Progressing Alzheimer's Diagnosis with Ensemble CNN Model

[1]Ashutosh Pardhan,[2] Aryan Shandhilya, [3]Sarthak Dwivedi, [4]Vaibhav Tyagi, [5]Atin Joshi
[1]*Associate Professor, R.D. Engineering College, R.D. Engineering College, Uttar Pradesh, India*
[2345] *Department of Computer Science & Engineering, R.D. Engineering College, Uttar Pradesh, India*

Abstract—This paper proposes an Alzheimer's disease prediction model using CNN, implemented on a system with AMD Radeon Vega 8 Graphics to improve computational traceability. The research is encouraging because the implicates of the model touched the 97% accuracy of the disease prediction by MRI images of patients. The integration of the Vega 8 GPU allows the system to process large datasets and perform computations at a significantly faster rate, thereby reducing training time. The MRI dataset used in this study is highly imbalanced, with four classes: Non-Demented or Non-D, Very Mild Dementia or V.M.D, Mild Dementia or M.D, Moderate Demented or M.D.A. CNN was chosen for its capability in highlight extraction and learning from MRI pictures, without requiring human interference. The show was run with parallel and multiclass datasets, and IT got 97% exactness. The systematic analysis of the test shows that the system can diagnose Alzheimer's right at the initial stage of the disease development. This approach shows how CNNs with the aid of AMD Radeon Vega 8 Graphics perform well in automating Alzheimer's diagnosis while breaking the barriers associated with manual feature extraction and orthodox dependence on experts.

Index Terms—Alzheimer's Disease Prediction, MRI Image Analysis, Adaptive Synthetic Oversampling, Neuroimaging, Early Diagnosis, Convolutional Neural Network.

I. INTRODUCTION

Alzheimer's disease (AD) is a chronic, irreversible neurodegenerative disorder that initially progresses without symptoms [1]. This affects cognitive functions such as learning, memory, reasoning, and judgment resulting in sever reduced ability to perform instrumental activities of daily living, to complete dependency. AD is estimated to occur in 2% of people at 65 years and rises to 35% at 85 years of age [2]. More than 55 million people are estimated to be affected by 2020, according to some projections, the number is likely to hit 152 million by 2050 [3]. Moreover, the pathological hallmarks of alpha-synuclein aggregation in neurons and synapses are seen even at least two decades before the onset of clinical manifestations [4]. Therefore, a time-consuming diagnosis is of great importance in extending the life expectancy of the patient and ameliorating the disease course. Moreover, it enables the detection and isolation of better drugs and treatments, as Ahmad et al pointed out in their paper on new therapies

The framework that was employed to roll out this CNN- based method makes use of the AMD Radeon™ Vega 8 Graphics that present major computational benefits. Hu et al. also mention that this GPU's parallel architecture is highly beneficial with large image data sets used in AD diagnosis. Vega 8 also has a gargantuan capacity for graphic processing and this helps the CNN overcome limitations occasioned by imbalanced MRI datasets. To rectify this anomaly, an adaptive synthetic oversampling technique was used which evenly distributes the number of non-demented, mild, moderate, and severe patients. This balance enhances CNN's generalization capability concerning different states of sickness. The AMD Radeon Vega 8 Graphics provide profound improvement in the computational nature of the model by learning faster from big data inputs while the accuracy of the model remains high. The model developed in this work yielded a training accuracy of 0.97 in Alzheimer's disease classification whether in binary or multiclass manner. This performance catalyzes the call for early diagnosis since it can greatly enhance disease management, and in turn, the quality of life of patients [5].

The combinational use of CNNs and GPUs also enhances the efficiency of diagnosis-making in healthcare organizations [6]. Such detection systems help relieve the burden on doctors, thus providing quicker and more accurate diagnoses. It at least provides some relief also to the family and the patients suffering the worse effects of Alzheimer's by reducing the financial and emotional stress the illness creates [7]. Therefore, the proposed CNN-based method for Alzheimer's diagnosis is search and more efficient compared to the myriad studies utilizing high-end GPUs like GTX 1080 Ti or Titan XP as well as reduced time consumption yet equally successful in identifying early-stage

AD. The combination of deep learning and advanced graphics processing units enables early detection and treatment of AD, leading to become a global health concern.

II. LITERATUREREVIEW

Alzheimer's disease (AD) is still a concern for physicians, and diagnosis of the disease continues to be a research interest [8]. For example, DenseNet and a softmax classification layer were utilized for classification using Alzheimer's datasets, and the results were 88.9% for classification, which is still a positive result, but that could have been boosted [9] Yildirim at al also employed a four-class set and used a hybrid model that was based on ResNet50; they proved that their chosen model was better than ResNet50, demonstrating that their model outperformed pre-trained CNNs with a 90% accuracy rate [10]. These studies shed light on some issues that have been revealed concerning the detection of AD. They have also discussed Sparse autoencoder and 3D CNNs that outperformed 2D convolutional in previous work. Nevertheless, pre-trained weights are applied but fine-tuning is not employed, which means that a potential improvement of the results may be achieved through additional fine-tuning [11], [12].

Many researchers have used CNNs and DL algorithms for the classification of AD in different works. For example, LeNet5 with 94.79% accuracy whereas GoogleNet was 96.84% when trained on Alzheimer's fMRI and sMRI datasets [13]. DL models are more used in medical imaging than other methods for their high results. Some modifications of autoencoders are used to enhance its performance including CONV-AE, which uses convolutional layers, especially 3D convolution [14], [15]. Transfer Learning (TL) is highlighted in other works as a better practice than directly training CNNs from scratch, through fine-tuning them. More specifically, a study conducted on the application of TL in medical imaging of a patient's brain for AD diagnosis has proven very accurate [16]. In another, the features were extracted using sparse filtering and unsupervised neural networks, before following sparse filtering and softmax classification [17]–[19]. Other techniques, including Boltzmann machines and sparse coding, have been used to capture large data to analyze [20]. Surviving analysis of behavioral patterns over time utilizing cerebrospinal fluid data obtained from the ADNI dataset, the researchers attained an accuracy of 95% using machine learning with Bluetooth signal sign. Other techniques that were used included Boltzmann machines and scattered coding for dealing with big data [21]. From the MRI data of the ADNI dataset, the behavioral pattern over time was analyzed using Cerebrospinal fluid samples with the help of ML incorporating Bluetooth beacons at an accuracy of 95%.

Hippocampal surface features for early-stage AD detection were discussed in the paper by Gerard et al., the authors achieved 83% classification rate [22], [13]. Other works have shown that despite using deep learning it is possible to improve image classification accuracy by using transfer learning. For instance, the effectiveness of a CNN model based on the VGG16 architecture of detecting AD from MRI brain images was determined to be 95.7% [13].

Another group of studies has been focused on biosignals, as the ways to diagnose AD and distinguish it from other conditions. Imbalanced data was counteracted through oversampling and undersampling which proved that the Bayes classifiers are more efficient in diagnosis than linear classifiers [23]. Kim expanded the application of ML algorithms to identify new AD biomarkers and found that models using multiple biomarkers achieve greater accuracy than those relying on a single gene. [3]. Other works like, have shown the applicability of biosignals in AD identification using the oversampling and undersampling schemes on the datasets [13]. However, these results indicate that the use of the Bayes classifier improves diagnostic capability over the linear classifiers in this application. Kim also applied and expanded ML algorithms for the identification of new biomarkers for AD, and he discovered that the models with multiple biomarkers have higher accuracy than the single gene [24].

Algorithm 1 VGG16 Architecture

```
Input: Image tensor of shape 224 ×224×3
Output: Classification probabilities for n classes
Feature Extraction:
Block 1:
    Conv(3 ×3,64)
    Conv(3 ×3,64)
    MaxPool(2×2,stride = 2)
Block 2:
    Conv(3 ×3,128)
    Conv(3 ×3,128)
    MaxPool(2×2,stride = 2
Block 3:
    Conv(3 ×3,256)
    Conv(3 ×3,256)
    Conv(3 ×3,256)
    MaxPool(2×2,stride = 2)
Block 4:
    Conv(3 ×3,512)
    Conv(3 ×3,512)
    Conv(3 ×3,512)
    MaxPool(2×2,stride = 2)
Block 5:
    Conv(3 ×3,512)
    Conv(3 ×3,512)
    Conv(3 ×3,512)
    MaxPool(2×2,stride = 2)
Fully Connected Layers:
    Flatten the feature map
    Dense (4096)
    Dense (4096)
    Dense(n) (Number of classes)
Softmax:
    Apply softmax activation to get class probabilities.
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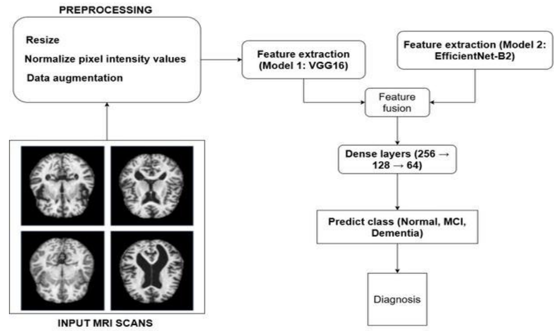

Fig 1 Processes used for Alzheimer's disease detection

Some biosignals have also been employed in several studies to identify dementia and other related neurodegenerative diseases [25]. In a study that focused on the elderly, Han et al. pointed out that they had detected dementia but called for a bigger sample to be used. Hazarika et al. developed an inexpensive approach for diagnosing AD with DenseNet121 achieving 87% accuracy. They proceed with the merging of AlexNet and LeNet with the specificity of the models to get a 93% accuracy rate on the detection of diseases. Likewise, researchers employed CNNbased transfer learning using VGG16, thus; we attained 95.7% accuracy. Other studies including, have primarily aimed at dealing with class imbalance problem in AD datasets that results in fitting and high rates of errors [26]. These studies reflect trends in the use of DL and TL techniques for AD classification, as well as challenges such as class imbalance and limited datasets that hinder achieving high performance.

III. PROPOSEDMETHODOLOGY

The approach for early AD diagnosis utilizes DL and ensemble classifier models. The workflow diagram illustrating the detection process is presented in Figure 1

A. Dataset

The study used two publicly available AD datasets from Kaggle. The primary dataset consisted of four classes Non- Demented (ND), Very Mild Demented (VMD), Mild Demented (MD), and Moderate Demented (MOD) [27]. The analysis of demented images is shown in Figure 3 The second dataset was a binary class with an S-selected comparison between Alzheimer's disease (AD) and mild cognitive impairment (MCI) labels. Attributed to the skewed representation of images of disease detection [28].

1) Ensemble Deep Learning and Transfer Learning:

In this work, ensemble, deep-learning models were deployed to improve the diagnosis of Alzheimer's disease. VGG16 and efficient net B2 were to be used for pre-training as a part of the ensemble method [29], [30]. These models were then adjusted and stacked in an end-to-end configuration to obtain the architecture shown in Figure 2. This was achieved using dropout layers and batch normalization in order not to overtrain the network. The final two fully connected were trained under categorical cross-entropy loss and Adam optimizer. To increase the models' accuracy and to save the training time that would be otherwise needed for fine-tuning, pre-trained models were employed where the models themselves were trained on other large image classification datasets.

B. Performance Measures

Performance metrics are measurable indicators used to evaluate effectiveness, while dimensions serve as quantitative tools to assess the efficiency of the model to solving a certain problem [31]. Additionally, the classification of the model's outcomes can be categorized in 4 classes. It means that the individual approaches are correctly classified cases, or false positive (FP) and false negative (FN), cases respectively (FP) and false negative (FN) [32]. The number of targets true positive, TP, is the number of (objects) correctly classified as positive, the number of incorrect negative predictions made on non-objs is referred to as the TN. FP and FN present incorrectly classified as positive and incorrectly classified as negative, respectively. In this study, which were the evaluation parameters that were used the recall, precision, accuracy, AUC, and F1 score [2].

$$\text{Accuracy(A)} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision(P)} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall (R)} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{F1-score} = 2 \times \frac{P \times R}{P + R} \quad (4)$$

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \quad (5)$$

IV. RESULTS

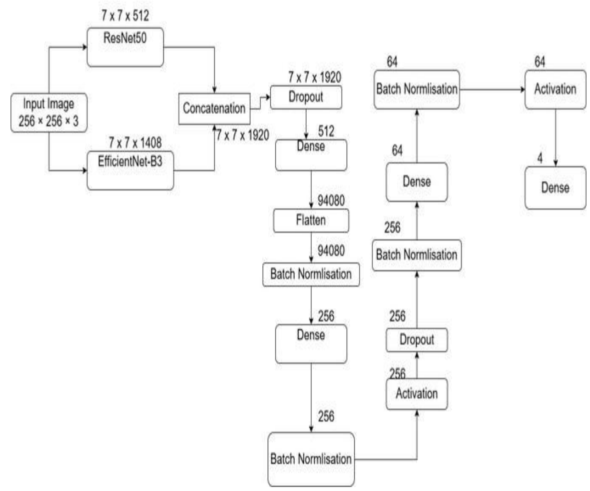

Fig. 2. Architectural illustration of ensemble model

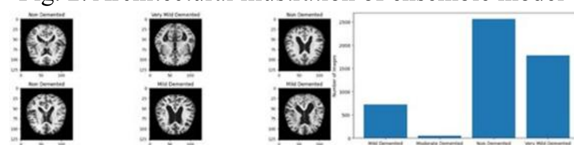

Fig. 3. Classification of mild, very mild, moderate, and non Demented images

A. Performance of Individual Models

The considerate results were recorded with the EfficientNet- B2 path reaching an accuracy of 95.89% and a recall of 95.95%. Out of the four models, DenseNet-121 delivered the worst result on each of the mentioned criteria. VGG16 and CNN are found to have almost similar classification rates whereas the Xception stands at 75.04% with a slightly better AUC of 93.70%.

B. Ensemble Model Outcomes

The proposed EfficientNet-B2 combined with VGG16 showed the highest efficiency reaching 97.35% accuracy and 99.64% AUC. The group number second, integrating EfficientNet-B2 and DenseNet-121 has obtained a remarkable 96.96% accuracy and 99.60% AUC. To compare the performance of ensembles, their accuracy was compared to a set of single models, some of which improved by as much as 18%. The training accuracy and loss and validation accuracy and loss of the proposed model are demonstrated in Figures 4 and 5. The confusion matrix is also shown in Figure 6 to analyze the performance of the proposed model.

C. Imbalanced Datasets

Therefore, secondary models or ensemble models, including the core spectral models, had good results on the imbalanced data set, but the overall accuracy was down 7-8% as compared with the verification on the balanced data sets [33]. Danny's results under these conditions were the highest and were obtained with the EfficientNet-B2 + DenseNet-121 ensemble and reached the value of 92.82%.

D. Hyperparameter Tuning and Cross-Validation

The chosen learning rate of 0.0001 proved to be quite stable, and the results shown by the combination of VGG16 + EfficientNet-B2 were quite comparable [34]. Cross-validation further supported the stability of ensemble models, showing fluctuation of accuracies ± 0.03 – 0.04 SD.

E. Comparison with Previous Studies

The proposed ensemble approach outperforms previous methods including the hybrid CNN-based and single-model methods as also validated by the current research demonstrating better accuracy and flexibility.

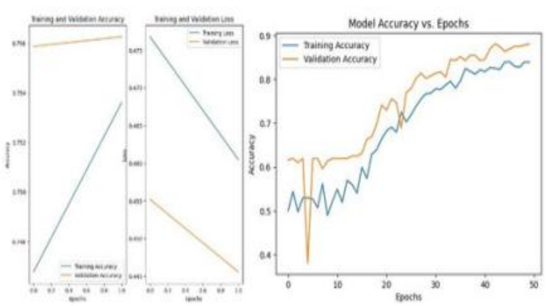

Fig.4. Comparisonoftrainingandvalidationaccuracy

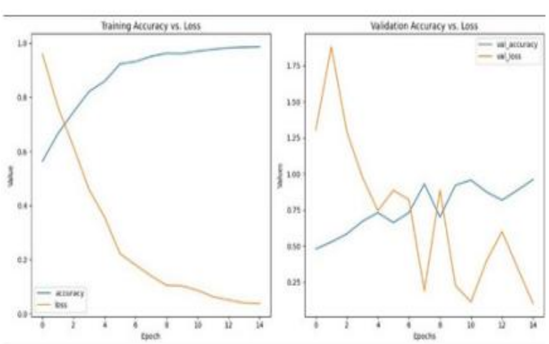

Fig. 5. Training accuracy vs loss graph (left) and validation accuracy vs loss graph (right)

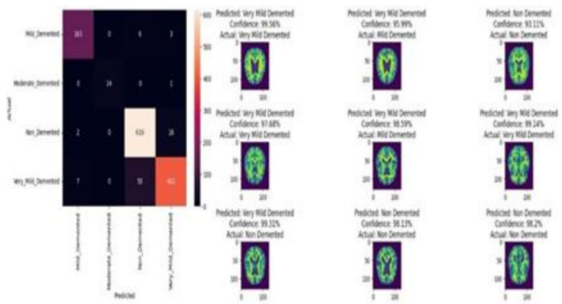

Fig.6. Comparison between actual and predicted results

V. CONCLUSION

This research explores innovative approaches and emerging opportunities in deep learning, ensemble modeling, and transfer learning to diagnose Alzheimer's disease (AD). Identifying AD and determining its stages are challenging diagnostic tasks, especially due to variations in MRI data. In response to these features, the current study proposed an ensemble deep learning model and used a comparable transfer learning approach towards improving AD diagnosis. As mentioned earlier the raw data collection was heavily skewed, with only a few instances belonging to one of the classes. This approach made it possible that the machine learning models trained on this data are not overfitting with the majority class. Of the different architectures of the ensembles of the two models, the combination with the least error margin of 2.65, VGG16 and EfficientNet-B2 obtained the highest accuracy of 97.35%. Secondly, the DenseNet-121 and Xception model provided 18% better when compared to both the individual models separately, while the second ensemble was 1.46% higher than that of just the EfficientNet-B2 separately.

The proposed ensemble model has a significant advantage It also does not require manually designed features and it can take advantage of deep features from the MRI images. This capability greatly improves the efficiency of the model and ensures that even when using rather small images, the model will produce high-quality results. Furthermore, the proposed architecture incorporates features that were pulled by other models with the MRI pattern representation which enhances the essence of the architecture in capturing more detailed aspects of Alzheimer's disease for classification. From the computational point of view, the adopted ensemble model achieved low training time proving that the proposed approach could be valuable for real-time clinical applications where timely and accurate diagnosis is crucial. In the future, these recommendations can extend this study to a large scale because the increasing data scale can enhance the generalization ability of the model.

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