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An ensemble of CNN architectures for early detection of alzheimer's disease using brain MRI

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ABSTRACT

Early detection of Alzheimer's disease (AD) has proven to be helpful and effective in preventing the disease. If the risks and symptoms of AD are detected earlier, then it seems rather promising that the death ratio of AD might decrease as it can help a lot of patients get treated before it's too late. Our study demonstrates promising results, achieving a remarkable accuracy of 96.52% through the utilization of the EfficientNetB2 and EfficientNetB3 models. By leveraging transfer learning, we leverage pre-trained models' knowledge to optimize the learning process, while ensemble learning further improves performance by aggregating predictions from multiple models. The integration of these methodologies provides an effective and efficient means of detecting Alzheimer's Disease at an early stage, thereby offering potential benefits to patients, caregivers, and healthcare providers alike. These findings pave the way for improved diagnostic tools and contribute to the advancement of AD research and patient care.

1. Introduction

Alzheimer's disease (AD), the most prevalent type of dementia in the senior population, is a progressive, degenerative brain condition that gradually impairs memory and cognitive function. Almost 50 million individuals worldwide suffer from Alzheimer's disease or another kind of dementia. [1] A patient cannot be adequately diagnosed with Alzheimer's Disease (AD) unless they have minor forms of the condition. To be effective in therapy and to avoid brain damage, AD must be identified and classified early.

Alzheimer's disease must be diagnosed using a variety of tests, including a comprehensive medical history, a mental state assessment, and a physical examination. However, the most affected and popular neuroimaging technology is the use of MRI scans to diagnose Alzheimer's disease patients. Recent research has demonstrated that MRI-based classification systems can be greatly enhanced by machine and deep learning methods [2].

Deep learning is a subtype of machine learning in AI that allows machines to learn categorization tasks from raw data due to its layered or ordered network structure [3,4,5,6]. Researchers can employ deep learning to analyze patient data and develop treatments for a variety of conditions. Deep learning has played a huge role to analyze MRI, CT scans, and X-ray images to classify many rare diseases such as mouth cancer, uterus cancer, and dermatology [7].

CNN is the most popular deep learning algorithm due to its excellent performance in image analysis and classification, and it is employed in neural networks to extract high-level features for classification and prediction [8, 9]. This algorithm is very good at recognizing patterns and working with images. It takes an image as input and uses it to train a model that can then extract features from the image and identify patterns in the image. CNN uses these patterns to determine the similarities between the new input and the pattern.

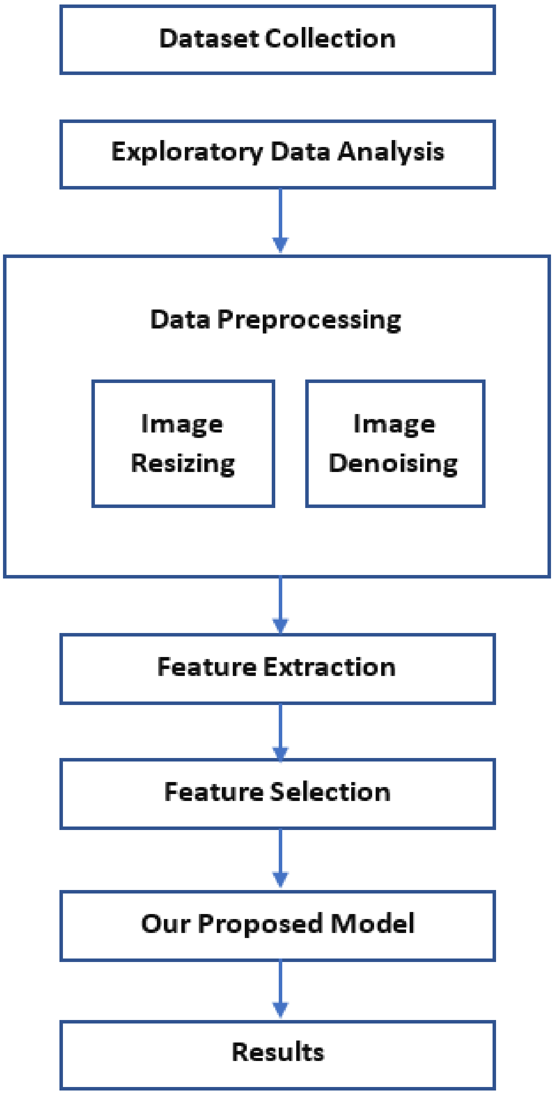

Fig. 1. Proposed Methodology

Since Alzheimer's disease detection using CNN is a well-established study area, we found remarkable works in this subject. Some genuinely impressive studies have been conducted in recent years on the OASIS dataset by means of Convolutional Neural Networks or Artificial Neural Networks (ANN). However, there are some limitations in the existing research works mentioned as follows:

1. The accuracy of some of them is far lower than that of others[10].

2. While some models have been shown to attain higher accuracy than others, their performance is not properly demonstrated against the pre-trained models [11].

3. Other studies have looked solely at the effectiveness of already-trained models for Alzheimer's detection, without offering any novel solutions [12].

Thus, the aim of this paper is to introduce a model that can address the aforementioned limitations. Our proposed model uses a transfer learning approach. It is an ensemble of three variants of each model that includes ResNet, VGG, DenseNet, and EfficientNet. We have applied these models to extracted feature. The output of these models is ensembled together by using a voting technique to get the final accuracy of the combined three variants.

This research paper's remaining section is divided into different sections: Section 2 covers significant study findings that are published in the literature; section 3 discusses the relevant approaches used to classify the stage of AD. The experimental results and discussion are presented in Section 4 and the conclusion of the current study project is covered in Section 5.

2. Related Work

Artificial intelligence has been beneficial in tackling challenging tasks that require extensive human efforts. AI-powered systems are deployed in various domains, including finance, telecommunication, healthcare, marketing, and many more. Developing automated systems in healthcare can save many lives by detecting diseases at a very early stage. AI technology has shown a vast potential to aid in the early diagnosis of dementia. Appropriate consideration should be given to deploying machine learning models and neural network methods to utilize brain MRI images to detect dementias such as AD.

The use of machine learning to identify Alzheimer's disease in its early stages has been the subject of extensive study lately. In [13], researchers have used data dimension reduction with SVM and multi-class classification on brain MRI data to distinguish between healthy brains and cognitively impaired brains. In [14], researchers have used manifold learning and deep belief network using MRI images. Multi-method analysis of MRI images has shown high accuracy in the early diagnosis of Alzheimer's, as shown in the literature [15-17]. Similar to these, researchers in [18] developed a multi-modal classification system using random forest on MRI image data and PET data.

Convolution neural network is already present in the form of AD detection models in the literature [19-23]. Moreover, the most accurate and widely deployed are a 12-layer CNN architecture to detect AD in [24] and an ensemble approach in [25]. Other widely used variations are PNN [26], ANN, and their variants.

In [1, 27], researchers extract various features from MRI images using Discrete Wavelet Transform (DWT), curvelet transforms (CuT), and complex wavelet transform (CWT) to detect AD. [28] suggests using a discriminative sparse autoencoder model to classify the disease into three stages by learning a set of bases from photos and using convolution to extract features from the dataset. In [29, 30] researchers used autoencoders along with 3D CNNs for AD detection.

Table 1 shows the comparison of various methods, and their accuracies.

Table 1

A comparison of different studies on Alzheimer's disease detection.

Research study	Model	Accuracy (%)
[31]	Multi-layer CNN	80
[32]	3D CNN	88
[33]	DenseNet169	87
[34]	VGG-19	88
[34]	SVM	81
[34]	Decision Tree	79
[34]	XBoost	80
[34]	Random Forest	81
[35]	Softmax Regression	94.5
[36]	Deep CNN	82
Proposed Approach	Ensembling + Transfer Learning	96.52

3. Methodology

The fundamental goal of the research was to create a reliable method for detecting Alzheimer's disease in 2D brain MRI images. The methodology implemented in this study is shown in Fig. 1.

Initially, the Open Access Series of Imaging Studies (OASIS) website was used to get the dataset. After collecting the images, Exploratory data analysis (EDA) was conducted on the dataset. In EDA various methods were applied including the mean, median and standard deviation on the brain MRI images. Thereafter, pre-processing was applied in order to enhance the images and resize them in a single shape of 225x225. Enhancement of the images was done by applying the histogram equalization algorithm implemented in the OpenCV library. Afterward, features were extracted from the brain MRI images, and three features were selected. Finally, several deep neural network algorithms were trained to classify the disease into four stages. Lastly, the performance of the trained models was validated based on accuracy.

3.1 Dataset Collection

The data for this study has been obtained from the OASIS website. The collection includes the records of 1379 participants, whose ages range from 42 to 96. Participants comprise 622 people at various stages and 755 adults with normal cognitive function. It includes four classes: Mild-Demented, Moderate Demented, Non-Demented, and Extremely Mild Demented.

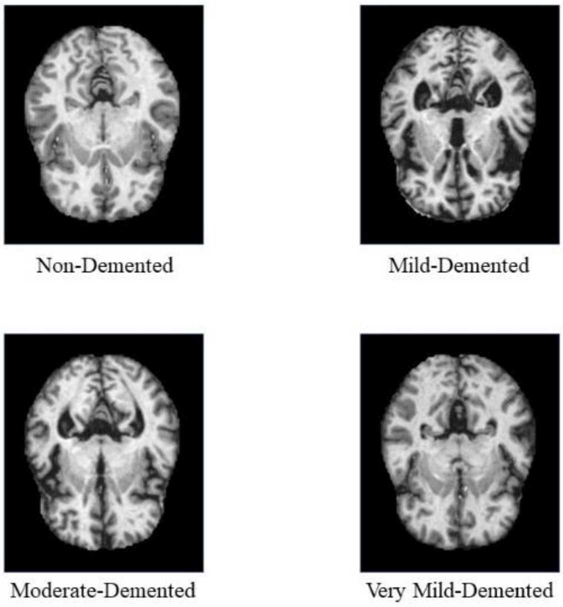

Fig. 2. Four classes present in the dataset

3.2 Exploratory Data Analysis

Exploratory data analysis is often done in order to remove outliers from data or to get significant insights from the data. After collecting the data from the OASIS website, we applied exploratory data analysis (EDA) to get insights from the dataset. We first found out the number of samples in the training and test set. As a result, the Non-Demented class has the most samples in both training and test sets while Moderate-Demented has the fewest samples among all classes as can be seen in Fig 3 and Fig. 4.

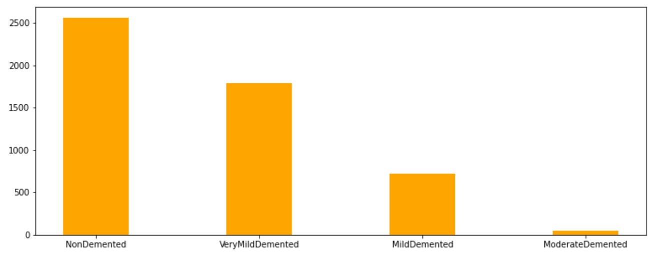

Fig. 3. Samples in the training set

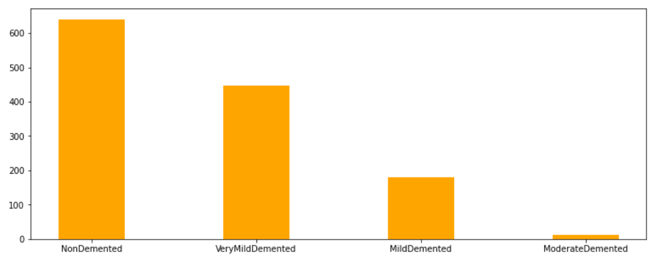

Fig. 4. Samples in the test set

In order to understand the central tendency of the dataset, we calculated the arithmetic mean of each class. As can be seen in Fig. 5, the mean of non-demented and moderately demented tend to show higher/darker obstruction around the image.

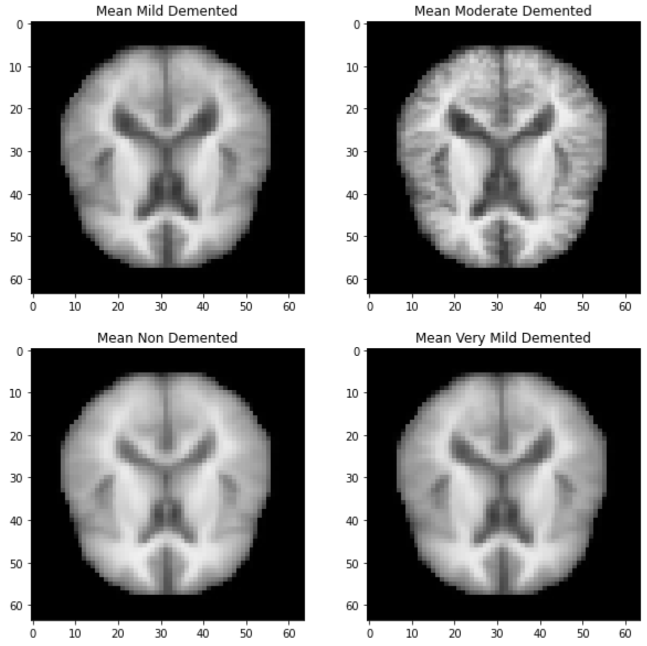

Fig. 5. Mean of each class

Thereafter, the median of each class was calculated in order to understand the central tendency and distribution of the classes in the dataset. Fig. 6 shows the median of each class available in the dataset.

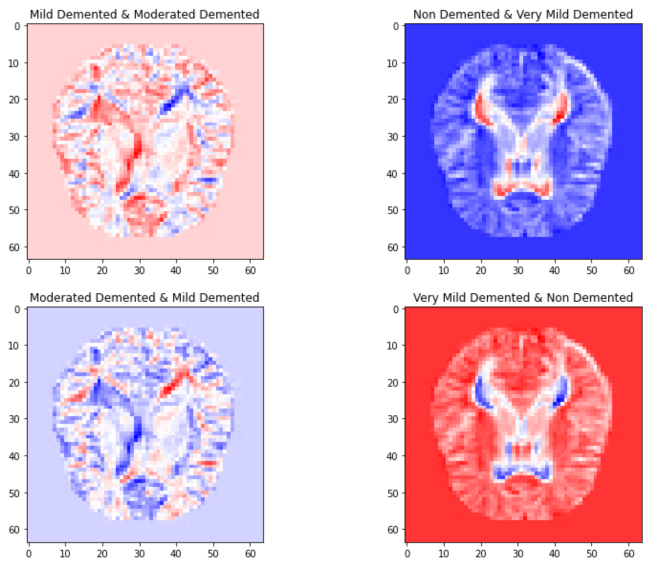

Fig. 6. Median of each class

3.3 Data Pre-processing and Feature Extraction

Pre-processing is often done to improve the overall quality of the images. In this study, Images were resized in 225 x 225 to bring uniformity to the dataset. To extract relevant information from the data, a feature extraction technique was employed. The OpenCV Library was utilized to extract three distinct features - edge, enhancement, and saliency - from the image. The edge detection is obtained using the canny edge detection algorithm Fig. 7(a).

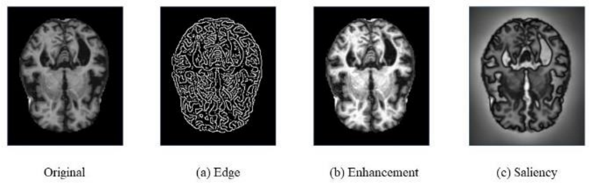

Fig. 7. Extracted features from the original brain MRI image

Enhancement has been achieved using the histogram equalization method as shown in Fig. 7(b). Finally, Saliency is extracted from the original MRI image. It was achieved using the static saliency method available in the OpenCV library as shown in Fig. 7(c).

3.4 Feature Selection

After feature extraction three features were selected. These features include Edge, Enhancement, and Saliency.

3.5 Proposed Model

The proposed model for our research is shown in Fig 8. Our model is an ensemble of two to three variants of a deep learning model. In this model, a 2D brain MRI is fed into the system, three features are extracted from Input MRI images as discussed above and then transfer learning is applied to each feature via fine-tuning the pre-trained model after that two or three models are ensembled via a voting technique which decides the result by the highest number of votes given to the particular class.

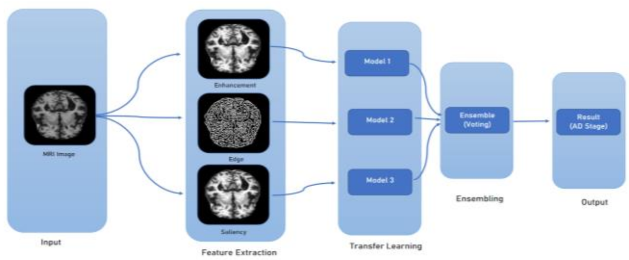

Fig. 8. Proposed model for early Alzheimer's disease detection

We have experimented with a variety of pre-trained deep-learning model variants such as ResNet, VGG, DenseNet, and EfficientNet. Further details about the variants are given in Table 2.

Table 2

Variants of pre-trained deep learning models.

Model	Variant-1	Variant-2	Variant-3
ResNet	ResNet-18	ResNet-50	ResNet-101
VGG	VGG-16	VGG-19	VGG-19
DenseNet	DenseNet-121	DenseNet-169	DenseNet-201
EfficientNet	EfficientNetB1	EfficientNetB2	EfficientNetB3

More detailed explanation of the model architecture used is given in Table 3. The pre-trained model acts as a base model and then various layers are added in order to optimize and get more accurate results.

Table 3

Model architecture used in experiments.

Layer	Output	Parameters
Input layer	(None, 7, 7, 512)	14714688
Dropout layer	(None, 7, 7, 512)	0
Flatten layer	(None, 25088)	0
Batch Normalization	(None, 25088)	100352
Dense layer	(None, 1024)	25691136
Batch Normalization	(None, 1024)	4096
Activation layer	(None, 1024)	0
Dropout layer	(None, 1024)	0
Dense layer	(None, 1024)	1049600
Batch Normalization	(None, 1024)	4096
Activation layer	(None, 1024)	0
Dropout layer	(None, 1024)	0
Dense layer	(None, 1024)	4100

In order to prevent overfitting and improve the generalization performance of our models, we applied a number of techniques to address the possible overfitting issue caused by training. Firstly, we applied augmentations like rotation, scaling, and cropping to the original data using data augmentation techniques to create additional training instances. To make the training set bigger and more varied, we specifically added random horizontal and vertical flips, rotations, zooming, and shear to the images. We also used dropout regularization throughout the training phase, randomly eliminating 30% of the neurons.

For the training purpose, we have used hyperparameters such as the learning rate was set to 0.01, for 100 number of epochs, 64 as batch size, and categorical cross entropy as loss as shown in Eq. 1.

$$L(\theta) = -\sum_{i-1}^{n} y^{i} \log(\hat{y}i) \quad (1)$$

Where y^i is the actual value, $\hat{y}i$ is the prediction and n corresponds to the total number of samples.

The performance of the models has been evaluated using the accuracy metrics as shown in Eq. 2.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP+FP+TN+FN})} \quad (2)$$

Where TP and TN stand for true positive and true negative, respectively.

4. Results and Discussion

The experimental results obtained in this study are presented in this section. In this research, we have performed experiments on the three extracted features and three variants of pre-trained models. Table 3 shows the performance of each variant of pre-trained models on three unique features. EfficientNetB2 achieves the best accuracy of 95.71% on saliency features, and EfficientNetB3 achieved an accuracy of 93.34% on the enhanced feature. All other models and their variants achieved the highest accuracy of between 84.18% and 91% on the saliency feature. Fig. 9-12 shows the validation accuracy graph of each model on three features. DenseNet was the best performing model after EfficientNet which achieves the highest accuracy of 91.72% on saliency and 91.32% on the enhanced features. Overall, EfficientNet performed well on the saliency as well as enhanced features, and all the models including EfficientNet did not achieve impressive performance on edged features.

Tables 5 and 6 show the performance of two and three features ensembled. As we can see the proposed ensemble model achieved encouraging results on two features ensembled with EfficientNetB2 and EfficientNetB3 with the highest performance of 96.52%. Overall models trained on saliency and enhanced features perform well in the combination while edged features reduce the overall performance of the models.

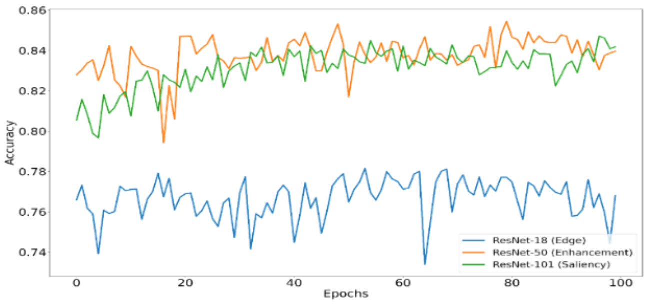

Fig. 9. Validation accuracy of ResNet variants on three features

However, in three features ensembled, we achieve the highest accuracy using the EfficientNet variants at 91.09% due to the performance of the EfficientNetB1 on edge feature.

Table 4

Performance of various models on three unique features.

Model	Feature	Accuracy
ResNet-18	Edge	76.18%
ResNet-50	Enhancement	83.97%

Model	Feature	Accuracy
ResNet-101	Saliency	84.18%
VGG-16	Edge	79.95%
VGG-19	Enhancement	87.84%
VGG-19	Saliency	88.81%
DenseNet-121	Edge	83.15%
DenseNet-169	Enhancement	91.63%
DenseNet-201	Saliency	91.72%
EfficientNetB1	Edge	86.24%
EfficientNetB2	Enhancement	93.34%
EfficientNetB3	Saliency	95.11%

Table 5

Ensemble of two features. Here E and S stand for Enhancement and Saliency.

Model	Accuracy
ResNet-18 and ResNet-50	80.11%
ResNet-18 and ResNet-101	81.22%
ResNet-50 and ResNet-101	85.62%
VGG-16 and VGG-19 (E)	83.89%
VGG-16 and VGG-19 (S)	84.38%
VGG-19 (E) and VGG-19 (S)	85.32%
DenseNet-121 and DenseNet-169	87.39%
DenseNet-121 and DenseNet-201	87.43%
DenseNet-169 and DenseNet-201	91.67%
EfficientNetB1 and EfficientNetB2	89.79%
EfficientNetB1 and EfficientNetB3	90.97%
EfficientNetB2 and EfficientNetB3	96.52%

Table 6

Ensemble of three features.

Model	Accuracy
ResNet-18, ResNet-50 and ResNet-101	86.33%
VGG-16, VGG-19 (E) and VGG-19 (S)	88.83%
EfficientNetB1, EfficientNetB2 and EfficientNetB3	92.03%

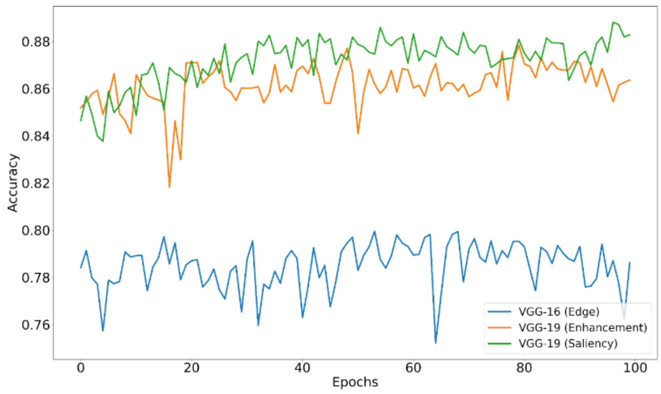

Fig. 10. Validation accuracy of VGG variants on three features

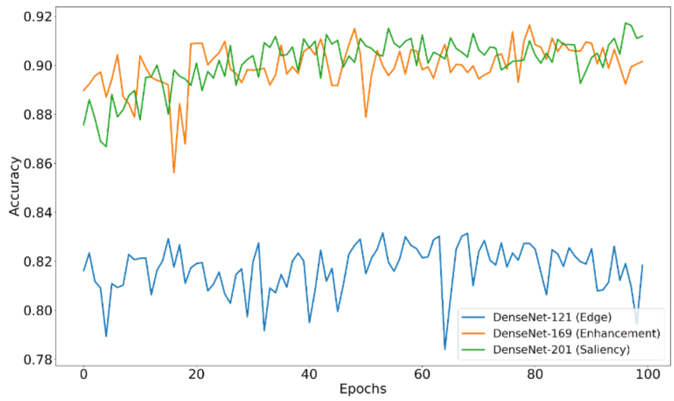

Fig. 11. Validation accuracy of DenseNet variants on three features

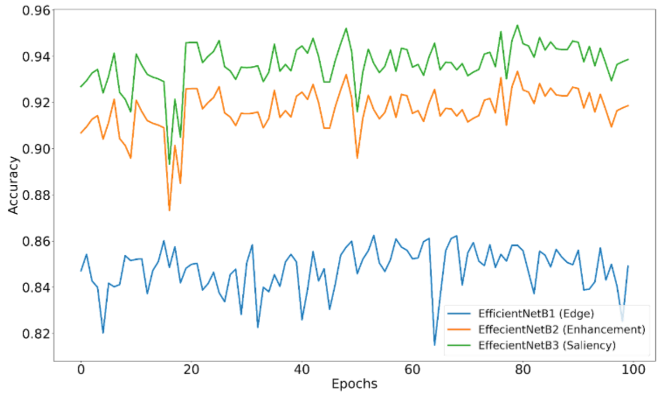

Fig. 12. Validation accuracy of EfficientNet variants on three features

5. Conclusion

In conclusion, this research has presented a novel approach for the early detection of Alzheimer's Disease (AD) using a combination of transfer learning and ensemble learning techniques. The significance of early detection of AD cannot be overstated, as it plays a pivotal role in improving patient outcomes and overall management of the disease. By identifying the risks and symptoms of AD at an early stage, we can offer timely interventions and treatments, potentially reducing the mortality rate associated with this devastating condition. The results obtained from our approach are highly promising, with an impressive accuracy of 96.52% achieved through the utilization of EfficientNetB2 and EfficientNetB3 models. Transfer learning proved to be an invaluable tool in leveraging the knowledge from pre-trained models, optimizing the learning process, and enhancing the predictive capabilities of our system. Additionally, ensemble learning further improved the performance by aggregating predictions from multiple models, resulting in a robust and reliable AD detection system. The findings of this research hold significant implications for the medical community, caregivers, and patients alike. By providing a more accurate and efficient means of detecting AD at an early stage, we aim to empower healthcare professionals to make informed decisions and design personalized treatment plans for affected individuals. While our study demonstrates promising results, we acknowledge that there are areas for future exploration and refinement. Further investigations into fine-tuning the model parameters and exploring different architectures could potentially yield even more accurate results. Moreover, expanding the dataset and conducting validation on a larger and more diverse population would strengthen the generalizability and real-world applicability of our approach.

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