Alzheimer's Disease Detection through MR images using Machine Learning and Deep Learning Techniques

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***Abstract*— A gradual and irreversible neurological ailment, Alzheimer's disease (AD) is typified by cognitive decline and memory loss. Early detection of AD is essential for decreased therapy and progression. Deep learning and machine learning algorithms have grown in importance as diagnostic tools in recent years for a wide range of illnesses. This study uses MRI images to examine the efficacy of machine learning and deep learning algorithms for Alzheimer's disease (AD) identification. A methodical approach is used to evaluate four classifiers: Random Forest, Support Vector Machine (SVM) with linear and polynomial kernels, Logistic Regression, and Convolutional Neural Network (CNN) using EfficientNetB0 architecture. The best accuracy, precision, recall, and F1-score are achieved by SVM with a linear kernel, according to the results, demonstrating the model's resilience in correctly differentiating AD patients from healthy controls. Logistic Regression also demonstrates strong performance, while Random Forest and EfficientNetB0 yield competitive results. These findings highlight the significance of model interpretation, hyperparameter optimisation, and algorithm selection for maximizing classifier performance in AD diagnosis tasks. By providing insights into efficient diagnosis techniques and opening the door for future research aimed at improving diagnostic accuracy and, ultimately, improving patient outcomes in AD therapy, the work advances machine learning and deep learning applications in healthcare.**

Index Terms— Alzheimer's disease (AD), Deep Learning, Machine Learning, Neurological disorder

I. INTRODUCTION

One of the most important issues facing modern medicine is Alzheimer's disease (AD). It is a neurodegenerative disease that causes severe cognitive deficits, such as disorientation, memory loss, and poor judgment, which ultimately results in a loss of independence and quality of life. With a rapidly aging global population, the prevalence of AD is predicted to escalate dramatically in the coming decades, necessitating urgent advancements in early detection and intervention.

Therefore, it's early detection is crucial before it reaches the danger stage. One of the stages of AD is MCI, which appears as a disease during the prodromal stage. MCI is a stage of memory loss or a reduction in other cognitive functions (such as language, visual, or spatial perception) in people who are still able to perform most of their daily chores on their own.

Even with great progress in comprehending the underlying biological mechanisms of AD, the diagnosis of the disease is still primarily clinical and frequently verified only after death. The potential efficacy of current medications is compromised by this diagnostic delay, which also reduces the opportunity to discover effective disease-modifying drugs. As a result, there is a growing interest in developing trustworthy and easily comprehensible predictive models for Alzheimer's disease among scientists and medical professionals.

The goal of research is to develop a simple and accurate approach to identifying Alzheimer's disease before any symptoms manifest. With the advancement of technology, efforts have been made to generate a tool that can be used to properly diagnose AD by detecting it in its earliest stages. In this quest, machine learning and deep learning approaches have emerged to be promising in their ability to predict AD with the highest degree of accuracy based on the understanding from the large amounts of image data.

II. LITERATURE SURVEY

For the prompt identification of Alzheimer's disease, Prasanalakshmi Balaji et al. [1] proposed a hybrid deep learning technique. The proposed model uses CNN with Long Short-term Memory Algorithm, multimodal imaging, and standard neuropsychological test scores in conjunction with MRI and PET. Their model's accuracy rate was 98.5%. A deep neural network approach was developed by Ruhul Amin Hazarika et al. [2] to classify AD. A selection of 12 of the most widely used DNN models were made for implementation. Although it took longer to compute, DenseNet outperformed the other models in terms of performance. Even while LeNet and AlexNet had faster computation times than DenseNet, their performance was slightly worse.

Duaa AlSaeed and Samar Fouad Omar created a model for classifying AD [3]. These came from datasets used in MRIs. Softmax, SVM, and RF algorithms were applied in addition to the CNN architecture ResNet-50 that had already been trained. The results show that Softmax and ResNet50 fared better in terms of accuracy than some of the most recent models.

Comprehensive review and study of early detection and classification of AD were presented by Doaa Ahmed Arafa et al. [4]. They talked about the difficulties in classifying data and preparing images while reviewing several preprocessing methods. Gopi Battineni et al. [5] utilized six different classifiers for the purpose of AD categorization. According to the findings, the gradient boosting strategy produced a higher AUC score and accuracy of classification.

CNN-based paradigm for AD classification was proposed by Yousry AbdulAzeem et al. [6]. For the binary classification of AD and Cognitively Normal (CN), accuracy values of 99.6%, 99.8%, and 97.8% were provided. In the case of multi-classification, however, an accuracy of 97.5% was attained.

In a study, Nitika Goenka and Shamik Tiwari [7] listed the many factors that must be looked into in order to create a model for AD prediction. Additionally, they looked into the neuroanatomical methodologies used by different deep learning frameworks from multiple angles. A CNN architecture was proposed by Suriya Murugan et al. [8] for the classification of AD. The accuracy, area under the curve, and Cohen's Kappa value of the proposed model were 95.23%, 97%, and 0.93, respectively.

With the aid of machine learning and deep learning, Protima Khan et al. [9] provided a survey on the four most dangerous brain disease detection methods. They came to the conclusion that using hybrid algorithms and a blend of methods using both supervision and un-supervision can yield superior outcomes.

To classify AD, Mahjabeen Tamanna Abed et al. [10] used three different DNN models. VGG19, ResNet50, and Inception v3 are some of these models. Accuracy scores of 90%, 85%, and 70% were determined with VGG19, Inception v3, and ResNet50, in that order. Suhad Al-Shoukry et al. [11] reviewed relevant publications that analyze AD detection using MRI data and deep learning techniques.

SVM and Decision Tree machine learning algorithms were used by J. Neelavani and M.S. Geetha Devasana [12] to predict AD using psychological data such as age, the number of visits, the Mini Mental State Examination (MMSE), and education. Accuracy was achieved with SVM at 85% and with Decision Tree at 83%.

A methodology for classifying AD, moderate cognitive impairment, and normal control was created by Swathi S. Kundaram and Ketki C. Pathak [13]. By using the CNN architecture for this goal, they were able to achieve an accuracy of 98.57%. The Alzheimer's disease neuroimaging project (ADNI) provided the dataset used in this study, which included 110 AD, 105 MCI, and 51 NC individuals.

Using 3D structured brain MRI scans, Srinivasan Aruchamy et al. [14] segregated the brain's white and gray matter before extracting 2D slices in the coronal, sagittal, and axial planes. PCA is used to extract its features. Later, four classification models were created: LR, NB, SVM, and Adaboost. The results show that white matter slices from a coronal perspective can achieve an accuracy of up to 90.9%.

Details on the most recent deep learning-based segmentation methods for examining brain MRI data to diagnose AD were provided in a paper by Nagaraj Yamanakkanavar et al. [15]. They also discussed how to diagnose AD and how to examine the brain's anatomical structure using various CNN designs. This study shows that applying deep learning techniques to the segmentation of brain anatomy and the categorization of AD has produced useful outcomes over enormous amounts of data.

A comparison of the methods utilized in diverse research articles can help us understand the types of datasets, their modalities, and the types of models that can function with greater efficiency. In Table 1, summary of different studies that have employed a hybrid approach in the diagnosis of AD has been described. We have compared the approaches used by them by combining more than one model, showing the performance of each model, the type of image, the datasets that they used, and the algorithms or classifiers used by them.

Table 1: A Comparative study on recent works

References	Dataset		Algorithms	Evaluation Result
	Name	Modality		
Prasanalakshmi Balaji et al. (2023) [1]	Kaggle	MRI PET	CNN + LSTM	Accuracy = 98.5%
Ruhul Amin Hazarika et al. (2023) [2]	ADNI	MRI	LeNet, AlexNet, VGG16, VGG19, Inception-V1, Inception-V2, Inception-V3, ResNet50, MobileNet-V1, EfficientNet-B0, Xception, DenseNet-121	DenseNet-121 provided highest accuracy of 86.5%
Duaa AlSaeed and Samar Fouad Omar (2022) [3]	ADNI MIRIAD	MRI	ResNet50 + Softmax ResNet50 + SVM ResNet50 + RF	ResNet50 + Softmax achieved highest accuracy of 96%
Gopi Battineni et al. (2021) [5]	OASIS	MRI	Random Forest Naïve Bayes Gradient Boosting	Gradient Boosting performed better with AUC score = 0.98
Yousry AbdulAzeem et al. (2021) [6]	ADNI	MRI	CNN	Accuracy of 97.5% in case of multi-classificatio n
Suriya Murugan et al. (2021) [8]	Kaggle	MRI	CNN	Accuracy = 95.23% AUC = 97%
Mahjabeen Tamanna Abed et al. (2021) [10]	ADNI	MRI PET	VGG19 Inception-V3 ResNet50	Highest accuracy of 90% provided by VGG19
J. Neelaveni and M.S. Geetha Devasana (2020) [12]	-	Psychological parameters like age, number of visit, MMSE and education	SVM Decision Tree	SVM provided highest accuracy of 85%
Swathi S. Kundaram and Ketki C. Pathak (2020) [13]	ADNI	MRI	CNN	Accuracy = 98.57%
Srinivasan Arunchamy (2020) [14]	OASIS	MRI	Logistic Regression Naïve Bayes SVM Adaboost	Accuracy = 90.9% from naïve bayes and adaboost.

III. PROPOSED METHOD

A. Dataset

The goal of the proposed endeavor is AD early detection. Due to the fact that the model must be trained for optimal performance, the dataset is crucial in this process. We employed the Open Access Series of Imaging Studies (OASIS-3) T1-weighted cross-sectional MR brain images, which are freely accessible, for this investigation. The OASIS-3 collection includes biomarkers, clinical, neuroimaging, and cognitive data for both AD and normal aging.

The dataset consists of 6400 images and is divided into 4 classes based on the severity of Alzheimer's disease. Specifically, Non-demented (ND), Moderate demented (MoD), Mild demented (MD) and Very Mild demented (VMD) of different patients. The number of images for each classes are 3200, 64, 896 and 2240 for ND, MoD, MD and VMD respectively. The sample MR imaging data for the four groups is displayed in Figure 1.

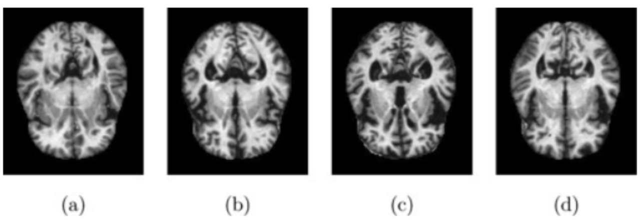

Figure-1: MR Image samples for different dementia stages: (a) Non-demented (ND), (b) Moderate demented (MoD), (c) Mild demented (MD) and (d) Very Mild demented (VMD), from left to right respectively.

B. Preprocessing

Preprocessing reduces noise and increases image accuracy. There needs to be as little noise as possible while keeping the best possible visibility because brain images are more sensitive than other types of medical imaging. Preprocessing an image includes tasks like converting it from color to grayscale, scaling, reshaping, sharpening, and more.

We have augmented our model with data to prevent overfitting issues. The method of data augmentation contributes to a greater diversity of images within each class. Several methods, including cropping, moving, rotating, flipping, shearing, and zooming, are included in this.

C. Proposed Framework

Figure 2 displays the suggested framework's schematic view. There are several processing phases to it. Preprocessing and data augmentation are the first steps. At this point, the dataset of MR images is imported and preprocessed. The dataset is then divided into validation and training sets. And on it, feature extraction is done. To choose the most noticeable characteristics, the principal component analysis (PCA) is used on these features as a stage in the feature reduction process. Following this stage, four distinct classifiers—SVM (both linear and polynomial kernel), Random Forest, Logistic Regression, and CNN (EfficientNetB0)—are selected to classify the presence of Alzheimer's disease based on the prominent features specified. Comparisons between the efficiencies of these classifiers are studied and analyzed in the last section.

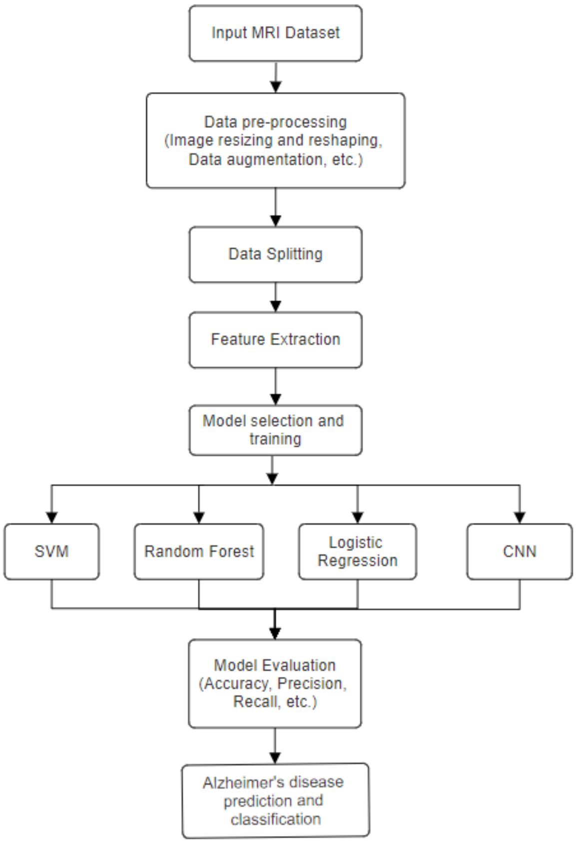

Figure-2: Flowchart representation for the proposed analysis framework

The various classifiers used in the proposed method are described as follows:

1. Support Vector Machine (SVM)

Depending on the amount of features, the SVM is a machine learning classifier that divides the data points into several dimensions by identifying a hyperplane. Regression analysis and classification can both be done with it. SVM generates a decision boundary called a hyperplane, to separate the data into distinct classes. Support vectors are the extreme points or vectors that SVM selects to draw the hyperplane. This model is implemented in this study with both polynomial and linear kernels. Computational efficiency and resistance to overfitting are two benefits of using linear kernels. However, by adding non-linearity to the decision boundary, polynomial kernels allow SVMs to capture more intricate correlations between features and classes. Finally, the performance of its categorization or prediction is examined using the confusion matrix.

2. Random Forest (RF)

The RF model is a bootstrap aggregating (bagging) model that computes a weighted average of the nodes reached. It is accomplished using a series of randomly generated decision trees or by employing the divide and conquer strategy with random sampling. The number of decision trees to be employed in the random forest ensemble is specified by the n_estimators variable, which we have set to 100. The technique builds many decision trees during training using randomly chosen feature subsets and bootstrapped training data samples. The target variable is separately predicted by each decision tree in the ensemble, and the final forecast is produced by adding the predictions of all the trees.

3. Logistic Regression (LR)

The LR classifier uses dependent and independent variables and is a linear type that is implemented similarly to the SVM. For optimization in this investigation, we employed 1000 iterations. LR models the probability of the positive class during training by utilizing the logistic function, often known as the sigmoid function, to comprehend how the binary target variable and the input attributes relate to one another.

4. CNN Model

The proposed pre-trained CNN model (EfficientNetB0) has an architecture made up of several convolutional blocks with depth-wise separable convolutions, which reduces computational complexity and allows for effective feature extraction. In addition, it makes systematic adjustments to the scaling coefficients using compound scaling, which maximizes the performance of the model within computing limitations. Together, these architectural characteristics make EfficientNetB0 an extremely effective solution for image classification applications, requiring little CPU power to achieve high accuracy.

Using Tensorflow and Keras applications, we have trained a CNN model called EfficientNetB0 on the MRI images. Pre-trained weights from ImageNet are used in the base model's configuration. Due to their ability to extract broad characteristics from a sizable and varied dataset, these pre-trained weights are advantageous for transfer learning.

The input form is 128 x 128 pixels with a single channel (grayscale), matching the dimensions of the input images. In order to minimize the spatial dimensions of the feature maps derived from the base models and provide a fixed-length feature vector for every image, a global average pooling layer is applied after the base model. The global average pooling layer is followed by a dense output layer with softmax activation. This layer forecasts the likelihoods of the input image belonging to each class in the classification task.

The model in our study is compiled using 'categorical_cassentropy' as the loss function for multi-class classification. The optimized used is Adam optimized with a specified learning rate of 0.001. Training is performed for 10 epochs and the batch size is kept as 32. Thus, transfer learning is leveraged by using a pre-trained EfficientNetB0 model, thereby achieving optimum performance.

Performance Metrics

The performance of each model can be described using a variety of metrics, including F1-score, accuracy, sensitivity, and precision. In order to differentiate between various models, model evaluation serves the objective of assisting in the determination of how effectively a given data model applies to fresh data in general.

Accuracy: The proportion of outcomes that were correctly classified out of all outcomes.

$$\mathrm{Acc}\ (\%) = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \times 100$$

Precision: The number of true positives divided by the sum of true positives and false positives.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

Recall (Sensitivity): This is the ratio of true positives to the sum of true positives and false negatives.

$$\mathrm{Sensitivity}\ (\%) = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

F1-score: This is calculated as the harmonic mean of precision and recall.

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

IV. RESULTS AND DISCUSSION

This section includes a description of the findings from our study on the use of MRI images to detect Alzheimer's disease. Four distinct classifiers were used: Random Forest, Convolution Neural Network (CNN) using EfficientNetB0 architecture, Logistic Regression, and Support Vector Machines (SVM) with linear and polynomial kernels. Our goal was to assess how well these classifiers performed using MRI image data to differentiate between patients with Alzheimer's disease and healthy persons.

To find out how well the classifiers predicted the existence of the disease, they were evaluated on a test data subset. The effectiveness of every classifier was assessed using a variety of common assessment metrics, including F1 score, recall (sensitivity), accuracy, and precision. Table 2 provides an overview of the four Alzheimer's disease categorization models' performance comparisons.

Table-2: Performance results of classifiers

N	Classifier	Accuracy	Precision	Recall	F-score
1	SVM (Linear)	98.28	0.97	0.99	0.98
2	SVM (Polynomial)	86.32	0.84	0.87	0.86
3	Logistic Regression	97.96	0.98	0.97	0.97
4	Random Forest	96.41	0.95	0.96	0.96
5	EfficientNetB0	95.62	0.95	0.95	0.95

The results indicate that all classifiers achieved promising performance in distinguishing between Alzheimer's disease patients and healthy individuals. The SVM classifier with a linear kernel achieved the highest accuracy of 98.28%, along with excellent precision, recall and F1-score, demonstrating its effectiveness in accurately classifying Alzheimer's disease patients from MRI images. Conversely, SVM with a polynomial kernel exhibited lower performance compared to the linear kernel variant, suggesting that a linear decision boundary might be more appropriate for this classification task.

Logistic Regression also performed impressively well, achieving an accuracy of 97.96% with high precision, recall, and F1-score. This demonstrates how well logistic regression models the connection between input features and target labels in binary classification problems.

Random Forest and EfficientNetB0, although slightly lower in accuracy compared to SVM and Logistic Regression, still demonstrated strong performance with accuracies of 96.41% and 95.62%, respectively. These results underscore the effectiveness of ensemble methods like Random Forest and deep learning architectures like EfficientNetB0 for Alzheimer's disease detection from MRI images.

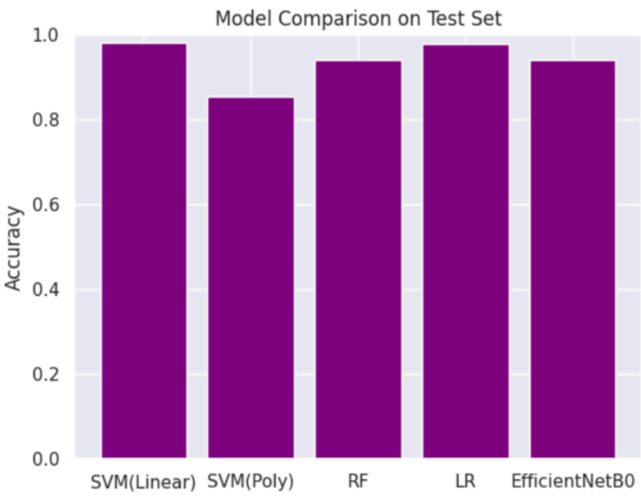

Figure-3: Comparison of accuracies of classifiers

The comparative analysis of classifiers for the identification of Alzheimer's disease from MRI images reveals the differences in performance between various detection methods when handling challenging duties related to medical diagnostics. The plot of the highest accuracies attained by each classifier is shown in Figure 3.

V. CONCLUSION

In conclusion, our study on Alzheimer's disease detection from MRI images offers valuable insights into the application of machine learning and deep learning algorithms for medical diagnosis. Through a comprehensive methodology involving the evaluation of various classifiers, including Support Vector Machine (SVM), Logistic Regression, Random Forest, and Convolutional Neural Network (CNN) with EfficientNetB0 architecture, we have demonstrated the effectiveness of these techniques in accurately distinguishing between Alzheimer's disease patients and healthy individuals. Our results highlight the robust performance of SVM with a linear kernel, achieving exceptional accuracy and performance metrics, followed closely by Logistic Regression, Random Forest, and EfficientNetB0. The comparative analysis underscores the importance of algorithm selection, hyperparameter tuning, and model interpretation in optimizing classifier performance for neurodegenerative disease detection tasks.

Furthermore, our study contributes to the broader understanding of machine learning and deep learning applications in healthcare by providing insights into the strengths and limitations of different classifiers for Alzheimer's disease diagnosis. The findings pave the way for future research directions, including the exploration of ensemble methods, deep learning architectures, and multimodal data integration to further enhance the accuracy and reliability of diagnostic models. Ultimately, our research aims to advance the field of medical imaging analysis and contribute to the development of innovative tools and technologies for early diagnosis and treatment of Alzheimer's disease, ultimately improving patient outcomes and healthcare delivery. Through continued collaboration and innovation, we can harness the power of machine learning to address complex medical challenges and make meaningful contributions to the field of healthcare.

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