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Improved Alzheimer Detection using Image Enhancement Techniques and Transfer Learning

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***Abstract*—Alzheimer Disease [AD] is a neuro-degenerative disease which, supported by its 'progressive nature' causes loss of function of neurons. Despite substantial research on the application of deep learning algorithms for the identification of Alzheimer's disease, few studies have focused on the image preparation procedures, which are critical in any computer-aided diagnosis system. In fact, the image processing model proposed outlines the criteria for denoising, contrast enhancement, feature extraction, classification, segmentation, and other image processing operations. A central focus of our work is to advance AD detection via transfer learning and image enhancement techniques using magnetic resonance imaging (MRI). Image quality, which is improved during the preprocessing stage, can have a considerable impact on diagnosis. In this research paper, we are representing the image enhancement in multilevel classification of Alzheimer's disease using the kaggle dataset with a pre-trained VGG16 deep learning architecture. The MRI dataset was enhanced separately with the Contrast Limited Adaptive Histogram Equalization (CLAHE) method, the Fuzzy Color Image Enhancement (FCIE) algorithm, the Hyper column technique, and skull stripping followed by Gaussian smoothing. The retrieved deep features were concatenated to form an ensemble, followed by AD classification with SVM classifier, using all possible combinations of original and enhanced datasets taken three at a time. By combining deep features retrieved from the FC-8 layer of the VGG model trained on original, fuzzy enhanced, and CLAHE datasets, we attained the best accuracy of 99.33%. The obtained results demonstrate that the dataset enhancement strategy has been proven to improve the proposed approach's prediction success.**

Keywords—Alzheimer Detection, Fuzzy Image Enhancement, Histogram Equalization, Hypercolumn technique, MRI, Transfer Learning

I. Introduction

Alzheimer's disease (AD) is a progressive and irreversible neurological (brain) syndrome that results in a serious loss of cognitive ability that worsens with time. The disease is named after Dr. Alois Alzheimer, who first detected abnormalities in his patient's brain tissues after she died from an uncommon mental ailment. It is the most prevalent cause of dementia, contributing to 60–70% of the total cases and, presently, the seventh biggest cause of mortality in the world among all diseases [1]. It damages the memory as well as the thinking ability of the individual, causing trouble in carrying out even the simplest of tasks [2]. Dementia mostly affects individuals who are older, and therefore, its symptoms are misinterpreted as signs of normal aging. The common symptoms include forgetfulness, poor concentration as well as social behaviour, problems in performing familiar tasks, etc. Although the medical fraternity has been unable to find a sure-shot treatment for AD-related diseases, there are still certain methods including pharmacological and non-pharmacological techniques, which are known to slow down its further succession. These techniques help provide a better quality of life for the patient. Therefore, an early diagnosis of AD is necessary. To do this, it is necessary to detect the current stage of AD in the patient.

Over the years, many medical imaging techniques have been used to diagnose AD, such as Computed Tomography (CT scan), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET) scan. Among them, MRI is the preferred technique most frequently used in the detection of diseases. Unlike CT and PET scans, which expose the patient to ionizing radiation, MRIs do not use ionizing radiation and are non-invasive imaging technologies that provide good spatial and temporal resolution [3]. To determine the severity of developing dementia, experts typically have to conduct detailed clinical assessments of patients. The clinical diagnosis of AD thus requires an extremely high level of precision and accuracy. However, this manual technique may be time-consuming, prone to errors, and can compromise life. As a result, the development of computer-aided systems with high accuracy is critical for the early identification and diagnosis of Alzheimer's disease, which will also help reduce the workload of doctors.

Compared to classical machine learning, which requires handcrafted image features, deep learning methods are capable of efficiently learning meaningful representations and characteristics automatically from raw data. As a result, feature extraction and classification tasks are combined into a single problem, resulting in an improved training procedure [4, 5]. Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), has recently shown to be an excellent technique for visual feature extraction, delivering state-of-the-art (SOTA) solutions in medical image analysis. As a result, a deep learning-based strategy was used in this study to categorize AD based on its severity utilizing the brain MRI modality. The primary objective of the proposed approach is to emphasize the effects of different image enhancing techniques in medical image classification. To begin, the original MRI dataset was individually enhanced with Contrast Limited Adaptive Histogram Equalization (CLAHE), the Fuzzy Color Image Enhancement (FCIE) algorithm, the Hypercolumn technique, and skull stripping, followed by a Gaussian filter. Then, using all the possible combinations of original and enhanced datasets, selecting three at a time, deep features were extracted from the pre-trained Visual Geometry Group-16 (VGG16) convolution neural network architecture and concatenated to form an ensemble of efficient features, followed by multi-class classification of AD using the support vector machine (SVM) classifier. The results are evident that our proposed methodology, which primarily focuses on the role of the image enhancement process in disease detection, led to an improved classification performance.

Our paper is divided into various sections, which are organised as follows: Section 2 discusses relevant work by other authors, while Section 3 covers the dataset, deep learning model, and enhancement strategies that we have investigated in our workflow. Section 4 contains a report of the findings and Section 5 concludes the study by summarizing results drawn from our current work.

II. Related Paper Works

Several studies have lately been undertaken by various researchers employing deep learning models and related approaches for the detection of Alzheimer's disease. A number of research papers have used the Kaggle dataset, which is described further in Section 3. This section contains some of the work linked to our study.

In [6], a CNN model was developed for the categorization of AD using the kaggle dataset, and SMOTE was employed to alleviate the problem of class imbalance. The network with reduced parameters obtained a 95.23% accuracy and a 97% AUC score. The study [7] used CNN, VGG16, and VGG19 architectures for multi-class classification of the kaggle AD dataset. Image data normalization and augmentation were performed. Among the three models evaluated, VGG19 performed the best by achieving an accuracy of 77.66%, while the basic CNN model achieved the lowest computation time. The researchers of [8] classified AD into four categories using a simple CNN architecture and transfer learning models such as VGG16, ResNet50, and Alexnet. In place of the conv-conv-pooling layer, Alexnet was changed to incorporate a conv-pooling layer. With an accuracy of 95.70 percent, the modified AlexNet with parameter tweaking surpassed the other networks. A hybrid approach was employed in [9] wherein the deep features extracted from the Darknet53, InceptionV3, and Resnet101 models were concatenated, followed by optimization using the mRMR feature selection technique and classification using KNN and SVM classifiers. In the proposed hybrid model, the KNN classifier obtained better results compared to the SVM classifier, achieving an accuracy of 99.1%. The study [10] employed the grey wolf optimization technique for texture-based feature retrieval along with decision tree, KNN, and CNN model for AD classification and achieved 96.23% accuracy. Several pre-trained CNN architectures were employed for AD diagnosis in the research [11]. In addition, a hybrid method was developed that involved fine-tuning of the Resnet-50 base model. The success rate obtained in the proposed model (90% accuracy) was higher than the pre-trained CNN models. In [12], 3D MR image data was split into two-dimensional MRI scans and binary classification was performed using transfer learning models. The VGG16 deep learning model attained an accuracy of 93% whereas the success rate with MobileNet architecture was 98%. Capsule Network, which works by adding structures called capsules to a convolutional neural network and replaces max-pooling with the Routing-By-Agreement algorithm was employed in [13] for prediction of AD. The proposed approach attained an accuracy of 93.5%.

As per related literature, deep convolutional neural networks and transfer learning approaches have been devised in this domain. However, the majority of these investigations failed to account for the essential pre-processing measures to increase the quality of MR images. In comparison to the studies reviewed in the literature, our proposed methodology focused on a slightly different perspective by incorporating transfer learning and different image enhancement techniques to improve both the quality of brain MRI as well as aid early detection of AD.

III. Methods and Materials

A. *Dataset*

The dataset was obtained from the Kaggle platform and total of 6,400 MR images in JPG format are available. The dataset is divided into four categories, representing the four different stages of AD. These classes are Mild Demented (MID), Moderate Demented (MOD), Non-Demented (NOD), and Very Mild Demented (VMD) [14]. The images have a resolution of 208 x 176. Table 1 shows the distribution of images in each class.

TABLE I. Dataset Distribution

Class	Number of Images
Mild Demented (MID)	896
Moderate Demented (MOD)	64
Non Demented (ND)	3200
Very Mild Demented (VMD)	2240

Besides implementing different image enhancement techniques, the MR images in each of the datasets were resized using bicubic interpolation to a size of 224 x 224 pixels so as to match the input dimension necessities of the VGG16 model. Due to the high level of noise along the edges in MR images, this interpolation technique was preferred since it preserves the fine details better and produces a smoother curve compared to other methods [15]. Normalization was used to scale the intensity values between the range of 0 and 1 before feeding the preprocessed input data to the fine-tuned VGG16 model so as to speed up the training procedure for optimal learning. Fig. 1 depicts an example of data for each class.

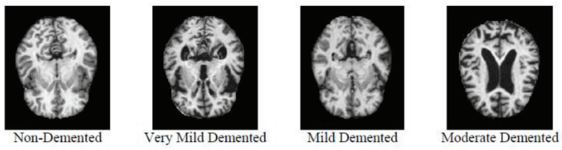

Fig. 1. MRI Dataset

B. *Data Augmentation*

If the dataset in a deep learning model is rich and adequate, the model performs better and is more accurate.

Image data augmentation can provide image variations that can improve the generalization performance of the model, i.e., the capacity of the neural network to adapt effectively to new unseen data, thus decreasing model overfitting, particularly when data is limited. As a result, multiple on-the-fly data augmentation procedures were utilized to minimize overfitting, address the class imbalance problem and boost the model performance. These include horizontal flipping, random rotation (0-15 degrees), and brightness level change.

C. *HyperColumn Technique*

For classification or recognition tasks, CNNs often use the output of the dense layer as a feature representation vector. However, the information in this layer is too imprecise in terms of spatial resolution to allow for exact localisation since the features of the ConvNet are more generic in the initial layers and more specific to the source dataset in the deeper levels of the network. With the help of the hypercolumn technique, the local discriminative signals derived from the layers located at the varying levels of the deep neural networks can be retained [16]. This allows spatial position information from earlier layers to be brought in along with the semantic information, thereby resulting in a more accurate prediction result. This approach stacks the efficient feature maps acquired from the convolutional and pooling layers of the CNN model's hierarchy on top of the original image, resulting in a hyper vector of pixels that holds activations of all CNN units above that pixel.

D. *Skull stripping followed by Gaussian Smoothing*

Since the background of the MRI image does not contain much relevant information and just adds to the processing time, therefore to eliminate the skull part, Otsu Thresholding was first used to automatically determine the threshold value and segment the image into background and foreground. Then, using connected component analysis, which groups image pixels into components based on pixel connectivity, was performed to extract the region of interest from the MRI. Thereafter, a Gaussian filter was employed to improve the image quality while minimizing noise for better diagnosis since brain MRI images are more susceptible to noise than any other medical image [17].

E. *Contrast Limited Adaptive Histogram Equalization*

CLAHE is a type of adaptive histogram equalization (AHE) that restricts contrast amplification in order to reduce the noise amplification that exists in traditional histogram equalization (HE). It functions differently from HE in the respect that it operates on small portions called tiles rather than the entire image, calculates multiple histograms, each corresponding to a specific region of the image, and then redistributes the portion of the histogram that exceeds the clip limit equally across all histograms [18]. To remove artefacts, bilinear interpolation technique is used to connect the neighbouring tiles after equalization. In a nutshell, CLAHE is an image processing technique that efficiently enhances the image by conducting histogram equalisation in tiny patches with high precision and contrast limiting, preventing over-enhancement of noise and reducing the edge shadowing impact of AHE.

F. *Fuzzy Color Image Enhancement*

The FCIE algorithm is one of the preferred techniques for improving the quality of low-contrast images, which in turn increases the perceptibility of the image. Each image is first transformed from the spatial domain to the fuzzy domain, where each pixel has a membership degree assigned to it that defines the level of fuzzy partitioning based on its position in the histogram, followed by the maximisation of the fuzzy level parameters of the image by using a membership function that changes the image from low to high contrast [19]. Finally, the transformed fuzzy enhanced picture is defuzzified and translated back into the spatial domain.

G. *Network Architecture: VGG16*

The term “VGG” stands for Visual Geometry Group, a group of scholars at the University of Oxford who developed this architecture. The architecture of VGG16 consists of 13 convolutional layers and three fully connected (FC) layers. The first two dense layers contain 4096 channels each, while the third has 1000 units, each corresponding to a specific class in the ImageNet dataset. The last layer employs a soft-max activation function to determine the conditional probability of each class given a 224x224 input image. A 3x3 or 1x1 filter is used. For 3 x 3 convolutional layers, the stride and padding are kept to 1 pixel so as to ensure that the spatial resolution is retained after convolution. The overall structure consists of five sets of cascaded convolutional layers, followed by MaxPooling which is done across a 2×2 pixel window with a stride of 2. As we proceed through the network to higher levels, the number of channels increases in subsequent layers since the deeper layers can capture more complex characteristics and thus require a larger receptive field [20]. All the hidden layers utilize the Rectified Linear Units (ReLU) activation.

The VGG16 model was modified by introducing a new untrained dense layer, containing neurons equal to the number of classes in our classification task, at the end of the network. The dropout layers (with dropout rate of 0.2) were also included in the classifier portion of the model since it is an excellent regularisation strategy for reducing overfitting and improving the generalisation of the trained model. The categorical cross entropy loss function was employed for multiclass classification. Fig 2 shows the flow chart for AD classification using the fine-tuned VGG16 model.

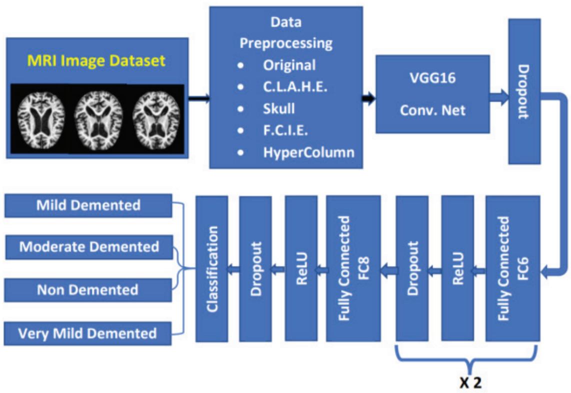

Fig. 2. Flow diagram of the proposed methodology

The original architecture was initially trained on a dataset containing natural images, but since our application domain i.e. classification of medical images is slightly different, therefore we used ConvNet as weight initialization, unfroze all the layers and trained the entire network which enabled all the weight parameters of the fine-tuned model to change in. order to learn the subtle changes unique to our task [20]. The categorical cross entropy loss function was employed for multiclass classification. Table 2 depicts the specified important parameter values for the fine-tuned VGG16 model.

TABLE II. IMPORTANT PARAMETERS OF VGG16 NETWORK

Hyperparameter	Name/Value
Input Size	224 x 224 x 3
Optimizer	Stochastic Gradient Descent (SGD)
Loss Function	Cross Entropy
Initial Learning Rate	0.001
Momentum	0.9
Decay	1e-6
Batch Size	64
Epochs	75 with early stopping

H. Support Vector Machine

The Support Vector Machine, abbreviated as SVM, is a well-known supervised machine learning algorithm for classification applications. It utilizes a technique known as the kernel trick to transform input data into a higher dimension till it becomes linearly separable, and then SVM determines an optimal decision boundary in the N-dimensional feature space, where N is the number of features in the dataset, that effectively distinguishes the data points into their respective classes. It also incorporates two important hyper-parameters, C and Gamma. The soft margin cost function parameter C governs the influence of each individual support vector, whereas gamma specifies the amount of curvature in a decision boundary [15]. This study employs the two most often used kernel functions in the SVM classifier: (1) Polynomial kernel and (2) Radial Basis Function (RBF) kernel. The gamma and C values were set to [0.0001, 0.001, 0.01, 0.1, 1] and [1, 10, 100, 1000, 10000] respectively, and optimal values of these hyper parameters were selected for each of the classification tasks using the Random Search approach.

IV. RESULTS

The following evaluation metrics 1-4 were used in the experiment:

Recall - Recall can be defined as the ratio of accurately predicted positive examples to all the positive examples in a given class.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{1}$$

Precision - It is defined as the proportion of accurately predicted positive samples to the total predicted positive samples in a given class.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Accuracy - It refers to the total number of observations predicted correctly by the model in percentage.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

F1 Score - F1 Score is the weighted average of the model's precision and recall.

$$\text{F1 Score} = \frac{2*TP}{2*TP+FP+FN} \tag{4}$$

TP = True Positive TN = True Negative
FP = False Positive FN = False Negative

First, we trained the original dataset with the VGG16 model, and got an overall accuracy of 97.65% on the test set. In the second stage, the same dataset was reconstructed using the Hypercolumn technique, skull stripping followed by a Gaussian filter, and the CLAHE and FCIE methods. Then the VGG16 model was separately trained on each of the enhanced MRI datasets. The overall accuracy success rate using the Hypercolumn technique was 94.37%. Classification using skull-stripped dataset followed by Gaussian smoothing yielded an accuracy of 97.81%. The classification success rate for data enhancement using the FCIE approach was 96.56%. The highest success rate was obtained with the CLAHE dataset, achieving an accuracy of 97.97%. Bar plot depicting model's performance with different enhanced datasets for multi-classification of AD is shown in Fig 3.

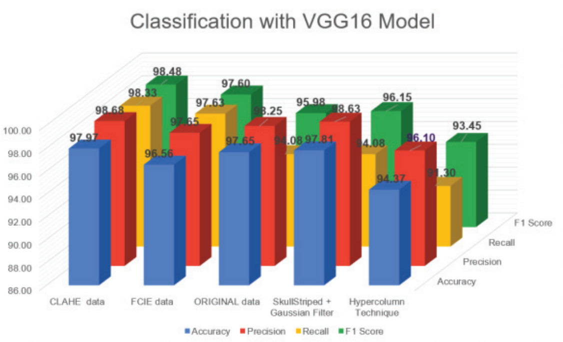

Fig. 3. Performance of VGG16 with different enhancement datasets

The next phase of the experiment involved feature extraction using the Fully Connected-6 (FC) layer of the VGG16 model and developing a hybrid of deep features followed by SVM classification. Using all the different possible combinations of original and recreated datasets, selecting three at a time, which resulted in a total of 10 combinations ($^5C_3$), 4096 deep features extracted from each of the three feature sets were concatenated to form a new feature set containing 12,288 features. The SVM was then used to classify the combined feature set. The classification yielded a maximum accuracy rate of 99.07% using the ensemble of deep features obtained from the original dataset, CLAHE, and Hypercolumn techniques. Fig. 4 shows the class-wise f1-score obtained for different hybrid datasets by using the output of FC-6.

The overall success rate in this phase yielded a more successful outcome than in the first two phases. However, since the train data contained too many features (12,288), we performed re-classification using the output of the FC-8 layer as a deep feature extractor. The procedure used in the third stage was repeated in this stage as well, with the only difference being the number of features. In the fourth step, 1000 deep features were extracted and concatenated to develop a new set of features containing a total of 3000 features, followed by classification using SVM. This time, the best success rate was obtained using the combination of the original dataset, FCIE and CLAHE methods, with an accuracy of 99.33%. Fig. 5 shows the class-wise f-1score obtained for different hybrid datasets by using the output of FC-8.

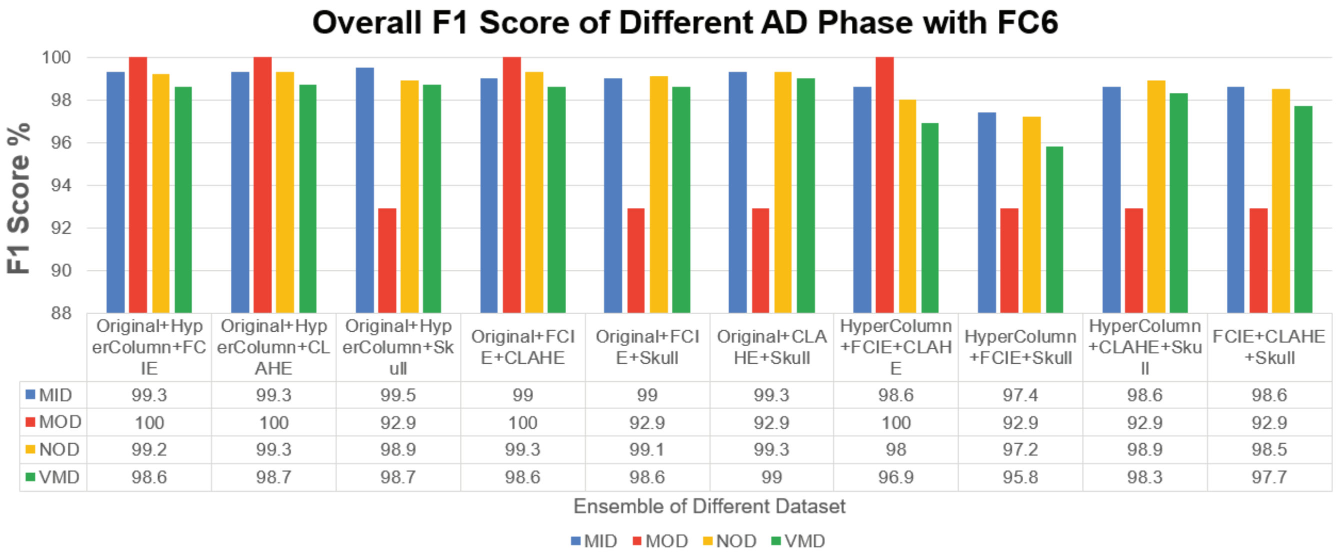

Fig. 4. F1-Score of different ensembles for each AD phase using feature extraction from FC-6

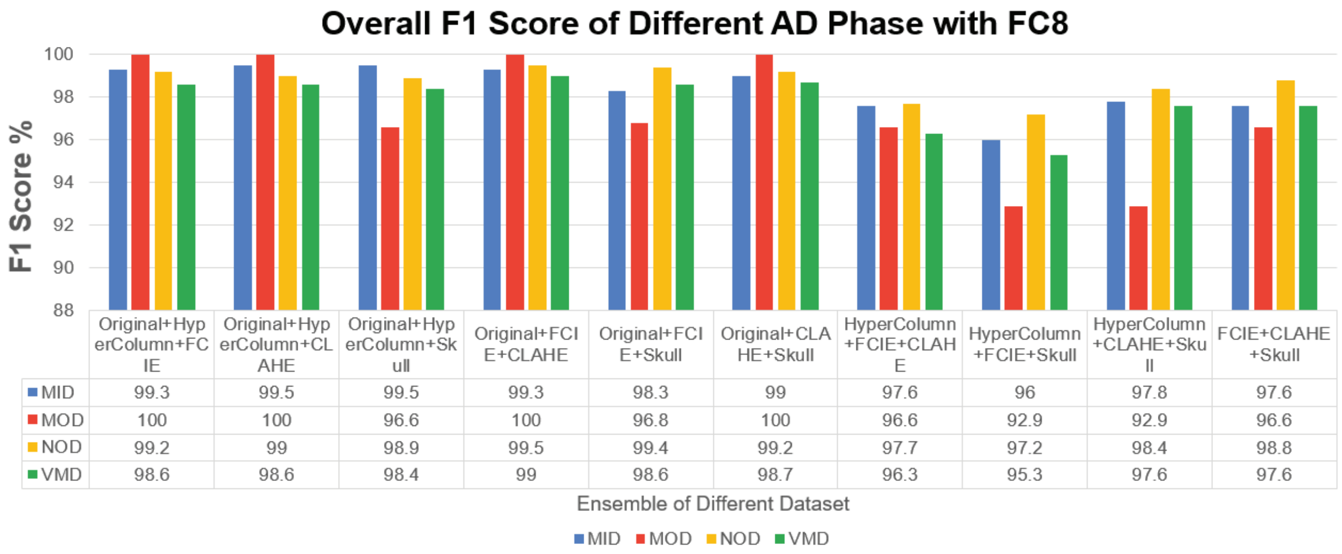

Fig. 5. F1-Score of different ensembles for each AD phase using feature extraction from FC-8

Fig. 6 provides a comparative analysis between the obtained overall accuracies for different hybrids using the outputs of the FC-6 and FC-8 layers followed by the SVM classifier.

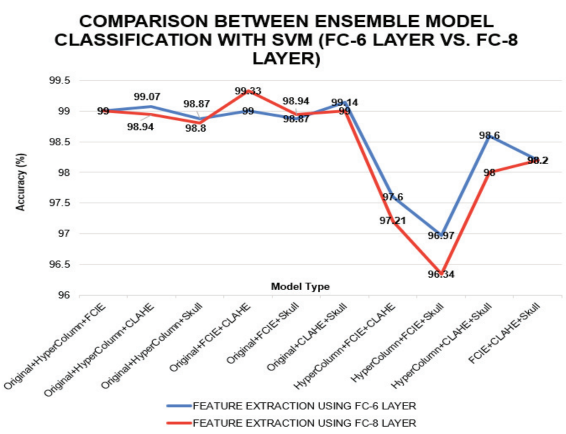

Fig. 6. Ensemble Model Accuracy comparison with FC-6 and FC-8 Layer

Though there isn't much of a difference in terms of accuracy between the classification models using feature extraction from the FC-6 and FC-8 layers of the VGG16 model, the number of characteristics were lowered in this phase. Further, we noticed that SVM with polynomial kernel performed better than other kernels.

V. Discussion and Conclusion

Image preprocessing is the first and foremost step in the CAD system that involves improving the quality of brain MR images in order to make them suitable for further processing. The brain MRI picture contains low contrast and different forms of noise. Image enhancement methods and noise reduction not only improves the visual quality of the image but also make it easier to extract information from the original image, thus leading to an increase in the efficiency of the classification models. The intricate structure of the brain makes it difficult for experts to determine a person's Alzheimer's stage. Through this research work, we proposed a methodology that integrates image processing and transfer learning techniques to improve decision-making as well as simplify this complex process. Different types of image enhancement techniques were utilized to validate their effectiveness in improving the classification of AD.

The goal here was to successfully categorise the phases of Alzheimer's disease using the deep learning approach. The fine-tuned VGG16 network was employed as a deep feature extractor in this study. Various measures were undertaken to prevent overfitting of the models including dropout layers, data augmentation and early stopping. The highest accuracy of 99.33% was achieved by combining deep features from the FC-8 layer of the VGG16 deep learning model trained on original, fuzzy enhanced (FCIE), and CLAHE datasets. The experimental examination of this work showed that by employing data-enhancing methodologies and procedures, MR images provided good outcomes in the detection of AD phases. We intend to test our suggested model further with additional datasets in order to validate its usefulness, as well as to combine it with other techniques.

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