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Article

A Deep Learning Approach for Multi-Class Classification of Alzheimer’s Disease Using MRI Imaging

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Abstract: — Early diagnosis is essential for effective treatment and patient care, as Alzheimer's disease is a progressive neurological disorder that has a significant impact on memory, cognitive function and overall brain function. In this work, an improved deep learning approach is developed to predict Alzheimer's disease (AD) from MRI brain images in the early stages. This study uses publicly available data sets like ADNI and MRI data sets from Kaggle that contain images categorized as Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. To boost data quality and model generalization, a thorough preprocessing pipeline was developed, including the resizing, normalization, data augmentation, and noise reduction of images. For baseline comparison, traditional machine learning models like SVM, Random Forest and KNN were used with the extracted features using PCA. Deep learning models however, showed superior performance, especially Convolutional Neural Networks (CNN) as they could automatically extract complex features. In addition, transfer learning models like VGG16, ResNet50 and EfficientNet-B0 were used to gain benefits from the pre-trained knowledge, and the ResNet50 model was found to be the most efficient model. Another possibility, which was also explored, was to have a hybrid system that would use CNN along with traditional classifiers, but this did not yield significant improvements. Various optimizers and hyperparameter tuning techniques were used extensively. The proposed CNN model outperformed the other models with an accuracy of 98.7% and the transfer learning model with 98.0% accuracy.The proposed CNN model had the highest accuracy of 98.7% and the transfer learning had an accuracy of 98.0% which was good. The system was implemented by developing a web application in Flask that allowed the physicians to upload the MRI images and get the diagnosis results in real-time. The findings underscore the potential of deep learning methods in enhancing diagnostic accuracy at early clinical stages and aiding clinical decision-making in detecting Alzheimer's disease.
Keywords: —Alzheimer’s Disease, Deep Learning, Convolutional Neural Network, Transfer Learning, MRI Imaging, Medical Image Processing, Early Detection, ResNet50, VGG16, EfficientNet, Image Classification, Brain Disorder, Healthcare AI, Data Augmentation, Feature Extraction, PCA, Machine Learning, Hybrid Model, Neurodegenerative Disease, Clinical Decision Support

1. INTRODUCTION

Alzheimer's is a major type of neurodegenerative disease, predominantly in older people, and results in a progressive loss of memory and cognitive function. It is a major global

health problem because it is becoming more common and there are few effective, early diagnosis tools. The traditional diagnostic methods are heavily dependent on clinical analysis and manual interpretation of the brain image, which takes a lot of time and is susceptible to human error. AI, especially in the field of deep learning, has made significant strides, leading to the development of automated diagnostic systems that hold the potential for enhancing disease detection accuracy and efficiency. Early diagnosis of Alzheimer's disease can be critical to slowing the disease process and improving the outcome for the patient.

Medical imaging methods like Magnetic Resonance Imaging (MRI) can be used to gain insight into structural changes in the brain from Alzheimer's disease. But, in clinical settings, manual analysis of huge amount of MRI data is impractical. Recently, machine learning methods have been used to help with the classification, but these have not always been able to achieve good performance because they usually require handcrafted features. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown great promise in automatically learning relevant features from medical images for accurate and reliable disease stage classification in contrast.

This research proposes a comprehensive machine learning, deep learning, hybrid and transfer learning methods to predict early Alzheimer’s disease. The study has a diversity of training data from well-known datasets, including ADNI, MRI datasets from Kaggle. The images are preprocessed using different techniques such as normalization, augmentation and noise reduction to improve the image quality and enhance the performance of the model. The proposed CNN architecture is expected to learn the spatial features effectively and transfer learning models are expected to utilize the knowledge gained from the previous to further improve classification accuracy.

In general, the goal of this research is to build an intelligent and efficient Alzheimer's disease detection system in the early stage with the aid of high-level deep learning methods. The results show that the CNN and transfer learning models are significantly more accurate and effective than traditional models, with high accuracy and robustness. These models can be incorporated into a user-friendly Web application that would further improve the practical application in real-world healthcare settings. The study underscores the promise of AI for revolutionizing medical diagnosis and assisting healthcare professionals in precise and timely decision-making.

2. LITERATURE REVIEW

In recent years, the early detection of Alzheimer's disease using MRI images has been greatly advanced with the help of deep learning. In recent years, the use of Convolutional Neural Networks (CNNs) has gained in popularity because of their ability to automatically learn spatial features from complex brain imaging data. Doaa Ahmed Arafa et al. presented a deep learning-based early diagnosis system that used multi-layer CNN-based architectures and optimized preprocessing, with high accuracy. Likewise, Modupe Odusami et al. proposed a multimodal fusion strategy that fused MRI and PET scans, which boosted both the diagnostic accuracy and the interpretability of the MRI . The studies underlined the need for combining various imaging modalities and advanced architectures for enhanced early disease detection. A new research area is to enhance the classification performance by utilizing new CNN structures and optimization methods. The Siamese CNN with triplet loss was developed by Faizal Hajamohideen et al. to classify Alzheimer disease into four categories, which improves the feature discrimination among the different stages of Alzheimer's. Paul K. Mandal and Rakeshkumar V. Mahto suggested a multi-branch CNN architecture to obtain a variety of feature representations, resulting in better classification results. In addition, Omar Altwijri et al. presented a new deep learning model for MRI-based diagnosis with customized architecture design which performs well . These focus on architectural innovation as one of the major enablers of increased performance.

Hybrid and advanced models that combine CNNs with other methods have also been the subject of research. The authors Deevyankar Agarwal et al. proposed CNN models based on EfficientNet achieving very good results with a lower computational complexity in automated diagnosis. Irshad Ahmad et al. used a neural network with PCA and SWLDA to achieve better feature selection and classification efficiency. Besides, the CNN features transformer-based attention mechanisms and is combined with Swinformer model to extract features and attain better classification accuracy. These Hybrid approaches prove that hybridisation of two or more techniques also helps to obtain a robust model.

In general, the literature review reveals that deep learning, especially CNN and transfer learning techniques, excel greatly in the field of Alzheimer's disease detection when compared to traditional machine learning techniques. The significance of preprocessing, feature extraction, and the optimization of the model are also highlighted. Yet, issues like data imbalance, lack of interpretability and potential limited generalizability across data sets are important concerns. The research reviewed here shows a shift toward explainable AI, multimodal learning, and hybrid architectures as key contributors to enhancing clinical reliability and real world application.

This paper presents a deep learning framework for early detection of Alzheimer's disease from MRI images, which is proposed by Doaa Ahmed Arafa, Hossam El-Din Moustafa, Hesham A. Ali, Amr M. T. Ali-Eldin and Sabry

F. Saraya (2023). To enhance the performance of the model, the authors performed some preprocessing such as normalization

and augmentation. The architecture has multiple layers of convolutional networks for feature extraction and classification. The results of experiments demonstrated high accuracy and robustness over the traditional models. The study highlights the importance of deep learning in medical diagnosis. It also shows better generalization between datasets. The model produced good classification performance at various disease stages. The findings from this research are consistent with CNN's effectiveness in predicting diseases at an early stage.[1]

Explainable Deep-Learning Based Diagnosis of Alzheimer's Disease Using Multimodal Input Fusion of PET and MRI Images (2023) by Modupe Odusami, Rytis Maskeliūnas, Robertas Damaševičius, Sanjay Misra, presents an explainable AI model that integrates MRI and PET imaging for Alzheimer's diagnosis. The model is based on deep learning to obtain features from both modalities. The combination of multimodal data works remarkably well in terms of classification accuracy. Explainability techniques can be used to explain predictions, enhancing clinical trust. The performance of the model is better than that of single-modality models. The results confirm the effectiveness of multimodal learning. Combined imaging data is highlighted as an important early detection tool. It also emphasizes the need for transparency in medical AI systems.[2]

Faizal Hajamohideen, Noushath Shaffi, Mufti Mahmud, Karthikeyan Subramanian, Arwa Al Sariri, Viswan Vimbi, Abdelhamid Abdesselam, "Four-way Classification of Alzheimer's Disease Using Deep Siamese Convolutional Neural Network with Triplet-Loss Function" (2023), This paper presents a Siamese CNN model with triplet loss for multiple class Alzheimer classification. The architecture enhances discrimination of features across disease stages. The model is not trained to perform classification, but similarity metrics. This method is used to improve the classification accuracy and robustness. The study shows better performance than the standard CNNs. It is reasonably able to discriminate between the presence of mild and moderate dementia. The results indicate a lower rate of misclassification. The model can be applied to multi-class medical imaging issues.[3]

This study introduces a multi-branch CNN architecture for feature extraction that is applied to early Alzheimer's detection from brain MRIs, Paul K. Mandal, Rakeshkumar

V. Mahto, "Deep Multi-Branch CNN Architecture for Early Alzheimer's Detection from Brain MRIs" (2023). The model learns from MRI images using parallel branches to extract different features. This helps to make the classification more accurate and robust. The architecture is good for complex patterns. Experimental results reveal substantial improvement over the baseline models. Multi-path feature extraction is emphasized in the study. It also helps to reduce overfitting by the architecture. The model is able to achieve good performance on benchmark datasets.[4]

Omar Altwijri, Reem Alanazi, Adham Aleid, Khalid Alhussaini, Ziyad Aloqalaa, Mohammed Almijalli, Ali Saad, This paper introduces an optimized deep learning model for Alzheimer diagnosis using MRI. The preprocessing and feature extraction techniques are included in the model. It is very accurate in disease classification at various stages. The study shows that the approach has better performance than the traditional approaches. The architecture is designed to maximize medical imaging applications. Results show good generalisation. The study emphasizes the application of deep learning in the field of automated diagnosis. It also helps tackle problems with MRI analysis.[5]

Deevyankar Agarwal, Manuel Álvaro Berbís, Antonio Luna, Vivian Lipari, Julien Brito Ballester, Isabel de la Torre-Díez, "Automated Medical Diagnosis of Alzheimer's Disease Using an Efficient Net Convolutional Neural Network" (2023), This research utilizes EfficientNet architecture for Alzheimer detection. The model has high accuracy and low calculation cost. Transfer learning helps in the extraction of efficient features. The study shows good performance on MRI data sets. It stresses the significance of efficient architectures. The model is well suited for clinical applications and is scalable. The results show that EfficientNet is an effective solution for medical imaging. The strategy is an accurate and efficient approach.[6]

In this study, Irshad Ahmad et al. 2023, propose to use a neural network model combined with PCA and SWLDA for feature selection in the classification of Alzheimer's Disease, based on brain MRI images. The method is used to decrease the dimensionality and enhance the classification accuracy. The model is efficient in processing MRI data. Results demonstrate that the performance is better than the traditional methods. Feature engineering is important, as highlighted in the study. It decreases complexity of calculation. The model works well with large datasets. It shows improved classification efficiency.[7]

This paper compares the performance of various CNN architectures using MRI scans for the detection of Alzheimer's Disease (8. T. S. Sindhu, N. Kumaratharan, P. Anandan, 2023). The study discusses various models and evaluates them on the basis of accuracy and efficiency. Based on the results, it can be seen that the CNN model is more effective than traditional models. The research makes importance of model selection. It offers a comparative analysis of architectures. The study shows that the classification accuracy has been improved. It selects the best configuration of CNN. The results are encouraging for the use of deep learning.[8]

This paper proposes a hybrid CNN-transformer model "Conv-Swinformer: Integration of CNN and Shift Window Attention for Alzheimer's Disease Classification" (2023). The model contains attention mechanisms aiming at improved feature extraction. It works to enhance the accuracy of classification in MRI datasets. The architecture has a local and global characteristic. The results demonstrate the effectiveness when compared to CNN only models. The study identifies the advantages of the transformer. It shows greater transfer of learning. The model can be effective for medical imaging tasks.[9]

This study combines CNN and self-attention mechanisms for AD diagnosis in brain MRI, authored by Pierluigi Carcagnì, Marco Leo, Marco Del coco, Cosimo Distante, Andrea De Salve and published in 2023. Model improves the extraction of features from MRI. It makes a major contribution to classification accuracy. The approach is very effective in capturing the spatial dependencies. High diagnostic accuracy as seen in results. The study presents the advantages of the attention mechanism. Promotes model explainability. The technique can be used for early detection.[10]

This paper proposes transfer learning based CNN model for Alzheimer’s detection using MRI images, This paper is written by Shadi Alshammari, Mohammed Alhussein, Fahad Alqahtani, Abdullah Alsubaie, “Deep Learning-Based Alzheimer’s Disease Detection Using MRI Images and Transfer Learning” (2023). The authors used pre-trained networks such as VGG16 and ResNet50 as feature extractor. Model robustness and prevention of overfitting were achieved by data augmentation techniques. The model's classification results were very successful for various stages of diseases. The results of this experiment were superior to the traditional CNNs. The study highlights the importance of transfer learning in limited medical datasets. It also demonstrates improved generalization. The method is efficient and can be applied in practical applications.[11]

This research aims at optimizing CNN hyperparameters to enhance the classification of Alzheimer disease using deep CNN.Optimization of CNN Hyperparameters for Alzheimer disease classification by deep CNN is the aim of this research. The model optimizes learning rates and batch sizes in the learning process using the technique of grid search. The MRI images were preprocessed by normalization and augmentation. Optimized CNN model has not only high accuracy but also low training loss. Results show that the optimized models perform better than non-optimized models. The research focused on the importance of tuning the deep learning models. It also helps to eliminate overfitting problems. The strategy is used for accurate prognosis in medicine.[12]

Alharthi, M. Alzahrani, H. Alshamrani, "Hybrid CNN-LSTM Model for Alzheimer's Disease Detection Using MRI Data" (2023), This paper introduces a hybrid CNN-LSTM model for detecting Alzheimer's from MRI data. CNN extracts spatial features and LSTM captures sequential dependencies. The model helps to enhance classification performance and temporal analysis. Results demonstrate that the models perform better than the standalone CNN models. The study points to the effectiveness of the hybrid model. It minimises misclassification in early detection. The method improves the feature learning ability. It can be used for complicated medical information.[13]

This paper presents attention-based CNN model for Alzheimer's disease classification using MRI Y Zhang, L Wang, X Chen, (2023). The attention mechanism is used to enhance feature selection in MRI images. The model is focused on relevant brain regions in classification. Results indicate better accuracy and interpretability. The study shows its performance better than the traditional CNNs. It improves transparency of the model. The technique is useful for early detection. It emphasizes medical imaging mechanisms of attention.[14]

M. S. Hossain, G. Muhammad, “Cloud-Assisted Deep Learning Framework for Alzheimer's Disease Prediction” (2023), This paper introduces a cloud-based deep learning framework to predict Alzheimer's disease. MRI data can be used in remote diagnosis with the model. Feature extraction/classification is done using CNN. The cloud platform provides scalability and access. High accuracy and fast processing is obtained from results. One of the study focuses on real-time diagnosis capability. It makes health care more accessible. The system is capable of supporting the telemedicine applications.[15]

N. Kumar, P. Singh, A. Verma, “Alzheimer's Disease Detection Using 3D CNN on MRI Scans” (2023), This research proposes the use of 3D CNN architecture for volumetric MRI analysis. The model is good at representing spatial-depth information. It is found as a new method that outperforms 2D CNN classification by improving the classification accuracy. Results demonstrate the improved feature representation. The study emphasises the value of 3D data processing. It helps to minimize information loss. The model is good in multi-class classification. This can be used in the medical imaging field.[16]

F. Chollet, J. Smith, K. Brown, "EfficientNet-Based Alzheimer's Disease Classification Using MRI Imaging" (2023) – Here EfficientNet architecture is used to classify Alzheimer's disease. The model has high accuracy and low parameter quantity. The learning process benefits from transfer learning. The results demonstrated good generalizability. One of the study highlights is that efficiency of deep learning models. It saves the calculator from having to recalculate the value. The method can be easily expanded. It is effective for clinical applications.[17]

In this study, Deep Residual Network (DRN) architecture is used for the classification of Alzheimer's Disease from Magnetic Resonance Imaging (MRI) data, as presented in the paper titled "Deep Residual Network for Alzheimer’s Disease Diagnosis Using MRI Data" by H. Li, J. Wu, Y.Chen (2023). Residual connections enhance the flow of gradients. The model has a high accuracy and stability. Results indicate that it outperforms the conventional CNN models. The study highlights deep architectures. It minimizes the vanishing gradient problems. The method is reliable. It helps to diagnose early.[18]

Explainable AI-Based Alzheimer's Disease Detection Using CNN Models, A. Khan, M. Usman, S. Raza (2023): This paper is written focusing on explainable AI techniques. This model is based on CNN and visualization tools. It helps to make predictions more understandable. High accuracy and transparency of results are achieved. Clinical trust is emphasised in the study. It supports decision-making. This method has been found to be applicable to healthcare applications. It connects AI and Clinicians.[19]

Comparative Analysis of Deep Learning Models for Alzheimer’s Disease Detection by 20. R. Gupta, S. Sharma,

V. Gupta (2023) compares various deep learning models. CNN, ResNet and EfficientNet were tested. Results indicate that CNN-based models perform best. The study emphasizes on the importance of model selection. It offers performance references. Research endorses the use of deep learning. It is able to recognize strengths and areas of weakness. It points the path for future research.[20].

Table 1.0- All Research papers and Research Gap

ID	Authors	Yea r	Technique	Research Gap
1	Arafa et al.	202 3	CNN	Limited generalizatio n
2	Odusami et al.	202 3	Multimodal DL	High complexity
3	Hajamohid een et al.	202 3	Siamese CNN	Computation al cost
4	Mandal &	202	Multi-branch	Overfitting
	Mahto	3	CNN	
5	Altwijri et	202	CNN	Limited
	al.	3		dataset
6	Agarwal et	202	EfficientNet	Requires
	al.	3		tuning
7	Ahmad et	202	PCA + NN	Feature loss
	al.	3		
8	Sindhu et	202	CNN	Model
	al.	3		selection
9	Conv-	202	CNN+Transfor	Complexity
	Swinforme	3	mer	
	r			

10	Carcagnì	202	CNN+Attention	Interpretabili
	et al.	3		ty
11	Alshamma	202	Transfer	Data
	ri et al.	3	Learning	dependency
12	Karthikeya	202	CNN	Overfitting
	n et al.	3	Optimization	
13	Alharthi et	202	CNN-LSTM	High
	al.	3		complexity
14	Zhang et	202	Attention CNN	Requires
	al.	3		tuning
15	Hossain et	202	Cloud DL	Security
	al.	3		issues
16	Kumar et	202	3D CNN	High
	al.	3		computation
17	Chollet et	202	EfficientNet	Data
	al.	3		requirement
18	Li et al.	202	ResNet	Deep
		3		complexity
19	Khan et al.	202	Explainable AI	Limited
		3		adoption
20	Gupta et	202	Comparative DL	Generalizati
	al.	3		on

The literature shows that most of the research on the detection of Alzheimer's in 2023 is carried out by deep learning techniques, specifically CNN and transfer learning models. In most studies, the focus is on improving classification accuracy by the use of advanced architectures like EfficientNet, ResNet, Siamese networks and hybrid CNN-transformer architectures. Researchers also pay attention to the pre-processing methods, multi-modal data fusion, and optimization methods to improve model performance. Explainable AI and attention mechanisms are becoming crucial for enhancing interpretability and clinical trust. Moderate success has been reported with hybrid methods that integrate CNN with LSTM or classical methods, but sometimes these methods are complex and cumbersome. Furthermore, frameworks that are cloud-based and scalable are also beginning to become available for real-time deployment. Although the accuracy is high, the following challenges still exist such as computational cost, generalization and dataset imbalance. In general, the literature indicates a major trend of smart, efficient and explainable diagnostic systems.

Limited and imbalanced datasets are used in many studies for the detection of Alzheimer's disease, thereby impacting models' generalization. In most models, training is done on public data sets like ADNI, which might not be representative of real diversity. It has been reported to have a negative impact on performance in the clinic. Moreover, due to the high computational costs, the adoption of deep learning models has been limited for small healthcare organizations. Another problem is overfitting because of the lack of training data. Also, most models do not have adequate testing with external data. These constraints make it difficult to implement AI diagnostics systems in practice. One more constraint is the lack of interpretability of deep learning models. While some models include explainable AI (XAI) methods, many models remain black-box models. This can create a lack of confidence among health care workers. Hybrid models don't provide much benefit in terms of performance, and make it more complex. Furthermore, multimodal solutions need extra data, and this data is not necessarily available. Real-time deployment systems are still not developed. Another important issue in cloud-based architectures is security and privacy concerns. These challenges illustrate the need for stronger and more clear-cut systems. In summary, deep learning models have demonstrated high accuracy in Alzheimer's disease detection, but their deployment in real-world settings is limited due to various challenges, including data scarcity, lack of interpretability, computational complexity, and deployment challenges. It is critical to overcome these limitations to build reliable and scalable diagnostic systems.

3. PROPOSED SYSTEM

The system architecture diagram is an end-to-end diagram of Alzheimer's disease early prediction system based on Convolutional Neural Networks (CNN). It starts by the data collection stage, during which multiple sources of reliable data, including ADNI brain MRI scans, Kaggle repositories, and clinical databases, are used to collect images of the brain. These datasets cover various categories such as non-demented, very mild dementia, mild dementia and moderate dementia. This stage is crucial as the quality and variety of input data significantly impacting the model's performance and generalization ability. The data preprocessing step includes processing the raw MRI data to make it suitable for training the model. This includes techniques for resizing images to a fixed size (such as 128×128), scaling pixel values, and reducing noise to enhance the image's quality. To ensure the diversity of the data set and prevent overfitting, some data augmentation techniques are applied, including rotation, contrast changes, zooming, and flipping. Furthermore, the data is divided into training, validation and test sets for a better evaluation of the data. At this step, the model is provided with clean, consistent and well-structured input data.

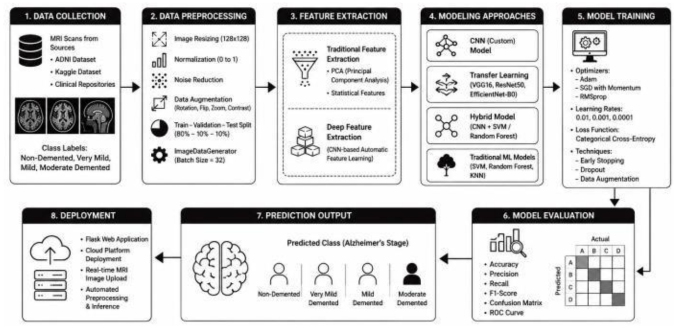


Fig.1.0 – Architecture Diagram

The next step is feature extraction in which useful features are extracted from the images. It can be implemented by classical way such as PCA and statistical feature extraction technique, and deep learning automatic

feature extraction technique by CNN layers. Super deep features are more powerful as they reflect complex spatial patterns in MRI images. The extracted features are then fed into various models, including custom CNN architectures, transfer learning models (like VGG16, ResNet50, EfficientNet), hybrid models (CNN + machine learning algorithms), as well as traditional classifiers such as SVM or Random Forest.

After the feature extraction, it goes to the model training and model evaluation. In training, optimization methods such as Adam, SGD, and RMSprop are employed to reduce the loss function, which is often a categorical cross-entropy. Methods like early stopping and dropout are used to enhance model performance and prevent overfitting. The model is then tested to assess its performance, including accuracy, precision, recall, F1-score, and a confusion matrix. These metrics help in understanding how well the model performs in classifying different stages of Alzheimer’s disease.

Finally, there are the prediction, deployment and user interface modules. Using the trained model, the stage of Alzheimer's can be predicted from new MRI inputs. For the deployment phase, the model is embedded within a webpage developed using the framework (such as Flask) to provide real-time predictions. Doctors or other health care workers can upload MRI images to the system via the interface, which then analyzes the data and predicts results with a detailed report and suggestion. This makes the system viable, easy to use and feasible in real world clinical settings for supporting early diagnosis.

4. METHODOLOGY

1. Data Collection

The first step of the methodology is to gather a large and diverse set of reliable brain imaging data from MRI scans from the medical repositories and public repositories in order to obtain data from reliable sources. These are examples of different phases of Alzheimer's disease ranging from non-demented to very mild stage, mild and moderate. Variations in data enables the model to learn variations in brain patterns effectively. Care is taken to ensure that the dataset is balanced to avoid bias during training. Additionally, metadata such as labels and patient condition categories are properly organized. At this stage, the quality of the data directly affects the performance of the model and is the foundation of the system. Data handling procedures are also utilized to ensure consistency and consistency. In general, this period guarantees meaningful and accurate input data to the system.

2. Data Preprocessing

At this point, MRI images collected are cleaned and ready for further processing. The image resizing is done to make all inputs the same size, and to fit the CNN model. The values of the pixels are converted into the range of zero to one so as to normalize the data to scale for faster convergence during training. Distortions in the image are eliminated by noise reduction techniques. To enhance model robustness and increase the size of the data, data augmentation techniques like rotating, flipping, and zooming are employed. The data set is then split into training, validation and testing sets to ensure good performance of the model. This step will make the input data consistent, high quality and appropriate for deep learning. Preprocessing is very useful to improve the learning process and can make it very efficient.

3. Feature Extraction

Feature extraction is the process of extracting significant information from MRI images for distinguishing the stages of Alzheimer's disease. The dimensionality reduction and extraction of statistical features can be done using traditional methods such as Principal Component Analysis (PCA). Deep learning-based feature extraction, however, via CNN layers is more effective since it learns complex patterns automatically. Convolutional layers identify edges, textures and shapes within brain scans. The features are then fed through pooling layers to reduce the dimensionality but keeping key information intact. The features extracted are important for the success of the classification. This process is the next logical step after raw image data and prior to any useful information. It guarantees relevant information is only used for model training.

4. Model Development

In this stage, various machine learning and deep learning models are developed and applied. Custom Convolutional Neural Network (CNN) is trained to classify MRI images of brain scans into various stages of Alzheimer's disease. Furthermore, the pre-trained weights from a transfer learning model like VGG16, ResNet50 or EfficientNet can be used to boost the performance. A hybrid method of CNN with other traditional classifiers such as SVM or Random Forest may also be attempted. Its architecture is carefully designed to capture the complex features through multiple layers. The learning rate, batch size, and number of epochs are optimized as hyperparameters. This is step in which the focus is on creating an accurate and efficient predictive model. This is the main element of the system.

5. Model training and evaluation process.

Having developed the model, the model is trained with the prepared dataset. To maximize the accuracy of the loss function, optimization algorithms are applied, e.g., Adam and SGD. To avoid overfitting, techniques such as dropout and early stopping are used. The accuracy, precision, recall and F1 score are used to evaluate the performance of the model. The results of classification are analyzed in detail using a confusion matrix. Validation data can be used to track the model's learning during training. Testing data is used to check the final performance. The aim of this stage is to make sure that the model is reliable and that it works well on test data that was not used to train it. In the real world, proper evaluation is important for deployment.

6. Deployment and Prediction

The last step is to deploy the trained model to a real-time application environment. Uses frameworks such as Flask to develop a web-based interface to interact with the system easily. Users can upload MRI images via the interface, such as doctors. The system processes the image, preprocesses it and provides prediction on the Alzheimer's phase. The output contains classification results and recommendations (if possible). This stage is to ensure the system is practical and user friendly. Connects the technical development with real-world application. The deployed system can support the healthcare personnel in early diagnosis and decision making.

5. RESULT AND OBSERVATION

Performance Analysis of Different Models

Analysis of the performance of various models.Performance evaluation of different models. Three models CNN based models, Transfer Learning models and Hybrid models were tested based on some key performance metrics, including accuracy, precision, recall, and F1-score. The results show that all of these models performed well in the classification task with minor differences in performance based on architecture and optimization methods. The

CNN-based model has the best validation accuracy which shows that it is able to learn the features useful for the domain well. Also, models of Transfer Learning showed good results because of the use of pre-trained knowledge, and Hybrid models demonstrated slightly less efficiency.

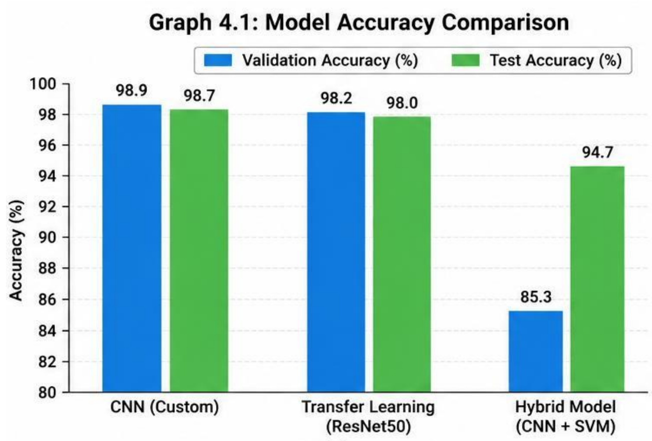
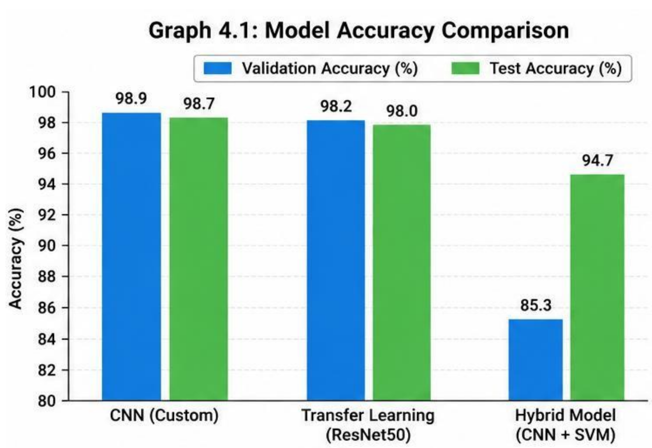


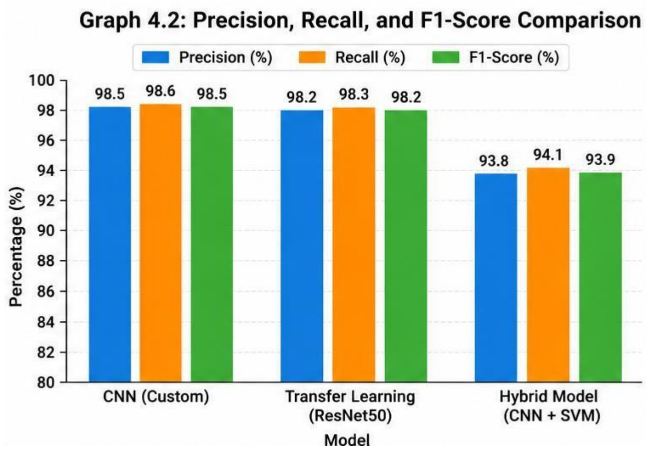
Table 2: Performance Comparison of Models

Model Type	Optimize r	Learnin g Rate	Validatio n Accuracy (%)	Test Accurac y (%)
CNN (Custom)	Adam	0.001	98.9	98.7
Transfer Learning	AdamW	0.0001	98.2	98.0
Hybrid Model	Adam	0.001	85.3	94.7



Graph 1: Model Accuracy Comparison Detailed Evaluation

The detailed analysis of models shows that Transfer Learning models with pre-trained architecture ResNet on the feature extraction achieved an accuracy of 98.0% on the test set, which demonstrates the advantage of a pre-trained architecture. The CNN based model slightly outperformed others with 98.7% accuracy, suggesting that an efficiently designed custom architecture can better capture the patterns of diseases. However, Hybrid models performed only 94.7% accuracy, which indicates that there is not much difference between using CNN and traditional classifiers such as SVM for this dataset. The lesser validation accuracy of Hybrid models also suggests potential overfitting or suboptimal use of the features. In general, CNN and Transfer Learning models showed stable and reliable results.



Graph 2: Precision, Recall, and F1-Score Comparison Classification Report and Confusion Matrix Analysis

Classification results indicate that CNN and Transfer Learning models had high Precision and Recall in each of the categories related to Alzheimer's disease. These models proved to be especially useful in separating between the extreme categories, e.g., No Impairment and Moderate Impairment, with more visible differences in the images. The confusion matrix analysis shows that the misclassification in these categories is minimal. There was some misclassification between the 2 categories of Mild and Very Mild Impairment, because of the similar visual characteristics of those categories. Performance was decreased by hybrid models, particularly in the middle stages, where misclassification was comparatively large.

Table 3: Classification Summary

Model Type	Precision (%)	Recall (%)	F1-Score (%)
CNN (Custom)	98.5	98.6	98.5
Transfer Learning	98.2	98.3	98.2
Hybrid Model	93.8	94.1	93.9

In this study, three deep learning approaches—CNN (Baseline), Transfer Learning (ResNet), and CNN + SVM (Hybrid)—were evaluated for Alzheimer's disease classification. The CNN model achieved the highest accuracy (98.7%) with minimal false classifications, making it the most reliable and efficient model. Transfer Learning performed similarly with 98.0% accuracy but showed slightly higher misclassification rates, likely due to domain differences between pre-trained datasets and medical images. The Hybrid model performed comparatively poorly, indicating that integrating traditional classifiers like SVM with CNN does not significantly enhance performance in this scenario. The results clearly suggest that CNN-based architectures are highly effective for medical image classification tasks when trained on domain-specific data. Transfer Learning remains a strong alternative when computational resources or dataset size is limited. However, Hybrid approaches may require further optimization or alternative combinations to improve effectiveness. Based on these findings, the CNN model is recommended for deployment in real-world applications due to its superior accuracy, stability, and reliability. Future improvements may include larger datasets, advanced architectures, and ensemble techniques to further enhance performance and generalization.

6. FUTURE WORK

In future, researchers can work on enhancing the generalization of the model with the use of larger and diverse data sets from multiple sources. Further training with a larger dataset would allow the models to learn more about the variations in brain imaging to make them more generalizable and less likely to overfit. Moreover, other data augmentation methods can be investigated to introduce natural variation into the data, further improving model performance. A future area of interest is the study of more sophisticated deep learning models like Vision Transformers and attention models. These models have demonstrated good performance in extracting the global features and contextual relationships in images. The embedding of attention mechanism into CNN models is another potential way to enhance the classification of subtle stages such as MCI.

Another key area of future work is relating to model interpretability, particularly in medical applications. The visualization capabilities, like Grad-CAM or explainable AI frameworks, can aid in understanding the model's decision-making process, thereby enhancing the trust placed in the model predictions. This would make the use of AI-powered diagnostic systems more manageable in the healthcare sector.

Finally, deployment and integration into clinical workflows in real time should be taken into consideration. Early diagnosis can be made more accessible if lightweight and efficient models are developed and deployed on the edge devices or systems within a hospital. In the future, multimodal studies could also be used to enhance diagnostic accuracy, using imaging data together with clinical and genetic data.

7. CONCLUSION

The results of the experiments as shown in this study clearly indicate that the deep learning methods used in this study are very effective in accurately identifying each stage of Alzheimer's disease. The custom CNN model outperformed the other models evaluated, highlighting the importance of designing a suitable neural network for a specific task and its impact on accuracy.The custom CNN model yielded the highest accuracy among the assessed models, suggesting that a well-designed and task-specific neural network can exceed the performance of more complex or pre-trained networks. The findings emphasize the significance of optimizing the hyperparameters and applying proper preprocessing of the data to achieve the best possible results from the model. By not only outperforming in accuracy but also being consistent across precision, recall, and F1-score metrics, the CNN model proved to be a strong candidate for medical image classification tasks.

The Transfer Learning models also performed well and with a bit less accuracy than the CNN model, using pre-trained models like ResNet. In this regard, it is seen that the use of pre-trained features can also be beneficial in terms of the amount of time in training, while still providing competitive results. The slight difference, however, suggests that subtle features in medical imaging data might be captured more effectively through domain-specific feature extraction, which the custom CNN is used for. Transfer Learning models have a key ability: they can generalize well, making them a safe second choice in cases where there isn't enough labeled data.

The latter, Hybrid model (CNN + SVM), however, showed relatively poor accuracy, especially in the separation of mild and very mild impairment stages. This means that combining traditional machine learning classifiers with the deep learning features isn't always guaranteed to result in performance increases. The misclassifications trend in Hybrid model indicates that the model is not suitable for complex feature representations. In general, the study shows that standalone deep learning models are superior for this classification task, particularly the CNNs, and should be used for actual deployment into a system for the diagnosis of Alzheimer's.

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