Alzheimer's Disease Detection and Classification Using Deep Learning Methods

Santosh Vishwanathan[1*], Shankar Tejasvi[1], Anusha Jain[1], Sharon Thomas[2], Swetha S[3]
[1] Department of ISE, RV College of Engineering, Bengaluru, Karnataka, India (BE)
[2]Department of CSE, RV College of Engineering, Bengaluru, Karnataka, India (BE)
[3] Department of ISE, RV College of Engineering, Bengaluru, Karnataka, India (Assistant Professor)
santoshv.is20@rvce.edu.in*, shankar.is.rvce@gmail.com, anushajain.is20@rvce.edu.in, sharonthomas.cs20@rvce.edu.in, shwetha.ise@rvce.edu.in

ABSTRACT

An accurate diagnosis of Alzheimer's disease (AD) is crucial for patient care, particularly in its early stages. To better understand Alzheimer's disease (AD), data analysis using machine learning algorithms has become increasingly popular in recent years. Recent medical imaging and image analysis developments have made it possible to generate and extract useful neuroimaging data. Automatic classification techniques offer analytical tools for delving into this data to discover hidden patterns connected to diseases. These classifiers have been applied to predict the transition from mild cognitive impairment to AD as well as to distinguish healthy individuals from AD patients. This work is an endeavor to use deep learning architecture to developa classification model of AD, employing pre-trained models such as Resnet50, InceptionV4 and BrainNet to accurately predict the severity of AD in patients to mitigate the harmful effects of the disease at a later stage by providing suitable medical attention. This study uses a comparative analysis of various machine learning model types to comprehensively analyze AD prediction. In the recorded experiments, a considerable performance gain was achieved in the classification of all diagnosis groups.

Keywords
Alzheimer's disease, Deep learning, Classification model, Comparative analysis

1. Introduction

Alzheimer's disease is a degenerative brain disorder that steadily impairs thinking and memory abilities, as well as the capability to carry out even the most fundamental responsibilities. Alzheimer's disease is a brain disease that regularly reduces one's ability to even perform fundamental cognitive functions like thinking and remembering. Maximum Alzheimer's sufferers revel in their first signs in their later years. Scientists are nevertheless running to completely understand the complex brain modifications related to Alzheimer's ailment.Changes inside the mind can also go on for ten years or longer earlier than the onset of symptoms. The brain is present to process damaging modifications at this early stage of Alzheimer's, which includes abnormal protein buildups that bring about amyloid plaques and tau tangles. As soon as-healthful neurons begin to malfunction, they lose contact with neighboring neurons and ultimately die. Numerous other sophisticated brain modificationsare also thought to have an impact on Alzheimer's disease. The brain's two regions most crucial for memory formation—the entorhinal cortex and the hippocampal—seem to be the first to suffer damage. As more neuronsdie, greater regions of the brain are affected and reduced. While Alzheimer's reaches its very last level, the damage is intense and the mind tissue has notably diminished. [27]

The disease's early signs and symptoms consist of forgetting current conversations or activities. An Alzheimer's patient will become increasingly incapable of carrying out easy responsibilities

and could be afflicted by excessive reminiscence loss. The outcomes of the medicine may also quickly enhance the signs and symptoms or gradual their rapid deterioration. These treatments can, on occasion, assist patients to hold their independence and perform to their full capability. The spread of Alzheimer's disease cannot be halted by meansof any known remedy at present. In the later stages, several brain complications arise, such as dehydration, malnutrition, and infection, eventually leading to the patient's demise.[28]

Numerous machine learning techniques have been proposed to aid in the prognosis of AD, that rely on high dimensional features extracted from diverse neuroimaging biomarkers, subclass MRI, and PET. In additionto automatically distinguishing AD subjects from standard control (NC) subjects, these machine learning techniques also need to foretell the likelihood that MCI subjects will develop into AD. Consequently, MCI instances may be classified as both MCI non-converters (ncMCI) or MCI converters (cMCI), depending on theprobability of progression. As a result, it is possible to naturally version the early prognosis of AD as a multi- class classification problem.[11]

To create reliable and representative models that can later be used to predict MCI conversion, models should first be trained in using all available AD instead of CTL statistics. Using computerized classification strategies, it is feasible to observe neuroimaging statistics and see underlying disease-related patterns. These classifiers have been employed to separate AD patients from healthy individuals and to anticipate moderate cognitive impairment's development into AD. When handling high-dimensional input, some techniques call for characteristic selection techniques. However, it is unclear whether there are different patterns of AD-related atrophy and whether there are different subtypes of AD depending on how they manifest clinically.[26]

2. Literature Review

[26]shows a method for the use of deep learning to make an early prognosis of AD. With little reliance on earlier expertise in the course of model optimization, the approach performs AD diagnosis as a multi-class classificationtask. It also contains dimensionality reduction and statistics fusion concurrently to maintain the synergy between record modalities. This establishes the viability of extracting excessive-level biomarkers from smaller biomedical datasets through the use of multi-layered parametric learning models.

With the help of magnetic resonance imaging (MRI) data, [1] uses a deep learning approach using convolutional neural networks to predict the conversion to Alzheimer's disease. Age correction and other processing are used to prepare the MRI images. Local patches are then taken from these images and assembledinto 2.5 dimensions. Then, a CNN is trained to recognize the deep learning features of mild cognitive impairment subjects using samples from AD and normal individuals. Following that, structural brain image features are extracted by FreeSurfer to help the model. Finally, a deep learning classifier is fed both types of features to predict the AD conversion. With an optimum balance of specificity and sensitivity, this method maintains accuracy of 79.9%.

A CNN model is suggested in [4] to analyze brain MRI images and categorize them into various stagesof AD. The Inception-V4 network served as an inspiration for the model. Following pre-processing, a stem layeris applied to the input. Inception, convolution, and reduction layers are then applied to it. Based on average pooling and the results, the severity of AD is categorized as non-demented, very mild, mild, and moderate. TheOASIS dataset was used to train the model.

Data augmentation methods like reflection and scaling have been used to prevent overfitting in the network, and an accuracy of 73% was obtained.

In [5], AD stages are expected using records from the structural mind image dataset (503 MRI images), Single Nucleotide Polymorphism (808 patients), and electronic health statistics (2004 patients). The gadget entails three data fusion techniques: function-level combinations with the use of shallow models, Intermediate- degree combinations using deep models, and selection-stage combinations using shallow models. Internal cross-validation and an outside test set are used to evaluate these cases. The first step is to get rid of 10% of the facts from the outside test set. Tenfold cross-validation is completed at the remaining 90%, with 81% of the entire facts used for education and 9% for internal cross-validation. The version is optimised for the usage of the inner move-validation records set. This analysis suffers from shortcomings along with confined dataset sizes.

[6]provides a comparative evaluation of feature reduction techniques used in Alzheimer's disease categorisation. To demonstrate the robustness of the proposed method, an extensive database of MRI images isused, with over one thousand patients, and multiple subdivisions of training test sets. To discover and classify the healthy subjects, MCI patients, and AD patients, an SVM model is created to categorise MRI pictures as both normal or identified with Alzheimer's disease. This emphasizes the significance of all available data to perform the category and the assignment of extracting relevant facts for the classification task by means of illustrating how using dimensionality reduction in this use case, caused worse type accuracy, both using featurereduction and feature selection.

[7]The daily activities of Alzheimer's patients have been connected to the disorder stage through the use of a novel method. The technique consists of two stages: a pre-processing stage that shortens andhomogenizes the record point durations in accelerometer sequences, and a supervised studying stage that buildsa CNN that predicts the stage of Alzheimer's disease. Mobility issues are recognized as one of the earliest symptoms proven by sufferers of Alzheimer’s disease. This method analyses mobility facts from accelerometersensors and applies a deep learning model based on convolutional neural networks to identify patterns in patientmovement. With an F1 score of 0.897, the CNN model had an accuracy rate of 91%.

In [8], the prediction of MCI to AD conversion was investigated using cross-sectional neuroimaging, baseline longitudinal cognitive performance, baseline CSF biomarkers, and baseline demographic data. The multi-modal and longitudinal nature of the data at hand is leveraged by this technique to identify non-linear styles associated with MCI progression. An analysis of the overall performance outputs from three different schemes—the "baseline," "single modal," and "proposed"—was accomplished to determine the benefits of the technique. More than one GRU has been used to utilise longitudinal multi-domain data and all subjects with each modality of data. Each modality's input was transformed into a feature vector in the first training step in order that it could be used by one modality to predict MCI conversion. Thus, capabilities unrelated to the singlemodality's role in AD progression can be eliminated. The likelihood of filtering out functions that can't be extracted using a single modality, but can instead be best explained by a collection of multimodal data is also high.

[9] employs the VGG19, Inception V3, and ResNet50 models. The convolutional neural network

VGG-19 successfully classified more than a million images from ImageNet. A structural MRI image dataset from ADNI was gathered and processed to make the image data pliable for the model. It was discovered that AD affected the eyes and that the regions of the eyes of people with Alzheimer's disease can be distinguished from those of people with normal cognitive function. The proposed system involves the following stages- Structural MRI data acquisition, Data pre-processing, Grouping into classes, and Classification using CNN models.

[10]evaluates a variety of performance metrics, including F1 score, recall, accuracy, and precision. 5-fold cross-validation is carried out using Decision Tree, SVM, Random Forests, XGBoost, and Voting to find the best parameters for each model. The accuracy of each model is then contrasted. A learning model was created to identify individuals with true Alzheimer's disease within a population. A cutting-edge machine learning classifier was created and validated to predict and separate individuals with actual Alzheimer's disease.

In [12], an end-to-end deep 3D CNN pipeline is proposed, using the entire image volume as input to identify multiclass AD biomarkers. The pipeline consists of three key phases: domain adaptation, 3D CNN processing, and brain extraction. There was no use of domain-specific AD knowledge in the completely automated, speedy approach.

3. Methodology

A. The Architecture of Deep Learning Models Used

VGG-16 Architecture

VGG-16 is the CNN Architecture which won the ILSVRC 2014 Data Challenge as a successor of AlexNet. The VGG-16 architecture consists of 13 convolutional layers with filter size (3,3), 5 max-pooling layers, 3 fully connected layers and the final softmax activation layer with 1000 input categories. Results from this pre-trained model are extremely accurate because it was trained using the extensive and comprehensive ImageNetdatabase. The VGG-16 model will accept input photos with a dimension of (224,224). This design uses the ReLU activation function to generate extremely precise and reliable conclusions depending on input data, solving the vanishing gradient problem. When the complete VGG-16 model is trained on the ADNI dataset, this model accounted for 14,815,044 trainable parameters after shrinking the network.

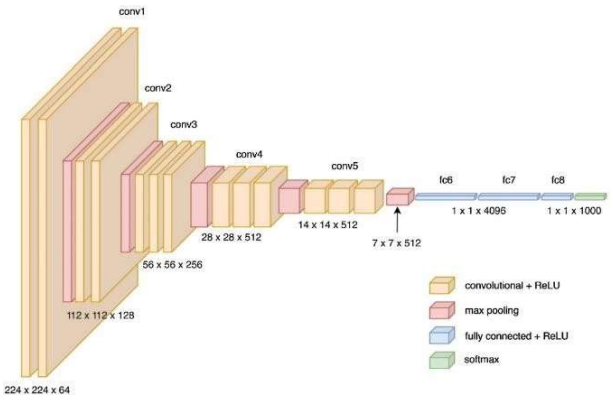

Figure 1. VGG-19 Architecture [31]

ResNet50 Architecture

ResNet, or Residual Networks, is the common neural network that forms the basis for numerous computer vision applications. The vanishing gradient issue is successfully eliminated by the ResNet model with the help of Skip connections, which is to add the original input to the convolutional block's output which will thereby improve the accuracy and train the model with larger attributes extracted from the input data at higher epochs. The ResNet-50 model is composed of five stages, each with convolution and an identity block. Each convolution block consists of three convolution layers. ResNet-50 has approximately 23 million trainable parameters. ResNet is also referred to as "network-in-network architectures," which is a special kind of architecture based on micro-architecture modules.

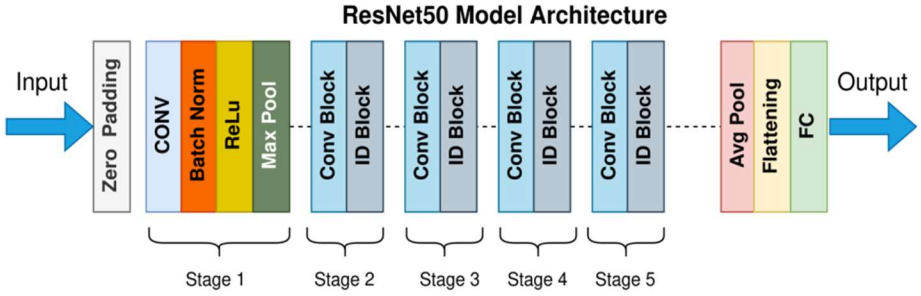

Figure 2. ResNet50 Architecture [29]

Inception V-3 Architecture

The naive version of Inception V3 Architecture is composed of a 3x3 max pooling layer, 1x1, 3x3, and 5x5 factorized convolutional layers. The primary benefit of the Inception V3 architecture is the Spatial Factorization into Asymmetric Convolutions i.e. replacement of 3x3 convolutional layers with, for example, 1x3 and 3x1 layers, which is significantly less expensive in terms of time and space complexity given the same number of input and output filters. Auxiliary classifiers are included in the Inception V3 model to enhance the rate of convergence in very deep neural networks. The inception V3 model has 42 layers in total, which is a little more than the inception V1 and V2 models. Training high-quality networks on relatively small training sets are made possible by Inception V3's incorporation of batch-normalized auxiliary classifiers, extra regularization, and label smoothing. After the preprocessing stage, the dataset was used to train different types of CNNs: VGG16, Inception V3, and ResNet50. The developed deep learning architecture heavily utilizes the Tensorflow Python library, which has a main sub-module named Keras.

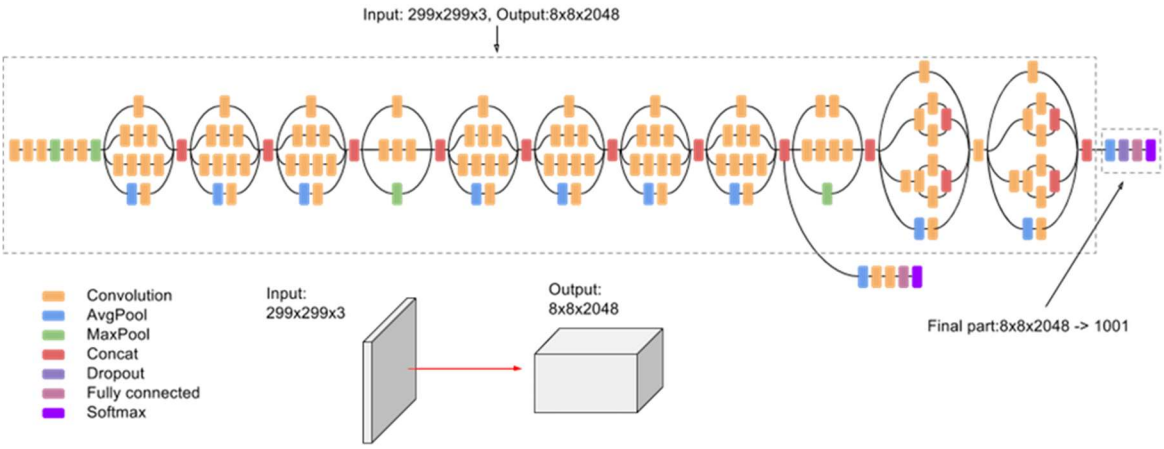

Figure 3. Inception V-3 Architecture [30]

B. Workflow of the proposed system

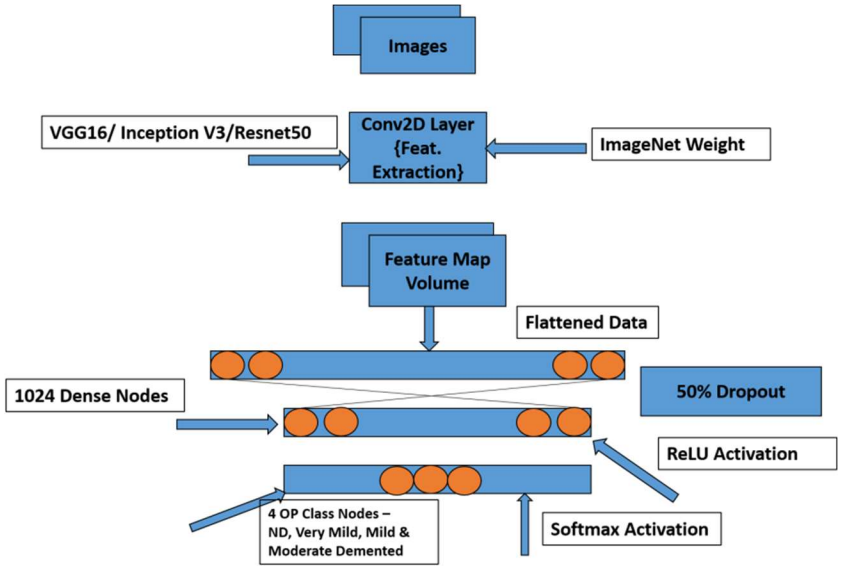

Figure 4. Methodology flowchart

The model is designed to predict Alzheimer disease using Convolutional Neural Networks (CNN) into the severity classes - ND, mild, very mild and moderately demented. The brain MRI images were split into Train (5121 images), Test (1025 images) and Validation (254 images) datasets. These images were resized to 224x224 dimension using Imagedatagenerator module under Keras. Each image is pixelated and rescaled (1/255 factor) to obtain preprocessed images suitable for applying the transfer learning model. Concept of transfer learning Using Resnet50, InceptionV3 and VGG16 is applied on the conditioned image data in feature extraction stage. Weights of each image in the CNN model is randomised using Imagenet in the conv2D feature extraction layer.

The pre-trained CNN model consists of 1024 dense nodes each with 50% dropout and ReLU activation function to eliminate overfitting. The final output layer with Softmax activation function provides well defined set of weights which are passed to SVM classifier to provide final output divided to 4 classes - No Dementia, Very Mild Demented, Mild Demented, and Moderate Demented classes to predict severity stage of Alzheimer's disease detected in the patient.

Dataset Procurement

The proposed model is trained with the use of brain MRI images taken from the ADNI dataset incorporating deep learning principles based on Alzheimer's ailment prediction. The dataset is based totally on MRI and PETscans of 195 patients, under observation. This dataset is split into four classes: no-dementia, slight dementia, mild dementia, and moderate dementia.

Data Analysis and Preprocessing

The dataset is divided into three batches using ImageDataGenerator from the TensorFlow library. The Train (5121 images), Test (1025 images), and Validation (254 images) datasets each contain a set of images that havebeen rescaled to (224,224) dimensions and pixelated (Rescale Factor = 1/255). Now, the processed image inputcan be viewed using the “imshow()” function under Tensorflow.

Principal Component Analysis (PCA)

In the Feature Extraction stage, PCA (Principal Component Analysis) is performed on different classes of the dataset to reduce the dimensionality of the data. When the model is trained using the dataset, PCA helps minimizeinformation loss. It is known that "Dimensionality Curses" can occur in neuroimaging studies when subjects have a disproportionately high number of attributes. The dimensionality of high-dimensional imaging is reducedby selecting important indicative features based on Principal Component Analysis. The smallest measurements of each feature are thus removed, and only the largest and most representative measures are included. Each instance of the PCA schema to the k-dimensional spatial domain in k<d, yields new features that are a linear composition of the initial traits and vectors in each dimensional domain. Every image in the Alzheimer's dataset is transformed into a two-dimensional format. To create uniform input data for the deep learning model, the data is also standardized for mean and variance.

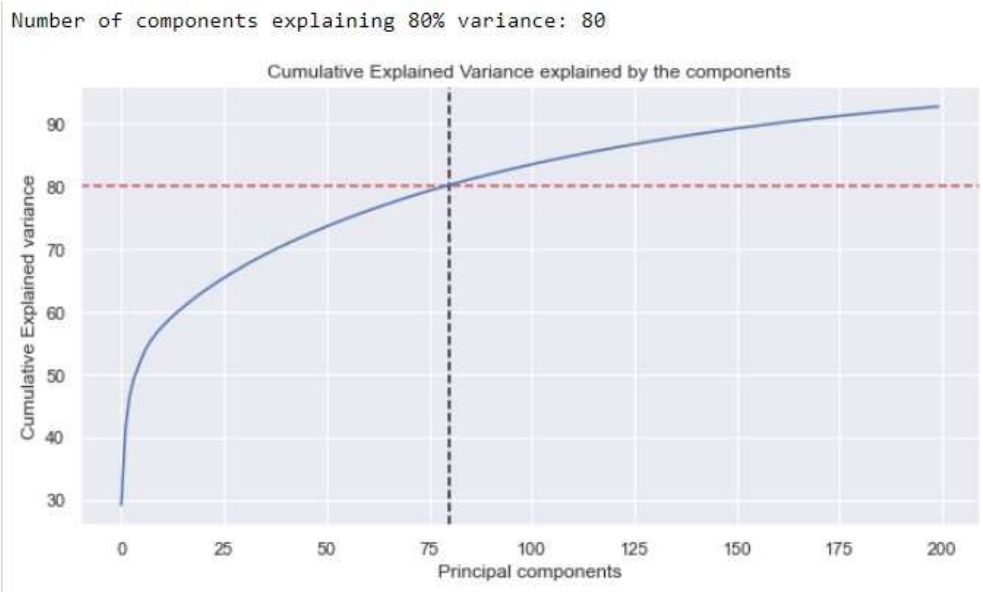

Figure 6. PCA Analysis

Training the Deep Learning Model

This paper proposes the use of pre-trained models, namely- ResNet50, VGG16, and Inception V3, which provide better accuracy than the proposed models, thus capturing the essence of the Transfer Learning strategy in Machine Learning.

To implement the ensemble learning technique in the deep learning infrastructure, images are first trained under the Conv2D/ Feature Extraction layer. In this layer, pre-trained models are employed, and the weights are randomised using ImageNet in the Conv2D layer.

The developed deep learning model is designed as a 2-model ensemble with Batch Normalization and Pooling layers. Flattened image data is passed through an SVM-CNN network with dense nodes in the hidden layer coupled with the Relu activation layer with a dropout of 50% to prevent overfitting of the ML model. Finally, the output - Softmax activation layer is split into 4 classes - No Dementia, Very Mild Demented, Mild Demented, and Moderate Demented. This ML model, on passing the input image, can predict the severity stageof Alzheimer's disease diagnosed in the patient.

Results

```
loss, auc, accuracy = modelvgg.evaluate(validation_dataset)
print("Loss: ", loss)
print("AUC: ", auc)
print("Accuracy: ", accuracy)
```

```
80/80 [==============================] - 3s 37ms/step - loss: 0.7392 - auc: 0.9071 - a
cc: 0.6747
Loss:  0.7391741871833801
AUC:  0.9070690274238586
Accuracy:  0.6747459173202515
```

Figure 7. VGG-19 Accuracy

```
accuracy = model_res.evaluate(validation_dataset)
print("Test Loss : AUC Score : Validation Accuracy: ", accuracy)
```

```
8/8 [==============================] - 19s 2s/step - loss: 0.7507 - auc: 0.9034 - acc: 0.7047
Test Loss : AUC Score : Validation Accuracy:  [0.7506507039070129, 0.9033986330032349, 0.7047244310379028]
```

Figure 8..ResNet50 Accuracy

```
accuracy = model_inc.evaluate(validation_dataset)
print("Test Loss : AUC Score : Validation Accuracy: ", accuracy)
```

```
8/8 [==============================] - 13s 2s/step - loss: 1.6506 - auc: 0.8829 - acc: 0.6693
Test Loss : AUC Score : Validation Accuracy:  [1.6506344079971313, 0.8829308748245239, 0.6692913174629211]
```

Figure 9. InceptionV3 Accuracy

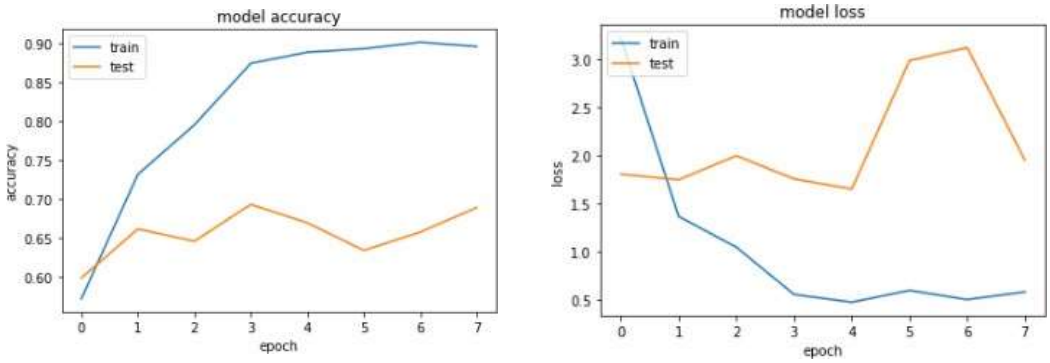

Figure 10. InceptionV3 Analysis

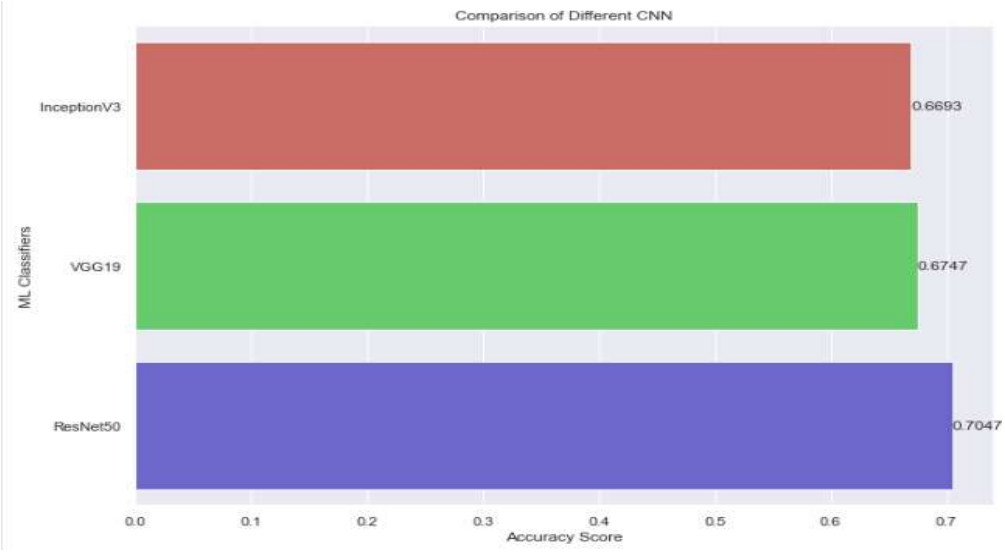

Figure 11. Comparison of different CNNs

C. Alzheimer's Disease Classification using Ensemble Learning

Exploratory data evaluation was performed on the OASIS dataset which includes longitudinal MRI informationcategorized into demented and non-demented classes. The data set consists of the MRI identity, age, dominant hand (left/right), number of visits, gender, years of schooling, socio-economic popularity, medical dementia rating, envisioned total intracranial extent, normalised entire brain volume, and atlas scaling component. This dataset shows that males and females experience dementia at different rates. Age and normalised whole brain volume (nWBV) had been found to have a negative correlation. Compared to individuals who weren't demented,men appear to have a better dementia threat. Additionally, patients with dementia were relatively less educated.

Analysis

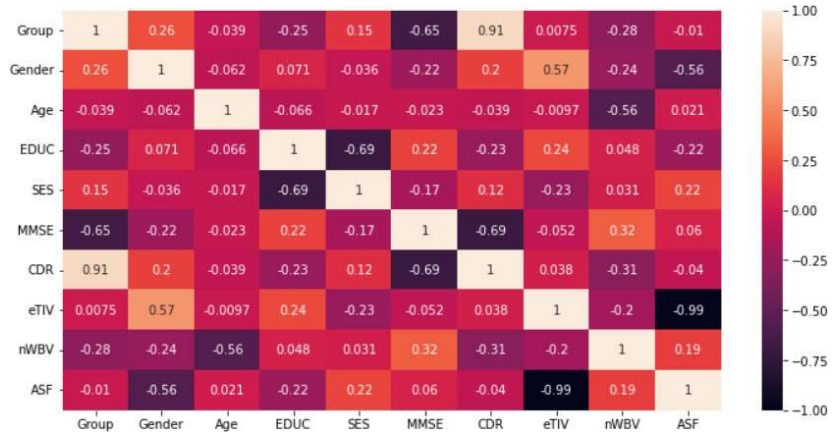

Figure 12. Confusion Matrix

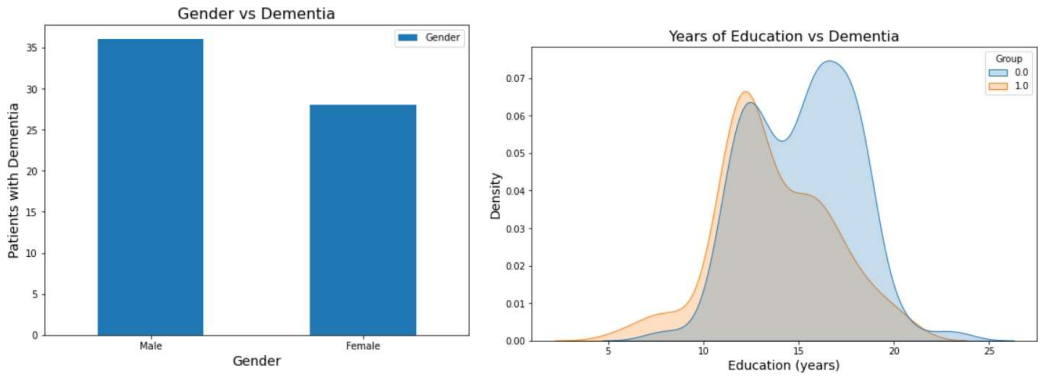

Figure 13. Outcomes of EDA[Group 1: Demented, Group 0:Non-Demented]

In a bid to boost the model's stability and predictive capacity, the ensemble learning technique mixes individual models. The goal of the ensemble learning technique is to increase the predictability and stability of the modelby combining different models. This strategy allows for stronger predictive performance than a single model. The ensemble technique searches for ways to combine different machine studying fashions right into a single predictive version to lessen variance in the use of bagging, bias using boosting, or improve predictions throughthe use of stacking. Ensemble methods may be divided into two groups: sequential ensemble strategies and parallel ensemble techniques. Base beginners, i.e., Adaboost, are sequentially created in sequential ensemble strategies.

Development of the model

The models used for ensemble sequential learning classification were logistic regression, KNN, Decision Tree Classifier, Neural Network (MLP Classifier), Random Forest Classifier, Gradient Boosting Classifier, and AdaBoost Classifier. The dataset was preprocessed using the StandardScaler method and a train-test split was performed with a test-to-train ratio of 3:7. Except for the decision tree classifier, all models' accuracy rates were 100%; however, the decision tree

classifier's accuracy rate was 97.78%. The F1 score for the decision tree classifier was 0.9697, whereas the other models had an F1 score of 1.

Results

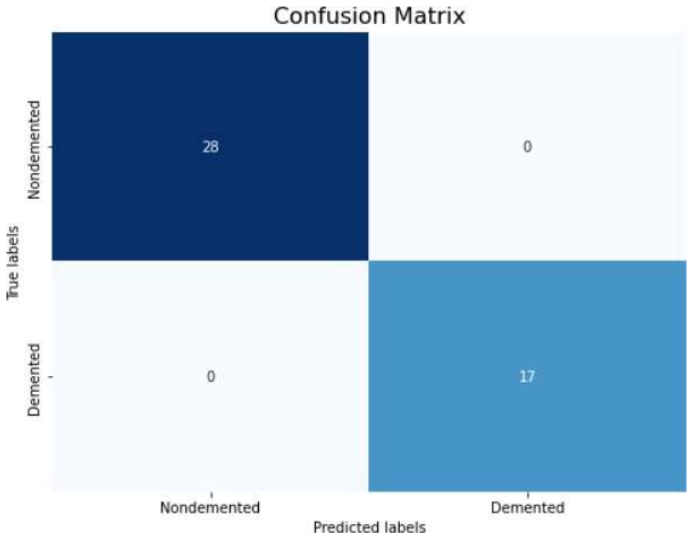

Figure 14. Comparison of model prediction outcomes

D. User Interface Design

This paper recommends developing a web application for the benefit of patients to minimise the need for frequenthospital visits with MRI reports that can predict whether a patient will be diagnosed with a disease or not. This website is intended to serve as a portal for sick people. After logging in and responding to a few straightforwardquestions about their health, users are directed to a page where they can upload their MRI reports and, after submitting them, find out whether they have the disease or not. If the test is positive, the severity of Alzheimer's disease is indicated so that the user can proceed with the necessary medical care to lessen the effects of the fatal condition.

Results

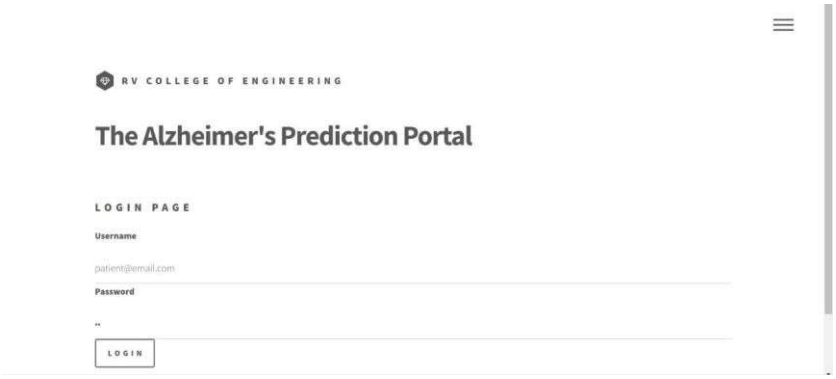

Figure 15. Login Page for the Website

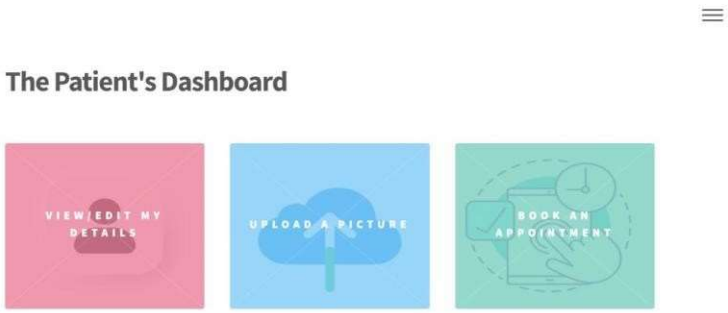

Figure 16. The patient's dashboard

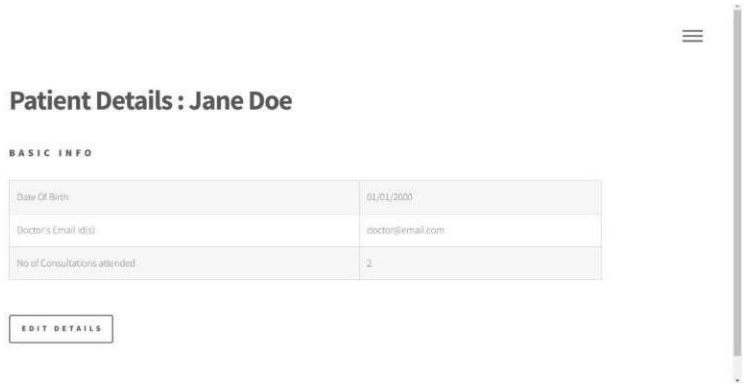

Figure 17. Patient details page

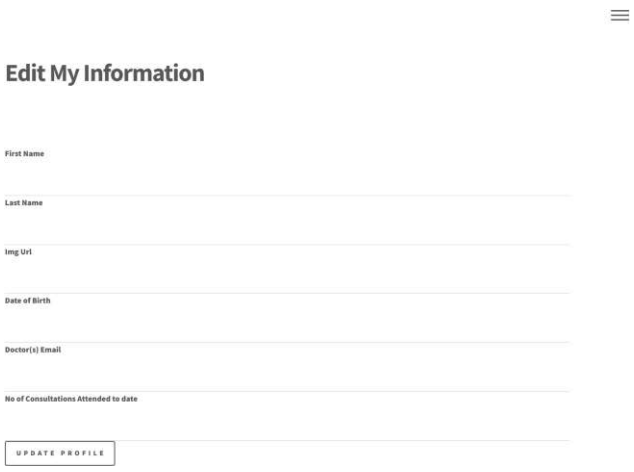

Figure 18. MRI scan upload portal

4. Conclusion

This paper presents a holistic analysis of publicly available MRI and PET datasets to detect Alzheimer's disease in patients at an early stage, which would aid in preventing adverse health

effects caused by the disease. This study makes accurate prediction of Alzheimer's disease in patients with MRI scans possible by using state-of- the-art pre-trained CNN models - ResNet50, VGG19, and Inception V3. The publicly available OASIS dataset is used to classify and hence provide an end-to-end analysis of Alzheimer's disease in patients, which is fed intothe machine learning model to precisely predict Alzheimer's disease in patients with very high accuracy scores. This research aims to develop advanced techniques for accurately diagnosing disease, which will be extremely useful in the medical field. The efficacy of the system is demonstrated for tracking the progression of AD without the use of specialist equipment or medical supervisors. In contrast to unquestionably in carefully chosen research situations with strict inclusion-exclusion bounds, experienced doctors must thoroughly examine and validate various multivariate and systems learning strategies in contrast to conventional analysis in a clinical situation. In conclusion, this work represents a significant advancement in the use of computer-aided diagnostics for the early diagnosis and classification of Alzheimer's disease, allowing for the delivery of appropriate clinical care and possibly even curing the condition.

5. Limitations and Future Studies

The deep learning model used to classify the MRI images is very slow and requires high computer processing speed. This model can be can be optimized by using callbacks to ensure continuous improvement of accuracy in each epoch of training phase. K-fold cross validation technique could be used along with the transfer learning model in order to provide highly precise and accurate output. In the future, optimization of the deep learning model with the use of optimizers [Bayesian Optimization], callbacks and changes to the learning rate can provide greater accuracy of the result and ensure fast response from the web application. Website can display color-based indication of the severity of Alzheimer’s disease i.e., green for ND [Non-demented], yellow [Very Mild Demented], orange [Mild Demented] and red [Moderate Demented]. This model can be used by patients to assess their risk level of acquiring the disease and obtain early medical care to mitigate the harmful effects of the disease in future.

Dataset Availability

The Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu) provided the information for this article. A public-private partnership known as the ADNI was established in 2003 under the direction ofPrincipal Investigator Dr Michael W. Weiner. The main objective of ADNI has been to determine whether serialMRI, PET, other biological markers, and a clinical, and neuropsychological evaluation can be used together to track the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD).

References

Islam, J., & Zhang, Y. (2017). A Novel Deep Learning Based Multi-class Classification Method for Alzheimer’s Disease Detection Using Brain MRI Data. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 10654 LNAI, 213–222. https://doi.org/10.1007/978-3-319-70772-3_20

Falahati, F., Westman, E., & Simmons, A. (2014). Multivariate data analysis and machine learning in Alzheimer’s disease with a focus on structural magnetic resonance imaging. Journal of

Alzheimer's Disease, 41(3), 685–708. https://doi.org/10.3233/JAD-131928

Venugopalan, J., Tong, L., Hassanzadeh, H. R., & Wang, M. D. (2021). Multimodal deep learning models for early detection of Alzheimer's disease stage. Scientific Reports, 11(1), 1–13. https://doi.org/10.1038/s41598-020-74399-w

Herrera, L. J., Rojas, I., Pomares, H., Guillén, A., Valenzuela, O., & Baños, O. (2013). Classification of MRI images for Alzheimer's disease detection. Proceedings - SocialCom/PASSAT/BigData/EconCom/BioMedCom 2013, 846–851. https://doi.org/10.1109/SocialCom.2013.127

Khan, T. K. (2016). Clinical Diagnosis of Alzheimer's Disease. Biomarkers in Alzheimer's Disease, 27–48. https://doi.org/10.1016/b978-0-12-804832-0.00002-x

Ji, H., Liu, Z., Yan, W. Q., & Klette, R. (2019). Early diagnosis of Alzheimer's disease using deep learning. ACM International Conference Proceeding Series, 87–91. https://doi.org/10.1145/3341016.3341024

Ebrahimighahnavieh, M. A., Luo, S., & Chiong, R. (2020). Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review. Computer Methods and Programs in Biomedicine, 187, 105242. https://doi.org/10.1016/j.cmpb.2019.105242

Khan, A., Liu, L. S., Usman, M., & Fong, S. (2016). Early diagnosis of Alzheimer disease using instance-based learning techniques. Journal of Medical Imaging and Health Informatics, 6(4), 1111–1118. https://doi.org/10.1166/jmihi.2016.1808

Jo, T., Nho, K., & Saykin, A. J. (2019). Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data. Frontiers in Aging Neuroscience, 11(August). https://doi.org/10.3389/fnagi.2019.00220

Yang, S., Bornot, J. M. S., Wong-Lin, K., & Prasad, G. (2019). M/EEG-Based Bio-Markers to Predict the MCI and Alzheimer's Disease: A Review from the ML Perspective. IEEE Transactions on Biomedical Engineering, 66(10), 2924–2935. https://doi.org/10.1109/TBME.2019.2898871

Folego, G., Weiler, M., Casseb, R. F., Pires, R., & Rocha, A. (2020). Alzheimer's Disease Detection Through Whole-Brain 3D-CNN MRI. Frontiers in Bioengineering and Biotechnology, 8(October). https://doi.org/10.3389/fbioe.2020.534592

Dyrba, M., Ewers, M., Wegrzyn, M., Kilimann, I., Plant, C., Oswald, A., Meindl, T., Pievani, M., Bokde, A. L. W., Fellgiebel, A., Filippi, M., Hampel, H., Klöppel, S., Hauenstein, K., Kirste, T., & Teipel, S. J. (2013). Robust Automated Detection of Microstructural White Matter Degeneration in Alzheimer's Disease Using Machine Learning Classification of Multicenter DTI Data. PLoS ONE, 8(5). https://doi.org/10.1371/journal.pone.0064925

Klöppel, S., Stonnington, C. M., Chu, C., Draganski, B., Scahill, R. I., Rohrer, J. D., Fox, N. C., Jack, C. R., Ashburner, J., & Frackowiak, R. S. J. (2008). Automatic classification of MR scans in Alzheimer's disease. Brain, 131(3), 681–689. https://doi.org/10.1093/brain/awm319

Sudharsan, M., & Thailambal, G. (2021). Alzheimer's disease prediction using machine learning techniques and principal component analysis (PCA). Materials Today: Proceedings, xxxx.

https://doi.org/10.1016/j.matpr.2021.03.061

Lee, G., Nho, K., Kang, B., Sohn, K. A., Kim, D., Weiner, M. W., Aisen, P., Petersen, R., Jack, C. R., Jagust, W., Trojanowki, J. Q., Toga, A. W., Beckett, L., Green, R. C., Saykin, A. J., Morris, J., Shaw, L. M., Khachaturian, Z., Sorensen, G., … Fargher, K. (2019). Predicting Alzheimer's disease progression using multi-modal deep learning approach. Scientific Reports, 9(1), 1–12. https://doi.org/10.1038/s41598-018-37769-z

Al-Shoukry, S., Rassem, T. H., & Makbol, N. M. (2020). Alzheimer's diseases detection by using deep learning algorithms: A mini-review. IEEE Access, 8, 77131–77141. https://doi.org/10.1109/ACCESS.2020.2989396

Lancioni, G. E., Singh, N. N., O'reilly, M. F., Sigafoos, J., Buonocunto, F., Sacco, V., Navarro, J., Addante, L. M., & D'agostino, I. (2010). Persons with acquired brain injury and multiple disabilities access stimulation independently through microswitch-based technology. Perceptual and Motor Skills, 111(2), 485–495. https://doi.org/10.2466/15.17.23.PMS.111.5.485-495

Ortiz, A., Munilla, J., Górriz, J. M., & Ramírez, J. (2016). Ensembles of Deep Learning Architectures for the Early Diagnosis of the Alzheimer's Disease. International Journal of Neural Systems, 26(7), 1–23. https://doi.org/10.1142/S0129065716500258

Queiroz, L., Nucci, A., Facure, N. O., & Facure, J. J. (1979). Massive Spinal Cord Necrosis in Schistosomiasis. Archives of Neurology, 36(8), 517–519. https://doi.org/10.1001/archneur.1979.00500440087021

Leong, L. K., & Abdullah, A. A. (2019). Prediction of Alzheimer's disease (AD) Using Machine Learning Techniques with Boruta Algorithm as Feature Selection Method. Journal of Physics: Conference Series, 1372(1). https://doi.org/10.1088/1742-6596/1372/1/012065

Sarraf, S., & Tofighi, G. (2016). Classification of Alzheimer's Disease Structural MRI Data by Deep Learning Convolutional Neural Networks. 8–12. http://arxiv.org/abs/1607.06583

Sarraf, S., DeSouza, D. D., Anderson, J., Tofighi, G., & Initiativ, for the A. D. N. (2017). DeepAD: Alzheimer's Disease Classification via Deep Convolutional Neural Networks using MRI and fMRI. BioRxiv, 070441. https://www.biorxiv.org/content/10.1101/070441v4%0Ahttps://www.biorxiv.org/content/10.1101/070441v4.abstract

Che, H., Liu, S., Member, S., Cai, W., Pujol, S., Kikinis, R., & Feng, D. (2014). CO-NEIGHBOR MULTI-VIEW SPECTRAL EMBEDDING FOR MEDICAL CONTENT-BASED RETRIEVAL BMIT Research Group , School of IT , University of Sydney , Australia Surgical Planning Laboratory , Brigham & Women ' s Hospital , Harvard Medical School , Boston , USA. 911–914. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6868019

Bringas, S., Salomón, S., Duque, R., Lage, C., & Montaña, J. L. (2020). Alzheimer's Disease stage identification using deep learning models. Journal of Biomedical Informatics, 109(February), 103514. https://doi.org/10.1016/j.jbi.2020.103514

Abed, M. T., Fatema, U., Nabil, S. A., Alam, M. A., & Reza, M. T. (2020). Alzheimer's Disease

Prediction Using Convolutional Neural Network Models Leveraging Pre-existing Architecture and Transfer Learning. 2020 Joint 9th International Conference on Informatics, Electronics and Vision and 2020 4th International Conference on Imaging, Vision and Pattern Recognition, ICIEV and IcIVPR 2020. https://doi.org/10.1109/ICIEVicIVPR48672.2020.9306649

Kavitha, C., Mani, V., Srividhya, S. R., Khalaf, O. I., & Tavera Romero, C. A. (2022). Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models. Frontiers in Public Health, 10(March), 1–13. https://doi.org/10.3389/fpubh.2022.853294