The Early diagnosis of Alzheimer's Diseases from Brian MRI using Deep Learning Approaches.

1. Introduction

Alzheimer's Diseases(AD), one of the main causes of Dementia has seen rapid increases in cases worldwide. This increase has resulted in alarming financial burden on persons or families affected (DeTure & Dickson 2019). De Leon et al. (2004) stated that, the worldwide incidence of AD is projected to double by 2050 without any recognised diagnosis for early AD detection.

Dr Dahal (2022) defined AD as a degenerative neurological condition that is characterised by initial forgetfulness, decline in intelligence which can eventually lead to poor conduct, speech impediments, mobility issues etc. Currently, majority of AD cases have no viable treatment options, and the basic causes of the condition are unclear, except in a tiny percentage of family cases caused by genetic mutations (DeTure & Dickson 2019). As a result, diagnosing AD early is essential for timely intervention, treatment planning and patient care (Rasmussen & Langerman 2019).

In the field of medical imagining, Magnetic Resonance Imaging(MRI) stands out as an effective means in the detection and monitoring of AD (Filippi et al., 2012). Vemuri and Jack (2010) added that, neuroimaging provides detailed structural information about the brain, enabling the identification of disease-related changes, such as brain atropy, ventricular enlargement, and the presence of biomarkers related to neurodegenerative diseases.

To address these challenges, researchers have turned to deep learning techniques, particularly Convolutional Neural Networks (CNNs), for automated analysis and interpretation of MRI data (Sarvamangala & Kulkarni 2022). CNNs have demonstrated impressive success in several computer imaging tasks, including image classification, object detection, and semantic segmentation (Lu & Zhang 2016). Suk et al. (2014) also reaffirmed the role of CNNs in medical image analysis, especially AD diagnoses from MRI scans, due to their capacity to learn hierarchical representations straight from raw data.

In the case of AD, however, training CNN models from scratch demands a huge amount of labelled data, which may be scarce and expensive to obtain. (Alzubaidi et al., 2023). To defeat this drawback, transfer learning has emerged as an effective technique to address this constraint because of its ability to leverage knowledge from pre-trained models. (Sarker, 2021). This knowledge transfer leads to better generalization of the CNN models and improved AD diagnosis and interpretation. (Oh et al., 2019).

1.1. Research Problem

The research problem at hand is the pressing need for early diagnosis of Alzheimer's disease (AD). AD being a progressive neurodegenerative disorder means early diagnosis is important as it allows for timely intervention and implementation of appropriate treatment measures (Rasmussen & Langerman, 2019). Early detection provides an opportunity to slow down the progression of the disease, improve the efficacy of therapeutic interventions, and potentially improve the overall quality of life of affected individuals (Qiu et al., 2022). In addition, early diagnosis enables individuals and their families to make informed decisions about future care plans, fostering a supportive environment and facilitating access to specialized resources (Prince et al., 2016). Therefore, the focus of this research lies in leveraging the power of deep learning models, specifically CNN and transfer learning, to analyse MRI data and achieve high accuracy rates in the early detection of AD. This study will involve developing a robust and accurate tool for early AD detection and will aim to contribute to the advancement of medical practices, ultimately benefiting individuals at risk and society.

2. Background

The performance of Deep Learning (DL) methods, such as CNNs, has been shown to outperform that of existing Machine Learning (ML) methods (Baker et al., 2016). Also, most existing studies on AD diagnosis, concentrated on binary classification problems, like distinguishing AD patients from healthy older adults (Islam & Zhang 2017). However, to establish an early diagnosis, we must distinguish between the four stages of AD, resulting in a multi-class classification problem (Helaly et al., 2022).

2.1. Related Work

Several studies have explored the use of DL techniques, specifically CNNs, in diagnosing AD from MRIs. This section reviews previous research in this field, highlighting the models employed and the results achieved.

To begin with, Sarraf et al. (2016) classified AD from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset using the LeNet-5 CNN architecture (binary classification) achieving an accuracy of 97%. The study by Hosseini et al. (2016) developed a deeply supervised Adaptive 3D-CNN classifier predicting AD. The CAD-Dementia dataset was used to train three layered 3D Convolutional Autoencoder (3D-CAE) networks with no skull stripping pre-processing. The model was executed using the ADNI dataset achieving an accuracy of 97.6%.

Furthermore, Basaia et al. (2019) tested a CNN model to identify AD, c-MCI, and s-MCI using 3D MRI. All classifications were accurate, with the highest rates achieved in the AD vs Healthy Controls (HC) classification tests using both the ADNI dataset alone (99%) and the combined ADNI + non-ADNI dataset (98%). Similarly, Pan et al. (2020) proposed model attained an average accuracy of 0.84 ± 0.05 for AD vs. HC. The model was based on the ADNI Dataset with less than 3000 images.

One notable study by Zhang et al. (2021) extracted multi-scale features from pre-processed pictures using a densely CNN, they extended the convolution technique to 3D to collect MRI spatial information. Their proposed approach was 97.35% accurate in distinguishing AD patients from HCs, 87.82% accurate in distinguishing Mild Cognitive Impairment (MCI) converters from HCs, and 78.79% accurate in distinguishing MCI converters from non-converters.

Juan et al. (2020) constructed a 3D Densely Connected CNN (3D DenseNets) used in 3D MRI scans for 4-way classification, attaining 83% accuracy using the ADNI dataset. Similarly, Raees and Thomas, (2021) proposed a cutting-edge, simple, and early automated deep learning-based approach to predict Alzheimer's disease using a ADNI MRI dataset of healthy and ill people. It identified 111 participants in the database as MCI, AD, or Normal. Support Vector Machines (SVM) and several models of Deep Neural Network (DNN) algorithms were used for classification. Deep learning systems predicted AD with an accuracy of roughly 80-90% better than SVM with 74.2%.

In a closely related multiclass classification, Pradhan et al. (2021) developed a model which uses brain MRI samples from Kaggle, which outputs whether a person has mild, moderate, or no AD. For this classification, they employed the VGG19 and DenseNet169 architectures, providing a comparative accuracy of 88% and 78% respectively.

Lastly, Helaly et al. (2022), achieved some good results for 2D and 3D multi-class AD stage classifications, 93.61% and 95.17%, respectively. The VGG19 pre-trained model was also fine-tuned to an accuracy of 97% for multi-class AD classifications using ADNI Dataset.

Table_1:_Summary_of_literature_review

Researchers	Year	Dataset Used	Technique Used	Model Accuracy
Sarraf et al.	2016	ADNI	LeNet-5 CNN architecture	97%
Hosseini et al.	2016	CAD-Dementia	3D Convolutional Autoencoder (3D-CAE)	97.60%
Basaia et al.	2019	ADNI, non-ADNI	CNN model using 3D MRI	99% (AD vs. HC, ADNI)
Pan et al.	2020	ADNI	Proposed model based on ADNI dataset	84% (AD vs. HC)
Zhang et al.	2021	ADNI	Densely connected neural network	97.35% (AD vs. HC)
Juan et al.	2020	ADNI	3D Densely Connected Convolutional Networks	83%
Raees and Thomas	2021	ADNI	SVM and Deep Neural Network algorithms	74.2%, 80-90% (AD prediction)
Pradhan et al.	2021	Kaggle	VGG19, DenseNet169	88%, 78%
Helaly et al.	2022	ADNI	CNN models	93.61% (2D), 95.17% (3D)

The related work discussed above provides valuable insights and serves as a foundation for the project on early AD detection using MRI data. While previous studies have explored the use of Deep Learning (DL) techniques, specifically CNNs, in diagnosing AD, this research aims to contribute to this field by employing alternative methods and leveraging a new dataset. Specifically, a MRI dataset obtained from Kaggle, consisting of 40,000 brain MRIs, which provides a substantial and diverse collection for

analysis. The primary objective of my research is to develop and evaluate DL models, focusing on CNNs and transfer learning approaches, to achieve high accuracy in detecting AD at its early stages. By aiming for an accuracy range of 95-98%, my project seeks to facilitate early detection of AD, enabling timely interventions and fostering better management of the disease.

3. Objectives

The research objective of this study is to explore the effectiveness of transfer learning and CNN models in diagnosing the stages of Alzheimer's disease (AD) through the analysis of MRI scans. The specific objectives at the end of this study are as follows:

1. Develop a comprehensive understanding of transfer learning techniques and CNN models for AD diagnosis using MRI data.
2. Deliver a comprehensive report documenting the research methodology, findings, and recommendations for future work.
3. Acquire and pre-process a large MRI dataset containing 40,000 images to ensure data integrity and consistency.
4. Implement and fine-tune pre-trained CNN models, such as VGG19, VGG16, ResNet and Inception, using transfer learning approaches specifically tailored for AD diagnosis.
5. Investigate the impact of different hyperparameters and architecture variations on the CNN model's performance to optimize its accuracy.
6. Evaluate the performance of the developed CNN model by measuring its accuracy, and other relevant metrics.
7. Compare the performance of the CNN model with other existing approaches and assess its superiority in terms of accuracy and efficiency.

4. Methodology

The methodology employed in this study as shown in fig.1 illustrates the flow of data and the integration of different modules to achieve the desired output. It intends to use CNN and transfer learning techniques to aid in the early detection of AD. The project's implementation plan includes a structured design that makes use of the Python, TensorFlow, and Scikit-learn libraries. The methodology is as follows:

The training dataset, consisting of brain MRIs, is fed into the model. The model receives the data and undergoes training using DL techniques.

fig.1_Proposed_Methodology

Once the model has been trained, the system proceeds to validate their performance. The test dataset, which is distinct from the training dataset, is utilized for this purpose. The trained model is evaluated against the test dataset to obtain the testing or validation accuracy. By comparing the achieved accuracy with predefined thresholds or benchmarks, the effectiveness of the model in accurately classifying brain conditions can be determined.

5. Experiments

To achieve this objective, an MRI dataset of various AD patients at different stages and healthy individuals will be acquired. The MRI scans will undergo pre-processing steps, including Data augmentation and image resizing, to enhance the discriminative information related to AD pathology. CNN and Multiple pre-trained CNN models will be explored, and their transferability will be evaluated and compared in the context of AD detection.

5.1 Data Acquisition

The dataset used in this study comprises MRIs obtained from Kaggle, an open online dataset library, which contains four classes of images: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The dataset is organized into two folders, namely augmented images, and originals. The originals folder was utilized for testing purposes consisting of 6400 images whilst the Augmented dataset was used for both training and validation purposes, consisting of 33,984 images, distributed across the four classes as follows: Mild Demented (8,960 files), Moderate Demented (6,464 files), Non demented (9,600 files), and Very Mild Demented (8,960 files).

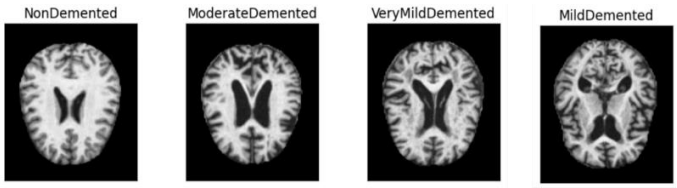

fig.2_Sample_AD_MRI_of_dataset_after_pre-processing

5.1.2 Data Augmentation

Augmented images play an important role in improving the generalization and robustness of DL models utilized for Alzheimer's disease diagnosis (Lu et al., 2022). It involves applying a variety of transformations and modifications to existing data samples to generate new, diverse, synthetic samples and aids in addressing the scarcity of labelled data, which is often a challenge in medical imaging research (Kayalibay et al., 2017).

5.2. Baseline Model

The baseline model used is a convolutional neural network consisting of two convolutional blocks. Each block contains a Conv2D layer with 32 and 64 filters, respectively, using a 3x3 kernel and ReLU activation. After each Conv2D layer, a MaxPooling2D layer with a 2x2 pool size is added. The output tensor from the second block is then flattened. Following that, a Dense layer with 128 units and ReLU activation is added. Finally, a final Dense layer with 4 units (corresponding to the four classes) and SoftMax activation is included. The model is compiled with the stochastic gradient descent (SGD) optimizer using a learning rate of 0.01 and binary cross-entropy loss. It is trained for 20 epochs using the training data and evaluated on the validation data.

5.3 Hyperparameter Optimization

Zahedi et al. (2021) argued that hyperparameter tuning is a crucial step in optimizing the performance of the baseline models. In this study, the hyperparameters of the model were fine-tuned to improve its performance in early Alzheimer's disease detection. The model was compiled using the Adam optimizer with a learning rate of 0.001, beta_1 = 0.9, and beta_2 = 0.999. The loss function chosen was CategoricalCrossentropy, suitable for multi-class classification tasks (Sarki et al., 2020). Experimenting with different image sizes aided the model to train properly and identify minor features within the dataset. To prevent overfitting and optimize training, two callbacks were implemented. The Early Stopping callback was set to monitor the validation loss and stop training if there was no improvement with a patience of 5 epochs, while the Model Checkpoint callback saved the best model based on validation loss. The model was trained using the fit() function with the specified number of epochs and the defined callbacks.

5.4 Proposed Model

The proposed model is a modified VGG19 model based on a pre-trained CNN architecture. VGG19 is chosen due to its effectiveness in image analysis and classification tasks (Hameed et al., 2020). The model is composed of 5 convolutional blocks, each followed by a max pooling layer. Each convolutional block consists of two or more convolutional layers with a filter size of 3x3 and a stride of 1. The model utilizes the pre-trained weights from the ImageNet dataset. The last four layers of the VGG19 are set as trainable while keeping the remaining layers frozen thus to allow fine-tuning of the model's learned features. The output of the VGG19 is flattened, and a dense layer with L2 regularization is added. The final layer consists of a SoftMax activation function with four units, corresponding to the four classes.

The model is fed with MRIs with image size 224x224 and is compiled with the Adam optimizer, using a learning rate of 0.0001 and categorical cross-entropy loss. Early stopping and model checkpointing callbacks are defined. The model is trained using the training data and validated on the validation data for 15 epochs. The training metrics and test results are visualized, including accuracy and loss.

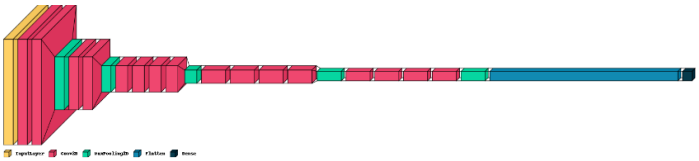

fig.3_Visual_representation_of_proposed_VGG19_model

5.5 Other Transfer Learning Models

Additionally, ResNet50, ResNet152, InceptionV3, and VGG16 models were also utilized as part of the hyperparameter tuning process. These models followed a similar procedure of loading pre-trained weights, changing input image sizes, freezing the layers, adding specific classification layers, compiling the model, defining callbacks, training the model with the dataset, and saving the best model based on validation loss.

Lastly, the models would be evaluated using accuracy, classification report, confusion matrix, training and validation accuracy and loss by epochs and the total training time recorded.

6. Evaluation

The objective was to evaluate the proposed model, a modified VGG19 architecture, against the baseline model and other experimented models as well as those from similar work done. Due to the high compute level of the project, the model was trained and evaluated using Google Colab Pro with 13gb RAM and 40gb GPU RAM. The evaluation focused on model accuracy, training time, confusion matrixes and classification reports to determine their effectiveness.

6.1 Proposed Model, vs. Baseline & Experimented models

The results of the evaluation revealed significant differences in the performance of the models. The proposed model achieved an impressive accuracy of 99.08% on the test data. It outperformed all other models, including the baseline model, which had an accuracy of only 52.47% due to an underfitting issue. The modified InceptionV3 model achieved an accuracy of 95.44%, while VGG16 achieved an accuracy of 98.70%. The CNN model attained an accuracy of 96.61%. These results demonstrate the superiority of the proposed model in accurately classifying different stages of Alzheimer's disease.

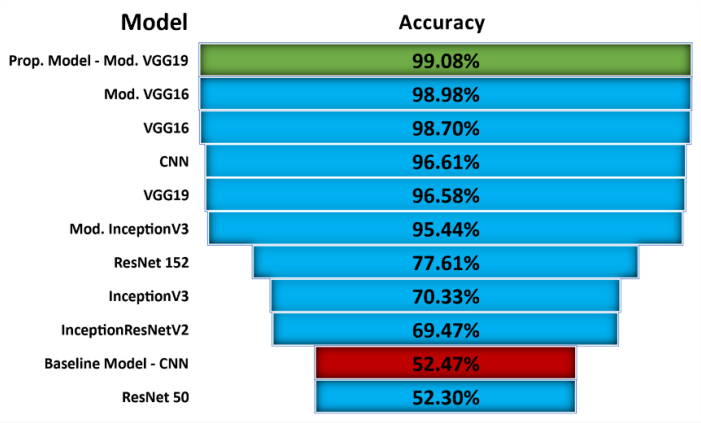

fig.4_Funnel_plot_of_model_accuracies

The average classification accuracies for the four stages of AD were significantly higher when using the proposed model, reinforcing its diagnostic capabilities. It exhibited exceptional weighted precision, recall, and f1-scores across all classes, including mild, moderate, normal, and very-mild. This indicates the model's ability to accurately predict each category. Similarly, the VGG19 model attained over 99% true-positive rates across three classes and 100% moderate classification. The modified InceptionV3 and VGG16 models also demonstrated high precision, recall, and f1-scores, while the CNN model showed slightly lower but still satisfactory performance.

Table_2:_Summary_of_Model_Performance_Metrics

Model	% Achieved	WAVG Precision	WAVG Recall	WAVG F1-score	Training Time (minutes)
Baseline Model - CNN	52.47%	54%	52%	42%	12.89
CNN	96.61%	97%	97%	97%	11.5
ResNet 50	52.30%	61%	52%	53%	63.03
ResNet 152	77.61%	80%	78%	78%	32.08
InceptionV3	70.33%	73%	70%	71%	37.71
InceptionResNetV2	69.47%	72%	69%	70%	63.96
VGG16	98.70%	99%	99%	99%	62.13
VGG19	96.58%	97%	97%	97%	62.41
Mod. VGG16	98.98%	99%	99%	99%	6.63
Mod. InceptionV3	95.44%	95%	95%	95%	45.88
Prop. Model - Mod. VGG19	99.08%	99%	99%	99%	18.04

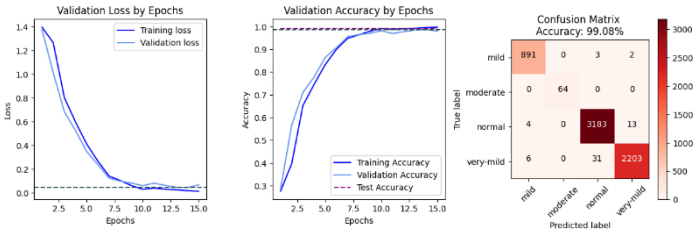

fig.5_Validation_Loss,_Accuracy_by_Epochs_&_Confusion_Matrix_of_Proposed_Model

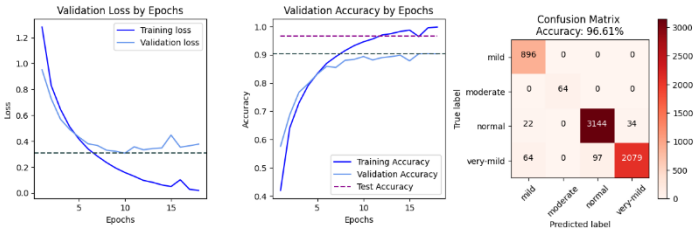

fig.6_Validation_Loss,_Accuracy_by_Epochs_&_Confusion_Matrix_of_CNN_Model

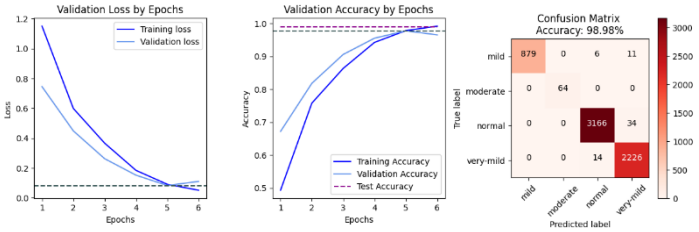

fig.7_Validation_Loss,_Accuracy_by_Epochs_&_Confusion_Matrix_of_VGG16_Model

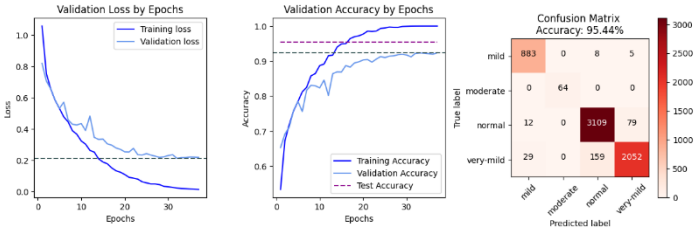

fig.8_Validation_Loss,_Accuracy_by_Epochs_&_Confusion_Matrix_of_Modified_InceptionV3

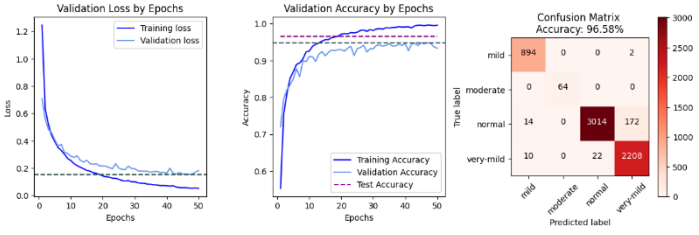

fig.9_Validation_Loss,_Accuracy_by_Epochs_&_Confusion_Matrix_of_VGG19_Model

Considering the training time, the proposed model exhibited a training time of 18.04 minutes. This was relatively shorter compared to some other models, such as ResNet50 and InceptionResNetV2, suggesting that the proposed model can achieve high accuracy without requiring extensive training time during deployment stage. Due to early stopping techniques employed, the CNN and the modified VGG16 models achieved acceptable

accuracies and trained in almost 7minutes and 12 minutes lesser than the modified VGG19 model. Also, a look at the accuracy curves of these two models showed that they failed to generalise properly with unseen data.

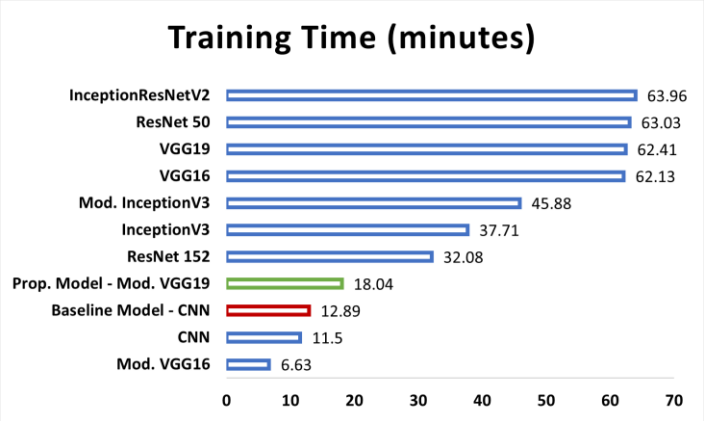

fig.10_Bar_chart_of_model_training_times_(minutes)

6.2 Proposed Model, vs. Related work

The comparison of the models used in previous studies with the performance of the proposed model reveals some interesting findings. The existing models, such as LeNet-5 CNN architecture employed by Sarraf et al. and the 3D Convolutional Autoencoder (3D-CAE) utilized by Hosseini et al., demonstrated impressive accuracies of 97% and 97.6% respectively. Similarly, Basaia et al. achieved an outstanding accuracy of 99% using a CNN model with 3D MRI data. However, it is important to note that these models focused primarily on binary classification, distinguishing between Alzheimer's disease (AD) and healthy controls (HC). Additionally, other studies like Zhang et al., Juan et al., Raees and Thomas, Helaly et al., focused on binary classification tasks for AD prediction, achieving accuracies ranging from 74.2% to 95.17%.

However, Pradhan et al., employed VGG19 and DenseNet169 architectures in solving a multiclass classification problem providing a comparative accuracy of 88% and 78% respectively. Nevertheless, the proposed model stands out as it tackles the multiclass classification of early stages of Alzheimer's disease. The proposed model's performance is noteworthy considering the complexity of distinguishing between multiple disease stages. It utilizes a modified VGG19 architecture, which has shown remarkable capabilities in image classification tasks (Hameed et al., 2020). The higher accuracy (99.08%) achieved by the proposed model suggests its efficiency in providing a more comprehensive diagnosis, allowing for the identification and classification of various disease stages.

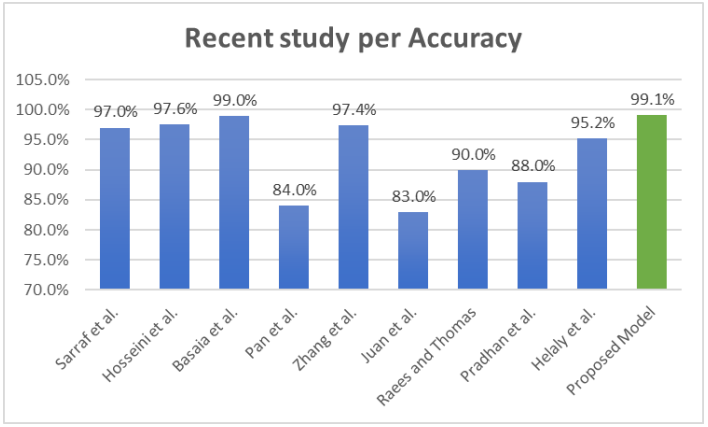

fig.11_Comparison_of_discussed_work_vs_Proposed_Model

In summary, the modified VGG19 model outperformed baseline models and previous work in early Alzheimer's disease diagnosis, with higher accuracy, precision, recall, and f1-scores. Its efficiency and reliability are supported by its shorter training time, making it a valuable tool for early diagnosis and monitoring.

7. Conclusion and Future Discussions

This project aimed to address the critical challenge of early Alzheimer's disease diagnosis using advanced deep learning techniques. Through an in-depth analysis and experimentation with various models, including the proposed modified VGG19 architecture, it has demonstrated the potential of deep learning in accurately classifying different stages of Alzheimer's disease. The proposed model, achieving an impressive accuracy of 99.08% on a multiclass classification task, outperformed several state-of-the-art models, showcasing its efficiency in detecting subtle patterns indicative of early Alzheimer's stages.

While this project marks a significant step in Alzheimer's disease diagnosis, there are still exciting avenues for future exploration. One such area is the application of the proposed model to other datasets beyond the Kaggle database, thus expanding its applicability and evaluating its performance across diverse populations. Moreover, exploring the potential integrations of data, such as combining MRI scans with genetic or clinical information, could lead to even more accurate and comprehensive diagnostic models.

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