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PAPER

Hybrid Deep and Machine Learning Framework for Predicting Alzheimer's Disease

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ABSTRACT

Dementia is term related to many symptoms regarding brain abilities for old people. These symptoms include losing memory and thinking abilities. There are many causes leading to dementia, such as vascular dementia, Parkinson's disease, and also severe head injury. But one of the biggest reasons is Alzheimer's disease. Diagnostic of Alzheimer's is challenging for the psychiatrists. There are many ways to diagnostic Alzheimer's from conducting tests for memory to thinking skills to being evaluated by a healthcare professional. Brain-imaging as MRI, can be used to diagnose Alzheimer's dementia earlier. This paper proposes a hybrid model to predict Alzheimer's early by combining different machine learning (ML) models with deep learning models. Many models in this hybrid are used to get the powerful from each model and increasing the accuracy and to overcome the shortage of other models if it exist. We use two datasets of MRI for the brain from Kaggle. The result shows some hybrid models achieved outstanding results, as MobileNet with KNN scores the highest accuracy of 0.96, precision of 0.96, recall of 0.96, and F1-score of 0.96. This suggests that KNN is highly effective in leveraging the MobileNet. These top classifiers from the hybrid models indicate that combining robust feature extractors such as MobileNet, InceptionV3, and VGG16 with effective ML algorithms such as KNN, MLP, and random forest (RF) provides the best results for Alzheimer's disease prediction.

KEYWORDS

Alzheimer's disease, dementia, deep-learning, machine-learning (ML), feature-extraction

1 INTRODUCTION

Alzheimer's disease is getting concern from World Health Organization (WHO) as one of the most common diseases recently for affecting on the memory and abilities [1]. Diagnostic of Alzheimer's is challenging for the psychiatrists. There are many ways to diagnostic Alzheimer's from conducting tests for memory and thinking skills and magnetic resonance imaging (MRI) to being evaluated by a healthcare professional. MRI shows the changes in the brain that help in the diagnosis

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process [2]. ML techniques help us diagnose disease due to their ability to analyze complex data and analyze patterns in images [3–6]. They help us analyze brain images and diagnose several diseases.

The theoretical framework of this paper includes a comprehensive review of existing literature related to the utilization of ML techniques in brain image analysis to predict Alzheimer's disease. The study begins with a review of the scientific foundations of Alzheimer's disease, focusing on the neurobiology and neurostructural and functional changes that occur in the brain. Then, the study discusses various applications of ML in analyzing brain images, from algorithms and traditional methods to techniques for extracting features and performing the process of standardization. Despite the progress in the field, there are challenges facing scholars, like the volume and diversity of data and several other issues [7, 8]. Finally, future trends and opportunities in this field are explored and suggested, with an emphasis on improvements in ML models, integration of multi-source data, and the use of explanatory ML techniques to enhance understanding and interpretation of forecasting results. The image in Figure 1 represents an MRI image of the brain, which is a sample of existing images from the data that have been considered in this study.

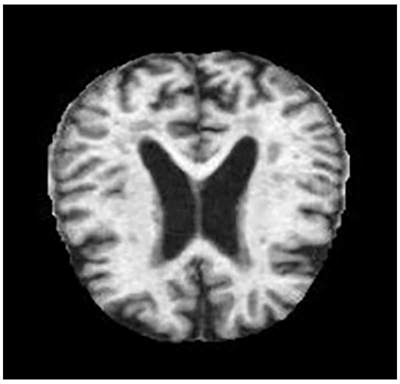

Fig. 1. MRI

2 RELATED WORK

The integration of deep learning and ML techniques has led to advances in the diagnosis and prediction of Alzheimer's disease. This section reviews the relevant literature with an emphasis on methodologies.

Recently, deep learning, especially convolutional neural networks, has proven its ability to analyze medical images and has been used to analyze and classify brain images, which has helped us diagnose Alzheimer's disease. In [9], authors used deep neural networks to diagnose and predict Alzheimer's disease and cognitive impairment using MRI and achieved high accuracy and remarkable performance. Likewise, Islam and Zhang in [10] used deep learning architectures to diagnose and predict the disease, which led to improved accuracy.

In [11], the authors used 3D onset-based convolutional neural network (CNN) with MRI and MD-DTI data fusion to diagnose Alzheimer's disease. It turns out that there is a noticeable improvement in the process of prediction and classification. The concept of transfer learning has demonstrated its effectiveness in fine-tuning specialized applications, which enhances their diagnostic capabilities.

Also, ML algorithms have been widely applied in predicting Alzheimer's disease, and some of the algorithms used were support vector machine SVM, random forest (RF), and KNN. The study works in [12, 13] demonstrated the effectiveness of deep recurrent neural networks (RNN) in diagnosing and predicting mild cognitive impairment using MRI images and achieved predictive performance. These methods excel when the data is well organized.

Combining ML and deep learning techniques provides a hybrid approach that can leverage the strengths of both. In [14], features were extracted from a CNN with an SVM classifier, which led to improved diagnosis of Alzheimer's disease.

Image preprocessing is effective for medical images, as it enhances the performance of the predictive model. The paper in [15] used histogram equalization in a preprocessing pipeline for MRI images. This led to better results in the classification process. This process (pre-processing) ensures the quality and reliability of the input data used in prediction models.

3 DATASET DESCRIPTION

The data that have been considered in this study represent an MRI of the brain, where four types could be found: three for Alzheimer's disease and one for non-Alzheimer's disease. The first dataset comprises three types of Alzheimer's disease: "mild dementia," "moderate dementia," and "very mild dementia," while the fourth type is non-Alzheimer's disease. The number of people with moderate dementia is 6528, the number of people with mild dementia is 4674, and the number of people with severe dementia is 6528. There are 11200 people with Alzheimer's disease and 12800 people without Alzheimer's disease, so the total number of data is 35202. We notice that the first data is somewhat imbalanced, and this will affect the quality of the diagnosis and may also cause the problem of overfitting. Hence, data reduction has been considered to resolve this issue, where we took the first four thousand images of each type until the data became more balanced, and therefore, the number of data (images) became sixteen thousand images. For the second dataset, the number of people with moderate dementia is 64, the number of people with mild dementia is 896, the number of people with severe dementia is 2240, and the number of people without dementia is 3200. Thus, the total number is 6400. The two datasets could be downloaded from https://www.kaggle.com/datasets/arjunbasandrai/medical-scan-classification-dataset and https://www.kaggle.com/datasets/yasserhessein/dataset-alzheimer. Figures 2 and 3 provide some statistics regarding the first and the second datasets, respectively.

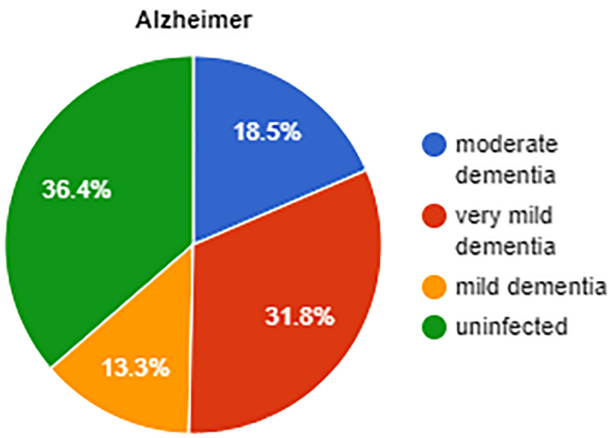

Fig. 2. Alzheimer's first dataset

Tables 1 and 2 provide some information regarding the classes in both datasets with their frequencies.

Table 1. First data description

Class	Original Frequency	After Data Reduction
Moderate Dementia	6,528	4000
Very Mild Dementia	11,200	4000
Mild Dementia	4,674	4000
Uninfected	12,800	4000

Table 2. Second dataset description

Class	Number
Moderate Dementia	64
Very Mild Dementia	2240
Mild Dementia	896
Uninfected	3200

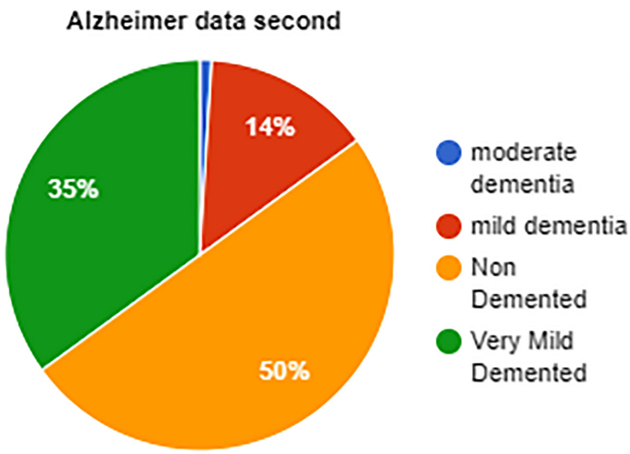

Fig. 3. Alzheimer's second dataset

4 METHODOLOGY

The methodology of this study is described in Figure 4 and consists of the following main phases:

4.1 Phase 1: Data collection

The datasets have been collected to predict and diagnose Alzheimer's disease. These datasets are MRI of the brain on which operations and processing were performed to ensure the quality and importance of the data (images). In this study, the considered datasets were collected from the Kaggle website.

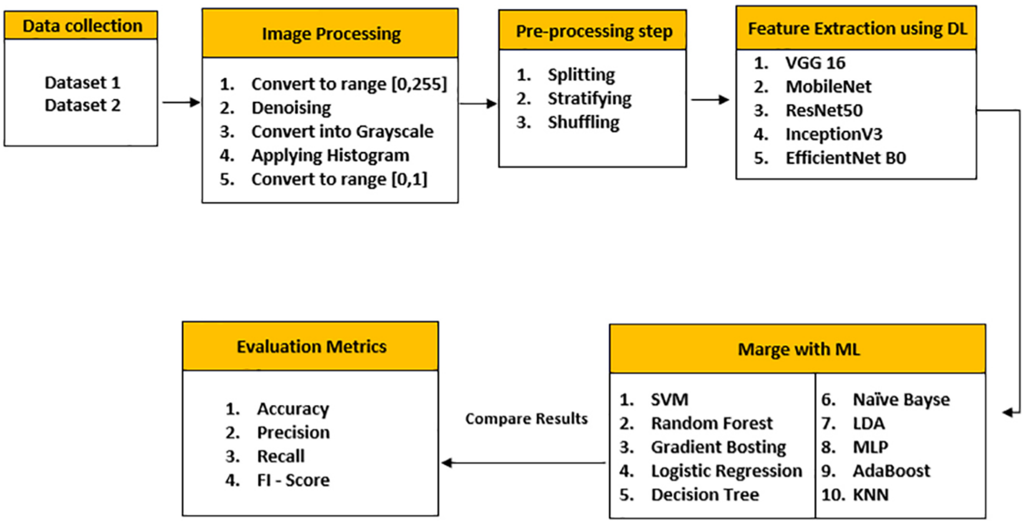

Fig. 4. Research methodology

4.2 Phase 2: Image processing

Regarding this main step, the following tasks have been applied to the collected datasets:

A) Convert Images to Range [0, 255] to Use OpenCV: The first thing we do is to convert the values inside the image to integer values ranging from 0 to 255, which is necessary in order for us to complete the next processing operations so that they are also compatible with the OpenCV library [15–21]. The equation for converting values is [21–23]:

$$y = ((x - min(x))/(max(x) - min(x))) * 255 \text{ ......} \quad (1)$$

B) Denoising Using Gaussian Blur: Gaussian blur is a visual effect used to soften the edges of images and make them smoother. This is done by using a Gaussian filter. It uses a Gaussian function, which is a bell-shaped curve, to determine the weight of all pixels in the image surrounding the pixel being processed [24–28].

How it works:

- Gaussian function: The mathematical function determines the effect of each pixel on the central pixel; the closer we get to the central pixel, the greater its effect and vice versa [29, 30, 31].
- Boundaries: The Gaussian filter is applied to all pixels in the image. Then the value of the new pixel is calculated by multiplying the value of each neighboring pixel by its weight based on the Gaussian function, then summing the results [32–35].
- Result: Softens the edges, reduces noise in the image, and makes the image smoother [36, 37].

C) Convert the Image to Grayscale: It is the process of converting images that contain a third of the red, blue, and green color channels into an image that contains one channel (the brightness channel) [38, 39], meaning that the pixel value is only the brightness value without any color.

D) **Histogram application:** A histogram is a graphical representation of the distribution of pixel values in an image. It displays the number of pixels for each brightness value, usually from 0–255 in 8-bit images. It is used to analyze image properties such as contrast and brightness and improves image quality through processes such as smoothing.

4.3 Phase 3: Data splitting and preprocessing

In this paper, we split the data into two sets: 80% training set and 20% testing set. Splitting the data in this way ensures that the model has enough data to learn from and enough data to evaluate its performance. The main preprocessing tasks that have been carried out in this study are as follows:

1. **Stratified Sampling:** Stratified sampling is a statistical technique applied to training and testing sets to ensure that each category of data is adequately represented. This technique is important to avoid biases and to ensure that each category is represented adequately.
2. **Shuffling Data:** This process is reordering the records randomly for the data to avoid bias in learning and testing processes.

4.4 Phase four: feature extraction for Deep Learning Models Merged with ML

1. **VGG16:** VGG 16 model is a CNNs model. The main characteristics of VGG16 are:
   - Simple and efficient architecture: It consists of 16 trainable learning layers, 13 of which are convolutional and 3 are fully connected.
   - Small-size convolutional filters: It uses 3×3-dimensional filters, allowing the model to take advantage of the fine-grained gradient.
   - Relies on deep networks: The deep architecture helps in learning complex, multi-level representations of data.

   In this study paper, the VGG16 model was employed to diagnose Alzheimer's disease, which classifies four images through the following steps: We loaded the VGG16 model with the weights trained on the ImageNet dataset. We froze the upper layers specialized in data classification so that we could add classification layers for Alzheimer's disease. We created a Flatten layer, whose function here is to convert the outputs of the convolutional layers into a vector that we pass to the fully connected layers. After that, we added a dense layer containing 1024 units with ReLU activation to increase the model's ability to learn from patterns. We also added a dropout layer by 50%.

   To reduce overfitting by randomly disabling some units during training, and finally a classification layer, which is Softmax, to calculate the probability of each class. We freeze the base VGG16 layers to prevent their weights from being updated during training, allowing the model to benefit from previously extracted features from the ImageNet dataset. We trained the model over 10 episodes. The number of episodes is the number of times the model weights are updated based on the training data. This number helps in tuning the model and improving its performance. We set up an initialization to save the model with the best performance on the validation set. The model is saved at the lowest validation loss. Training stops if performance does not improve after a specified number of episodes, which helps in avoiding overfitting.

Applying VGG16 only without ML models gives the following results: Accuracy: (0.89), Precision: (0.89), Recall (0.89), and F1-measure (0.89). The performance of the baseline VGG16 model is very good on all four metrics, indicating its high effectiveness in classifying medical images associated with Alzheimer's disease. Considering the first dataset, the findings of applying different ML algorithms with VGG16 are as follows:

- **Support Vector Machine:** SVM is a classification algorithm that classifies data in a multidimensional space using an optimal hyperplane. SVM takes advantage of the features extracted from VGG16 to find an optimal hyperplane that separates the different Alzheimer's classes. The margin between the classes is maximized to ensure accurate classification. SVM's performance was lower than expected (accuracy = 0.64). This may be because the data contains complex overlaps that SVM cannot handle efficiently using the extracted features.
- **Random Forest:** RF is an algorithm that relies on a set of random trees to make a classification decision. Each tree in the forest is trained on a random subset of the data, which reduces bias and variance. The algorithm (RF) takes advantage of the features of VGG16 to train multiple trees and use majority voting to determine the final class.
- **Gradient Boosting:** It is an algorithm that enhances the performance of a classification model by correcting the repeated errors of previous models. It creates a series of models, where each new model is improved based on the errors of the previous model. Gradient boosting takes advantage of the features extracted from VGG16 by attempting to improve the classification of each model based on the complex representations extracted. Gradient boosting performed well (accuracy = 0.79), but was lower than RF. This may be because the algorithm needs more than incremental improvements to achieve performance similar to random forest.
- **AdaBoost:** An algorithm that combines a set of weak classification models to create a strong model. AdaBoost takes advantage of the features extracted from VGG16 by boosting the classification accuracy by iteratively handling the recurring errors. AdaBoost performed significantly lower (accuracy = 0.60). This suggests that the algorithm may not be well suited for the complex features extracted from VGG16.
- **KNN:** KNN is a simple classification algorithm that classifies data based on nearest neighbors in a multidimensional space. KNN leverages the features extracted from VGG16 to determine the image class based on the classes to which the closest features in the extracted space belong. KNN showed excellent performance (accuracy = 0.93), indicating that the features extracted from VGG16 retain enough information to accurately distinguish classes when using KNN.
- **Logistic Regression (LR):** LR is a classification algorithm that relies on a statistical model to estimate the probabilities of belonging to certain classes. It leverages the features extracted from VGG16 by representing the relationships between features and classes using a logistic function, which facilitates image classification. LR performed moderately (accuracy = 0.69), indicating that the algorithm may be too simple to handle the complexity present in the features extracted from VGG16.
- **Decision Tree (DT):** DT is a classification algorithm that relies on making sequential decisions based on data features. DT leverages the features extracted from VGG16 by creating a decision tree where each node represents

a decision based on a given value of the extracted features. The DT performed less than expected (accuracy = 0.66), suggesting that the algorithm may be prone to overfitting on the training data.

- **Naive Bayes (NB):** NB is a classification algorithm based on probability theory to classify data. NB used the extracted features from VGG16 to select the most likely class. NB shows the lowest performance among all other algorithms, which makes NB not suitable with VGG16.
- **LDA:** LDA is an approach to reduce a large number of features to find a Linear combination. LDA used the features from VGG16 to maximize the separation between classes. This model shows lower performance than RF and KNN.
- **MLP:** MLP is a simple multilayer neural network used for data classification. MPL has three main layers: one input layer, at least one hidden layer, and one output layer. MPL has the ability to learn from the features in the training process to use the model in prediction. MPL showed excellent performance from the extracted features from VGG16.

Table 3 depicts the evaluation results for merging VGG16 with several classification models with respect to the first dataset.

Table 3. Merging VGG16 with several ML models considering the first dataset

VGG16 + ML	Accuracy	Precision	Recall	F1-Score
VGG16	0.89	0.89	0.89	0.89
VGG16 + SVM	0.64	0.65	0.64	0.64
VGG16 + RF	0.87	0.87	0.87	0.87
VGG16 + GB	0.79	0.79	0.79	0.78
VGG16 + AB	0.60	0.59	0.60	0.59
VGG16 + KNN	0.93	0.93	0.93	0.93
VGG16 + LR	0.69	0.68	0.69	0.68
VGG16 + DT	0.66	0.66	0.66	0.66
VGG16 + NB	0.56	0.54	0.56	0.54
VGG16 + LDA	0.78	0.78	0.78	0.78
VGG16 + MLP	0.83	0.84	0.83	0.82

The following are the analysis the result with respect to the Second dataset.

- **SVM:** SVM achieved an accuracy of 0.55. This indicates that SVM performed less effectively in classifying patient data based on the features extracted from VGG16.
- **RF:** RF recorded an accuracy of 0.84. This reflects the strong performance of RF in leveraging the extracted features to improve classification accuracy.
- **GB:** GB obtained an accuracy of 0.76. This shows that GB performed well but did not reach the level of RF in handling the extracted features.
- **AB:** AB achieved an accuracy of 0.51, which is the lowest among the algorithms used. This suggests that AdaBoost was less suitable for the complex features extracted from VGG16.
- **KNN:** KNN demonstrated the highest accuracy of 0.95, highlighting KNN's ability to exploit the extracted features for highly accurate classification.

- **LR:** LR obtained an accuracy of 0.64, indicating that LR was less effective than some other algorithms in dealing with the complexity of the features.
- **DT:** DT achieved an accuracy of 0.62. This shows that DT was less capable of generalizing compared to some of the other algorithms.
- **NB:** NB recorded an accuracy of 0.56, the lowest among all algorithms. This reflects the unsuitability of NB's assumptions for the features extracted from VGG16.
- **LDA:** LDA achieved an accuracy of 0.75, indicating good performance but lower than RF and KNN.
- **MLP:** MLP demonstrated an accuracy of 0.74, suggesting that MLP was effective in handling the extracted features but did not achieve the exceptional performance seen with KNN.

These results highlight those algorithms such as KNN and RF performed better due to their ability to leverage the extracted features from VGG16, while algorithms such as AdaBoost and NB were less effective in managing the complexity of the data.

Table 4 depicts the evaluation results for merging VGG16 with several classification models with respect to the second dataset.

Table 4. Merging VGG16 with several ML models considering second dataset

VGG16 + ML	Accuracy	Precision	Recall	F1-Score
VGG16	0.81	0.85	0.68	0.72
VGG16 + SVM	0.55	0.26	0.30	0.27
VGG16 + RF	0.84	0.66	0.58	0.60
VGG16 + GB	0.76	0.72	0.60	0.64
VGG16 + AB	0.51	0.58	0.36	0.39
VGG16 + KNN	0.95	0.96	0.96	0.96
VGG16 + LR	0.64	0.48	0.43	0.44
VGG16 + DT	0.62	0.45	0.46	0.45
VGG16 + NB	0.56	0.54	0.56	0.54
VGG16 + LDA	0.75	0.79	0.75	0.77
VGG16 + MLP	0.74	0.77	0.67	0.70

2. **MobileNet:** The MobileNet model is a lightweight and effective convolutional brain network intended to be reasonable for versatile and inserted gadgets on account of its capacity to accomplish elite execution while lessening computational and boundary prerequisites [39]. Google acquainted the MobileNet model with work on the exhibition of models on asset-compelled gadgets, for example, cell phones, by decreasing model intricacy while keeping up with precision. The MobileNet model after customization achieved positive results in predicting Alzheimer's disease. The main metrics were as follows: Accuracy: (0.94), Precision: (0.95), Recall: (0.94), and F1-Score: (0.94). Following is the analysis of the results of ML algorithms with extracted features from MobileNet with respect to the first dataset.
   1. KNN: KNN achieved the highest performance with an accuracy of 0.96, indicating that KNN was the most effective in exploiting the extracted features from MobileNet to predict Alzheimer's disease.

2. MLP: MLP showed a very good accuracy of 0.94, reflecting the effectiveness of the multi-layer neural algorithm in prediction.
3. SVM, LDA, and RF: all performed well with a range of accuracy from 0.8 to 0.84.
4. GB and LR: GB and LR achieved average performance with an accuracy of about 0.77 and 0.78.
5. AB, DT, and NB: AB, DT, and NB showed lower performance, with an accuracy ranging from 0.56 to 0.62.

These results show that KNN is performing the best with MobileNet features in the prediction process for Alzheimer's disease.

Table 5. Merging MobileNet with several ML models considering the first dataset

Model	Accuracy	Precision	Recall	F1-Score
MobileNet	0.94	0.95	0.94	0.94
MobileNet + SVM	0.80	0.80	0.80	0.80
MobileNet + RF	0.84	0.84	0.84	0.83
MobileNet + GB	0.77	0.77	0.77	0.77
MobileNet + AB	0.58	0.59	0.59	0.58
MobileNet + KNN	0.96	0.96	0.96	0.96
MobileNet + LR	0.78	0.78	0.78	0.78
MobileNet + DT	0.61	0.62	0.62	0.62
MobileNet + NB	0.56	0.54	0.56	0.53
MobileNet + LDA	0.81	0.81	0.81	0.81
MobileNet + MLP	0.94	0.94	0.94	0.94

Following is the analysis of the results of ML algorithms with extracted features from MobileNet with respect to the second dataset. The MobileNet model exhibited an excellent baseline performance with an accuracy of 0.93, a precision of 0.95, a recall of 0.85, and an F1-Score of 0.89, highlighting its efficiency in capturing features for classification.

- SVM: Combining MobileNet with SVM resulted in an accuracy of 0.68, a precision of 0.54, a recall of 0.44, and an F1-Score of 0.44.
- Random Forest: Random Forest with MobileNet features achieved an accuracy of a 0.83, precision of 0.90, a recall of 0.62, and an F1-Score of 0.67. This combination showed good performance but was not as high as KNN.
- Gradient Boosting: Gradient Boosting with MobileNet provided an accuracy of 0.74, precision of 0.68, recall of 0.60, and F1-Score of 0.62. While effective, it was slightly less efficient compared to Random Forest.
- AdaBoost: The AdaBoost model combined with MobileNet achieved an accuracy of 0.50, precision of 0.59, recall of 0.42, and F1-Score of 0.46. The lower performance indicates AdaBoost inefficiency with MobileNet feature set.
- KNN: KNN with MobileNet features achieved an accuracy of 0.80, precision of 0.82, a recall of 0.77, and F1-Score of 0.79.
- Logistic Regression: LR combined with MobileNet produced an accuracy of 0.55, a precision of 0.36, a recall of 0.32, and an F1-Score of 0.31. The lower performance suggests that LR did not leverage MobileNet features effectively.

- Decision Tree: DT with MobileNet achieved an accuracy of 0.62, precision of 0.56, recall of 0.52, and F1-Score of 0.53. The results reflect DTs limited effectiveness with MobileNet features.
- Naive Bayes: NB with MobileNet resulted in an accuracy of 0.40, precision of 0.38, recall of 0.45, and F1-Score of 0.30. The performance was the lowest, indicating NB poor fit with MobileNet features.
- LDA: LDA with MobileNet showed an accuracy of 0.79, precision of 0.82, recall of 0.80, and F1-Score of 0.81.
- MLP: MLP with MobileNet resulted in an accuracy of 0.62, precision of 0.45, recall of 0.40, and F1-Score of 0.40. The performance indicates that MLP did not fully leverage MobileNet features. Table 6 depicts the evaluation results for merging MobileNet with several classification models with respect to the second dataset.

Table 6. Merging MobileNet with several ML models considering the second dataset

MobileNet + ML	Accuracy	Precision	Recall	F1-Score
MobileNet	0.93	0.95	0.85	0.89
MobileNet + SVM	0.68	0.54	0.44	0.44
MobileNet & + RF	0.83	0.90	0.62	0.67
MobileNet + GB	0.74	0.68	0.60	0.62
MobileNet + AB	0.50	0.59	0.42	0.46
MobileNet + KNN	0.80	0.82	0.77	0.79
MobileNet + LR	0.55	0.36	0.32	0.31
MobileNet + DT	0.62	0.56	0.52	0.53
MobileNet + NB	0.40	0.38	0.45	0.30
MobileNet + LDA	0.79	0.82	0.80	0.81
MobileNet + MLP	0.62	0.45	0.40	0.40

3. **ResNet50:** The ResNet50 model is a deep neural network model known for its design based on skip connections or residual connections. [40, 41]. It improves training and generalization performance as it facilitates the flow of information through the network [42, 43].

   The ResNet50 model after customization achieved moderate results in predicting Alzheimer's disease [44, 45]. The main metrics were as follows: Accuracy: 0.56, Precision: 0.53, Recall: 0.56, F-Score: 0.53. These results indicate that the ResNet50 model has some effectiveness in extracting features and enabling machine learning algorithms, but there is room for improvement. The results suggest that using the ResNet50 model with the same strategies applied to VGG16 yielded moderate performance in the Alzheimer's disease prediction task.

   The performance of the machine learning algorithms integrated with the features extracted from the ResNet50 model varies significantly. A brief analysis of the results is as follows:

- Random Forest: RF achieved the highest performance with an accuracy of 0.78, indicating that the RF algorithm was the most effective in exploiting the features extracted from ResNet50 to predict Alzheimer's disease. Although this performance is good compared to other results in this context, it is not as good as the best results that reached 0.96.

- Linear Discriminant Analysis (LDA): LDA showed a good accuracy of 0.77, reflecting the effectiveness of the LDA algorithm in prediction. However, it does not reach the top performance level achieved by other models.
- GB and KNN: Both models performed acceptably with an accuracy of 0.70 and 0.73, respectively, indicating their ability to exploit the extracted features at an average level.
- MLP and DT: Both models achieved average performance with accuracy of 0.67 and 0.59, respectively.
- LR and AB: LR and AB showed moderate performance with accuracy of 0.54 and 0.55, respectively.
- SVM and NB: Both models showed lower performance, with accuracy of 0.36 and 0.34, respectively.

ResNet50 is the best model to extract features of Alzheimer's disease, but choosing the ML algorithm is significant to the overall performance. Using RF and LDA with ResNet50 features achieved good performance but did not reach the high performance achieved by other models that reached an accuracy of 0.96.

4. **InceptionV3:** InceptionV3 is a deep learning model developed by Google. In this paper, the InceptionV3 model is adapted for Alzheimer's disease diagnosis by classifying brain images through the following steps:
   - **First step:** Loading the InceptionV3 model: The model is loaded with pre-trained weights from the ImageNet dataset. The upper layers of classification are removed to customize the model for the specific task.
   - **Second step:** Adding custom layers: Flatten layer: Converts the output from Inception units to a vector to be fed to the fully connected layers.
   - **Third step:** Dense layer: Adds a dense layer with 1024 units and ReLu activation to improve the model's ability to learn from features.
   - **Fourth step:** Dropout layer: Includes a 50% Dropout layer to reduce overfitting. Classification layer: Uses a dense layer with Softmax activation to output the probability of each class.
   - **Fifth step:** Freezing base layers: The layers from the pre-trained InceptionV3 model are frozen to preserve the extracted features, allowing only new layers to be trained. Sixth step: Number of epochs: The model is trained over 10 epochs, which is the number of times the model's weights are updated based on the training data.
   - **Sixth step:** Early Stop and Model Checkpoint: Tunes the model to the best performance based on the validation loss, ensuring that the best version is retained.
   - **Seventh step:** Early Stop: Stops training if the validation loss does not improve after a specified number of epochs, helping to avoid overfitting and save computational resources.

   When evaluating the modified InceptionV3 model using validation data, the results were as follows: Accuracy: 0.85 Precision: 0.85 Recall: 0.85 F1-score: 0.85. The performance of the machine learning algorithms integrated with the features extracted from the InceptionV3 model varies significantly. A brief analysis of the results is as follows:

   - KNN: KNN demonstrated superior performance with an accuracy of 0.87, highlighting its effectiveness in utilizing InceptionV3 features for Alzheimer's disease prediction. MLP also showcased strong performance, achieving an accuracy of 0.82, emphasizing the potential of deep learning architectures in this context.

- SVM, RF, and LDA: The three models exhibited moderate performance, with accuracies ranging from 0.74 to 0.78, indicating their capability to extract relevant information from the InceptionV3 features. On the other hand, algorithms such as AdaBoost, Decision Tree, and NB struggled, showing lower accuracies between 0.45 and 0.56, suggesting limitations in handling the complexity of the extracted features.

Table 7 depicts the evaluation results for merging InceptionV3 with several classification models with respect to the first dataset.

Table 7. Merging inceptionV3 with several ML models considering the first dataset

Inception V3 + ML	Accuracy	Precision	Recall	F1-Score
InceptionV3	0.85	0.85	0.85	0.85
InceptionV3 + SVM	0.79	0.79	0.79	0.79
InceptionV3 + RF	0.75	0.75	0.75	0.75
InceptionV3 + GB	0.70	0.70	0.70	0.70
InceptionV3 + AB	0.56	0.55	0.56	0.55
InceptionV3 + KNN	0.87	0.87	0.87	0.87
InceptionV3 + LR	0.75	0.74	0.75	0.74
InceptionV3 + DT	0.54	0.54	0.54	0.54
InceptionV3 + NB	0.49	0.46	0.49	0.45
InceptionV3 + LDA	0.79	0.79	0.79	0.79
InceptionV3 + MLP	0.82	0.82	0.82	0.82

5. **EfficientNetB0:** EfficientNetB0 is a highly efficient convolutional neural network model that achieves superior performance with fewer parameters and reduced computational complexity.

The EfficientNetB0 model specification showed the following results for predicting Alzheimer's disease: Accuracy: (0.25), Precision: (0.06), Recall: (0.25), and F1-score: (0.10). These results indicate that the EfficientNetB0 model, despite being specificities using the same strategy applied to the VGG16 model, did not achieve high performance in the Alzheimer's disease prediction task. The low accuracy and F1-score indicate that the model has difficulty accurately distinguishing between different classes, possibly due to the complex nature of the dataset and the relatively small number of training episodes. Additional fine-tuning and experimentation with the parameters may be necessary to improve performance. A brief analysis of the results is as follows:

- LDA: achieved excellent outstanding performance with an accuracy of 0.81.
- RF, GB, AB, and KNN: show good performance with an accuracy range from 0.72 to 0.53.
- SVM and LR: show lower performance with an accuracy of 0–3 to 0.34.

Table 8 depicts the evaluation results for merging EfficientNetB0 with several classification models with respect to the first dataset.

Table 8. Merging EfficientNetB0 with several ML models considering the first dataset

EfficientNetB0 + ML	Accuracy	Precision	Recall	F1-Score
EfficientNetB0	0.25	0.06	0.25	0.10
EfficientNetB0 + SVM	0.30	0.34	0.30	0.22
EfficientNetB0 + RF	0.72	0.72	0.72	0.72
EfficientNetB0 + GB	0.68	0.67	0.68	0.67
EfficientNetB0 + AB	0.53	0.52	0.53	0.53
EfficientNetB0 + KNN	0.61	0.61	0.61	0.60
EfficientNetB0 + LR	0.34	0.33	0.34	0.27
EfficientNetB0 + DT	0.57	0.57	0.57	0.57
EfficientNetB0 + NB	0.37	0.36	0.37	0.36
EfficientNetB0 + LDA	0.81	0.81	0.81	0.81
EfficientNetB0 + MLP	0.25	0.06	0.25	0.10

To summarize the main finding of the previous evaluations, the performance of various classifiers integrated with features extracted from pre-trained models highlights the effectiveness of specific combinations for Alzheimer's disease prediction. Among the models evaluated, the top performers are:

- MobileNet + KNN: Achieved the highest Accuracy of 0.96, Precision of 0.96, Recall of 0.96, and F1-score of 0.96. This suggests that KNN is highly effective in leveraging the MobileNet features for classification.
- MobileNet + MLP: Demonstrated excellent performance with Accuracy, Precision, Recall, and F1-score all at 0.94. This indicates that MLP performs exceptionally well with MobileNet features.
- MobileNet (base model): Provided strong overall performance with Accuracy, Precision, Recall, and F1-score all at 0.94. This model alone shows a robust ability to extract and use features.
- InceptionV3 + KNN: Achieved Accuracy, Precision, Recall, and F1-score of 0.87. The KNN classifier shows significant efficacy when combined with InceptionV3.
- InceptionV3 + MLP: Notable performance with all metrics at 0.82, demonstrating MLP's effectiveness when paired with InceptionV3.
- VGG16 KNN: Exhibited high performance with Accuracy, Precision, Recall, and F1-score all at 0.93.
- VGG16 + RF: Showed a solid performance with Accuracy, Precision, Recall, and F1-score all at 0.87.
- VGG16 + MLP: Achieved an Accuracy of 0.83 and F1-score of 0.82, reflecting the efficiency of MLP in predicting Alzheimer disease with VGG16 features.
- InceptionV3 Random Forest: Noteworthy with Accuracy, Precision, Recall, and F1-score all at 0.75.
- ResNet50 Random Forest: Recorded a respectable performance with Accuracy, Precision, Recall, and F1-score all at 0.78.

These top classifiers indicate that combining robust feature extractors such as MobileNet, InceptionV3, and VGG16 with effective machine learning algorithms such as KNN, MLP, and RF provides the best results for Alzheimer's disease prediction.

5 CONCLUSION AND FUTURE WORK

This study approached a hybrid model to diagnose Alzheimer's disease. Pre-trained models are used to extract features from datasets containing MRI images for brains with three categories of Alzheimer's disease level (mild, moderate, sever), and the four category is for healthy brain. We used VGG16, ResNet50, and EfficientNetB0 for feature extraction. Traditional machine learning algorithms are trained by extracted features to provide powerful framework. Results showed improved predictive performance. In this study, we used histogram equalization and Gaussian blur to enhance image quality and ensure that the input data was suitable for model training. Also, we used data reduction and augmentation techniques to make data balanced and adequate data for training model and validation step. There are several areas for improvement. At the beginning, we can improve the model by collecting more MRI images. Also, the integration of multi-source data, such as combining MRI images with other types of medical data, could provide a more comprehensive understanding of Alzheimer disease and improve prediction accuracy.

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