and diagnosis could be crucial to the effectiveness of treatment [5]. A wide variety of neuroimaging methods are becoming increasingly dependent on the diagnosis of dementia, and this is reflected in many new diagnostic criteria. Neuroimaging increases diagnosis accuracy for various subtypes of dementia using machine learning. Specific pre-processing steps are needed to implement machine learning algorithms. Extraction and selection of features, reduction of feature dimensionality and classifier algorithm are all phases of the machine learning-based classification process [6]. Such techniques need advanced knowledge and several optimization steps, which can be time-consuming.

Early detection and automatic AD classification have recently emerged and resulted in large-scale multimodal neuroimaging findings. Different modalities for AD study include MRI, Positron Emission Tomography (PET), and genotype sequencing results. It is time-consuming to analyze different modalities to take a decision. Furthermore, the patients can encounter radioactive effects in the modalities like PET [7]. In this research work, We believe that the MRI modality benefits from its greater imaging flexibility, excellent tissue contrast, lack of ionizing radiation, and ability to provide useful information on human brain anatomy [8]. It is considered important to develop a better computer-aided diagnostic system that can interpret MRI imaging and determine whether patients are healthy or have Alzheimer's disease. Conventional deep learning systems use the cortical surface to input the CNN to perform AD classification on raw MRI images.

This paper proposes a model that uses the convolutional neural network to extract the discriminative features. Class imbalance is addressed using the Synthetic Minority Oversampling Technique (SMOTE) technique [9]. The model is developed from scratch to classify the stages of AD more accurately by reducing its parameters and computation cost. The models are evaluated by training them over the MRI dataset from the Kaggle [10]. The dataset comprises four types of dementia such as Mild Dementia (MID), Moderate Dementia (MOD), Non-Demented (ND) and Very Mild Dementia (VMD). The results reveal that the suggested model with reduced parameter outperforms all previously reported work models.

The significant contributions of this work are as follows.

1. A new convolutional neural network architecture is proposed with relatively small parameters to detect the types of dementia which is suitable for training a smaller dataset and named DEMNET.
2. SMOTE technique is used to address the class imbalance problem in the dataset is by randomly duplicating the minority class of images in the dataset to minimize the overfitting problem.
3. We created the generalized model that learns from the smaller dataset with reduced parameters and computation cost, which still performs better for AD diagnosis.
4. The occlusion sensitivity map used to visualize the image features of dementia uses to make classification decisions. The multifocal ground-glass opacities (GGO) and consolidations were visualized effectively with the occlusion sensitivity maps [11].
5. We also compared the proposed model with deep features and hand-crafted features to detect AD stages in terms of Accuracy, AUC and Cohen's kappa score.

The related work is highlighted in section II, and the proposed approach discussed in section III. Sections IV presented to analyze the extensive experimental findings, while Section V summarises the paper's conclusion and potential directions.

II. RELATED WORKS

Deep learning has considered getting a lot of attention for its use in diagnosing Alzheimer's disease. Several deep learning approaches have recently been proposed as diagnostic aids for Alzheimer's disease, assisting doctors in making informed medical decisions. We present some of the studies that are closely related to this paper in this section. Lu *et al.* [12] proposed a novel multimodal deep neural network with a multistage technique to identify people with dementia. This method provides 82.4% accuracy in Mild Cognitive Impairment (MCI) prediction and those patients later exposed to Alzheimer's disease in three years. The model achieves a sensitivity of 94.23 % for the Alzheimer's disease class and an accuracy of 86.3 % for the non-demented class. Gupta *et al.* [13] proposed a diagnosis method for the classification of AD using the ADNI and National Research Center for Dementia (NRCD) dataset by combined features from cortical, subcortical, and hippocampus region from MRI images which achieve the better accuracy of 96.42% for classification of AD vs Healthy Control (HC). Ahmed *et al.* [14] proposed the ensemble CNN model for feature extractor and SoftMax classifier to diagnose AD diagnosis. This model prevents overfitting and achieves an accuracy of 90.05% by using the left and right hippocampus area in MRI images. Basher *et al.* [15] come up with a method to localize the target regions from large MRI volume to automate the process. Based on the left and right hippocampi, the method achieves the accuracies of 94.82% and 94.02%. Nawaz *et al.* [16] presented a pretrained Alexnet model to classify the stages of AD to address the class imbalance model. The pretrained model is used as the feature extractor and classified using Support Vector Machine (SVM), K-nearest neighbour (KNN) and Random Forest (RF) with the highest accuracy of 99.21%. Ieracitano *et al.* [17] propose a data-driven method for distinguishing subjects with AD, MCI, and HC by analyzing non-invasive recordings of EEG. The Power Spectral Density of the EEG traces of 19 channels reflects their corresponding spectral profiles in 2D Grayscale images. Then the CNN model is used to classify the binary class and multiclass from the 2D images with an accuracy of 89.8% and 83.3%, respectively.

Jain *et al.* [18] uses a pretrained VGG16 model for feature extraction, which uses a FreeSurfer for pre-processing, selecting MRI slices using Entropy and classification using transfer learning named $P_FS_EC_{TL}$ mathematical model. The researchers were able to achieve 95.73% accuracy for classifying Normal Control (NC), Early MCI (EMCI), and Late MCI (LMCI) using the ADNI database. Mehmood *et al.* [19] uses tissue segmentation to extract Grey Matter (GM) from each subject. The model attains the classification accuracy of 98.73% for AD vs NC and 83.72 % for EMCI vs LMCI patients. Shi *et al.* [20] proposed deep polynomial network which performs well for both small and large dataset to diagnose AD. The model achieves an accuracy of 55.34% for both binary and multi-classification using the ADNI dataset. Liu *et al.* [21] proposed Siamese neural networks to investigate the discriminative capacity of whole-brain volumetric asymmetry. The team used the MRI Cloud process to create low-dimensional volumetric features for pre-defined atlas brain structures, as well as a unique non-linear kernel method to normalize features and eliminate batch effects across datasets and populations. The networks achieve a balanced accuracy of 92.72% for the classification of MCI and AD using the ADNI dataset. Wang *et al.* [22] presented AD and MCI using a 3D ensemble model convolutional networks. 3D-DenseNets optimized by using a probability-based fusion approach. The model achieves the classification accuracy of 97.52% using the ADNI dataset. Shankar *et al.* [23] uses the grey wolf optimization technique with a decision tree, KNN, and CNN model to diagnose AD and achieve a 96.23 % accuracy. Janghel and Rathore [24] proposed a pretrained VGG16 to extract the features of AD from the ADNI database. For classification, they used SVM, Linear Discriminate, K means clustering and decision tree algorithm. They reach a 99.95% accuracy in functional MRI images and an average accuracy of 73.46 % for the PET images. Ge *et al.* [25] proposed a 3D multiscale deep learning architecture to learn AD features. On a subject segregated random brain scan-partitioned dataset, the system achieved a test accuracy of about 93.53%, with an average accuracy of 87.24 %. Bi and Wang [26] presented a Spike Convolutional Deep Boltzmann Machine model for early AD detection with hybrid feature maps and a multi-task learning technique to prevent overfitting. Sarraf *et al.* [27] presented a deep learning pipeline where the CNN model is trained with many training images to perform feature classification on the scale and shift-invariant processes. The model achieves 94.32% and 97.88% for functional MRI and MRI images. Afzal *et al.* [28] address the class imbalance problem in detection of AD by data augmentation framework and achieves the classification accuracy of 98.41% in a single view and 95.11% in 3D view of OASIS dataset. Table 1 provide the overview of literature survey. From the literature, numerous techniques exist for AD classification using machine and deep learning. However, the high model parameter and class imbalance in the multiclass AD classification is still an issue. We proposed a CNN model with fewer parameter to address this issue. We employed SMOTE technique for solving data class imbalance to accurately identify and predict four stages of dementia that can lead to AD.

TABLE 1. Overview of literature survey.

Ref	Method	No. of. Classes	Accuracy (%)
[12]	Multiscale deep learning	Binary class (AD vs HC)	82.4
[13]	Combined feature technique	Binary Class (AD vs HC)	96.42
[14]	Ensemble model	Four class (AD vs HC)	94.03
[17]	2D CNN	Binary Class (AD, MCI)	89.8
[18]	CNN	Three class (NC, EMCI, LMCI)	95.73
[19]	Transfer Learning	Binary class (AD vs NC)	98.73
[20]	Deep polynomial network	Multiclass (AD vs NC)	55.34
[21]	Siamese network	Binary class (MCI vs AD)	92.72
[22]	3D CNN	Binary Class (AD vs MCI)	97.52
[24]	VGG16	Binary Class (AD vs NC)	73.46
[25]	3D CNN	Binary Class (AD vs NC)	93.53
[28]	3D View model	Binary Class (AD vs NC)	95.11

III. PROPOSED WORK

Deep learning has seen immense work recently in wide variety of field such as malaria detection [29], cervical cancer [30], battery management systems [31], and brain imaging [32]. In our proposed methodology CNN method is employed to extract the discriminative features by effectively improving accuracy in AD classification. The proposed DEMNET model workflow is shown in figure 1. The model contains four main steps: data pre-processing, balancing dataset using SMOTE and classification using DEMNET. Each step of the proposed model is discussed below.

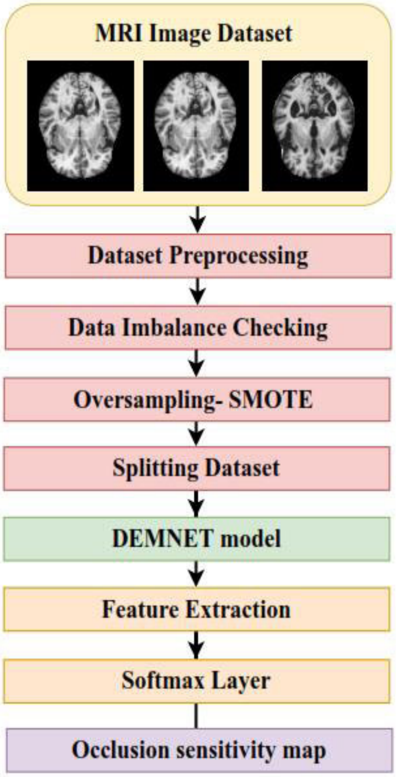

FIGURE 1. DEMNET model workflow process for classifying dementia stages.

A. DATASET DESCRIPTION

The Alzheimer's disease dataset was collected from the open-source platform Kaggle, which consists of 6400 MR Images of four classes with Mild Demented (MID), Moderate Demented (MOD), Non-Demented (ND), and Very Mild Demented (VMD). The dataset has an image size of 176×208. The images are resized into 176×176. The sample images of the four classes were shown in figure 2.

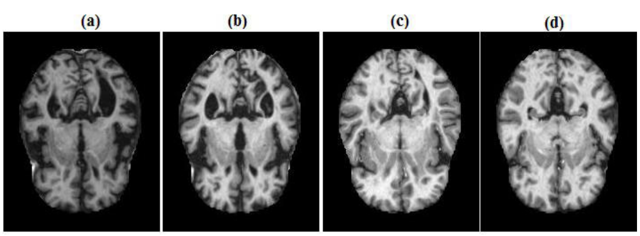

FIGURE 2. (a) MID (b) MOD (c) ND (d) VMD.

Table 2 provides dataset distribution with a number of images in the obtained dataset, which clearly state that the dataset is class imbalanced. The SMOTE technique is applied to the dataset to solve the class imbalance problem in the dataset by randomly duplicating minority classes in the dataset to match the majority classes [33]. With the random seed of 42, the minority classes oversampled using SMOTE technique. The benefits of using SMOTE include the ability to reduce knowledge loss and minimize over-fitting. Table 3 shows the dataset distribution after SMOTE technique increased to 12800 images, with each class contains 3200 images.

TABLE 2. Dataset distribution in obtained dataset.

Class	No of Images
Mild Demented (MID)	896
Moderate Demented (MOD)	3200
Non-Demented (ND)	2240
Very Mild Demented (VMD)	64

TABLE 3. Dataset distribution after SMOTE.

Class	No of Images
Mild Demented (MID)	3200
Moderate Demented (MOD)	3200
Non-Demented (ND)	3200
Very Mild Demented (VMD)	3200

The dataset is divided into 80% training, 10% validation, and 10% testing set from 12800. The images are normalized with the range of 0 to 1 to speed up the training process to learning optimal parameters [34].

B. AD DETECTION USING DEMNET

After the dataset pre-processing and normalization, the images fed into a CNN, which extracts discriminate features to identify the Alzheimer's affected area. The CNN model is designed from scratch to classify the dementia stages to detect AD in our work. The proposed architecture consists of two convolutional layers with Rectified Linear Unit (ReLU) activation function, 1 Max-pooling layer, four DEMNET blocks, two dropout layers, three dense layers and a SoftMax classification layer. The ReLU is a piecewise linear function that used as the hidden layer's activation function. The ReLU activation function can handle the vanishing gradient problem, allowing networks to learn and perform faster than other activation functions [35].

1) INPUT LAYER

The first layer in the DEMNET model is the input layer, where normalized and augmented MRI images given as an input.

2) CONVOLUTIONAL LAYERS

The convolutional layers are the backbone of the proposed DEMENT model. There are core layers accountable for the maximum computational task. This layer takes the input as an image, then convolve with weight filters and added with bias value to produce the feature map or response. Then the feature response is forwarded to the following subsequent layers.

3) POOLING LAYERS

Pooling layers are used between the convolutional layers to decrease representation in the spatial domain and computation space. The Maxpooling layers are used on each input in this work to lower the computational cost of subsequent layers by picking the maximum pixel value in the chosen kernel. The maximum pooling computed using equation 1.

$$MP = Floor\left(\frac{I_x - P}{s} + 1\right) \tag{1}$$

The input form is Ix, the pooling window size is P, and the stride is S.

4) DEMNET BLOCK

The DEMNET block consists of the stacked layer of 2 convolutional layers with ReLU activation, batch normalization layer and Maxpooling layer. The DEMNET block in the proposed model with different filters such as 32, 64, 128 and 256 are used to extracts the discriminative features for classifying the stages of AD. The different number of filters will help to extract the discriminative features. The ReLU activation function is used to output the input directly if the value is positive; otherwise, it will be zero. The ReLU is computed by equation 2.

$$F = \max(0, x) \tag{2}$$

The design of this architecture can extract the discriminative features as possible to highlight any dementia stages in an image. In the proposed architecture, we have four such DEMNET block. After the convolutional layer, batch normalization is performed to normalize the output of the previous layers. It helps to avoid the dynamic range of the values of the last input. The batch normalization is a regularization technique used in the DEMNET block to reduce overfitting in the proposed model.

5) DROPOUT LAYER

The dropout layer is used to random the proposed method to randomly dropping out some of the neurons in the hidden layer during the training. The dropout is also the regularization technique used to reduce the overfitting problem in the model. The best values of dropout values are ranges between 0.2 to 0.5. We have used 0.7 in dense_1 layer, 0.5 in dense_2 layer and 0.2 in dense_3 layer in the proposed method.

6) DENSE LAYER

After the convolutional layers, the flatten layer is used to converts the high-dimensional data into a single column vector. The flatten layer output is fed into the input for the dense layer. The dense layer is performing the same mathematical operations performed by the artificial neural network. In the proposed method, three dense layers are used where each and every neuron in the previous layer is connected to the neurons in the dense layer. After the dense layer, SoftMax is used where the number of neurons is equal to the number of the classes [36]. Categorical cross-entropy is used as a loss function to calculate the likelihood for each image over the C classes, as shown in equation 3. In the multiclass classification, the labels are one-hot encoding, and only the positive class is present in the loss term.

$$\frac{\partial}{\partial_{S_P}}\left(-\log\left(\frac{e^{s_p}}{\sum_j^c e^{S_j}}\right)\right) \tag{3}$$

where the S_p is the CNN score of the positive class, the gradient of the CNN's output neurons is computed in order to backpropagate it through the network and optimize the given loss function while tuning the network parameters. The loss terms from the negative groups are all equal to zero. However, since the SoftMax of the positive class is also dependent on the scores of the negative class, the loss gradient with respect to those negative classes is not cancelled. Thus, the gradient of the categorical cross-entropy is needed for each class. The gradient function of categorical cross-entropy is different for both positive and negative classes, as in equation 4 and equation 5.

$$\frac{\partial}{\partial_{S_P}}\left(-\log\left(\frac{e^{s_p}}{\sum_j^c e^{S_j}}\right)\right) = \left(\frac{e^{s_p}}{\sum_j^c e^{S_j}} - 1\right) \tag{4}$$

$$\frac{\partial}{\partial_{S_n}}\left(-\log\left(\frac{e^{s_p}}{\sum_j^c e^{S_j}}\right)\right) = \left(\frac{e^{s_n}}{\sum_j^c e^{S_j}}\right) \tag{5}$$

The general information about the DEMNET architecture is provided in Table 4. In the subsequent layer, Figure 3(a) illustrates the proposed DEMNET architecture for classifying the stages of dementia, and 3(b) shows the layers stacked in the DEMNET block.

C. OPTIMIZATION ALGORITHM

The Root means square propagation (RMS prop) optimizer is used as the optimization algorithm to train the proposed model. The RMS prop was developed as a chaotic mini-batch learning method. During backpropagation, the vanishing gradient problem is overcome by normalizing the gradient using the moving average of square gradients. This normalization is balancing the momentum (step size), decreasing the step for large gradients to avoid exploding gradient and increasing the step to avoid vanishing gradients. The RMS prop has the adaptive learning rate instead of treating the learning rate as a hyperparameter. It means the learning rate changes over time. This normalization balances the momentum by reducing the

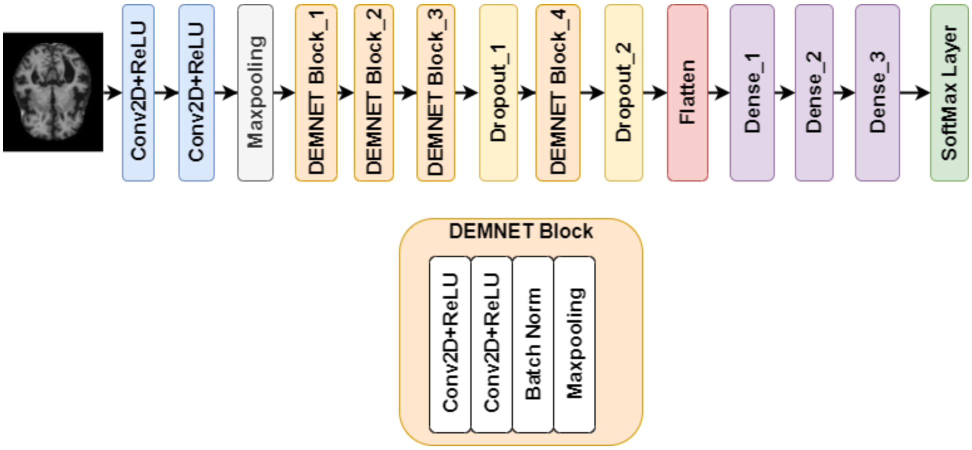

FIGURE 3. a) Architecture of DEMNET model for classifying dementia stages b) DEMNET block.

TABLE 4. DEMNET architecture details.

Layer Type	Output Shape	Parameters
Conv2D+ReLU	(None, 176, 176, 16)	448
Conv2D+ReLU	(None, 176, 176, 16)	2320
Maxpooling	(None, 88, 88, 16)	0
DEMNET Block_1	(None, 44, 44, 32)	14016
DEMNET Block_2	(None, 22, 22, 64)	55680
DEMNET Block_3	(None, 11, 11, 128)	221952
Dropout_1	(None, 11, 11, 128)	0
DEMNET Block_4	(None, 5, 5, 256)	886272
Dropout_2	(None, 5, 5, 256)	0
Flatten	(None, 6400)	0
Dense_1	(None, 512)	3279360
Dense_2	(None, 128)	66176
Dense_3	(None, 64)	8512
SoftMax Layer	(None, 4)	260
Total parameters: 4,534,996		
Trainable parameters: 4,532,628		
Non-trainable parameters: 2,368		

momentum for large gradients to avoid exploding gradients and increasing the momentum for small gradients to avoid vanishing gradients. RMS prop uses the adaptive learning rate. It signifies that the rate of learning fluctuates with time. The update rule is given by equation 6,7, and 8.

$$v_t = \gamma v_{t-1} + (1-\gamma) * g_t^2 \tag{6}$$

$$\Delta w_t = -\frac{\eta}{\sqrt{v_t + \in}} * g_t \tag{7}$$

$$w_{t+1} = w_t + \Delta w_t \tag{8}$$

where η is the initial learning rate, $\mathrm{v_t}$ is an exponential average of squares of gradients and $\mathrm{g_t}$ gradient at time t along with $\mathrm{w_t}$.

D. EVALUATION METRICS

The proposed model accuracy, precision, recall, F1-score, AUC and Cohen's kappa are evaluated from the confusion chart. The confusion chart is used to assess the efficiency metrics. The confusion matrix depicts the model's results. Accuracy is the main metric used to determine how much the model is accurate upon predicting the true positive and negative. The accuracy is calculated using equation 9.

$$Accuracy = \left(\frac{TP + TN}{(TP + TN + FP + FN}\right) \tag{9}$$

When the model predicts that the image is normal and the actual label is normal, the value is **TP**. When the model predicts an abnormal image and the real label is also abnormal, the value is **TN**. When the model predicts the image to be normal, but the real label is abnormal, the value is **FP**. When the model predicts an abnormal image and the real label is normal, the value is **FN**. The ratio of the true positive observation to the total positive prediction is known as Precision (PR). If the precision is equal to 1, the model is said to be good. The precision is calculated using equation 10.

$$PR = \left(\frac{TP}{TP + FP}\right) \tag{10}$$

The Recall (REC) is also known as the sensitivity, which indicates the classifier's ability to locate all positive samples. The recall is calculated using equation 11.

$$REC = \left(\frac{TP}{TP + FN}\right) \tag{11}$$

The harmonic mean of precision and recall is called F1-score, which demonstrates how well recall, and precision is balanced by using equation 12.

$$F1 - Score = \left(\frac{2 * PR * REC}{PR + REC}\right) \tag{12}$$

The meaning that you would expect if the two rates are independent must be compared to Cohen's Kappa (CK) ranking. The numerator is the difference between the observed likelihood of success and the probability of success if the worst-case scenario is assumed. Cohen's kappa score is calculated using equation 13.

$$CK = \left(\frac{OA - EA}{1 - EA}\right) \tag{13}$$

OA = observed accuracy, EA = expected accuracy.

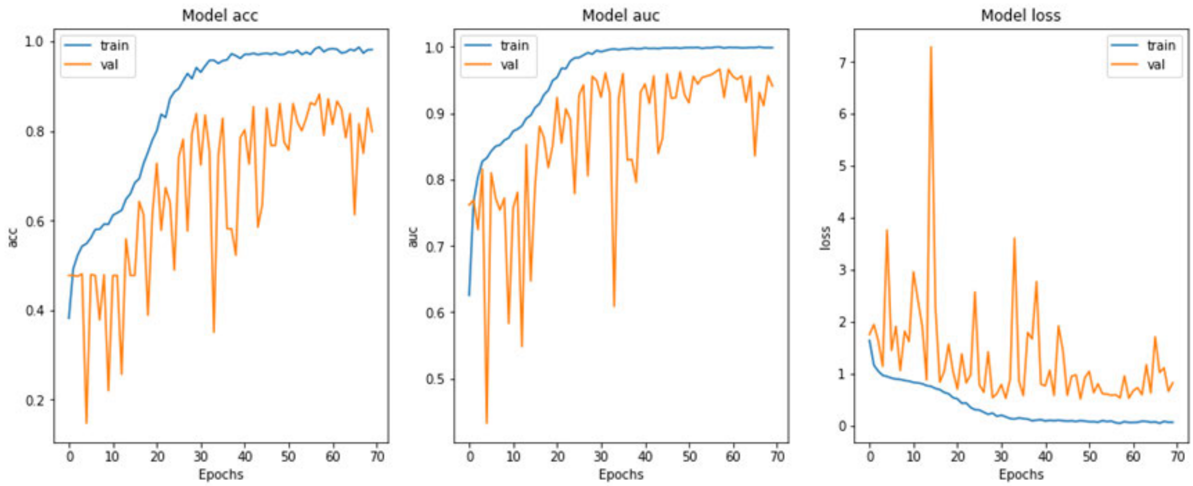

FIGURE 4. Training process accuracy, AUC and loss of DEMNET model without SMOTE.

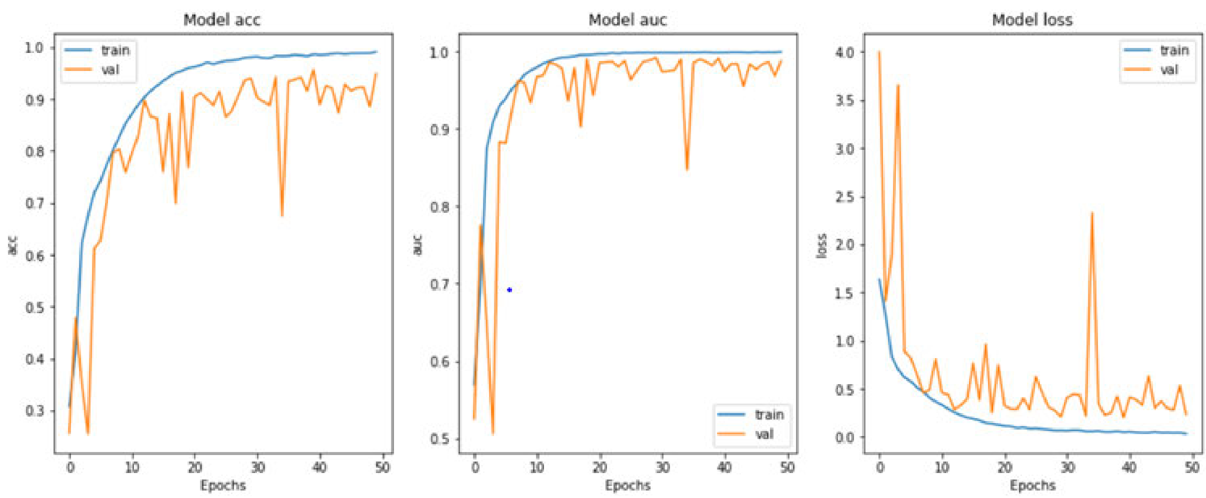

FIGURE 5. Training process accuracy, AUC and loss of DEMNET model with SMOTE.

IV. RESULTS AND DISCUSSIONS

A. PERFORMANCE SETUP

The proposed model has experimented on NVIDIA Quadra RTX6000 workstation with a 24GB GPU. The proposed model is trained with a parameter of 50 epoch, batch size of 16 and 0.001 as an initial learning rate. The RMS prop is an optimizer used to train the algorithm. The model is trained on two scenarios, one without applying the SMOTE and another one with SMOTE. The Area Under Curve (AUC) is determined for every epoch to identify whether the model correctly distinguishes the positive and negative class. Figure 4 shows the training and validation curve for accuracy, AUC and loss. The model without SMOTE technique has a training accuracy of 96% and validation accuracy of 78% due to the class imbalance and overfitting problem. Figure 5 shows the training process of the DEMNET model with SMOTE. The model with SMOTE technique achieves an overall training accuracy of around 99% and validation accuracy of 94%. After the training model, it is tested with the test set where the images present are not shown to the model during the training, from the model testing the confusion matrix. Figure 6 shows the confusion matrix of DEMNET architecture with SMOTE technique to classify the dementia stages to predict AD. The confusion matrix is plotted with the predicted class with labelled classes of the four different categories. The confusion matrix provides the model performance over the training dataset. The calculation is performed for a total of i) 326 images belonging to ND, ii) 309 images belonging to VMD, iii) 329 images belonging to MD, and iv) 316 images belonging to MOD. The individual class metrics are calculated from the confusion matrix and represented in table 5.

The overall precision, recall, and F1-score value of the ND VMD, MD, and MOD show some promising results with

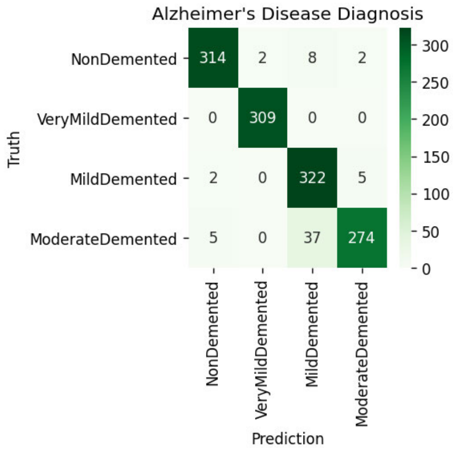

FIGURE 6. Confusion matrix of DEMNET model with four classes.

TABLE 5. Performance indices of individual class.

Diseases	PR	REC	F1-score	Support
ND	0.98	0.96	0.97	326
VMD	0.99	1.00	1.00	309
MD	0.88	0.98	0.93	329
MOD	0.98	0.87	0.92	316

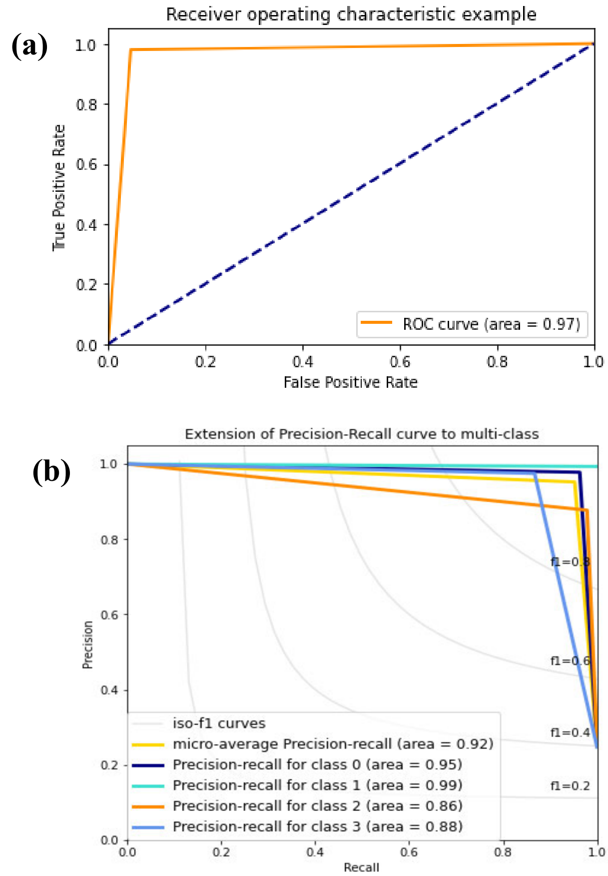

FIGURE 7. DEMNET architecture (a) ROC curve and (b) precision and recall curve.

the testing dataset. The DEMNET model testing the testing dataset and achieves the testing accuracy of 95.23% with SMOTE and 85% without SMOTE. The model achieves 97% with SMOTE and 92% without SMOTE for the area under the receiver operating characteristics curve for this model.

The AUC value shows the model can classify the positive and negative classes correctly. The average AUC curve is plotted for all class concerning the False Positive Rate and True Positive Rate with single threshold value, as shown in figure 7(a). The precision and recall curve are plotted for the different classes class 0 for ND, class 1 for VMD, class 2 for MD and class 3 for MOD. To find the model's effectiveness, the precision and recall curve is plotted and shown in 7(b).

B. DEMNET COMPARISON WITH OTHER MODELS

The DEMNET model is compared with different CNN models and traditional machine learning. The performance analysis of the DEMNET is compared with different models and image modalities with results reported in the literature paper. The accuracy, precision, recall, F1-measure and AUC are the metrics compared with the models discussed in the literature. The existing methods considered in the performance analysis are either trained for a multiclass or binary class problem with the ADNI dataset. The DEMNET with SMOTE and DEMNET without SMOTE have been trained on the obtained dataset of MR images. The DEMNET models are compared with the CNN models, such as VGG16 [18], Siamese Network [21], Convolutional Bi-LSTM [37] and Multi-layer perceptron (MLP) [37], and results are provided in Table 6. The model VGG16 [18] slightly has higher values in most of the metrics, but it has trained for three classes detection, and the number of parameters is around 138 million parameters. The DEMNET model clearly outperforms all the other models in terms of accuracy, precision, recall, F1-score, and Cohen's kappa value, as evidenced by the results by classifying four different classes with 4,534,996 parameters. The DEMNET model works well on the collected dataset. Cohen's Kappa score of 0.93 with SMOTE and 0.75 without SMOTE technique shows that the model has a perfect agreement with SMOTE and moderate agreement.

C. OCCLUSION SENSITIVITY MAP

Occlusion sensitivity [38] is a simple technique used for understanding what image features the neural network use to make a particular classification or to acquire the most significant regions in an image. A large portion of the image with a black or grey patch is occluded in this process, and the output obtained is recalculated. A heat map is produced when the likelihood of the target class starts to decrease, compared to the source image, and that portion of the image is therefore preferred to be relevant. This method is applied

TABLE 6. Performance analysis of DEMNET with different models.

Ref	Dataset	Modality	ACC	PR	REC	F1-score
DEMNET (SMOTE)	Kaggle (4 class)	MRI	95.23	96	95	95.27
DEMNET (Without SMOTE)	Kaggle (4 class)	MRI	85	80	88	83
Ensemble based classifier[14]	GARD (2 class)	sMRI	90.05	88.85	89.85	89.35
VGG16 [18]	ADNI (3 class)	MRI	95.73	96.33	96	95
Siamese Network[21]	ADNI (2 class)	MRI	92.72	95.23	89.92	93.72
MLP [37]	ADNI (3 class)	MRI	89	85	87	89
CBLSTM + GAIN[37]	ADNI (3 class)	MRI	82	79	82	82
CBLSTM + SMOTE[37]	ADNI (3 class)	MRI	82	78	88	82

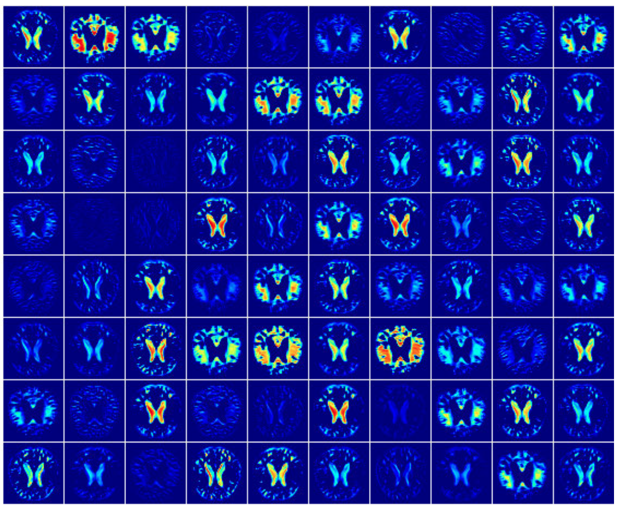

FIGURE 8. DEMNET occlusion sensitivity map.

to the last layer of the developed model in order to visualize the necessary human recognizable features. The occlusion sensitivity map of the proposed DEMNET model is shown in Figure 8.

D. DEMNET PERFORMANCE ON ADNI DATASET

Since the model performance is good on the Kaggle dataset, to check the robustness of the DEMNET on other AD MRI dataset, we run the experiment of 5-class classification of AD in the ADNI dataset, i.e., AD, MCI, EMCI, LMCI and NC [39]. ADNI dataset consists of 1296 images, and it is reshaped into 176*176 to fit into the DEMNET model. The DEMNET model achieves an accuracy of 84.83%, AUC of 95.62% and Cohen's kappa score of 0.81 with the same model parameters in the ADNI dataset.

V. CONCLUSION AND FUTURE SCOPES

In this work, CNN architecture is proposed to perform AD classification. The model is trained and validated using the standard Kaggle data for the classification of dementia stages. The major drawback of the dataset is a class imbalance. SMOTE technique is used to solve this issue. Our new model is tested with testing data consists of 4 classes and achieved an overall accuracy of 95.23% with 97% AUC when compared to the existing methods. Hence, it is well capable of identifying brain regions associated with AD and serving as an efficient decision support system for physicians in predicting the AD severity based on the level of dementia. To check the robustness of the model, it is tested with the ADNI dataset and achieved an accuracy of 84.83%.

In the future, the DEMNET model will be trained and tested on various datasets as a standalone framework for screening the dementia stages in order to diagnose Alzheimer's diseases. Inception Network and Residual Network will be used for building the classifier as a base model. We may obtain similar or better results by skipping pre-processing steps like skull stripping and intensity normalization. Furthermore, if the data used is adequate and the available resources can handle the increased computational complexity, the overall performance of the base model to be enhanced by fine-tuning the pre-trained convolutional layers.

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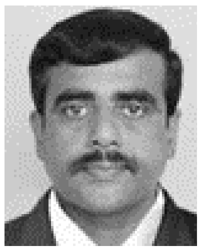

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