Automatic Diagnosis of Alzheimer’s disease using Hybrid Model and CNN

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Abstract

Since the past decade, the deep learning techniques are widely used in research. The objective of various applications is achieved using these techniques. The deep learning technique in the medical field helps to find medicines and diagnosis of diseases. The Alzheimer’s is a physical brain disease, on which recently many research are experimented to develop an efficient model that diagnoses the early stages of Alzheimer’s disease. In this paper, a Hybrid model is proposed, which is a combination of VGG19 with additional layers, and a CNN deep learning model for detecting and classifying the different stages of Alzheimer’s and the performance is compared with the CNN model. The Magnetic Resonance Images are used to analyse both models received from the Kaggle dataset. The result shows that the Hybrid model works efficiently in detecting and classifying the different stages of Alzheimer’s.

Keywords: Alzheimer’s, data preprocessing, VGG19, CNN, deep-learning

1. Introduction

Alzheimer's Disease (AD) is a progressive neurodegenerative illness that generally begins at an older age and starts deteriorating after some time. AD starts from the hippocampus (brain area where the memory is formed) and progresses in a centrifugal way towards different regions of the brain [1, 2].

The total cost spent on treating dementia across the world in 2015 was approximately US$ 818 billion which is equal to 1.1 % of global gross domestic product. Currently, the

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worldwide annual expenditure on treating dementia is US$ 1 trillion. According to World Health Organization (WHO), AD is the most popular type of dementia. Dementia not only affect older people but also affects individual below 65 and this accounts for up to 9% of affected cases. The AD advancement occurs in 3 stages. In the first stage of AD brain nerve cells start getting damaged. This stage is very difficult to differentiate from normal because an individual does not experience any detectable symptom. The next stage is Mild Cognitive Impairment (MCI). In this stage, individuals experience a problem related to thinking capability but individuals are not fully dependent on others for their tasks. The final level is Alzheimer's and at this level, individuals have more cognitive and behavioral changes that affect their daily activities [3].

No medicine can cure AD but could slow down the progression of AD. Recently a team of Bengaluru scientists discovered the small molecule TGR63 that can avoid the mechanism that results in neurons dysfunctionality in Alzheimer's disease [4]. In Alzheimer's patients, the tissues and cerebral cortex shrink, and cerebrospinal fluid expansion occurs in the brain chambers. These effects are used to find the progression of AD [5].

The doctors can recognize the AD by looking at the images obtained from Magnetic Resonance Imaging (MRI) of brain, with naked eye. Sometimes human errors might occur, and to reduce these errors, it is necessary to build the system that can automatically predict and detect the different stages of AD [6].

2. Related Work

This section briefly discusses few methods used by the authors to diagnose AD using an MRI dataset. The author Karthiga, M [8] used AdaBoost classifier with SVM to detect the AD at its earlier stage and received an accuracy of 95.66%. Braulio Solano- Rojas [9] used a three-dimensional DENSENET neural network for diagnosing AD using magnetic resonance imaging. With this classifier, the 0.86 mean accuracy and 0.91 area under the receiver operating characteristic curve for differentiating five different diseases like Cognitive Normal (CN), Significant Memory Concern, Early Mild Cognitive Impairment (EMCI), Mild Cognitive Impairment (MCI), Late Mild Cognitive Impairment (LMCI), and Alzheimer’s Disease (AD) were obtained. Pan D et al. [10] proposed a new classifier Ensemble developed by combining Convolution Neural Network (CNN) for feature extraction and Ensemble Learning (EL) for classification. The ensemble method performance was evaluated using a stratified fivefold cross-validation method 10 times and achieved an accuracy of 0.84% ± 0.05%. Feng et al [11] experimented a new method described as Universal Support Vector Machine-based Recursive Feature Elimination (USVM-RFE) and achieved a classification accuracy of 100% for CN vs AD, 90% for CN vs MCI, and 73.68% for MCI vs AD. Feng, W et.al [12] experimented with 3D-CNN-SVM method on the ADNI dataset for detection of AD. The author used 3D CNN for feature extraction and the SVM method for classification and achieved an accuracy of 95.74%. Sheng Liu et. al [13] used a Convolution Neural Network (CNN) to predict AD on the ADNI dataset and achieved an accuracy of 66.9%. Yildirim, M., & Cinar, A. [14] performed Classification of Alzheimer's Disease using MRI Images of Kaggle dataset. The author utilized CNN Based Resnet model with additional layers and achieved an accuracy of 90%. Rajendra Acharya [15] used Shearlet Transform (ST) and k-Nearest Neighbor (KNN) for feature extraction and classification models respectively. An accuracy of 94.54% was obtained, on the dataset from the University of Malaya Medical Centre. U. Thavavel, V et al [16] proposed a framework that employs Significance Analysis of Microarray (SAM) to select the most relevant features and used Ensemble Classifier for classification and achieved an accuracy of 87% performing the experiment on the Kaggle dataset. Acharya et al. [17] described the detection of AD using brain MRI through Shearlet Transform (ST) feature extraction technique and classified via the k-Nearest Neighbor method to achieve an accuracy of 94.54%. Few authors [18-22] used the deep neural networks and achieved an average accuracy of 88%±5%.

Many scientists have made sincere efforts to discover a variety of techniques to detect Alzheimer's using MRI data. Those techniques include the extraction of discriminative features from a large set of features and selecting efficient classification models from machine learning techniques. In the existing systems, the classification of AD is binary where it can be determined if it is Alzheimer's disease or not. Whereas in this proposed system, a four-way categorization of AD from MRI using Visual Geometry Group (VGG19) architecture is achieved. VGG-19 [7] is a deep neural network architecture that contains 19 layers, which is created to detect different stages of AD.

3. Proposed Work

The existing methods to diagnose AD discussed in section 2 produced average results. Therefore, to achieve the best efficiency, a deep learning model VGG19 with CNN is proposed.

3.1 Dataset

The Kaggle dataset [23] consisting of 4 classes of images is shown in fig. 1 where, 0 indicates Non-Dementia (ND), 1 indicates Very Mild dementia (VMID), 2 denotes Mild Dementia (MID), and 3 indicates Moderate Dementia (MOD). The data count of each class is given in table 1.

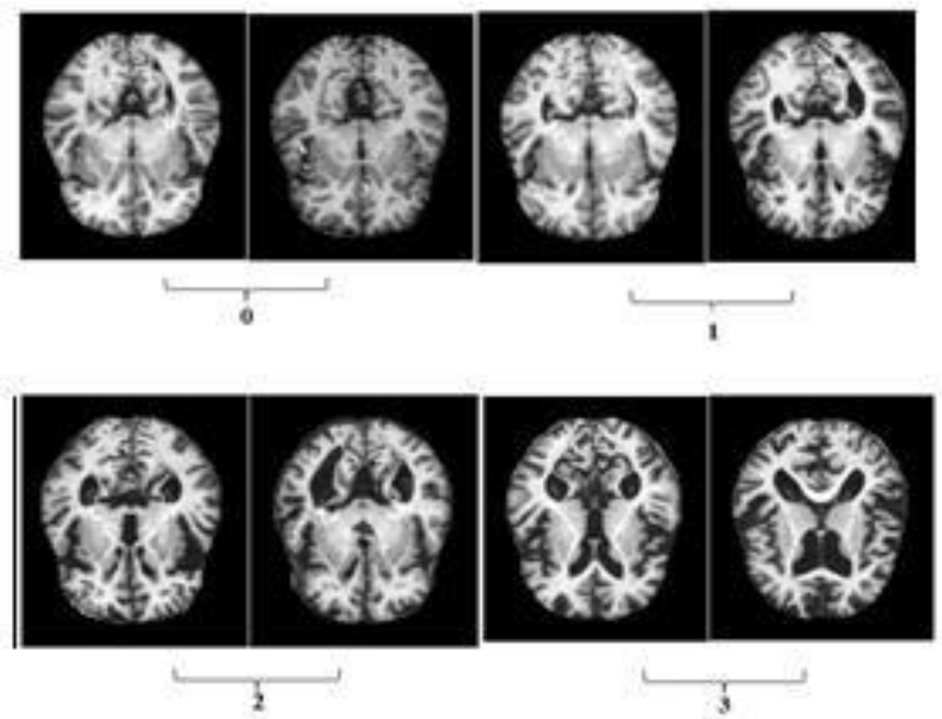

Figure 1. Kaggle dataset samples 0: ND, 1: VMID, 2:MID, 3:MOD

Table 1. Dataset Count

Classes/Count	Kaggle_Dataset_Count
ND	3200
VMD	2240
MID	896
MOD	64

3.2 Model 1: Hybrid model

The hybrid model is a combination of VGG19 and additional layers. VGG19 is used for feature extraction and additional CNN layers for classification. The VGG19 is a deep learning model that consists of 19 layers in depth which includes feature extraction layers and classification layers. In this work, the classification layer is not considered since the classification is performed by adding additional layers as shown in fig. 2.

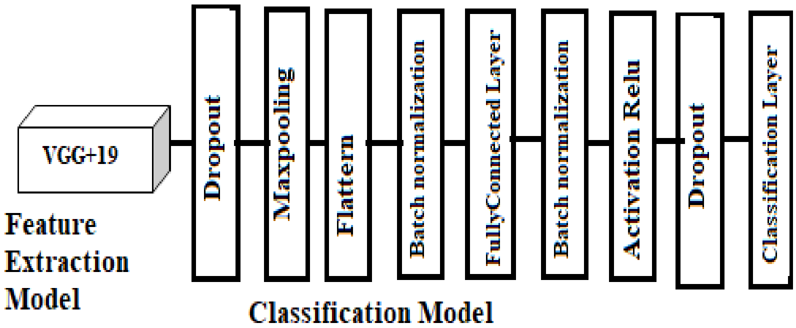

Figure 2. VGG19 and CNN

The input is passed through VGG19 for feature extraction. The input image is of size 176x176x3, where the first term indicates the height of the image, the second term denotes the width of the image and the third term indicates the number of channels. The output image from VGG19 is of size 5x5x512. The convolution and max-pooling layers are then applied to the output image. Finally, the image is progressed through the classification layers. Flatten is the input layer that receives input and routes it to the hidden layers i.e., the fully connected layers, where 3 layers with 256, 512, and 1028 neurons respectively are present. Finally, the image proceeds through the last layer i.e. classification layer that consists of 4 neurons for 4 classifications. This proposed hybrid model classifies the input with an accuracy of 95.52%.

3.3 Model 2: CNN model

The CNN model is considered for both feature extraction and classification, and the architecture of the model is shown in fig. 3. The feature extraction model consists of 5 convolution layers, each layer followed by the max-pooling layer. The convolution layer is used to extract the features and the pooling layer is used to shrink the input. The input image is of size 176x176x3 that is fed to the feature extraction model and the size of the output image is 5x5x256. This output is passed to the classification layer consisting of base layers, 5 dense layers connected together and the classification layer that consists of 4 neurons for 4 classifications. This model achieves an accuracy of 83.53%.

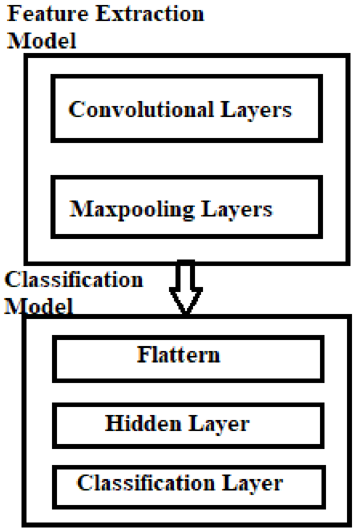

Figure 3. CNN model

3.4 Working Architecture

The working flow of the entire system is depicted in fig. 4.

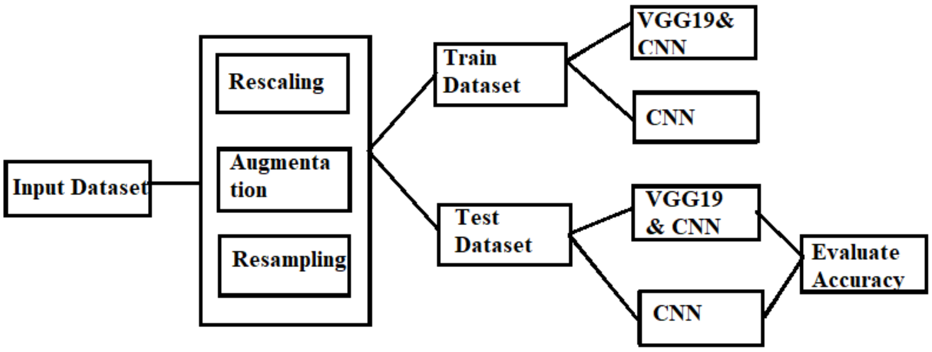

Figure 4. System architecture

To increase the performance of the system, input dataset is preprocessed by rescaling, augmentation, and data resampling. Rescaling is performed to represent the pixels of the dataset between 0 and 1 by dividing the pixels by 255.0. The rescaling is followed by augmentation, which is performed to boom the dataset as Deep learning technique is used, which require more datasets for learning. Augmentation is followed by resampling that is performed to avoid the model overfitting. After data preprocessing, it is divided into train and test datasets with ratio of 4:1. Train dataset is used to make the model learn and test dataset is used to evaluate the model.

Train dataset is divided into train dataset and validation dataset. The validation dataset is used to make the model generalize i.e., make the model distinguish new dataset that has never been seen before. Both the models make use of the ReLU (Rectified Linear Unit) function in intermediate layers and the softmax function at the classifier layer for multiple classifications. The output of ReLU is the same as input if it is positive, else gives false output. The Softmax selects the biggest one from the set of inputs. The ReLU and Softmax equations are represented in equations 1 and 2 respectively.

$$f(m) = n = \begin{cases} m & \text{if, } m > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where, m is the input and n is the output of ReLU.

$$\sigma(m)_i = \frac{e^{m_i}}{\sum_{j=1}^{k} e^{m_j}} \tag{2}$$

where $(m)_i$ is vector input to the softmax and e^{m_i} is exponential value of i^{th} input.

4. RESULT

This section discusses the results of both models. Model 1 and Model 2 are trained by making them run for 10 epochs. Figure 5 shows the history of accuracy and losses of model 1 and model 2.

Figure 5(A) shows the loss history of model 1, where the x and y axes denote epoch number and loss rate respectively. During the first epoch, the training data loss rate is 1.2 and reduces to 0.25 in the 10^{th} epoch. Regarding validation data loss rate, it is 1.8 in the 1^{st} epoch and 0.28 in the 10^{th} epoch.

The accuracy history of model 1 is shown in figure 5(B), where the x and y axes indicate epoch and percentage of accuracy respectively. As shown in the figure, accuracy of the model increases as the number of epochs increases. The training accuracy is 81% at 1st iteration and it increases to 95.52% at the 10th epoch.

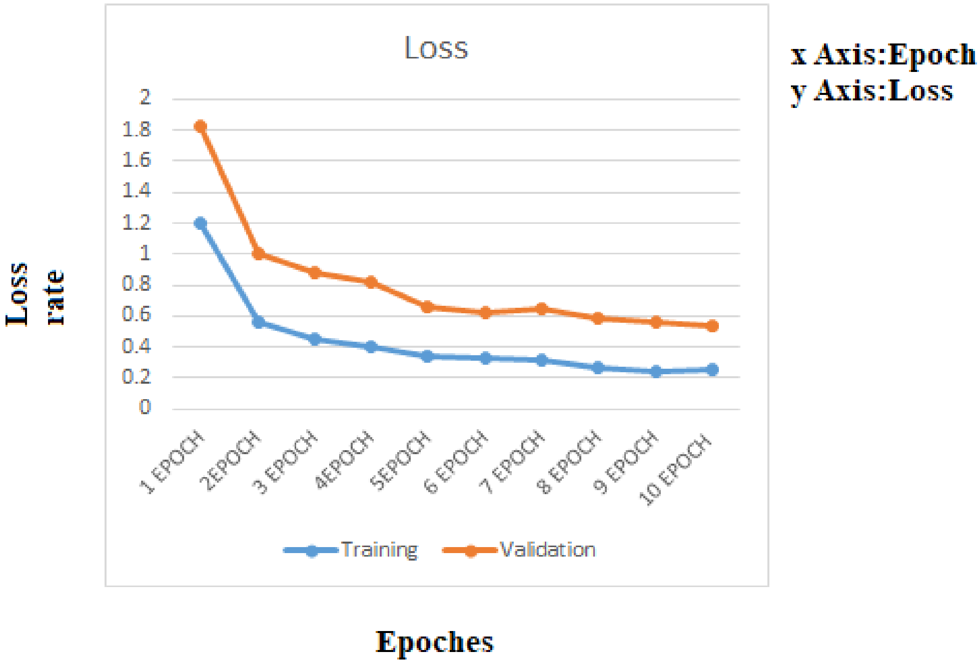

Figure 5(A). Loss history of model 1

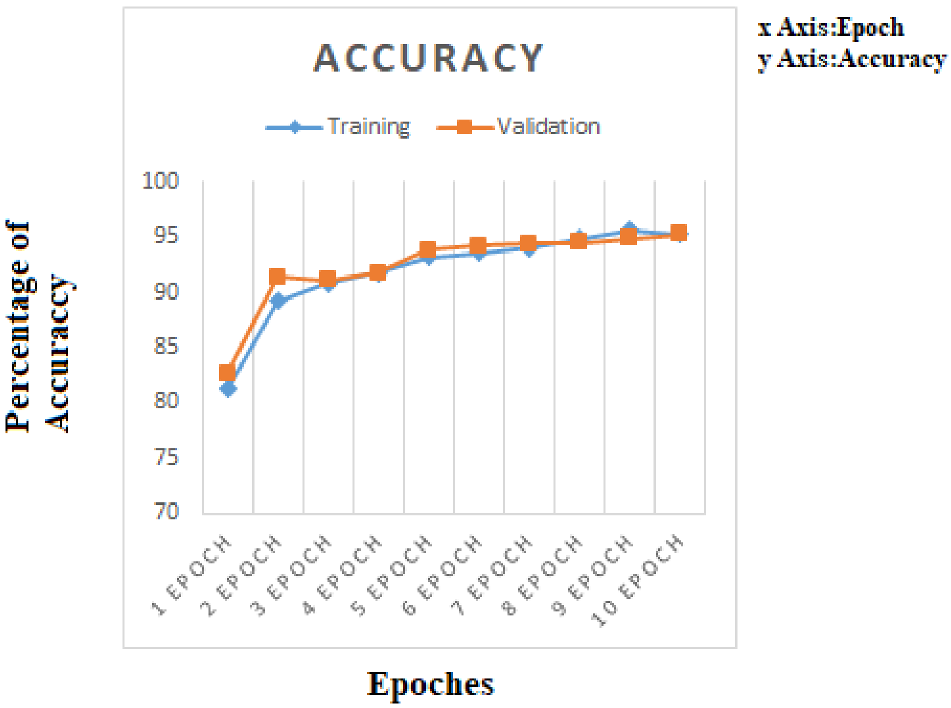

Figure 5(B). Accuracy history of model 1

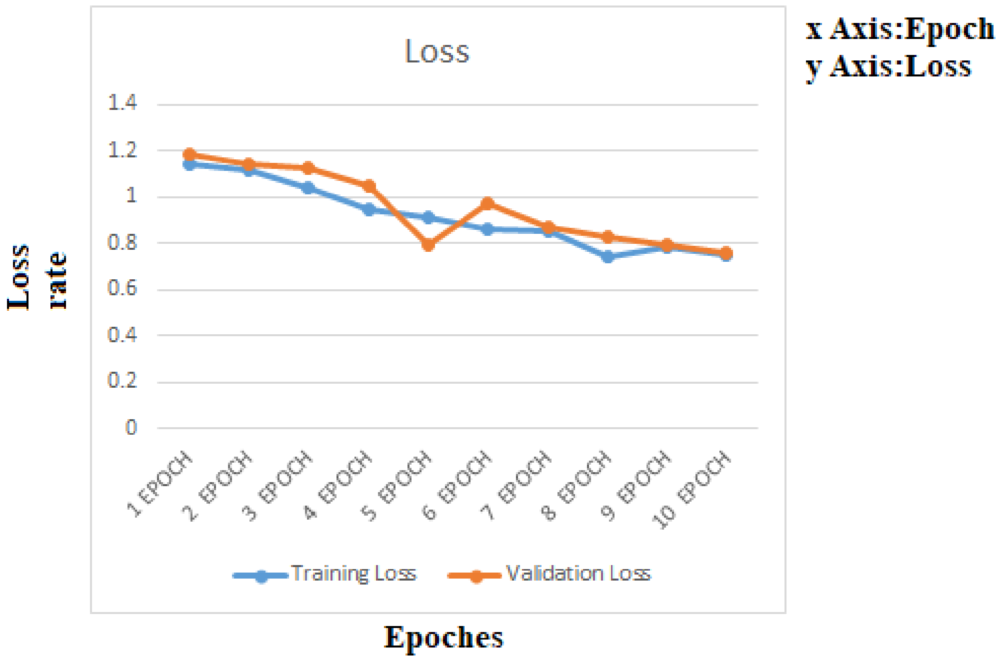

Figure 5(C). Loss history of model 2

The loss history of model 2 is shown in figure 5(C). At the 1st epoch, the training loss is 1.14 and it reduces to 0.74 at the 10th epoch. Concerning validation loss, it is 1.18 at 1st iteration and it reduces to 0.75 at the 10th epoch.

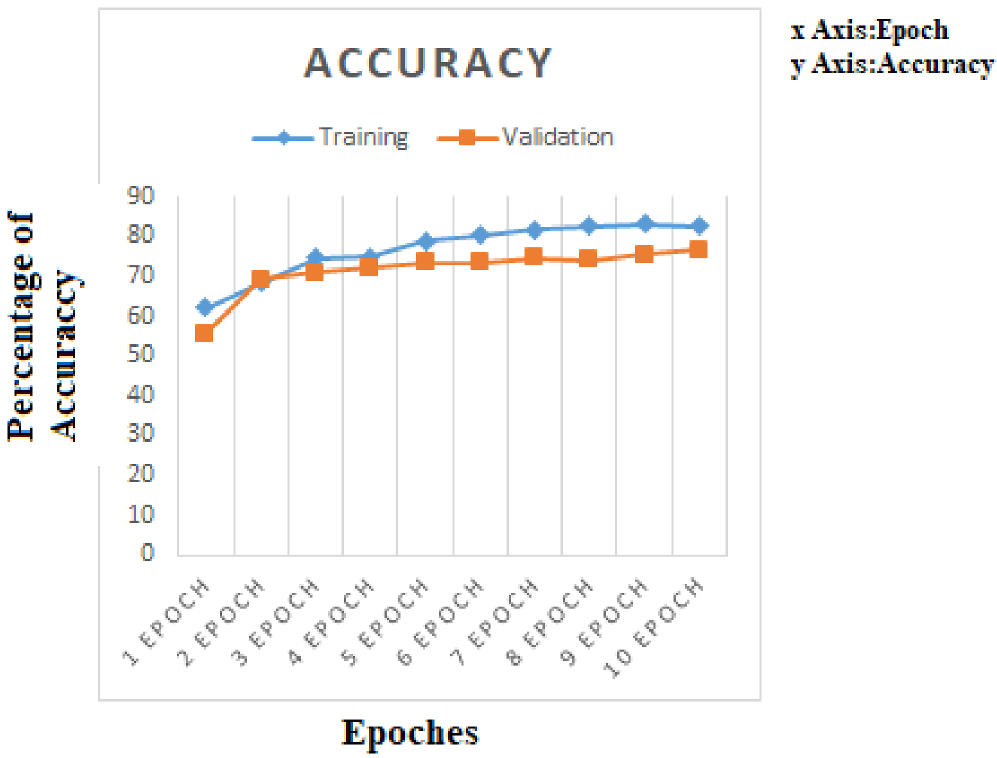

Figure 5 (D). Accuracy history of model 2

The figure 5(D) shows the accuracy history of model 2. The training accuracy is 62.34% at 1st epoch and increases to 82.65% at 10th epoch. With respect to validation data, accuracy is 55.67% at 1st epoch and 76.78% at 10th epoch.

The performance of models is evaluated using the confusion matrix. The performance of models is evaluated using the performance metric values such as accuracy, precision, sensitivity, specificity, and f1 score, and they are depicted in equations 3, 4, 5, 6 respectively.

$$Accuracy = \frac{T_P+T_N}{T_P+T_{N+F_P+F_N}} \text{ x } 100 \tag{3}$$

$$\text{Precision} = \frac{T_P}{T_P+F_P} \text{x}100 \tag{4}$$

$$\text{Sensitivity(Recall)} = \frac{T_P}{T_P+F_N} \text{x}100 \tag{5}$$

$$\text{Specificity} = \frac{T_N}{T_P+F_{NP}} \text{x}100 \tag{6}$$

$$f1 - Score = 2 * (Recall * Precission)/(Recall + Precission) \tag{7}$$

Accuracy predicts, how efficiently the model predicts the output. The precision indicates, how many positive inputs are correctly classified.

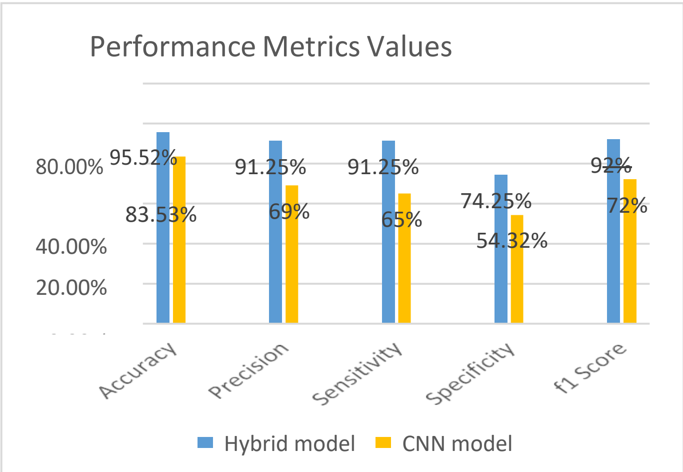

Figure 6. Performance metrics values

In fig. 6, the performance metric values of Model1 and Model 2 are compared. This shows that Model 1 works more efficiently in detecting and classifying the stages of Alzheimer's disease when compared to Model 2.

5. Conclusion

Alzheimer's is a neurodegenerative brain disease; no medicine can cure this disease but early detection can help patients to devise plans for their future. This paper experimented with two deep learning models for detecting and characterizing the stages of the disease. The Hybrid model shows the best performance compared to CNN by obtaining an accuracy of 95.52%. In the future, experiment may be performed with another dataset from different organization and different modality datasets could be used for the experiment.

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