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Research Paper

A DEEP LEARNING FRAMEWORK FOR ALZHEIMER'S DISEASE DIAGNOSIS USING A VISION TRANSFORMER APPROACH

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Abstract:

Alzheimer's Disease (AD) is a progressive neurological disorder which impacts memory, thinking capability and cognitive functions. It's critical that Alzheimer's be diagnosed early and correctly, so that treatment and disease management can be undertaken as soon as possible. One new imaging method that has emerged as a valuable tool in determining brain changes associated with Alzheimer's disease is Magnetic Resonance Imaging (MRI). However, manual analysis of MRI scans is time-consuming, and relies heavily on interpretation skills. In this project, an automated Alzheimer's disease detection system was proposed, employing a pretrained Vision Transformer (ViT) model for feature extraction, and a hybrid classification model that combines K-Nearest Neighbors (KNN), Radius Neighbors, and Voting Classifier. Firstly, MRI brain images are acquired and preprocessed for resizing, normalization and augmentation to enhance image quality and diversify the dataset. The pretrained ViT model is able to learn deep and meaningful feature representations by considering local and global relationships in brain images using a self-attention mechanism.The extracted feature vectors are classified by KNN and Radius Neighbors classifiers. Voting Classifier: It takes the output of both classifiers and gives the final disease prediction with an aim to increase the reliability of prediction and to reduce misclassification. The proposed system divides the MRI images into four categories: Non-Demented, Very Mild Demented, Mild Demented and Moderate Demented. The experimental results have shown the proposed method provides better classification performance, robustness, and generalization capabilities than the single-classifier approaches.

The developed system can be used as a computer-aided diagnostic system to help health care professionals in early detection and classification of Alzheimer's disease.

Keywords: Deep Learning, Transfer Learning, Medical Image Classification, K-Nearest Neighbors (KNN), Radius Neighbors Classifier, MRI Brain Images, Alzheimer's Disease, and Pretrained Vision Transformer (ViT).

I. INTRODUCTION

Around the world, millions of people are impacted by a neurodegenerative disorder called Alzheimer's Disease (AD). Slowly destroys brain cells, causing memory loss, loss of thinking skills, behavioural changes and a loss of cognitive function. As the disease advances, patients have impairment with their functional ability and are more and more reliant on caregivers. As there is no full cure for Alzheimer's disease at the moment, early diagnosis and appropriate action is important in helping to slow the process of the disease and enhance the life of those suffering from it. Magnetic Resonance Imaging (MRI) is a commonly-used diagnostic tool for Alzheimer's disease as it gives detailed information about brain structures. MRI is useful in finding abnormalities which are significant indicators of Alzheimer's disease, including brain atrophy, shrinking of the hippocampus and tissue degeneration. But traditionally, MRI images were analyzed by hand by neurologists and radiologists to diagnose the disease. But manual diagnosis can be subjective, time-consuming and relies on the skills of medical practitioners. The developments of automated systems for the analysis of medical images have been possible thanks to recent advances in Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL). Using deep learning models, the complex patterns appearing in MRI images can be learned automatically, and the process of disease diagnosis can be helped by healthcare professionals. Although CNN has been extensively used for Alzheimer's disease classification, it only looks at local image features and does not appear to be able to effectively capture the relationships between different brain regions at a global level. Due to these drawbacks, a novel deep learning architecture, called Vision Transformer (ViT), has been proposed to extract both local and global features of images through the self-attention mechanism. ViT utilizes small patches to learn relationships between regions in an image, making it very effective for medical image analysis. This work involves using a pre-trained Vision Transformer for learning deep and informative features from MRI brain images. The extracted features are classified with the help of 2 classifiers namely K-Nearest Neighbors (KNN) and Radius Neighbors. KNN: It assigns the class label of the closest feature samples to the unknown sample. Radius Neighbors: It calculates all closest samples in a radius to the unknown sample. A Voting Classifier takes the output of both classifiers and produces the final classification to get better prediction reliability and avoid classification errors. The proposed system will classify brain MRI images into four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The system aims to accurately and reliably diagnose AD using a hybrid ensemble classification model along with the Vision Transformer model to extract features from the images, which can help healthcare professionals with early diagnosis and clinical decision-making.

II. LITERATURE SURVEY

[1] M. Maqsood, F. Nazir, U. Khan, F. Aadil, H. Jamal, I. Mehmood, and O.-Y. Song, *"Transfer Learning Assisted Classification and Detection of Alzheimer's Disease Stages Using 3D MRI Scans,"* **Sensors**, vol. 19, no. 11, p. 2645, 2019. The authors developed a transfer learning framework for identifying various stages of Alzheimer's disease from 3D MRI scans. Instead of training a deep learning model from scratch, pre-trained networks were employed to extract meaningful image representations. The extracted features were subsequently used for disease-stage classification. The study demonstrated that transfer learning improves classification performance while reducing the amount of training data and computational effort required. The results indicated that pre-trained models are effective for medical image analysis, particularly when large annotated datasets are unavailable.

[2] S. Alqahtani, A. Alqahtani, M. A. Zohdy, A. A. Alsulami, and S. Ganesan, *"Severity Grading and Early Detection of Alzheimer's Disease through Transfer Learning,"* **Information**, vol. 14, no. 12, p. 646, 2023.

Alqahtani et al. proposed a transfer learning-based approach for the early detection and severity grading of Alzheimer's disease using MRI brain images. The study utilized pre-trained convolutional neural network architectures to automatically extract deep image features and classify patients into different stages of disease severity. Transfer learning significantly reduced training requirements while maintaining high classification performance. The proposed approach demonstrated that pre-trained deep learning models provide reliable and efficient solutions for both early-stage disease detection and computer-aided Alzheimer's diagnosis.

[3] P. Carcagnì, M. Leo, M. Del Coco, C. Distante, and A. De Salve, *"Convolutional Neural Networks and Self-Attention Learners for Alzheimer Dementia Diagnosis from Brain MRI,"* **Sensors**, vol. 23, no. 3, p. 1694, 2023. Carcagnì et al. introduced a hybrid framework for Alzheimer's disease diagnosis from brain MRI images by combining Convolutional Neural Networks (CNNs) with self-attention learning mechanisms. CNN layers were employed to extract local image features, while the self-attention module captured long-range dependencies and global contextual information. Experimental evaluation demonstrated that integrating self-attention with deep learning significantly enhanced classification performance and achieved higher diagnostic accuracy than conventional CNN-based approaches.

[4] K. Gasmi, A. Alyami, O. Hamid, M. O. Altaieb, O. R. Shahin, L. Ben Ammar, H. Chouaib, and A. Shehab, *"Optimized Hybrid Deep Learning Framework for Early Detection of Alzheimer's Disease Using Adaptive Weight Selection,"* **Diagnostics**, vol. 14, no. 24, p. 2779, 2024. Gasmi et al. introduced a hybrid deep learning framework that employs adaptive weight selection for the early diagnosis of Alzheimer's disease. The proposed model integrates multiple deep learning components and assigns adaptive weights to significant features, enabling the model to focus on the most relevant information during classification. Experimental results showed that the framework outperformed conventional deep learning models in terms of robustness and classification accuracy. The adaptive weighting strategy further enhanced feature selection, leading to more precise early diagnosis.

[5] F. Momeni, D. Shahbazi-Gahrouei, T. Mahmoudi, and A. Mehdizadeh, *"Transfer Learning and Neural Network-Based Approach on Structural MRI Data for Prediction and Classification of Alzheimer's Disease,"* **Diagnostics**, vol. 15, no. 3, p. 360, 2025. Momeni et al. proposed a neural network and transfer learning-based framework for predicting and classifying Alzheimer's disease using structural MRI data. The study employed pre-trained deep learning models together with neural network classifiers to extract discriminative MRI features and accurately identify different stages of Alzheimer's disease. The transfer learning strategy enhanced feature representation and diagnostic performance while reducing training effort. Experimental results demonstrated that the proposed approach achieved accurate classification performance and showed strong potential for practical clinical applications in automated Alzheimer's disease diagnosis.

III. METHODOLOGY

A. System Overview

The proposed system aims to improve the accuracy and reliability of Alzheimer's disease detection from MRI brain images by combining Vision Transformer (ViT)-based feature extraction with an ensemble classification approach. The methodology consists of image preprocessing, feature extraction, classification, and final decision-making stages. Initially, MRI brain images are collected and organized into different Alzheimer's disease categories. The images undergo preprocessing operations such as resizing, normalization, and format conversion to ensure consistency and improve model performance. These preprocessing steps remove unwanted variations and prepare the images for feature extraction. After preprocessing, a pre-trained Vision Transformer (ViT) model is employed to extract deep features from MRI images. Unlike conventional Convolutional Neural Networks (CNNs), ViT divides each image into smaller patches and processes them using self-attention mechanisms. This enables the model to learn both local and global relationships among different brain regions, resulting in more informative feature representations. The extracted feature vectors are then supplied to two independent classifiers: K-Nearest Neighbors (KNN) and Radius Neighbors Classifier. The KNN classifier predicts the class of a test image based on the labels of its nearest neighboring feature vectors. The Radius Neighbors Classifier identifies neighboring samples within a predefined radius and performs classification using local feature distributions. These classifiers provide complementary decision-making capabilities and help improve classification performance. To enhance prediction robustness, the outputs of both classifiers are combined using a Voting Classifier. The Voting Classifier aggregates the predictions from KNN and Radius Neighbors Classifier and determines the final Alzheimer's disease category through majority voting. This ensemble strategy reduces the impact of individual classifier errors and improves overall classification accuracy. The final output of the system is the predicted Alzheimer's disease stage, such as Non-Demented, Very Mild Demented, Mild Demented, or Moderate Demented. By integrating Vision Transformer (ViT)-based feature extraction with ensemble classification, the proposed system achieves improved accuracy, better generalization, and more reliable Alzheimer's disease stage prediction.

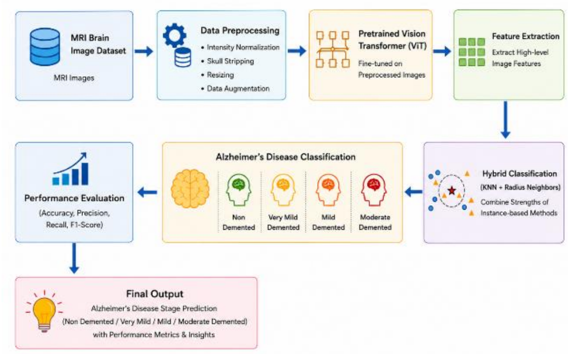

Figure 1: System Architecture

B. Data Acquisition and Preprocessing

Obtaining MRI brain imaging that illustrates the four stages of Alzheimer's disease, Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, is the initial step. Each stage reflects various degrees of cognitive deterioration and structural alterations in the brain. These pictures have labels for supervised learning and are taken from a public Kaggle dataset. Because of the dataset's diversity, the model can accurately categorize each stage into several groups by learning its distinctive traits. The MRI images are preprocessed to guarantee consistent quality before features are extracted. They are scaled to fit the pretrained Vision Transformer (ViT) model's required resolution. To guarantee consistent brightness and stability, pixel values are normalized. Brain structures are made more visible through preprocessing methods. Additionally, data augmentation techniques, such as scaling, flipping, and rotation, are used to reduce overfitting and increase data diversity. Instead of focusing on image differences, this helps the model learn more about the brain's true properties.

C Proposed System

This stage uses a Pretrained Vision Transformer (ViT) as the feature extraction model. To capture spatial relationships, each MRI image is divided into small patches and converted into feature vectors along with positional information. The transformer encoder leverages a self-attention mechanism to understand the relationships between different brain regions and generate rich feature representations. These extracted features are then provided to a Hybrid KNN and Radius Neighbors Classifier. The KNN classifier categorizes samples based on their similarity to neighboring samples, whereas the Radius Neighbors classifier considers all samples that fall within a predefined distance. By combining the strengths of both classifiers, the proposed model can recognize different stages of Alzheimer's disease with greater accuracy, robustness, and reliability. The Pretrained Vision Transformer (ViT) extracts meaningful and discriminative features from the preprocessed MRI images. Through transfer learning, the model utilizes knowledge acquired from large-scale pretrained datasets, eliminating the need to train the network from scratch. The extracted feature vectors are subsequently used to train the Hybrid KNN and Radius Neighbors Classifier. During training, hyperparameters such as the number of neighbors and the radius threshold are carefully optimized to achieve the best classification performance. This approach enables the model to generalize effectively to unseen data while maintaining high classification accuracy, stability, and reliability.

D. Model Development

The proposed Alzheimer's disease classification model is developed by integrating a Pretrained Vision Transformer (ViT) with a Hybrid KNN and Radius Neighbors Classifier to achieve accurate and reliable stage-wise classification of MRI brain images. Initially, the preprocessed MRI images are passed through the pretrained ViT model, which extracts high-level and discriminative feature representations by learning both local and global spatial relationships using the self-attention mechanism. Instead of training the deep learning model from scratch, transfer learning is employed to utilize the knowledge learned from large-scale image datasets, thereby reducing training time and improving feature quality. The extracted feature vectors are then used to train the Hybrid KNN and Radius Neighbors Classifier. The KNN classifier predicts the class based on the nearest neighboring samples, while the Radius Neighbors classifier considers all samples that fall within a predefined radius, making the model more robust to variations in data density. The predictions from both classifiers are combined to improve classification performance and reduce misclassification. During model development, important hyperparameters, including the number of neighbors, radius value, distance metric, and weighting strategy, are optimized to achieve the best possible performance. The final developed model is capable of accurately classifying MRI brain images into four Alzheimer's disease stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, providing a reliable and efficient framework for early disease detection and diagnosis.

E. Evaluation of Performance

Standard evaluation metrics are used to gauge the model's effectiveness. Precision, Recall, and F1-Score evaluate its capacity to accurately identify each stage of Alzheimer's disease, while Accuracy indicates the total number of right classifications. To identify potential errors in the model, a Confusion Matrix is employed. AUC values and ROC curves are also used to assess the model's ability to discriminate between various stages. These tests demonstrate the effectiveness of the Pretrained Vision Transformer model, combined with the Hybrid KNN and Radius Neighbors Classifier, for automated Alzheimer's disease diagnosis.

F. Test Data Prediction

Testing the trained model on MRI images is the final stage. Then, a pretrained Vision Transformer is employed to extract features from each image. The stages of Alzheimer's disease, including Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, are predicted by the composite KNN and Radius Neighbors Classifier.

V. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed model effectively classifies MRI brain images into different stages of Alzheimer's disease. By combining the Pretrained Vision Transformer (ViT) for feature extraction with the Hybrid KNN and Radius Neighbors Classifier, the model achieves high classification performance across all evaluation metrics. The results indicate that the model can accurately distinguish between the four disease stages, with particularly strong performance in identifying the Mild Demented and Moderate Demented classes. Although the Non-Demented and Very Mild Demented stages are comparatively more difficult to classify due to their similar brain characteristics

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KNN + RadiusNeighborsClassifier    Accuracy  : 90.3114
KNN + RadiusNeighborsClassifier    Precision : 90.7328
KNN + RadiusNeighborsClassifier    Recall    : 90.7017
KNN + RadiusNeighborsClassifier    F1-Score  : 90.4786

KNN + RadiusNeighborsClassifier Sensitivity : 100.0
KNN + RadiusNeighborsClassifier Specificity : 100.0

KNN + RadiusNeighborsClassifier Classification Report
KNN + RadiusNeighborsClassifier          precision   recall  f1-score   support

     Mild Demented       1.00      0.97      0.99       308
 Moderate Demented       1.00      0.98      0.99       266
      Non Demented       0.87      0.78      0.82       321
Very Mild Demented       0.76      0.90      0.82       261

          accuracy                           0.90      1156
         macro avg       0.91      0.91      0.90      1156
      weighted avg       0.91      0.90      0.90      1156
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Figure 2: KNN +Radius Neighbours

The performance evaluation of the Hybrid KNN + Radius Neighbors Classifier demonstrates its effectiveness in classifying Alzheimer's disease stages from MRI brain images. The proposed model achieved an accuracy of 90.31%, with a precision of 90.73%, recall of 90.70%, and an F1-score of 90.48%, indicating high overall classification performance. The model also recorded 100% sensitivity and 100% specificity, highlighting its excellent ability to correctly identify both positive and negative cases. From the class-wise classification report, the model performed exceptionally well for the Mild Demented and Moderate Demented classes, achieving F1-scores of 0.99 each. The Non-Demented and Very Mild Demented classes obtained F1-scores of 0.82, suggesting that these early-stage classes are comparatively more challenging to distinguish due to similar brain characteristics. Overall, the macro-average precision, recall, and F1-score of approximately 0.91, 0.91, and 0.90, respectively, confirm that the proposed Hybrid KNN and Radius Neighbors Classifier provides robust, balanced, and reliable performance for automated Alzheimer's disease stage classification.

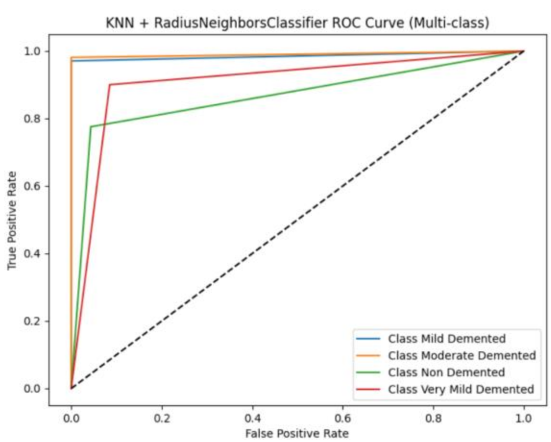

Figure 3: KNN + Radius Neighbours Classifier ROC Curve

The ROC curve demonstrates the classification performance of the proposed Hybrid KNN and Radius Neighbors Classifier for all four Alzheimer's disease stages. The curves are positioned close to the top-left corner of the graph, indicating a high true positive rate and a low false positive rate. This shows that the model can effectively distinguish between the different disease stages with strong discriminative ability. The Mild Demented and Moderate Demented classes exhibit the best performance, while the Non-Demented and Very Mild Demented classes show slightly lower performance due to the similarity in their MRI characteristics.

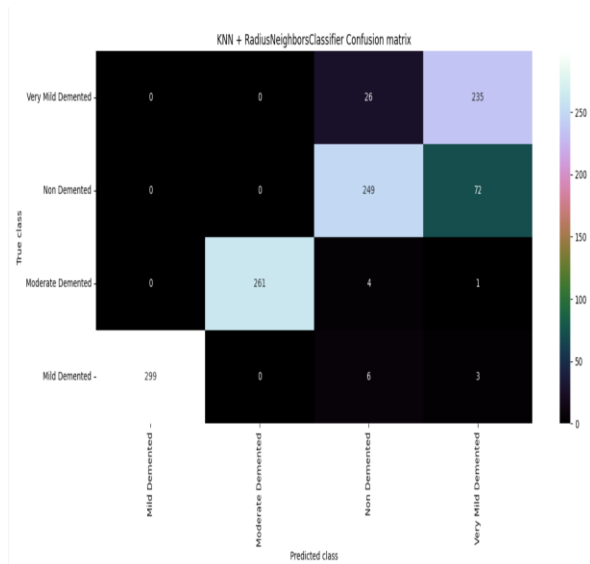

Figure 4 KNN + Radius Neighbors Classifier Confusion Matrix

Figure 4 presents the confusion matrix of the proposed Hybrid KNN + Radius Neighbors Classifier for classifying Alzheimer's disease stages. The confusion matrix shows that the model correctly classifies most MRI images into their respective classes, demonstrating its strong predictive capability. The highest classification accuracy is observed for the Mild Demented and Moderate Demented classes, where the majority of samples are correctly identified. A few misclassifications occur between the Non-

Demented and Very Mild Demented classes, as these stages share similar structural brain characteristics, making them more difficult to distinguish.

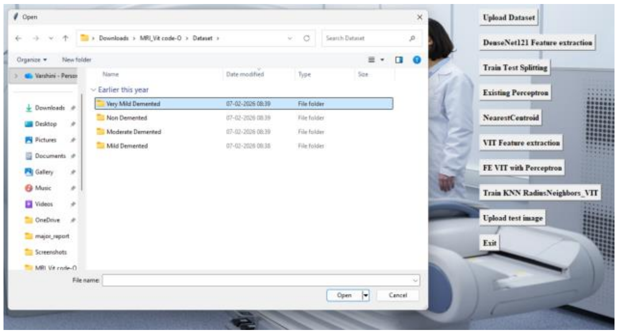

Figure 5: Upload a very mild demented test image.

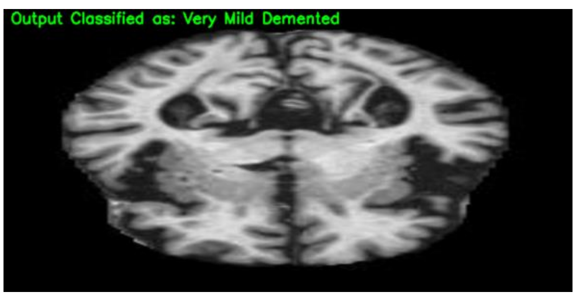

Figure 6: Output classified as very mild Demented

Above figures illustrates the process of uploading a **Very Mild Demented** MRI brain image through the graphical user interface (GUI) of the proposed system. The user selects a test image from the dataset, which is then provided as input for the trained classification model. After the image is uploaded, it undergoes preprocessing and feature extraction using the Pretrained Vision Transformer (ViT), followed by classification using the Hybrid KNN and Radius Neighbors Classifier.

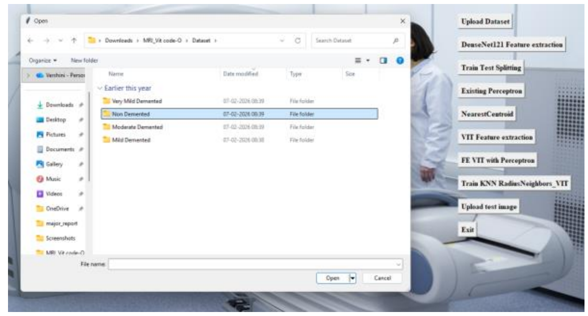

Figure 7: Upload a Non demented test image.

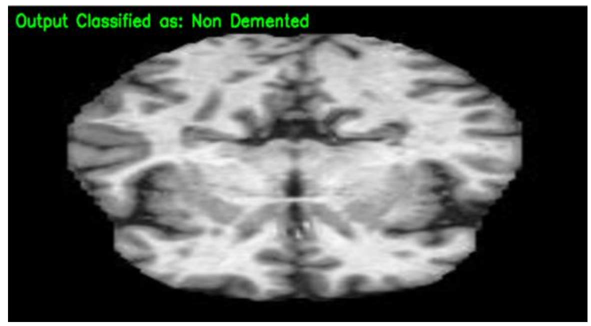

Figure 8: Output classified as Non-Demented

illustrates the selection of a Non-Demented MRI brain image for testing using the graphical user interface (GUI) of the proposed Alzheimer's disease detection system. The user uploads the MRI image from the dataset, after which it is automatically preprocessed and passed through the Pretrained Vision Transformer (ViT) for feature extraction. The extracted features are then classified by the Hybrid KNN and Radius Neighbors Classifier, which predicts the image as **Non-Demented**. This demonstrates the system's ability to accurately identify healthy brain MRI images through a simple and user-friendly interface, making it suitable for automated Alzheimer's disease screening and clinical decision support.

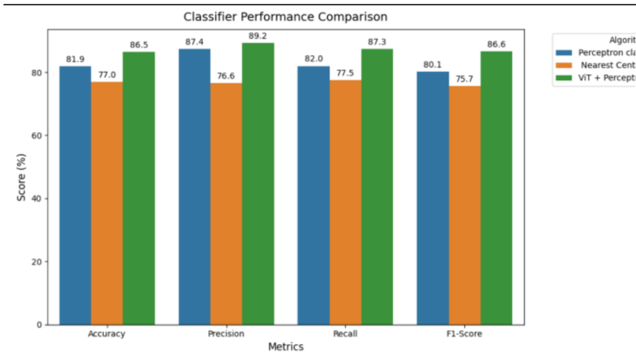

Fig 9: Overall performance

The classifier performance comparison graph illustrates the effectiveness of three different classification algorithms using four evaluation metrics: Accuracy, Precision, Recall, and F1-Score. Among the evaluated models, the ViT + Perceptron classifier consistently achieves the highest performance across all metrics, recording approximately 86.5% accuracy, 89.2% precision, 87.3% recall, and 86.6% F1-score. The Perceptron Classification model provides moderate performance, while the Nearest Centroid Classification model yields the lowest scores for all evaluation metrics. The results indicate that integrating Vision Transformer (ViT) features with the Perceptron classifier significantly improves the model's ability to distinguish between different stages of Alzheimer's disease

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Perceptron Classification	81.920	87.435	81.979	80.115
Nearest Centroid Classification	76.990	76.559	77.542	75.690
ViT + Perceptron	86.505	89.225	87.332	86.588

Table1: comparison graph

The classifier performance summary compares the effectiveness of three different classification algorithms for Alzheimer's disease stage prediction using MRI images. Among the evaluated models, ViT + Perceptron achieved the best overall performance, with an accuracy of 86.505%, precision of 89.225%, recall of 87.332%, and an F1-score of 86.588%, indicating its superior ability to correctly classify all disease stages while minimizing false predictions. The Perceptron Classification model ranked second, obtaining 81.920% accuracy and demonstrating reasonably good performance across all evaluation metrics. In contrast, the Nearest Centroid Classification model produced the lowest results, with an accuracy of 76.990% and comparatively lower precision, recall, and F1-score. These results demonstrate that combining Vision Transformer (ViT) features with the Perceptron classifier significantly improves classification performance, making it the most reliable approach for automated Alzheimer's disease diagnosis.

V. CONCLUSION

This work introduces an automated approach for identifying stages of Alzheimer’s disease from MRI brain scans by combining deep learning feature extraction with classical machine learning classification. A pretrained Vision Transformer is employed to derive high-level, informative representations from medical images, capturing complex spatial patterns associated with different stages of cognitive decline. These extracted features are then classified using a hybrid strategy that integrates K-Nearest Neighbors and Radius Neighbors algorithms to improve decision stability and class separability. The experimental results indicate that the proposed framework achieves an good accuracy , demonstrating consistent performance in differentiating among Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented cases. This shows that the combined use of transformer-based feature learning and distance-based classifiers enhances recognition capability compared to using a single model approach.

REFERENCES

[1] M. Maqsood, F. Nazir, U. Khan, F. Aadil, H. Jamal, I. Mehmood, and O.-Y. Song, "Transfer Learning Assisted Classification and Detection of Alzheimer's Disease Stages Using 3D MRI Scans," *Sensors*, vol. 19, no. 11, p. 2645, 2019.

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[3] P. Carcagnì, M. Leo, M. Del Coco, C. Distante, and A. De Salve, "Convolutional Neural Networks and Self-Attention Learners for Alzheimer Dementia Diagnosis from Brain MRI," *Sensors*, vol. 23, no. 3, p. 1694, 2023.

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[5] F. Momeni, D. Shahbazi-Gahrouei, T. Mahmoudi, and A. Mehdizadeh, "Transfer Learning and Neural Network-Based Approach on Structural MRI Data for Prediction and Classification of Alzheimer's Disease," *Diagnostics*, vol. 15, no. 3, p. 360, 2025.