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Alzheimer Disease Detection of 3D-CNN with SE-Net Model using SVM Classifier

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Abstract— Alzheimer disease is a fatal progressive neurological brain disorder. Earlier detection of Alzheimer's disease can help with proper treatment and prevent brain tissue damage. In this work we proposed two methods. First, proposed connected median filter using PSO feature extraction from MRI images and Analysis of Alzheimer's diseases state by using 3D-CNN based SE-Net. In the first phase, the algorithm first normalizes and removes skull from the MRI images. Connected median filter using Particle Swarm Optimization algorithm is used to partition the image into white matter (WM), grey matter (GM) and black holes (BH). The relevant diagnostic features are extracted from the segmented image component. The classifier is trained by the training data to predict the test data. The features are defined to construct classification model by using Support Vector Machine with Squeeze- Excitation block. Here, database contains total of 1000 images which are resized into 350 × 350 without loss of information. Deep Learning demands large number of images and its strength was increased as per requirement by augmentation technique. In the first phase of the method takes 1000 images of different features are selected to train SVM classifier and the accuracy obtained is 98.37% and contribution of this work is classification of images into categories such as Alzheimer (AD) and normal. First phase of work emphasized program specific applications to extract features. In the second phase the CNN multiple layers which are studied from lower level to the higher-level image characteristics.

Keywords- 3D-CNN, Squeeze and Excitation networks, optimization

I. INTRODUCTION

Alzheimer's disease (AD) is the most well-known cause of dementia. It is a degenerative brain disease that affects humans. Dementia, on the other hand, maybe caused by a variety of illnesses and disorders [1]. A reduction in memory depicts it, as does the ability to figure out and use language, critical thinking, and other intellectual abilities, all of which impact an individual's ability to conduct regular activities [2]. This loss in human capabilities occurs because nerve cells (neurons) in the parts of the brain involved with intellectual ability have been damaged and will never perform normally again [3]. In Alzheimer's disease, neuronal damage affects areas of the brain that enable a person to accomplish basic things like walking and swallowing in the long term. Alzheimer's disease is a lethal disease with no cure known yet. Dementia is a catch-all phrase for a wide range of adverse effects. Several types of dementia, including Alzheimer's disease, vascular dementia, dementia with Lewy bodies, and others. However, dementia of Alzheimer's (AD) is the most well-known cause of dementia [4-8].

Most forms of mental illnesses have been resolved based on clinical perception. These include the differentiating evidence of manifestations, which will typically classify the rate and bias of the symptoms to resolve, relapse, or become recurring. There is no cure for Alzheimer's disease, and we lack strong early demonstrative tools. AD is clinically detected by doing physical and neurological exams and examining several indicators of academic incapacity using conventional neuropsychological and psychological testing. Regardless of the aforesaid clinical parameters, the overall process is based on analysis by disposal, for example, administering everything else out until AD is the final option [9].

Measures from magnetic resonance imaging (MRI), positron emission tomography (PET), cerebrospinal fluid (CSF) protein profiles, and a study of familial risk profiles are included. However, they are expensive and difficult to scale to massive quantities. Unmistakably, there is a need to develop improved diagnostic tools for Alzheimer's disease diagnosis, maybe using data mining and data analysis processes, which we examine in this paper [15-17]. If new drugs or aversion approaches are developed and shown to be effective, an early analysis may enable mediation at an earlier stage, which would be of demonstrable benefit. However, it is arduous when the clinical decision is reached based only on the disease's symptoms and side effects. No one test can determine whether or not a person has Alzheimer's disease. While physicians can typically determine whether or not a person has dementia, determining the exact cause might be difficult. The paper is organized according to Section II literature review and critical evaluation. Section III describes the proposed Deep learning techniques. Section IV describes the results and discussion. Finally, conclusions are drawn in Section V.

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II. REVIEW OF LITERATURE

Many studies have recently done to precisely identify psychiatric disorders, such as Alzheimer's, and several methodologies have been presented for this purpose. In general, data extracted from structural and functional brain imaging data or cerebrospinal fluid is employed for a more accurate evaluation. Furthermore, the group has made many efforts, and several AD stages have lately been projected. The following are the absolute most concentrated works that have recently been done near there:

[2] The authors demonstrated an image analysis technique for AD forecasting. The system uses support vector machine classifier techniques to categorize Alzheimer's patients based on texture characteristics extracted from gray-level co-occurrence matrices and voxel-based morphometry neuroimaging data. The dataset utilized by the authors in this study is ADNI. [4] provide a technique for evaluating the OASIS [5] dataset. The approach is based on semi supervised learning, which takes just a small portion of the dataset as training data to accurately predict the labels for the remainder of the test material.

[6] Offer an approach based on a 3D convolutional auto-encoder. This model employs a deep 3D convolutional neural network to extract and benefit from AD related variables. Finally, the classification assignment is completed for different binary combinations of three topic groups (AD, MCI, and NC) and a ternary arrangement among them. The authors utilize the ADNI dataset in this case.

[7] A semi-supervised learning strategy is used in this approach to transform another biomarker of MCI to AD. The aging effects are removed from the MRI images using regularised logistic regression during feature selection. Finally, the developed biomarker is bonded with age and cognitive data concerning MCI participants using a supervised learning approach for the final classification done using a random forest classifier. The ADNI dataset was used to acquire data [8]. In this research, the authors suggest a deep learning technique for major level inactive and shared feature portrayal using neuroimaging modalities. They used a Deep Boltzmann Machine (DBM), a deep network with a limited Boltzmann machine as a structure obstruct, to find a latent hierarchical feature portrayal from a 3D fix, and then devised a precise technique for a joint feature portrayal from the combined patches of MRI and PET with a multimodal DBM. To validate the feasibility of the suggested method, they conducted experiments on the ADNI dataset compared to cutting-edge techniques.

III. METHODOLOGY

The first step in effectively classifying AD data is pretreatment. The pathologically demonstrated data set is treated to prevent class imbalance before being transformed to a readable data format. Deep learning algorithms perform effectively when the number of instances of one class is almost equal to that of other classes. To prevent class imbalance, data is oversampled using deep learning approaches such as SE-Net and 3D-CNN oversampling methodology, and data is oversampled to avoid class imbalance. The input data type is changed from numeric to nominal/numeric to nominal values for the algorithms that employ said data type to be implemented. In this work, we propose an end-to-end 3D CNN – SE Net for the multiclass AD biomarker identification task, using the whole image volume as input. Our pipeline is composed of three main steps: brain extraction and normalization, 3D CNN processing, and domain adaptation. This section provides details of our pipeline, including image preprocessing, CNN architectures, and optimization techniques. The model is divided into four stages, as shown in Figure 1.

1. Pre-processing using proposed connected median filter using PSO
2. 3D-CNN and SE-NET based Feature Extraction
3. Classification using SVM
4. Performance Evaluation

A. Dataset description

We will be using the longitudinal MRI data. The dataset consists of longitudinal MRI data of 150 subjects aged 60 to 96. Each subject was scanned at least once. Everyone is right-handed. 72 of the subjects were grouped as 'Nondemented' throughout the study. 64 of the subjects were grouped as 'Demented' at their initial visits and remained so throughout the study. 14 subjects were grouped as 'Non-demented' at the time of their initial visit and were subsequently characterized as 'Demented' at a later visit. These fall under the 'Converted' category.

B. Attribute Selection

Attribute selection comes all potential attribute combinations in the data to determine which subset of attributes works best for prediction and categorization. It is useful for reducing dimensionality and removing unnecessary characteristics. It may lead to improved classification accuracy or lower computing expenses. The third phase is based on categorization with little help and confidence utilizing Attribute mining.

C. Proposed Optimized Connected Median Filter Using Particle Swarm Optimization

The proposed optimized connected median filter functions both the process of “4- connected median filter” and “weighted 4-connected median filter”. In this method the function of 4-connected median filter was taken when the medical image pixel values stood at 0 or 255, otherwise the function of weighted 4-connected median filter was taken when its image pixel values lies in between 0 to 255 that is from 1 to 254. In the 4-connected median filter the middle pixel of the selected square window was replaced by a maximum of three viz. diagonal median, horizontal and vertical median, and the original middle pixel value. Proposed optimized median filter has taken maximum of four values to replace middle pixel of the square window. The fourth value was computed by the Particle Swarm Optimization with the fitness function of Peak Signal to Noise Ratio.

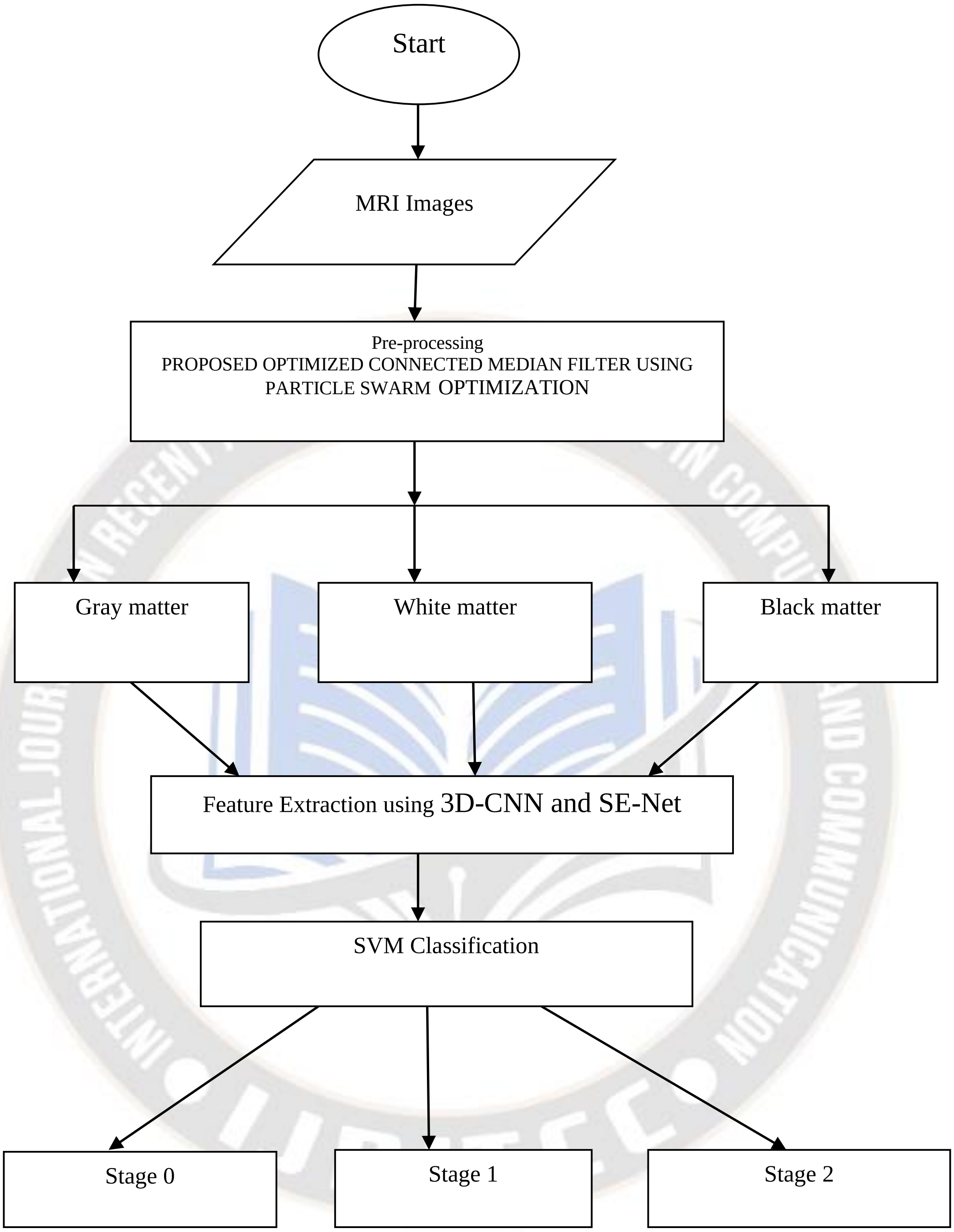

Figure 1 System Architecture

Particle Swarm Optimization

Particle swarm optimization technique was first originated by Eberhart and Kennedy. This technique was based upon the concept of food fetching by the birds and fishes. A moving group of birds or fishes is known as a swarm. Birds move together in search of foods. The bird first identifies the exact location of food for the swarm and directs them to obtain food. The concept of subsumed from the above technique is identification of optimum pixel value for replacing the middle pixel value in the 4-connected median filter. This technique refers individual pixel in the group as particle. The particle is denoted as xn and the group as X. The best value of xn in the X was identified with the help of Peak signal to Noise Ratio to replace the middle pixel value of X. In

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the best value xn selection process another factor was considered as vital for the execution is known as velocity and it is denoted as V. It refers to the movement distance from one pixel to another in completion of iterations. The velocity is computed with the following formula

$$V_i^{k+1} = wV_i^k + c1r1\left(pbest_i^k - X_i^k\right) + c2r2\left(gbest_i^k - X_i^k\right) \quad (1)$$

where, ‘w’ refers to the inertia weight
‘c1 and c2’ are constant value = 2
‘r1 and r2’ are random variables between 0 and 1.
‘pbest’ refers to the best of local neighbors and ‘gbest’ refers to the best of global neighbors.

In this paper, the proposed median filter is used to solve imbalance and dimensionality reduction problem. After applying the proposed median filter next step is to train the features based on 3D-CNN and SE-Net model.

D. 3D-CNN Architecture

The CNN is commonly formed of a Convolutional layer, a pooled layer, a completely associated layer, and a softmax arrangement layer as appeared in Fig. 2. The Convolutional layer performs nonlinear highlight extraction on pictures by utilizing an enactment work; the completely associated layer incorporates the separated highlights and afterward acquires the likelihood estimation of each sort of tag through the softmax work, subsequently foreseeing the mark of the picture [22-24]. Prior to the last forecast esteem is acquired, the organization’s hidden layer limits the mistake between the predictable value and the actual value through the misfortune work that decides the characterization execution of the model. This phase employs the Adam-Smith approach to restore and discover the group boundaries that influence model preparation and model yield; what is more, too inexact or arrive at the ideal incentive to limit the misfortune of work. In 3D-CNN, the value of the neuron at (a, b, c) is Eq. (2).

$$v_{ij}^{a,b,c} = h\left(\sum_m \sum_{x=0}^{x_i-1} \sum_{y=0}^{y_i-1} \sum_{z=0}^{z_i-1} w_{ijm}^{xyz} v_{(i-1)m}^{(a+x)(b+y)(c+z)} + k_{ij}\right) \quad (2)$$

Where i represents i^{th} layer of neurons and j defines j^{th} feature map, X_i,Y_i represent the height and width of the Convolutional kernel; Z_i is the dimension of the convolution kernel along with spectral breadth; m represents number of features connected to the preceding layer, related to the feature dimension of each layer, w is the weight of the $(x,y,z)^{th}$ neuron connected to the m^{th} feature; K_{ij} is the derivation of the j^{th} feature map on i^{th} layer neuron; and h is the activation function; the activation function of this phase is ReLU function. The function is represented below formulae Eq. (3)

$$h(x) = ReLU(x) = \{\, x \text{ if } x > 0 \,;\, 0 \text{ if } x \leq 0 \,\} \quad (3)$$

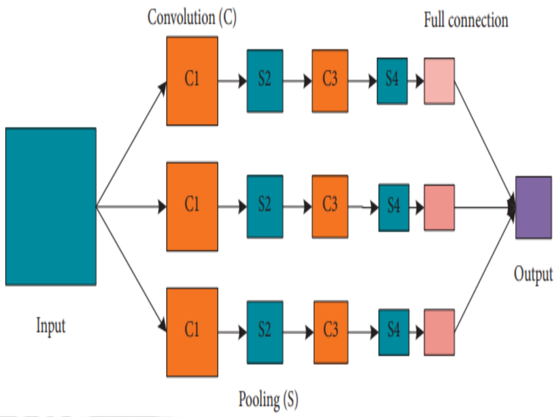

Figure 2: 3D-CNN Model

D. SE-NET Architecture

The medical image contains rich spatial information and spectral information. Different spectral features are suitable for distinguishing different types of Alzheimer’s stages, and there are strong correlations among spectral dimensions. SENet can automatically gain the importance of each feature channel by learning. And according to this importance, the features effective for the classification are improved and those less effective for the classification are suppressed. The weighted feature can effectively improve the classification performance of medical image classification. The proposed methods contain three modules such as 3D-CNN Module, SE-Block and Classification Module. First, the original medical image data are preprocessed and the sample library is obtained. Then, the sample library is divided into training samples and test samples according to different strategies. Consequently, the 3D-CNN network model is established, the related network parameters are determined, and the training samples are input into the established CNN network for model training.

The SE-Block module includes two operations, squeeze and excitation. the squeeze operation is a global average pooling of the features obtained from the convolution of the last layer in the CNN; the feature maps after the squeeze are reduced by a fully connected layer and are nonlinearized by the ReLU activation function, hereafter upgraded through the fully connected layer, and then weight is activated by sigmoid, that is, the excitation operation. Finally, the rescaled features are converted into one-dimensional vector and input to the fully connected layer, and the weights of the parameters in the network are updated by the loss function, and the network optimization is finished. In the Classification module, first the sample features obtained by the previous module are normalized, and the classification is performed by the SVM classifier. Aiming at the small samples problem caused by the difficulty in obtaining test samples, the module incorporates the idea of active learning ideas and uses a combination of uncertainty and differential strategies for sampling. The proposed algorithm is represented given below

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Begin: 3D-CNN and SE-Net Model
Input: Labeled data set, Training Samples S and test samples set T, Batch size for Training network

Steps
(i) Split the dataset into Train, Test and Validate.
(ii) Load and preprocess the sample data.
(iii)Train the data using 3D -CNN Net Model.
(iv) Save the features after the train the network.
(v) Perform the SVM algorithm.
(vi) End
Output: Classified image**,** Diagnosis Accuracy.
End

The features extracted from 3D-CNN with SE-Net are given to SVM for classification of MRI images. The performance of the proposed model is evaluated with the measures, such as, sensitivity, specificity, accuracy and precision rate. Those computations are processed with the four factors called True Positive (P), True Negative (Q), False Positive (R) and False Negative (S). The formulae for measuring the four evaluation factors, Diagnosis Accuracy (DA), Sensitivity, Specificity and Precision are presented below.

i. $DA(Diagnosis\ Accuracy) = \frac{P+Q}{P+Q+R+S}$ (4)

ii. $Sensitivity\ (Recall\ Rate) = \frac{P}{P+S}$ (5)

iii. $Specificity = \frac{Q}{Q+R}$ (6)

iv. $Precision = \frac{P}{P+R}$ (7)

Using the aforementioned equations, the performance efficiency of the proposed model in detecting Alzheimer's Detection is evaluated. Apply CNN to the MRI image of volume 350× 350× 350.When the convolution procedure is completed the depth of input is amplified by the number of filters used. When the Max pooling is applied depth remains the same and representation size is compressed. Next, add a dense layer to CNN model to achieve classification. Convolution layer result will be further flattened and provided to SoftMax function.

IV. RESULTS AND DISCUSSION

The result maps of dataset using three methods are shown in Figure 3. Table 1 shows a comparison of experimental results in the medical data experiment using the proposed method and several other classical methods in selecting different sample sizes and different axis such as axial, coronal and sagittal. In Table 1, the proposed method achieves a better classification effect. This shows that the deep learning method can deeply explore the intrinsic relationship among the spatial-spectrum characteristics of medical image, better extract the typical characteristics of different type's and achieve higher classification performance under small sample conditions. When 5, 10, and 20 samples are randomly selected as training samples for each category, the classification accuracy can reach 97.98%, 97.54%, and 97.92%, respectively.

Due to the advantages of SVM classifiers in dealing with small samples and nonlinear high-dimensional feature classification problems, compared with CNN methods, CNN-SVM can obtain better classification results than CNN's own softmax classifier. The method proposed in this paper considers the small sample problem and the complex correlation among spectra, 3D-CNN is used to extract different types of features, and SE-Block is integrated to optimize the weight of each spectral feature, further distinguishing the contribution of different spectral features to medical image classification. Finally, the SVM classification model is used for medical data classification, which improves the separabilty between different categories or stages of Alzheimer, thus achieving better classification performance. For example, when 20 samples are randomly selected for each category as the training samples, the classification accuracy is 98.37%, which is higher than the VGG 16 Net based SVM method, dilated 3D-CNN method respectively.

Table 1 Classifier performance on accuracy

Axis	VGG 16 Net based SVM	Dilated 3D-CNN Net based SVM	3D-CNN SE-Net based SVM
axial	92.45	94.56	98.25
coronal	93.42	96.29	98.34
sagittal	92.89	96.51	98.37

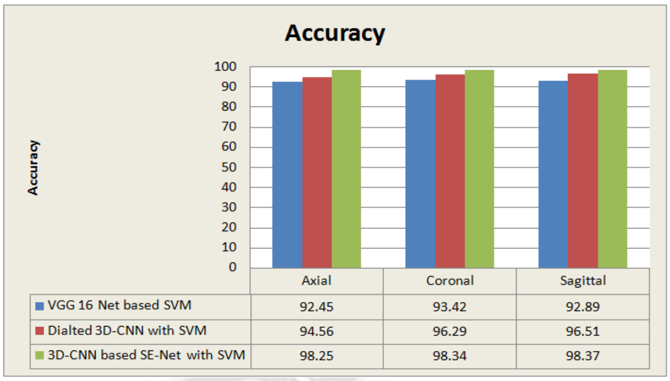

Figure 3- Accuracy Comparison results of Proposed Algorithm

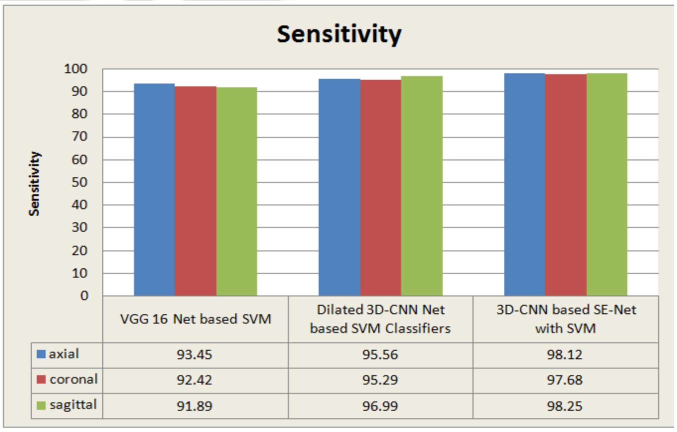

Figure 4- Sensitivity Comparison results of Proposed Algorithm

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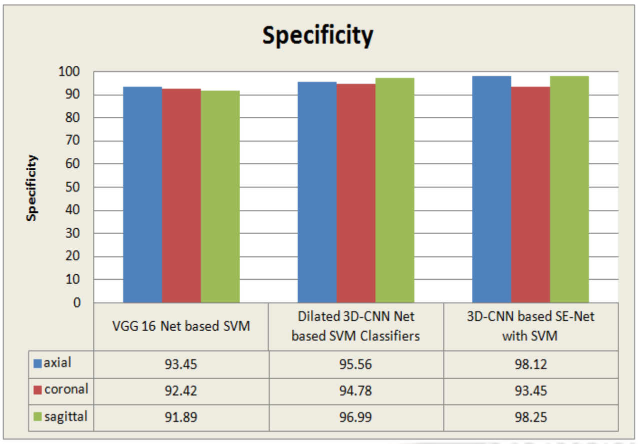

Figure 5- Specificity Comparison results of Proposed Algorithm

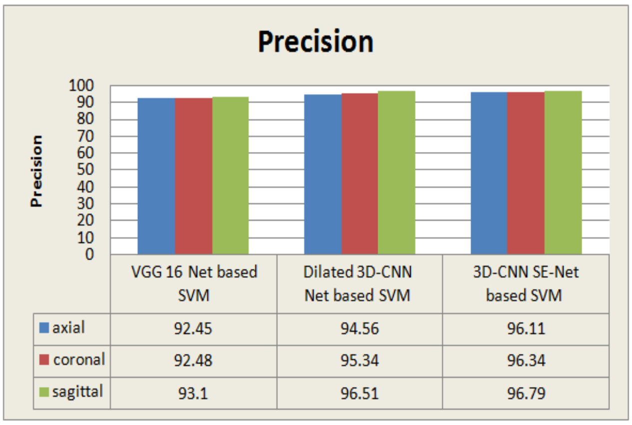

Figure 6- Precision Comparison results of Proposed Algorithm

From the figure 4 to 6we observe that 1.88% increased for diagnosis accuracy, 0.57 % increased sensitivity and 1.3% is improved for specificity and precision when compared with the existing works.

V. Conclusion

This paper develops a new model called Alzheimer's Disease Automated Detection (ADAD) for segmentation and classification of MRI images from input digital Images. Though there are several models in Brain issues diagnosis, achieving better rate of diagnosis accuracy has always been a challenge. For that, for enhancing accuracy, the model used Contrast limited adaptive histogram equalization filter for noise removal. Further, 3D-CNN with SE-Net Model for Feature Extraction is performed with respect to the segmented images. The extracted features are provided to SVM for training. The results show that the proposed model achieved higher rate of accuracy with minimal error rate compared with VGG 16 Net based SVM classifier and dilated 3D-CNN Approach. The convolutional neural network method can extract image features by autonomous learning and is widely used in medical image classification. 3D-CNN model can simultaneously extract the spectral and spatial features of data, which fully exploits the different stages of feature information hidden in the medical data. It meets the requirements of medical image classification and achieves better classification results. The proposed method integrated the SE-Block in the 3D-CNN structure and improved the network model to achieve better classification result by increasing the weight of the effective feature and reducing the feature weight with invalid or small effect.

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