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A Data Augmentation-Based Framework to Handle Class Imbalance Problem for Alzheimer's Stage Detection

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ABSTRACT Alzheimer's Disease (AD) is the most common form of dementia. It gradually increases from mild stage to severe, affecting the ability to perform common daily tasks without assistance. It is a neurodegenerative illness, presently having no specified cure. Computer-Aided Diagnostic Systems have played an important role to help physicians to identify AD. However, the diagnosis of AD into its four stages; No Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia remains an open research area. Deep learning assisted computer-aided solutions are proved to be more useful because of their high accuracy. However, the most common problem with deep learning architecture is that large training data is required. Furthermore, the samples should be evenly distributed among the classes to avoid the class imbalance problem. The publicly available dataset (OASIS) has serious class imbalance problem. In this research, we employed a transfer learning-based technique using data augmentation for 3D Magnetic Resonance Imaging (MRI) views from OASIS dataset. The accuracy of the proposed model utilizing a single view of the brain MRI is 98.41% while using 3D-views is 95.11%. The proposed system outperformed the existing techniques for Alzheimer disease stages.

INDEX TERMS Transfer learning, AlexNet, convolutional neural network, Alzheimer's disease, augmentation.

I. INTRODUCTION

AD is a cerebral degeneration mental disease. Which is destructive for brain cells causing reminiscence loss affecting the ability of a human being to perform the routine tasks in a normal way. The reason for AD is not easily identified [1] due to which no proper cure has been specified. However, through early identification of this disease, the life quality of AD patients can thus be improved. Symptoms of AD usually develop slowly till they become serious enough to affect with daily errands and self-care. However, cases showing a loss in motor and linguistic skills may lead to a need for permanent support. Yearly, millions of people suffer from this disease. As per an estimate, around 5.3 Million people suffered AD in 2015. In 2050, the number is expected to grow up to 16 Million [2]. Today in medical diagnosis, MRI is widely utilized in hospitals for AD identification because of its extraordinary resolution, good contrast and high availability [3], [4]. Regardless of the enhancement in the initial identification of AD, structural MRI remains a challenging task for prediction of progression of ailment and needs further exploration.

The Structural Magnetic Resonance Imaging (sMRI) is mostly utilized for the analysis of gradual neural aggravation. It captures the basic alteration in the brain, capturing the unavoidable damage caused due to neurodegeneration characteristic of AD alkalosis [5]. Most of the research discovered the degradation process, affecting regions in the brain such as hippocampus by utilizing the sMRI modality. The new MRI modality is centered on the movement of the

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water molecules in cerebral gray and white matter known as diffusion tensor imaging modality (DTI).

AD diagnosis involves a diversity of medical tests which leads to a huge amount of multivariate heterogeneous data. It is, therefore, an exhausting activity to manually compare, visualize, and analyze this data. Although the terms of machine learning and deep learning have been coined not so long ago, for decades their ideas have been applied to medicinal imaging. Particularly in the area of Computer Assisted Diagnosis (CAD) i.e. computer-aided diagnosis, systems performance is improved by utilizing a wide range of machine learning algorithms. To classify the characterized extracted features of AD, various conventional machine learning approaches have been proposed for the CAD. These features have been extracted from the volume of interests (VoI) and the regions of interest (ROI) [6]–[8]. In the same way, features were extricated from the varying gray matter (GM) voxels [9] and regions of the hippocampus [10]–[12]. Though leaving scope for more research and studies, these approaches provided better early diagnosis of Alzheimer. For adequate training in deep learning specifically convolutional neural network (CNN), a huge amount of data samples are required [13]. If the training dataset is not adequately extensive then overfitting issue occurs [14]. Which means minimizing training iterations to improve the cost function. A 'Dropout' approach which is basically augmentation of data and regularization approach, can prevent and resolve inadequacy of the data samples issues [14], [15]. Yet they remained limited in the case of AD studies because of small data samples. OASIS dataset though is publicly available, offers only a few data samples belonging to the demented subjects. This small dataset along with imbalanced class samples leads to unpredicted errors and even severe consequences in classification.

In this research, to diagnose the stages of AD, we utilized the pre-trained CNN model AlexNet for automatic classification of cerebral MRI. We assessed the importance of using natural image's features to classify the medical images addressing the shortcoming of inadequate data samples. The brain MRI scans attained from the OASIS source were augmented balancing the number of samples belonging to each class. The images were then tested under our proposed method encompassing the main MRI view as well as 3-D MRI views of the human brain. The proposed framework for AD stages detection has the following main key contributions:

1) We designed a transfer learning-based approach by utilizing a pre-trained model for accurate diagnosis of Alzheimer stages from MRI.
2) Overcoming the imbalanced data sample distribution using data augmentation techniques with different parameters.
3) Utilizing both the main view of MRI scans and 3-D view of MRI scans of the human brain for the classification of dementia stages.

II. LITERATURE REVIEW

Over the past few years, various AD diagnosis techniques have been proposed. These techniques can be generalized into categories based on machine learning, deep learning, and transfer learning-based models. Each of which is briefly discussed below in this section.

A. MACHINE LEARNING BASED TECHNIQUES

Machine learning-based approaches are widely utilized in medical applications [16] and have gained significant attention in the past few decades [17].

A multi-staged model was proposed by I. Beheshti *et al.* [18] including the pre-processing, segmentation of the image, feature extraction and selection, and classification. In the pre-processing stage, the approach segmented the input MRI images into segments of GM, White Matter (WM), and Cerebral Spinal Fluid (CSF). To construct the similarity matrices vector, the method utilized GM as ROI and through GM the statistical features were extracted. Wang *et al.* [19] proposed another technique utilizing feature selection techniques. The selected features were then classified using SVM giving an overall accuracy of 93.05%. Altaf et al. in [4] proposed a state-of-the-art technique for the AD diagnosis utilizing the bag of words model attaining 79.8% accuracy for multi-class classification and 98.4% for binary class classification. The respective accuracies were achieved over the ADNI dataset. Rupali et al in [20] proposed a model using KNN and tested over the OASIS dataset for the detection of AD. Luiz K. Ferreira et al. in [21] employed SVM to build a comparison in between the FDG-PERT and MRI. The respective images of the whole brain were obtained from the same individual followed by an SVM centered diagnosis. The results showed an overall accuracy of 68-71% for PERT and SPECT while a higher accuracy of 68-74% for MRI [22]. Beheshti et al in [23] considered sections showing remarkable GM variations for the AD identification. The VoIs and GM volume was used for the AD and healthy subjects' classification and achieved 92.4% accuracy by using SVM.

B. CONVOLUTIONAL NEURAL NETWORK BASED

In recent times, neural network-based methods have been extensively utilized in image classification and computer-vision. Cui *et al.* [24] presented a classification model based on the combination of Multi-layer Perceptron (MLP) and Recurrent Neural Network (RNN) for the longitudinal analysis of MRI images for the diagnosis of AD.

Firstly, they utilized MLPs to understand the spatial characteristics of MR images. Later they used the RNN with two levels of recurrent bidirectional cascade units formed on the MLP outputs for longitudinal extraction of the characteristics. They tested their proposed technique over ADNI datasets achieving an overall accuracy of 89.7%. Wang Yan et al. in [25] proposed a multi-class AD identification method over a balanced number of data samples. They proposed multimode-based, magnetic resonance-based and

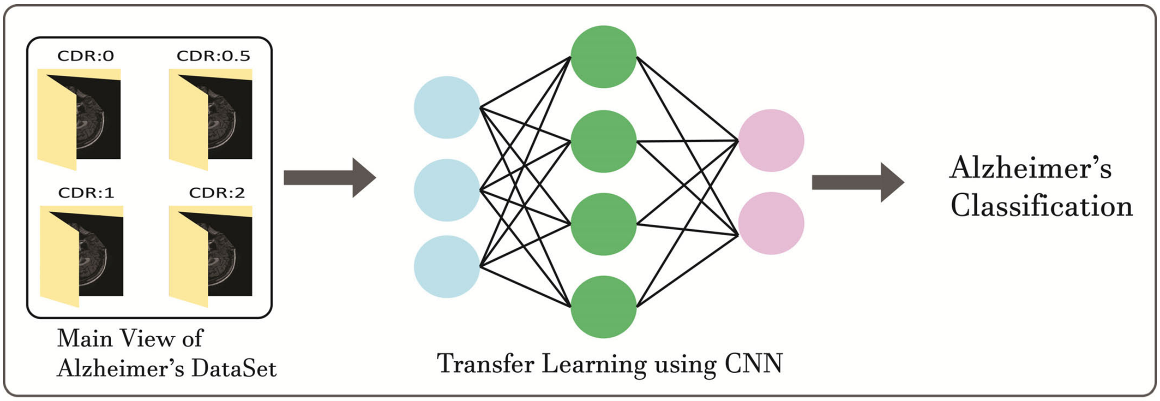

FIGURE 1. Transfer Learning-Based Model for the Main view of Brain.

CNN-based methods of analysis that are also suitable for the analysis of single-type MRI data. To extrapolate the human brain's network connectivity, a new CNN approach was proposed to classify AD, MCI, and NC. They achieved greater precision and accuracy of 92.06% by combining multimode magnetic resonance with the CNN core. Gunawardena et al. in [26] utilized 1615 complete brain MRI scans for the diagnosis of AD. At first, they employed the existing vector carrier method for detecting AD with an accuracy of 84.4%. Later, they proposed the CNN method for diagnosing AD in different data sets and obtained the highest accuracy of 96%.

C. TRANSFER LEARNING BASED TECHNIQUES

Due to an inadequate number of data samples, numerous research studies have proposed techniques to increase the publicly available datasets. In [27] researchers proposed transfer learning approach for prediction of the binary class Alzheimer's Disease by utilizing ADNI dataset. They attained 99.4% accuracy for AD vs NC. In [28] M. Maqsood et al. proposed a transfer learning approach by utilizing pre-trained AlexNet for multi-class classification of AD. They attained 92.85% accuracy for their findings on un-segmented images. In [29] researchers proposed a cross-modal transfer learning from sMRI to DTI. They trained the model on sMRI with augmentation and then transferred the information to DTI dataset. In [30] the researchers established the efficacy of utilizing pre-trained models as a starting point of other networks. They utilized GoogleNet and inception-ResNet instead of training the network from scratch. These networks are trained over dataset which is not medical related however the last layers are fine-tuned over the samples from the respective problem. Another study [31] utilized transfer learning approaches and data augmentation techniques to resolve the inadequate data samples issue, for the identification of MCI in MR images. Here they utilized OASIS2 and LIDC3 for the pre-training phase and attained a 90.6% accuracy for MCI vs NC.

For the diagnosis of AD, the DTI image maps are often considered as a good modality, thus the researchers in [32] classified samples into Normal Control, Alzheimer's Disease, and MC utilizing MD and FA maps. The results of these findings showed that the FA is not a good indicator as compared to MD. In [33] they used multi-auxiliary domain by utilizing MCI vs sMCI as an auxiliary domain for classification of AD vs NC. They attained 94.7% accuracy for AD vs NC whereas a relatively low accuracy of 82.1% for MCI vs NC. A different work in [34] used the ImageNet as the source domain. All the layers were initialized with the pre-trained model except the last fully connected ones. The methodology utilized resulted in an overall accuracy of 83.5% for AD vs NC. In [13] researcher utilized transfer learning to extract joint spatial features. In [35], researchers proposed a method using FA and MD with the Support Vector Machine classifier and utilized Plant's technique and IG measure for AD vs NC classification. They attained 80% accuracy for classification centered on FA and for MD they attained 83%.

Looking through the literature, numerous techniques exist for the classification of AD. However, having certain limitations of not handling the class imbalance issue in multi-class Alzheimer's classification, which needs to be considered for effective results in AD classification. Furthermore, inadequate samples of data are also a key challenge for researchers to achieve optimal results. To address these certain limitations, we proposed a framework based on transfer learning with augmentation of data to achieve effective results for multi-class AD classification.

III. PROPOSED METHODOLOGY

Deep Learning has seen immense work recently in numerous studies especially in computer-vision [36]–[38], image processing [39], [40], authentication system [41] and speech recognition [42], [43]. In our proposed methodology we used CNN for efficient and effective Alzheimer's classification. For AD classification we proposed two models, one with the utilization of a single main MRI view of the brain. Whereas, the second method incorporates 3D views. Figure 1 and figure 2 show the two proposed models. Both models comprise of three main steps as data pre-processing, data augmentation and classification using transfer learning. Each step of the proposed models is discussed in detail below.

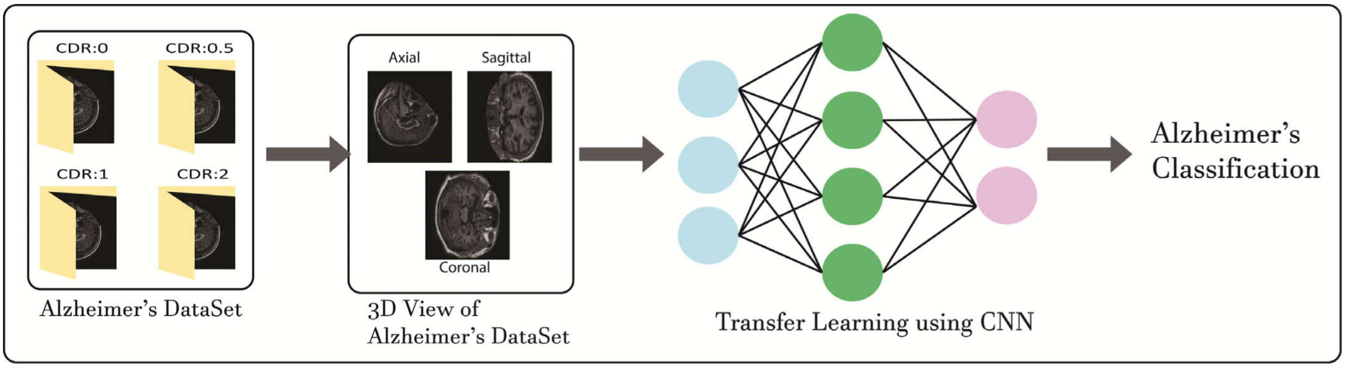

FIGURE 2. Transfer Learning Based Model for 3D- view of Brain.

A. IMAGE PRE-PROCESSING

To fulfill the basic requirements of a CNN model, image pre-processing is a fundamental part. To achieve ideal results, it serves an important purpose performing significant analysis of the information. In our proposed model, the data pre-processing step involves setting the dimensions of an input MRI scan to 227x227. Images acquired from the OASIS dataset are of size 256x256, where AlexNet requires input images of size 227x227. Image scaling is thus done over the input images of OASIS dataset.

B. IMAGE AUGMENTATION

A large number of data samples leads to effective deployment of numerous CNN models [44].

Overfitting is a common issue that may occur in training of the network due to insufficient data for training. This causes difficulty for the model to predict the unseen instances because the network tunes the cases along with the training data.

Along with the insufficient number of samples, the uneven distribution of samples belonging to different classes also poses a problem in effective classification. Minority samples offer the least contribution to the overall accuracy of the system thus leading to ambiguous results. To enhance accuracy and confidence and to stop the overfitting issue, more data is needed to be made part of the training set. In this research, the classification issue tackled also lacks an adequate number of data samples to be fed into the CNN model.

Looking at the insufficient and imbalanced number of samples we extend the current dataset by using distinct image augmentation approaches in both models. Table 1 shows the parameters utilized for the augmentation. Figure 3 shows the samples attained by the data augmentation, in which each sample is extended to 28 new samples. Samples belonging to class labels 0.5, 1 and 2 are extended using the data augmentation techniques.

C. ALZHEIMER'S DISEASE DETECTION USING A TRANSFER LEARNING MODEL

After pre-processing and augmentation of images, we apply the pre-trained CNN model. To deal with complex classification tasks AlexNet, a pre-trained CNN over ImageNet dataset is utilized. AlexNet consists of total of eight layers in which 5 are Convolutional layers and the last 3 are the fully connected layers. The 2 max-pooling layers lie in between the first and second convolutional layers. Due to the rectified linear unit (ReLU), nonlinearity layer and dropout regularization system the AlexNet framework is highly effective. The ReLU layer is basically a half-wave rectifier and fundamentally accelerate the training procedure and stop the overfitting problem. The dropout approach can be observed as a regularization mechanism randomly ignoring some of the neurons during training.

TABLE 1. Data augmentation parameters.

Sr. No	Data Augmentation	Parameters
1	Image Rotation	90°,270 °,180 °
2	Crop from right	90°,270 °,180 °
3	Crop from bottom	90°,270 °,180 °
4	Crop from left	90°,270 °,180 °
5	Crop from corner	90°,270 °,180 °
6	Crop from top	90°,270 °,180 °
7	Whole crop	90°,270 °,180 °

In the AlexNet architecture, this is characteristically utilized in completely linked layers. Figure 4 shows the detailed flow of steps for Alzheimer detection by utilizing the pre-trained transfer learning model. The stepwise description is explained in the section below.

1) LOAD PRE-TRAINED CNN MODEL

Once the input MRI scans are scaled and augmented to the equal amount of data samples for each class of the dataset, the pre-trained model AlexNet is loaded. The detail of the AlexNet framework is described in the following subsection.

2) INPUT LAYER

It is the first layer of the AlexNet model where scaled and augmented MRI scans are given as an input.

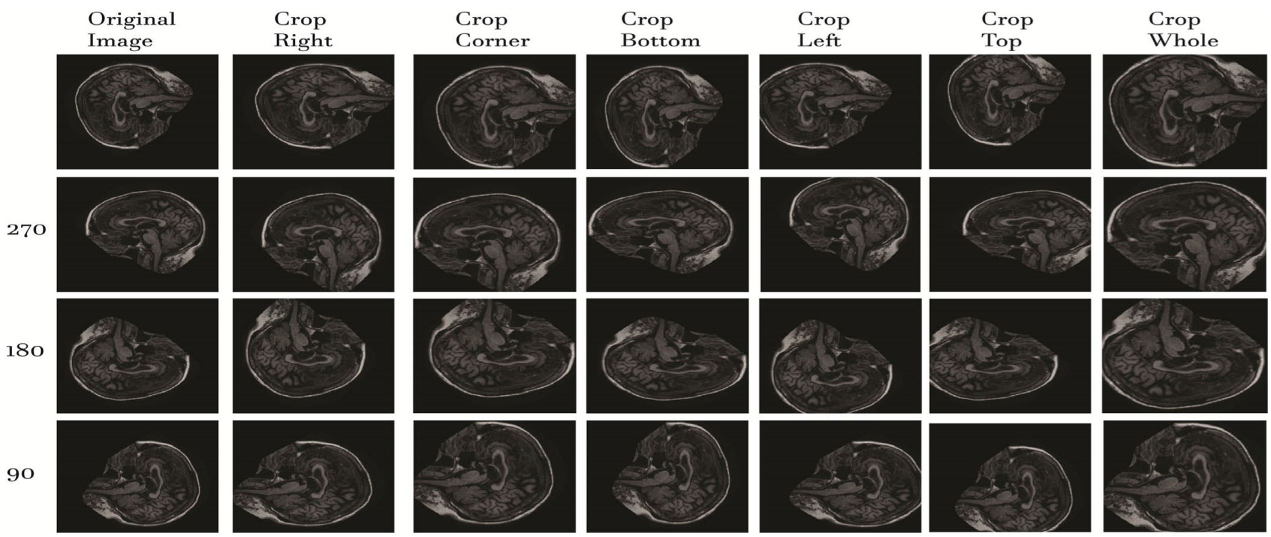

FIGURE 3. Augmented Image samples.

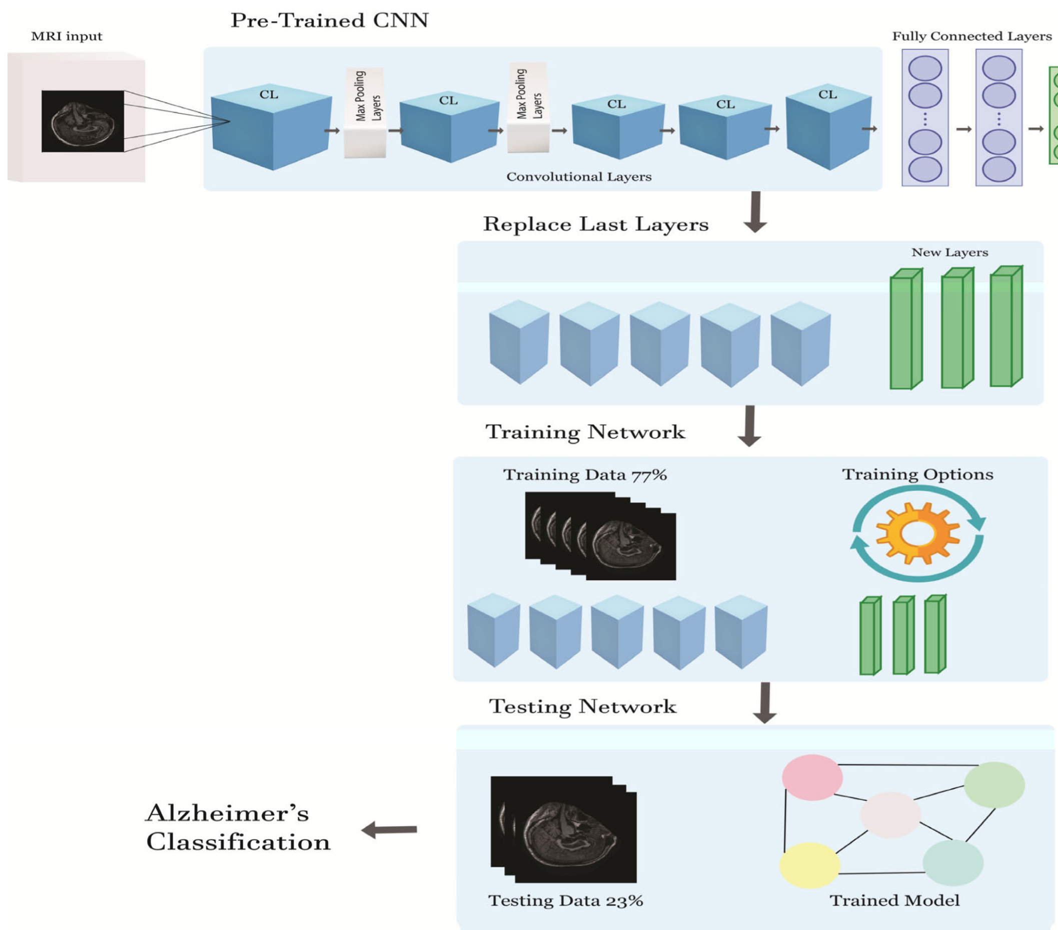

FIGURE 4. Proposed Methodology.

3) CONVOLUTIONAL LAYERS

In CNN architecture, Convolutional layers are the core building layers and these layers are accountable for the maximum computational task. Convolutional layers as indicated by the name performed the convolution operation over input and forwards the response to the next layers of the CNN architecture.

4) POOLING LAYERS

Pooling layers are in between the convolutional layers. These layers are utilized to decrease the spatial representation as well as computational space. It performs the pooling operations on each input reducing the computational cost for next convolutional layers.

5) FULLY CONNECTED LAYERS

The convolutional and pooling layer's applications result in the feature extraction and feature reduction from input images. The last output equal to the number of classes is generated by applying the fully connected layers.

According to the AlexNet framework, the very initial convolutional layer performs filtration over the input image of 224 x 224 x 3 in size with 96 number of kernels of size 11x11x3. The convolutional output is received through pooling layer where it is normalized and sent into the second convolutional layer as input and filtered with 256 kernels of 5x5x48. Similarly, the convolutional output from the second layer is reduced through the pooling layer and is connected to the 384 kernels of size 3x3x256 in the third convolutional layer. The next three layers are inter-connected to each other deprived of any intervention of the pooling layers. The fourth convolutional layer comprises of 384 number of kernels of 3x3x192 whereas, the fifth layer is having 256 number of kernels of 3x3x192 in size. Each of the fully connected layers has a total of 4096 neurons.

6) REPLACE LAST LAYERS

Initial layers of this pre-trained model comprise of features of low-level whereas the class-specific features are in the last layers. Thus, our focus is training the network on our Alzheimer's data, so we substitute the class-specific layers with new layers. We transferred the first five layers of this model and replaced the class-specific layers. The parameters utilized to generate the fully connected layer includes the weight-learn, bias-learn factor, and the output size. The output size of the fully connected layer is set to the number of output classes. For the weights in the layers, weight-learn factor controls the learning rate. For the bias in the layers the learning rate controlled by a bias-learns parameter.

7) NETWORK TRAINING

The network contains a total of 8 layers, 5 transferred layers from the pre-trained AlexNet and 3 new adaptation layers i.e. Fully Connected, softmax, and a classification layer. For correct classification, only new adaptation layers are trained in Alzheimer's data. We pass 77% of whole MRI scans to the network with some training options for training the network for Alzheimer's. These training options mainly contain epochs, batch-size, validation frequency, and learning rate. We utilize a max of 10 epochs for training. The algorithm apprises the weights and bias parameters through minimizing the loss function, by applying training parameters on the train data, the last replaced adaptation layers learn Alzheimer's classes features.

8) NETWORK TESTING

To assess the training procedure's performance, we pass the rest of the data as testing data to this trained network. Based on the accuracy measure, we assess the performance of the trained network. On test data, we can learn how fine a network is trained to classify AD.

TABLE 2. Statistics summary.

Characteristics	Normal	Early Stage
Age(year)	75.4±7.8	76±7.5
Sex (Male/Female)	29/46	20/55
Education (in years)	3.16±1.2	2.85±1.3
Mini Mental Score Exam	28.89±1.2	24±4.0
CDR	0	1
SES	2.5	2.87

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. DETAILED DATASET

The Alzheimer's dataset is taken from OASIS repository [10] which is publicly available having MRI scans of normal, very mild AD, mild AD, and severe Alzheimer patients. The present OASIS dataset comprises of individuals over the teen life expectancy. It incorporates 218 samples from age 18-59 years and 198 samples from age 60-96 yrs. Each group incorporates an around equivalent samples of both genders of the more established subjects, 98 having Clinical Dementia Rating score of '0', showing no AD, and other 100 having Clinical Dementia Rating score more prominent than 0 (70 having Clinical Dementia Rating score = 0.5, 28 having Clinical Dementia Rating score = 1,) Only 2 having Clinical Dementia Rating score = 2. This dataset is comprised of cross-sectional MRI scans including 3D-views of brain namely Sagittal, Coronal, and Axial which is also the main view of the brain. The images taken from the OASIS dataset are split into 2 parts i.e. train and test. The ratio of this splitting is 77% and 23%. Both the divisions are guaranteed to have all the four stages of AD and are ensured to be balanced in terms of a number using data augmentation techniques. Table 2 shows the demographic summary of Alzheimer's dataset taken from the OASIS repository.

B. PERFORMANCE EVALUATION

To assess the performance, we utilized the overall accuracy to assess the efficiency of our proposed models [45]–[49]. This accuracy can be defined as

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{A_c}}{\boldsymbol{A_t}} * \mathbf{100} \tag{1}$$

where A_c denotes the correctly classified results and A_t denotes the total classified results. The comparison is drawn between the accuracies achieved by the conventional machine learning algorithms.

C. RESULTS OF TRANSFER LEARNING MODEL FOR THE MAIN VIEW

The CNN parameters are set utilizing the ImageNet classification, mentioned as pre-trained over the dataset. The AlexNet model is pre-trained over 1.2 billion labeled images. These 1.2 billion images cover about 1 thousand different categories gathered over the network and human domain experts labeled these images. The procedure of familiarizing

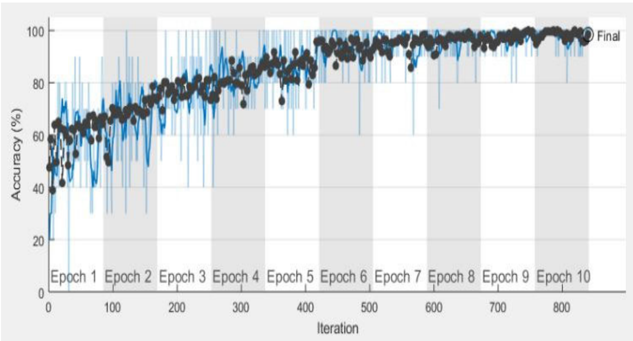

FIGURE 5. **Training process of Main view of brain with augmentation.**

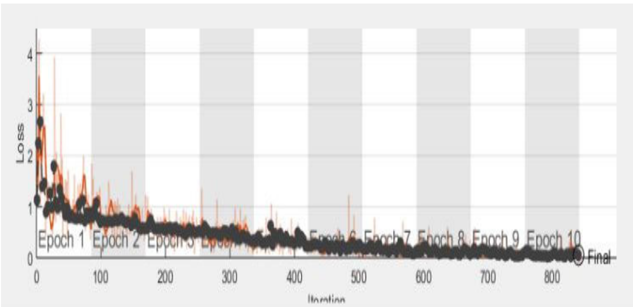

FIGURE 6. **Loss in accuracy process of Main view with augmentation.**

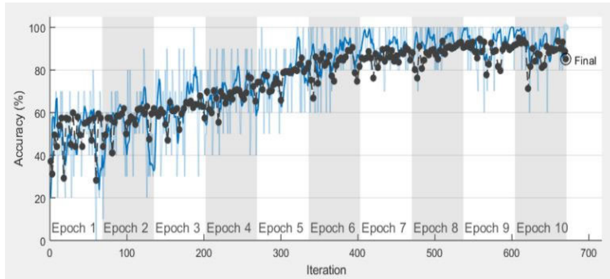

FIGURE 7. **Training process of Main view of brain w/o augmentation.**

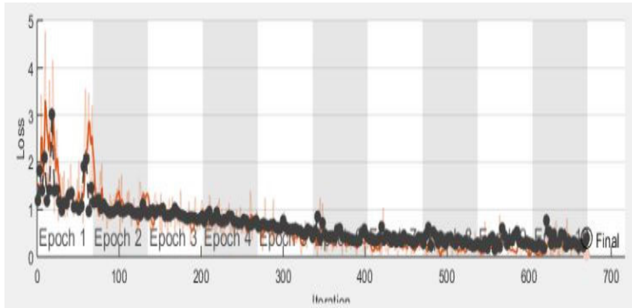

FIGURE 8. **Loss in accuracy process of Main view of brain without augmentation.**

to the pre-trained CNN to train over the AD dataset is referred to fine-tuning. In this transfer learning model, the procedure of extraction of features and then classification is completely automated. This model provides us with the required output by automatically learning from the given input. By changing the learning rate, learn rate factor and bias-learn factor training parameters, we fine-tuned this transfer learning process. To obtain the optimal results, we vary the training options. The learning rate is varied from 1e-1 to 1e-10, similarly, the Weight-Learn and Bias-Learn factor are varied from 10 to 100 and 1e-4 respectively to achieve optimal results. We performed the multi-class Alzheimer detection using the transfer learning (TL) approach on 6 epoch, 8 epoch, and 10 epochs to find the optimal number of epochs.

Figure 5 shows the training procedure using the main view for epoch size 10 with the data augmentation. The blue lines in figure 5 show the training data performance whereas the black points in figure 5 show the performance accuracy for validation data. We achieved 98.41% accuracy using the main view of the brain on epoch size 10 with augmentation of data.

Figure 6 shows the process loss in training using the main view of MRI on epoch size 10 with the data augmentation. The red lines in figure 6 show the training data loss whereas the black points in figure 6 show the loss of validation data. The performance increase of 7.54% is achieved in comparison with the results from epoch size 6 with epoch size 10.

The comparison for different epochs shows that the accuracy decreases on epoch size 6 by 7.54% and decreases by 3.57% for epoch size 8. For Alzheimer's classification, we compared the results achieved from a different number of epochs (6, 7, 8, 9 and 10) with the data augmentation and found that epoch size 10 produced the most optimal results. This pre-trained AlexNet model learns the training data and attained 75.79% accuracy on first epoch, 73.02% on second, 70.24% on third, 85.32% on fourth 89.29% on fifth and 90.87% on sixth and 91.27% on seventh, 94.84% on eighth and 97.22% on ninth epoch for multi-class Alzheimer's classification. For Alzheimer's dataset, we execute this transfer learning algorithm without the data augmentation on epoch size 6, 7, 8, 9 and 10. Figure 7 shows the procedure for the main view of MRI training on epoch size 10 without the data augmentation. The blue lines in the figure 7 show the training data performance accuracy whereas the black points in the figure 7 show the performance accuracy of validation data.

Figure 8 shows the process loss in training of the main view of the brain on epoch size 10 without the data augmentation. The red lines in the figure 8 show the training data loss whereas the black points in the figure 8 show the loss of validation data. We attained an accuracy of 85.11% for the main view of the MRI without the data augmentation on 10 epochs.

D. RESULTS OF TRANSFER LEARNING MODEL FOR THE 3D-VIEW

In our second experiment, we used the 3D-view transfer learning model where the procedure of extraction of features and classification is totally automated. We only give the 3D-views of brain namely Coronal, Sagittal and Axial data as input and obtained diagnosis results.

The 3D-view TL model provides us with the required output by automatically learning from the input. By changing the training parameters i.e. learning rate, learn rate

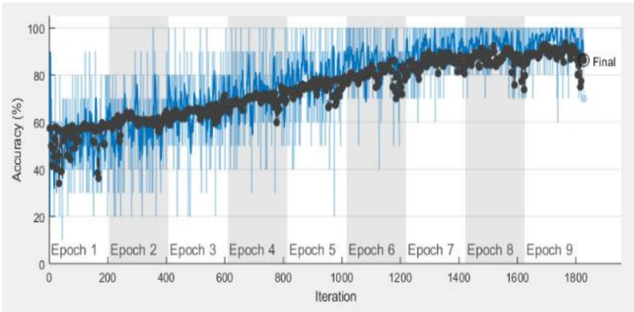

FIGURE 9. Training process of 3D-view of brain with augmentation.

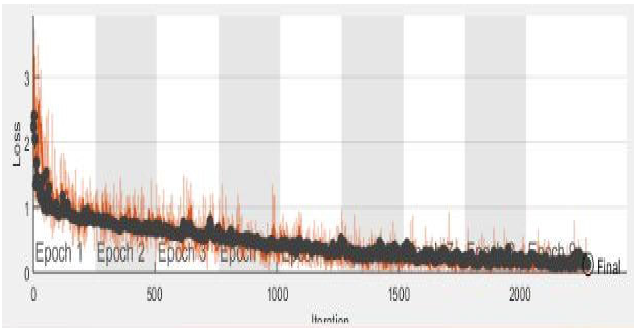

FIGURE 10. Loss in accuracy process of 3D- view with augmentation.

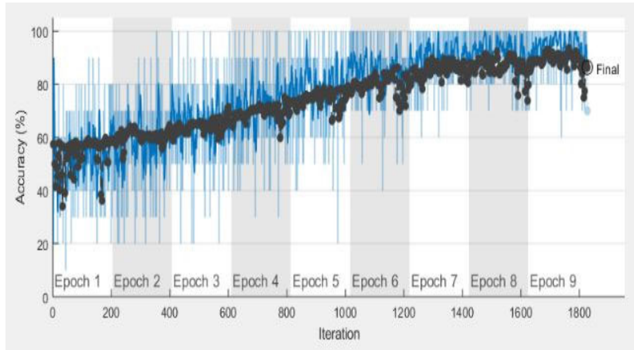

FIGURE 11. Training process of 3D-view of brain w/o augmentation.

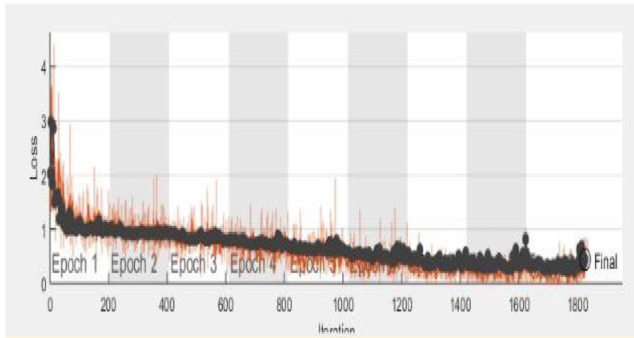

FIGURE 12. Loss in accuracy process of 3D- view w/o augmentation.

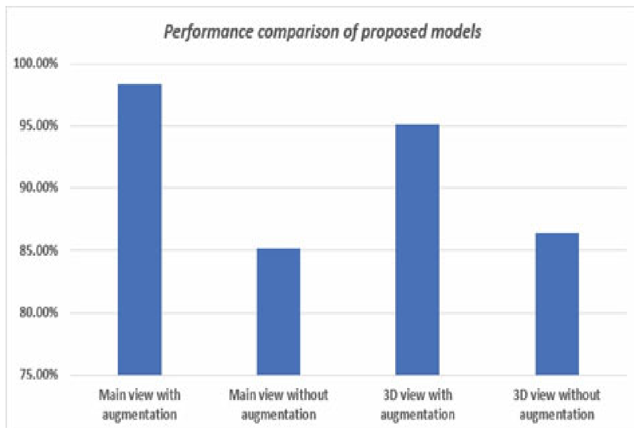

FIGURE 13. Comparison between proposed models.

factor and bias-learn factor, we fine-tuned this TL process. To obtain the optimal results, the learn rate vary from 1e-1 to 1e-10, similarly, the Weight-Learn and Bias-Learn factor from 10-100 and 1e-4 learning rate. We take the multi-class Alzheimer's data set and to find the optimal number of epochs, we executed the TL approach on 6 epoch, 8 epoch, and 10 epochs.

Figure 9 shows the procedure of 3D-view of brain MRI on epoch size 9 with the data augmentation. The blue lines in the figure 9 show the training data performance accuracy whereas the black points in the figure 9 show the performance accuracy of validation data. We attained 94.98% accuracy for the 3D- view of the brain on epoch size 9 with augmentation of data.

Figure 10 shows the process loss in training of 3D-view of the brain on epoch size 9 with the data augmentation. The red lines in the figure 10 show the training data loss whereas the black points in the figure 10 show the loss of validation data. In comparison with the results get from epoch size 6 with epoch size 9, we detected there is an increase in accuracy by 9.11% almost.

For multi-class Alzheimer's classification, we compared the results achieved from a different number of epochs (6, 7, 8, 9 and 10) with the augmentation of data and found that epoch size 9 produced optimal results in 3D-view of brain model. The pre-trained AlexNet model learns the training data and attained 64.0% accuracy on first, 74.63% on second, 77.13% on third, 80.71% on fourth, 77.15% on fifth and 86.13% on sixth and 91.81% on seventh, 89.56% on eighth and 94.98% on tenth epoch for 3D view multi-class Alzheimer's classification with the augmentation of data.

For Alzheimer's classification, we execute this 3D-view TL algorithm without the data augmentation on epoch size 6, 7, 8, 9 and 10. Figure 11 shows the procedure of 3D-view of brain training on epoch size 9 without the data augmentation. The blue lines in the figure 11 show the training data performance accuracy whereas the black points in the figure 11 show the performance accuracy of validation data.

Figure 12 shows the process loss in training of 3D-view of the brain on epoch size 9 without the data augmentation. The red lines in the figure 12 show the training data loss whereas

TABLE 3. Comparison with state-of-the-art technique.

Author	Methods	Targets	Accuracy
I. Beheshti et al [18]	Image Segmentation	AD vs NC	84.07%
S. Wang et al [19]	Support Vector Machine	3D displacement AD vs NC	93.05%
Muazzam et al. [28]	Transfer Learning	Multi-class classification of AD	92.85%
N. M et al [27]	Transfer Learning	AD vs NC	99.4%
Altaf et al. [4]	Bag of Words	AD vs NC	79.08%
Wang et al. [31]	Transfer Learning	MC vs NC	90.6%
Glozman et al. [34]	ImageNet Transfer Learning	AD vs NC	83.5%
	Multi-Auxilary domain Transfer Learning	AD vs NC	94.7%
		MCI vs NC	82.1%
Proposed Methods	**Pre-trained AlexNet model**	**AD vs NC**	**98.41% main view (Augmentation)**
			85.15% main view
			95.11% 3D-view (Augmentation)
			86.35% 3D-view

the black points in the figure 12 show the loss of validation data.

V. DISCUSSION

We compare the results obtained from with and without data augmentation for multi-class AD classification. We discovered that the first proposed pre-trained CNN transfer learning model of the main view with data augmentation performs well and achieve an accuracy of 98% for multi-class AD classification. The second proposed 3D-view model gives highest 95.11% accuracy on epoch 9 with the augmentation of data. Our model with data augmentation gives better results because augmentation improves the testing accuracy and to prevent overfitting problems. We utilized multiple augmentation operations. Figure 13 shows the comparison of the model with and without augmentation of the main view of the brain and 3D-view of the brain in term of multi-class accuracy for Alzheimer's classification, where model 1 shows the main view accuracy with augmentation, model 2 shows without augmentation performance accuracy while 3 and 4 show the 3D-view with and without augmentation. It is evident from the below figure 13 that the main- view with the data augmentation gives the highest result.

To evaluate the performance of our proposed models, we compared the performance result of our TL model with the state-of-art methods. Beheshti *et al.* [18], Wang *et al.* [19] and Altaf *et al.* [4] utilize different approaches for classification AD. In [27] N.M et al. proposed a transfer learning approach for prediction of the binary class AD and Maqsood *et al.* [28] proposed a transfer learning approach by utilizing pre-trained AlexNet for multi-class classification of AD.

Another researcher as shown in Table 3 utilizes the deep learning approaches on the different data set, they mostly use multi-domain transfer learning for classification of the Alzheimer's. Table 3 shows that our proposed model outperforms the other state-of-the-art methods.

VI. CONCLUSION AND FUTURE WORK

In this article, we proposed a TL based efficient technique to correctly classify the multi-class AD by utilizing pre-trained AlexNet model. We proposed two methods, one with the main view of the brain and the second with the 3D-view of the brain MRI with extensive image augmentation techniques to avoid overfitting issue.

We transfer the initial layers of the pre-trained model and trained on our AD dataset. We discovered that the main view of the brain (Axial) with the extensive augmentation of the data give higher performance accuracy i.e. 98.41% as compared with the performance accuracy of the 3D-view of the brain which is 95.11%. We also discovered that extensive augmentation approaches can prevent overfitting issues in class balance dataset, which is the major issue. Results show that our proposed TL model also outer performs the state-of-the-art-techniques.

REFERENCES

[1] I. Beheshti, H. Demirel, and Alzheimer's Disease Neuroimaging Initiative, "Feature-ranking-based Alzheimer's disease classification from structural MRI," *Magn. Reson. Imag.*, vol. 34, no. 3, pp. 252–263, Apr. 2016.

[2] S. Belleville, C. Fouquet, S. Duchesne, D. L. Collins, and C. Hudon, "Detecting early preclinical Alzheimer's disease via cognition, neuropsychiatry, and neuroimaging: Qualitative review and recommendations for testing," *J. Alzheimer's Disease*, vol. 42, no. 4, pp. S375–S382, Oct. 2014.

[3] Y. Zhang, S. Wang, P. Phillips, Z. Dong, G. Ji, and J. Yang, "Detection of Alzheimer's disease and mild cognitive impairment based on structural volumetric MR images using 3D-DWT and WTA-KSVM trained by PSOTVAC," *Biomed. Signal Process. Control*, vol. 21, pp. 58–73, Aug. 2015.

[4] T. Altaf, S. M. Anwar, N. Gul, M. N. Majeed, and M. Majid, "Multiclass Alzheimer's disease classification using image and clinical features," *Biomed. Signal Process. Control*, vol. 43, pp. 64–74, May 2018.

[5] G. B. Frisoni, N. C. Fox, C. R. Jack, Jr., P. Scheltens, and P. M. Thompson, "The clinical use of structural MRI in Alzheimer disease," *Nature Rev. Neurol.*, vol. 6, pp. 67–77, Feb. 2010.

[6] Y. Liu, L. Teverovskiy, O. Carmichael, R. Kikinis, M. Shenton, C. S. Carter, V. A. Stenger, S. Davis, H. Aizenstein, J. T. Becker, O. L. Lopez, C. C. Meltzer, "Discriminative mr image feature analysis for automatic schizophrenia and Alzheimer's disease classification," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent*, 2004, pp. 393–401.

[7] Z. Lao, D. Shen, Z. Xue, B. Karacali, S. M. Resnick, and C. Davatzikos, "Morphological classification of brains via high-dimensional shape transformations and machine learning methods," *Neuroimage*, vol. 21, pp. 46–57, Jan. 2004.

[8] G. Fung and J. Stoeckel, "SVM feature selection for classification of SPECT images of Alzheimer's disease using spatial information," *Knowl. Inf. Syst.*, vol. 11, no. 2, pp. 243–258, Feb. 2007.

[9] S. Klöppel, C. M. Stonnington, C. Chu, B. Draganski, R. I. Scahill, J. D. Rohrer, N. C. Fox, C. R. Jack, Jr., J. Ashburner, and R. S. J. Frackowiak, "Automatic classification of MR scans in Alzheimer's disease," *Brain*, vol. 131, no. 3, pp. 681–689, Mar. 2008.

[10] A. Chincarini, P. Bosco, P. Calvini, G. Gemme, M. Esposito, C. Olivieri, L. Rai, S. Squarcia, G. Rodriguez, R. Bellotti, P. Cerello, I. De Mitri, A. Retico, and F. Nobili, "Local MRI analysis approach in the diagnosis of early and prodromal Alzheimer's disease," *Neuroimage*, vol. 58, no. 2, pp. 469–480, Sep. 2011.

[11] E. Westman, L. Cavallin, J.-S. Muehlboeck, Y. Zhang, P. Mecocci, B. Vellas, M. Tsolaki, I. Kloszewska, H. Soininen, C. Spenger, S. Lovestone, A. Simmons, and L.-O. Wahlund, "Sensitivity and specificity of medial temporal lobe visual ratings and multivariate regional MRI classification in Alzheimer's disease," *PLoS ONE*, vol. 6, Jul. 2011, Art. no. e22506.

[12] O. B. Ahmed, J. Benois-Pineau, M. Allard, C. B. Amar, G. Catheline, and Alzheimer's Disease Neuroimaging Initiative, "Classification of Alzheimer's disease subjects from MRI using hippocampal visual features," *Multimedia Tools Appl.*, vol. 74, no. 4, pp. 1249–1266, Feb. 2015.

[13] J. Yang, Y.-Q. Zhao, and J. C.-W. Chan, "Learning and transferring deep joint spectral–spatial features for hyperspectral classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 8, pp. 4729–4742, Aug. 2017.

[14] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 1929–1958, Jan. 2014.

[15] K. Aderghal, M. Boissenin, J. Benois-Pineau, G. Catheline, and K. Afdel, "Classification of sMRI for AD diagnosis with convolutional neuronal networks: A pilot 2-D+ϵstudy on ADNI," in *Proc. Int. Conf. Multimedia Modeling*, Dec. 2016, pp. 690–701.

[16] J. Friedrich, R. Urbanczik, and W. Senn, "Code-specific learning rules improve action selection by populations of spiking neurons," *Int. J. neural Syst.*, vol. 24, Aug. 2014, Art. no. 1450002.

[17] G. Lee, M. Kwon, S. Kavuri, and M. Lee, "Action-perception cycle learning for incremental emotion recognition in a movie clip using 3D fuzzy GIST based on visual and EEG signals," *Integr. Comput.-Aided Eng.*, vol. 21, no. 3, pp. 295–310, Apr. 2014.

[18] I. Beheshti, N. Maikusa, H. Matsuda, H. Demirel, G. Anbarjafari, and Japanese-Alzheimer's Disease Neuroimaging Initiative, "Histogram-based feature extraction from individual gray matter similarity-matrix for Alzheimer's disease classification," *J. Alzheimer's Disease*, vol. 55, no. 4, pp. 1571–1582, Oct. 2017.

[19] S. Wang, Y. Zhang, G. Liu, P. Phillips, and T.-F. Yuan, "Detection of Alzheimer's disease by three-dimensional displacement field estimation in structural magnetic resonance imaging," *J. Alzheimer's Disease*, vol. 50, no. 1, pp. 233–248, Oct. 2016.

[20] R. S. Kamathe and K. R. Joshi, "A robust optimized feature set based automatic classification of Alzheimer's disease from brain mr images using K-NN and ADABOOST," *ICTACT J. Image Video Process.*, vol. 8, no. 3, pp. 1–8, Feb. 2018.

[21] N. Imperatore, A. Rispo, A. Testa, P. P. Mainenti, G. D. De Palma, M. Rea, O. M. Nardone, G. Luglio, N. Caporaso, and F. Castiglione, "OC. 08.4: Bowel damage in Crohn's disease: Direct comparison of ultrasonography-and magnetic resonance-based Lemann index," *Digestive Liver Disease*, vol. 49, pp. e97–e98, Mar. 2017.

[22] L. K. Ferreira, J. M. Rondina, R. Kubo, C. R. Ono, C. C. Leite, J. Smid, C. Bottino, R. Nitrini, G. F. Busatto, F. L. Duran, and C. A. Buchpiguel, "Support vector machine-based classification of neuroimages in Alzheimer's disease: Direct comparison of FDG-PET, rCBF-SPECT and MRI data acquired from the same individuals," *Revista Brasileira de Psiquiatria*, vol. 40, no. 2, pp. 181–191, Jan. 2018.

[23] I. Beheshti, H. Demirel, F. Farokhian, C. Yang, H. Matsuda, and Alzheimer's Disease Neuroimaging Initiative, "Structural MRI-based detection of Alzheimer's disease using feature ranking and classification error," *Comput. Methods Programs Biomed.*, vol. 137, pp. 177–193, Dec. 2016.

[24] R. Cui, M. Liu, and G. Li, "Longitudinal analysis for Alzheimer's disease diagnosis using RNN," in *Proc. IEEE 15th Int. Symp. Biomed. Imag. (ISBI*, Apr. 2018, pp. 1398–1401.

[25] Y. Wang, Y. Yang, X. Guo, C. Ye, N. Gao, Y. Fang, and H. T. Ma, "A novel multimodal MRI analysis for Alzheimer's disease based on convolutional neural network," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 754–757.

[26] A. Giersch and J. T. Coull, "TRF1: It was the best of time(s)," *Timing Time Perception*, vol. 6, pp. 231–414, Dec. 2018.

[27] N. M. Khan, N. Abraham, and M. Hon, "Transfer learning with intelligent training data selection for prediction of Alzheimer's disease," *IEEE Access*, vol. 7, pp. 72726–72735, 2019.

[28] M. Maqsood, F. Nazir, U. Khan, F. Aadil, H. Jamal, I. Mehmood, and O.-y. Song, "Transfer learning assisted classification and detection of Alzheimer's disease stages using 3D MRI scans," *Sensors*, vol. 19, no. 11, p. 2645, Jun. 2019.

[29] K. Aderghal, A. Khvostikov, A. Krylov, J. Benois-Pineau, K. Afdel, and G. Catheline, "Classification of Alzheimer disease on imaging modalities with deep CNNs using cross-modal transfer learning," in *Proc. IEEE 31st Int. Symp. Comput.-Based Med. Syst. (CBMS)*, Jun. 2018, pp. 345–350.
[30] T. D. Phong, H. N. Duong, H. N. Duong, N. T. Trong, V. H. Nguyen, T. V. Hoa, and V. Snasel, "Brain hemorrhage diagnosis by using deep learning," in *Proc. 2017 Int. Conf. Mach. Learn. Soft Comput.*, Jan. 2017, pp. 34–39.
[31] S. Wang, Y. Shen, W. Chen, T. Xiao, and J. Hu, "Automatic recognition of mild cognitive impairment from mri images using expedited convolutional neural networks," in *Proc. Int. Conf. Artif. Neural Netw.*, Oct. 2017, pp. 373–380.
[32] M. A. Nowrangi, C. G. Lyketsos, J.-M. S. Leoutsakos, K. Oishi, M. Albert, S. Moric, and M. M. Mielkea, "Longitudinal, region-specific course of diffusion tensor imaging measures in mild cognitive impairment and Alzheimer's disease," *Alzheimer's Dementia*, vol. 9, no. 5, pp. 519–528, Sep. 2013.
[33] B. Cheng, M. Liu, D. Shen, Z. Li, D. Zhang, and Alzheimer's Disease Neuroimaging Initiative, "Multi-domain transfer learning for early diagnosis of Alzheimer's disease," *Neuroinformatics*, vol. 15, no. 2, pp. 115–132, Apr. 2017.
[34] T. Glozman, J. Solomon, F. Pestilli, L. Guibas, and Alzheimer's Disease Neuroimaging Initiative, "Shape-attributes of brain structures as biomarkers for Alzheimer's disease," *J. Alzheimer's Disease*, vol. 56, no. 1, pp. 287–295, Jan. 2017.
[35] M. Dyrba, M. Ewers, M. Wegrzyn, I. Kilimann, C. Plant, A. Oswald, T. Meindl, M. Pievani, A. L. W. Bokde, A. Fellgiebel, M. Filippi, H. Hampel, and S. Klöppel, "Robust automated detection of microstructural white matter degeneration in Alzheimer's disease using machine learning classification of multicenter DTI data," *PLoS ONE*, vol. 8, May 2013, Art. no. e64925.
[36] K. Muhammad, J. Ahmad, Z. Lv, P. Bellavista, P. Yang, and S. W. Baik, "Efficient deep CNN-based fire detection and localization in video surveillance applications," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 49, no. 7, pp. 1419–1434, Jul. 2019.
[37] A. Ullah, J. Ahmad, K. Muhammad, M. Sajjad, and S. W. Baik, "Action recognition in video sequences using deep bi-directional LSTM with CNN features," *IEEE Access*, vol. 6, pp. 1155–1166, 2017.
[38] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," *Neurocomputing*, vol. 288, pp. 30–42, May 2018.
[39] J. Ahmad, K. Muhammad, J. Lloret, and S. W. Baik, "Efficient conversion of deep features to compact binary codes using Fourier decomposition for multimedia big data," *IEEE Trans. Ind. Informat.*, vol. 14, no. 7, pp. 3205–3215, Jul. 2018.
[40] J. Ahmad, K. Muhammad, and S. W. Baik, "Medical image retrieval with compact binary codes generated in frequency domain using highly reactive convolutional features," *J. Med. Syst.*, vol. 42, p. 24, Feb. 2018.
[41] M. Sajjad, S. Khan, T. Hussain, K. Muhammad, A. K. Sangaiah, A. Castiglione, C. Esposito, and S. W. Baik, "CNN-based anti-spoofing two-tier multi-factor authentication system," *Pattern Recognit. Lett.*, to be published.
[42] J. Ahmad, K. Muhammad, S.-I. Kwon, S. W. Baik, and S. Rho, "Dempster-Shafer fusion based gender recognition for speech analysis applications," in *Proc. Int. Conf. Platform Technol. Service (PlatCon)*, Feb. 2016, pp. 1–4.
[43] A. M. Badshah, B. N. Rahim, N. Ullah, J. Ahmad, K. Muhammad, M. Y. Lee, S. Kwon, and S. W. Baik, "Deep features-based speech emotion recognition for smart affective services," *Multimedia Tools Appl.*, vol. 78, no. 5, pp. 5571–5589, Mar. 2019.
[44] Y.-D. Zhang, Z. Dong, X. Chen, W. Jia, S. Du, K. Muhammad, and S.-H. Wang, "Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation," *Multimedia Tools Appl.*, vol. 79, no. 3, pp. 3613–3632, Feb. 2019.
[45] T. Ateeq, M. N. Majeed, S. M. Anwar, M. Maqsood, Z.-U. Rehman, J. W. Lee, K. Muhammad, S. Wang, S. W. Baik, and I. Mehmood, "Ensemble-classifiers-assisted detection of cerebral microbleeds in brain MRI," *Comput. Elect. Eng.*, vol. 69, pp. 768–781, Jul. 2018.
[46] M. Iqbal, M. A. Ghazanfar, A. Sattar, M. Maqsood, S. Khan, I. Mehmood, and S. W. Baik, "Kernel context recommender system (KCR): A scalable context-aware recommender system algorithm," *IEEE Access*, vol. 7, pp. 24719–24737, 2019.
[47] A. Kalsoom, M. Maqsood, M. A. Ghazanfar, F. Aadil, and S. Rho, "A dimensionality reduction-based efficient software fault prediction using Fisher linear discriminant analysis (FLDA)," *The J. Supercomput.*, vol. 74, no. 9, pp. 4568–4602, Sep. 2018.
[48] S. Khan, A. Khan, M. Maqsood, F. Aadil, and M. A. Ghazanfar, "Optimized Gabor feature extraction for mass classification using cuckoo search for big data e-healthcare," *J. Grid Comput.*, vol. 17, no. 2, pp. 239–254, Jun. 2019.
[49] F. Nazir, M. A. Ghazanfar, M. Maqsood, F. Aadil, S. Rho, and I. Mehmood, "Social media signal detection using tweets volume, hashtag, and sentiment analysis," *Multimedia Tools Appl.*, vol. 78, no. 3, pp. 3553–3586, Feb. 2019.

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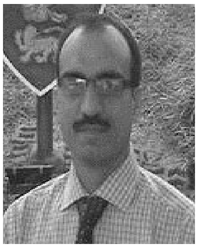

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