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Neuro Swin-Cloud: A Hybrid Swin Transformer Framework for Volumetric MRI Analysis

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ABSTRACT

Alzheimer's disease is the most common form of dementia among older individuals and poses a major global health challenge, with nearly 10 million new cases reported annually. This progressive neurological disorder leads to gradual neurodegeneration, beginning with mild memory impairment and advancing to severe cognitive decline, reduced social interaction, and loss of environmental awareness. According to Alzheimer Disease International (ADI), approximately 75% of dementia cases remain undetected, making early diagnosis critically important yet challenging. Currently, effective diagnostic and treatment solutions for halting disease progression are limited. In this work, high-quality Magnetic Resonance Imaging (MRI) scans are processed using a pretrained Shifted Window (SWIN) Transformer to extract high-dimensional visual features that capture subtle neurostructural variations across different stages of Alzheimer's disease, including Mild, Moderate, Normal, and Very Mild. These extracted features are evaluated using baseline classifiers such as Generalized Linear Model (GLM), Generalized Linear Vector Quantization (GLVQ), and Perceptron for comparative analysis. The proposed Optimal Rule Fit (ORF) classifier outperforms these methods by effectively modeling complex, non-linear relationships within the feature space. A Tkinter-based graphical user interface enables dataset upload, preprocessing, model training, evaluation, and visualization of confusion matrices and ROC curves. The system also supports remote prediction, allowing cross-device MRI-based diagnosis. Additionally, Explainable Artificial Intelligence techniques provide interpretable insights into brain atrophy, ventricular enlargement, and disease severity, enhancing clinical transparency and trust.

Keywords: Alzheimer's Disease, SWIN Transformer, ORF, XAI, Neuroimaging, Mild cognitive impairment.

1. INTRODUCTION

With a rapidly aging society, the number of people with Alzheimer's disease (AD) is increasing globally. Approximately 9.9 million new cases of dementia are reported annually, which implies that a new patient is diagnosed with the disease every 3.2 s. The number of people with AD is expected to exceed 100 million by 2050. However, an effective medical treatment for the disease is yet to be devised. Neuroimaging has been used for understanding the progression of AD, and considerable progress has been achieved in the use of deep learning for medical imaging in research and clinical medicine [1]. The macroscopic findings of AD have revealed diffuse brain atrophy.

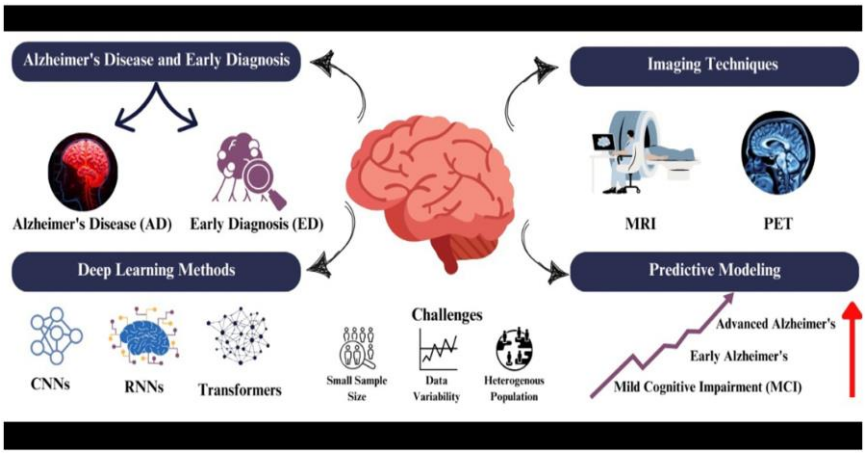


Fig. 1: Advancements in DL for early diagnosis of Alzheimer's disease

As shown in Fig 1 the classification accuracy of AD versus healthy control using deep learning of MRI is 91.4%, and that of mild cognitive impairment (MCI) versus AD is 70.1% [2].The economic evaluation of dynamic susceptibility MRI compared with nonenhanced computer-assisted tomography (CT) is USD 479,500 per quality-adjusted life year, whereas the corresponding comparison for single-photon emission computed tomography (SPECT) with CT is better (higher effectiveness and lower cost) [3].

2. LITERATURE SURVEY

E. Yagis et al. [4] described an investigation of the classification accuracy based on two publicly available data sets, namely, ADNI and OASIS, by building a 3D VGG variant convolutional network (CNN). They used 3D models to avoid information loss, which occurs during the process of slicing 3D MRI into 3D images and analyzing them by 3D convolutional filters. They also conducted a pre-processing of the data to enhance the effectiveness and classification performance of the model. Their proposed model achieved 73.4% classification accuracy on ADNI and 69.9% on OASIS dataset with 5-fold cross-validation (CV), outperforming 3D network models.

Alsubaie MG et al. [5] explored single- and multi-modality investigations, delving into biomarkers, features, and preprocessing techniques. Various deep models, including CNNs, recurrent neural networks (RNNs), and generative models, are evaluated for their AD detection performance. Challenges such as limited datasets and training procedures persist. Emphasis is placed on the need to differentiate AD from similar brain patterns, necessitating discriminative feature representations. highlights deep learning's potential and limitations in AD detection, underscoring dataset importance. Future directions involve benchmark platform development for streamlined comparisons. In conclusion, while deep learning holds promise for accurate AD detection, refining models and methods is crucial to tackle challenges and enhance diagnostic precision.

AlSaeed D et al. [6] proposed a pre-trained CNN deep learning model ResNet50 as an automatic feature extraction method for diagnosing Alzheimer's disease using MRI images. Then, the performance of a CNN with conventional Softmax, SVM, and RF evaluated using different metric measures such as accuracy. The result showed that our model outperformed other state-of-the-art models by achieving the higher accuracy, with an accuracy range of 85.7% to 99% for models with MRI ADNI dataset.

Abbasian P et al. [7] developed a subject-level 3D-CNN architecture enhanced by preprocessing techniques to improve classification accuracy between these groups. Our experiments utilized structural Magnetic Resonance Imaging (SMRI) data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, specifically the ADNI3 collection. included 446 subjects from the baseline and year 1 phases, comprising 164 individuals diagnosed with EMCI and 282 individuals with NC. When evaluated using 4-fold stratified cross-validation, our model achieved a validation AUC of 91.5%. On the test set, it attained an accuracy of 81.80% along with a recall of 82.50%, precision of 81.80%, and

specificity of 80.50%, effectively distinguishing between the NC and EMCI groups. Additionally, a gradient class activation map was employed to highlight key regions influencing model predictions. In comparative evaluations against pretrained models and existing literature, our approach demonstrated decent performance in early AD detection.

Lien W-C et al. [8] focused on overcoming this problem. In this study, the detection performance of five CNN models (MobileNet V2 and NASNetMobile (lightweight models); VGG16, Inception V3, and ResNet (heavier weight models)) on medical images was compared to establish a classification model for epidemiological research. Brain scan image data were collected from 99 subjects, and 4711 images were used. Demographic data were compared using the chi-squared test and one-way analysis of variance with Bonferroni's post hoc test. Accuracy and loss functions were used to evaluate the performance of CNN models. The cognitive abilities screening instrument and mini mental state exam scores of subjects with a clinical dementia rating (CDR) of 2 were considerably lower than those of subjects with a CDR of 1 or 0.5. They analyzed the classification performance of various CNN models for medical images and proved the effectiveness of transfer learning in identifying the mild cognitive impairment, mild AD, and moderate AD scoring based on SPECT images.

Agarwal D et al. [9] focused on pre-processing in four steps: N4 bias field correction, denoising, brain extraction, and registration. End-to-end-learning-based deep CNNs were used to discern between different phases of AD. Eight CNN-based architectures were implemented and assessed. The DenseNet264 excelled in both types of classification, with 82.5% accuracy and 87.63% AUC for training and 81.03% accuracy for testing relating to the sMCI vs. AD and 100% accuracy and 100% AUC for training and 99.56% accuracy for testing relating to the AD vs. CN. Deep learning approaches based on CNN and end-to-end learning offer a strong tool for examining minute but complex properties in MR images which could aid in the early detection and prediction of Alzheimer's disease in clinical settings.

Alqahtani S et al. [10] developed deep learning models that focus on early detection and classifying each case, non-demented, moderate-demented, mild-demented, and very-mild-demented, accordingly through transfer learning (TL); an AlexNet, ResNet-50, GoogleNet (InceptionV3), and SqueezeNet by utilizing magnetic resonance images (MRI) and the use of image augmentation. The acquired images, a total of 12,800 images and four classifications, had to go through a pre-processing phase to be balanced and fit the criteria of each model. Each of these proposed models split the data into 80% training and 20% testing. AlexNet performed an average accuracy of 98.05%, GoogleNet (InceptionV3) performed an average accuracy of 97.80%, and ResNet-50 had an average performing accuracy of 91.11%. The transfer learning approach assists when there is not adequate data to train a network from the start, which aids in tackling one of the major challenges faced when working with deep learning.

Mandal PK et al. [11] proposed a deep CNN architecture consisting of 7,866,819 parameters. This model comprises three different convolutional branches, each having a different length. Each branch is composed of different kernel sizes. This model can predict whether a patient is non-demented, mild-demented, or moderately demented with a 99.05% three-class accuracy. In summary, the deep CNN model demonstrated exceptional accuracy in the early diagnosis of AD, offering a significant advancement in the field and the potential to improve patient care.

Momeni F et al. [12] aimed to differentiate AD from NC and distinguish between LMCI and EMCI from the other two classes. Another goal is the diagnostic performance (accuracy and AUC) of SMRI for predicting AD in its early stages. 398 participants were used from the ADNI and OASIS global database of SMRI including 98 individuals with AD, 102 with early mild cognitive impairment (EMCI), 98 with late mild cognitive impairment (LMCI), and 100 normal controls (NC). They proposed model achieved high area under the curve (AUC) values and an accuracy of 99.7%, which is very remarkable

for all four classes: NC vs. AD: AUC = [0.985], EMCI vs. NC: AUC = [0.961], LMCI vs. NC: AUC = [0.951], LMCI vs. AD: AUC = [0.989], and EMCI vs. LMCI: AUC = [1.000].

Zhang P et al. [13] proposed Magnetic resonance imaging (MRI) has become the main tool for humans to study brain tissues. It can clearly reflect the internal structure of a brain and plays an important role in the diagnosis of Alzheimer's disease. MRI data is widely used for disease diagnosis. In this paper, based on MRI data, a method combining a 3D convolutional neural network and ensemble learning is proposed to improve the diagnosis accuracy. Then, a data denoising module is proposed to reduce boundary noise. The experimental results on ADNI dataset demonstrate that the model proposed in this paper improves the training speed of the neural network and achieves 95.2% accuracy in AD vs. NC (normal control) task and 77.8% accuracy in SMCI (stable mild cognitive impairment) vs. PMCI (progressive mild cognitive impairment) task in the diagnosis of Alzheimer's disease.

Hazarika RA et al. [14] proposed a hybrid technique incorporating LeNet and AlexNet that is light weight and capable of outperforming DenseNet. To extract important features, they replaced the traditional convolution Layers with three parallel small filters (1×1,3×3, and 5×5). The model functions effectively, with an overall performance rate of 93.58%. Mathematically, it is observed that the proposed model generates significantly fewer convolutional parameters, resulting in a lightweight model that is computationally effective.

Maqsood M et al. [15] proposed system works on an efficient technique of utilizing transfer learning to classify the images by fine-tuning a pre-trained convolutional network, AlexNet. The architecture is trained and tested over the pre-processed segmented (Grey Matter, White Matter, and Cerebral Spinal Fluid) and un-segmented images for both binary and multi-class classification. The performance of the proposed system is evaluated over Open Access Series of Imaging Studies (OASIS) dataset. The algorithm showed promising results by giving the best overall accuracy of 92.85% for multi-class classification of un-segmented images.

3. PROPOSED METHODOLOGY

The proposed system is a robust, automated framework for the early detection of Alzheimer's Disease from structural MRI scans, designed around a secure client-server architecture. As shown in Fig 2 it utilizes a Tkinter-based administrative interface for secure data management, where a Swin Transformer replaces traditional CNN to extract high-dimensional, context-rich feature embeddings that capture both local tissue textures and global brain structures. These features power a proposed ORFC, which is trained and benchmarked against baseline models like GLM and GLVQ to demonstrate superior classification accuracy. For real-world application, the trained system is deployed via a Flask web server that integrates an XAI layer powered by the Gemini model; this unique addition not only predicts the disease stage but also validates the input image and generates clinically interpretable reports detailing specific indicators like hippocampal atrophy and ventricle enlargement.

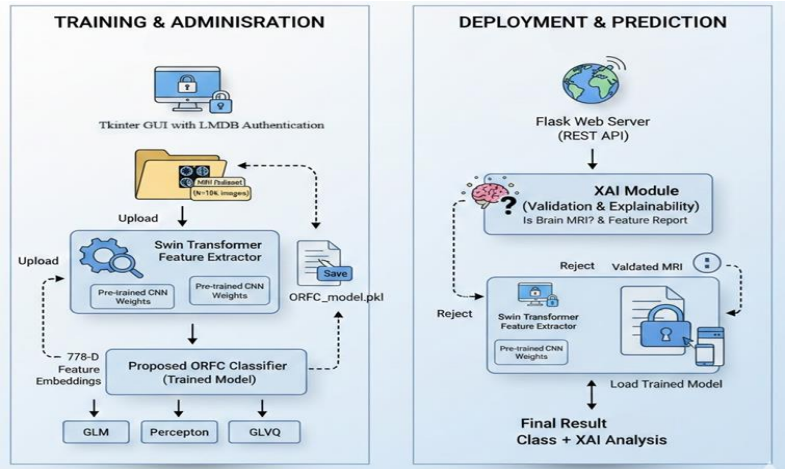


Fig. 2: Proposed system architecture

ORFC Model

The ORFC is the proposed, high-performance classification model in this research, designed specifically to utilize the complex, non-linear 768-D feature embeddings generated by the Swin Transformer. Unlike the linear GLM or the distance-based GLVQ, the ORFC operates as a robust ensemble model that iteratively identifies and combines numerous small, localized "optimal regions" within the feature space that strongly correlate with specific Alzheimer's stages. By aggregating the predictions from these weak, specialized classifiers through a weighted voting mechanism, the ORFC constructs a highly non-linear, resilient decision boundary, enabling it to achieve superior accuracy and generalized performance when differentiating the subtle differences between early and later stages of Alzheimer's disease as shown in Fig 3.

Initialization and Feature Segmentation

The ORFC begins by receiving the training set of 768-D feature vectors (X) and their corresponding Alzheimer's stage labels. Unlike simple linear models, the ORFC does not initialize a single hyperplane but rather a collection of weak, regional classifiers (often simple decision stumps or shallow trees). The training data is strategically sampled or segmented to focus the initial learning of these weak classifiers on different localized areas of the feature space, ensuring a broad initial coverage of all class distributions, particularly the subtle differences between early Alzheimer's stages.

Iterative Learning and Region Identification

The core of the ORFC relies on an iterative learning process, similar to boosting or aggregating methods. In each iteration, a new weak classifier is trained, but critically, it is trained to focus on the samples that were misclassified or marginally classified by the previously trained weak classifiers. This process iteratively searches for and defines small, "optimal regions" in the 768-D space where a simple decision rule can effectively separate one class from the others. Each new weak classifier is then assigned a weight reflecting its accuracy in classifying the current set of challenging samples.

Feature Selection and Dimensionality Management

Given the high dimensionality of the Swin Transformer features (768 dimensions), the ORFC incorporates an implicit or explicit feature selection mechanism within its weak learners. Instead of using all 768 dimensions for every regional split, each weak classifier only uses a small, random subset of features to determine its split point. This mechanism not only speeds up the training process but also enhances the model's robustness by ensuring that the final classification is not overly dependent on any single dimension, thereby mitigating the risk of overfitting to noise in specific features.

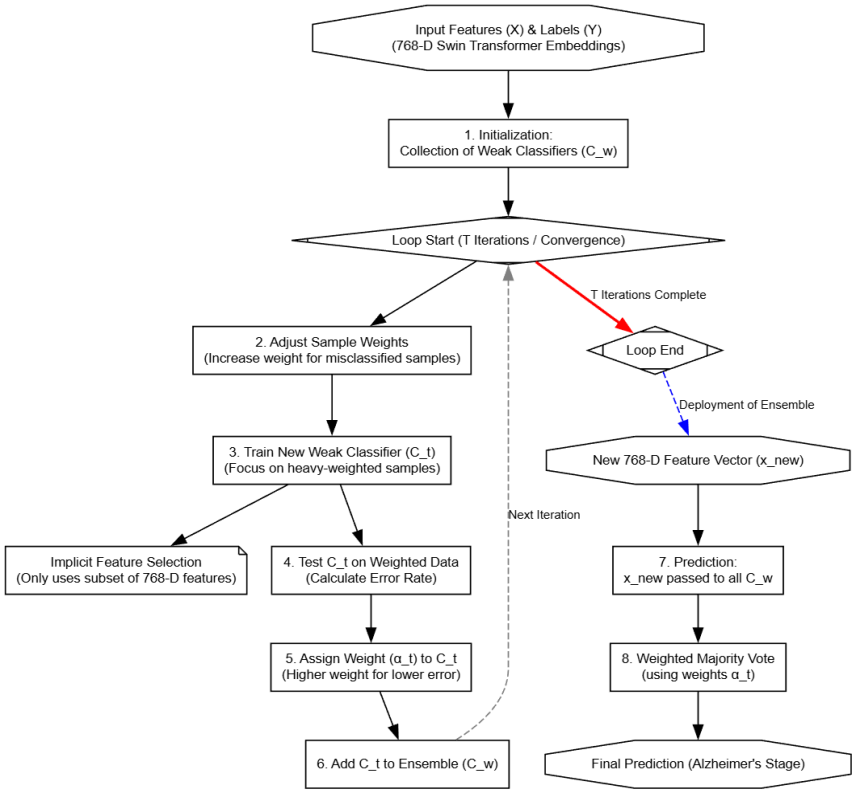


Fig. 3: Internal workflow of ORFC

Aggregation and Final Decision Boundary Formation

After a pre-defined number of iterations or when the learning process converges, all the individually trained weak classifiers are combined into a single, strong ensemble. When a new 768-D feature vector needs to be classified, it is passed through every one of these weak regional classifiers. The final prediction for the Alzheimer's stage is determined by a weighted majority vote of all the weak classifiers. The combined decision boundary is inherently non-linear and complex, as it is the superposition of numerous simple regional boundaries, allowing it to accurately model the convoluted boundaries present in the MRI feature space.

4. RESULTS DESCRIPTION

Fig. 4 confusion matrix represents the performance of the Existing Perceptron Classifier in distinguishing among the Alzheimer categories Mild, Moderate, Normal, and Very Mild using Swin Transformer feature embeddings. The matrix shows perfect classification for the Moderate class but reveals substantial misclassification across other classes, especially between Very Mild and Mild, where a large portion of Very Mild samples are predicted incorrectly. The Normal class displays a mixed pattern, with many samples confused with Very Mild, reflecting the Perceptron's limited ability to separate subtle structural differences in MRI features. Mild cases are mostly identified correctly, but the model still struggles with finer inter-class boundaries.

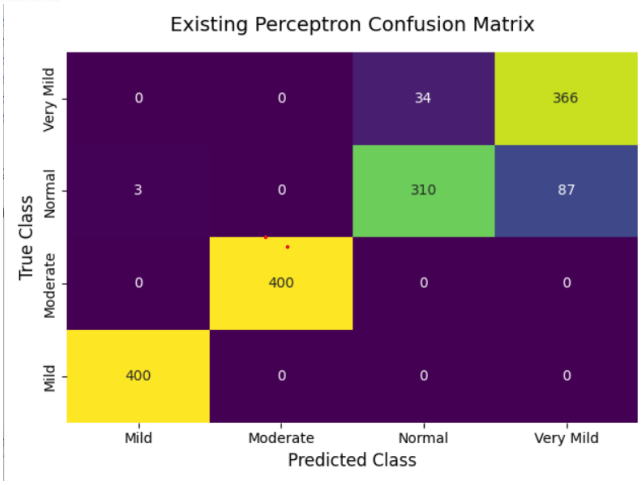


Fig. 4: Confusion matirx obtained using Perceptron

Fig. 5 shows ROC curve plot visualizes the one-vs-rest performance of the Existing Perceptron Classifier across the four Alzheimer categories Mild, Moderate, Normal, and Very Mild based on Swin Transformer embeddings. The curves show excellent separability for Mild and Moderate, each achieving a perfect AUC of 1.00, indicating the classifier handles these classes effectively. However, the Normal and Very Mild classes exhibit slightly lower AUC values of 0.97, suggesting reduced discriminative power and class overlap in early-stage MRI features. The micro-average AUC of 0.99 reflects strong and predictive ability despite inconsistencies seen in the confusion matrix. Compared against the diagonal random-guess baseline, all curves significantly out-perform chance, confirming that while the Perceptron classifier shows good numerical ROC performance, it fails to maintain consistent classification accuracy across subtle dementia categories.

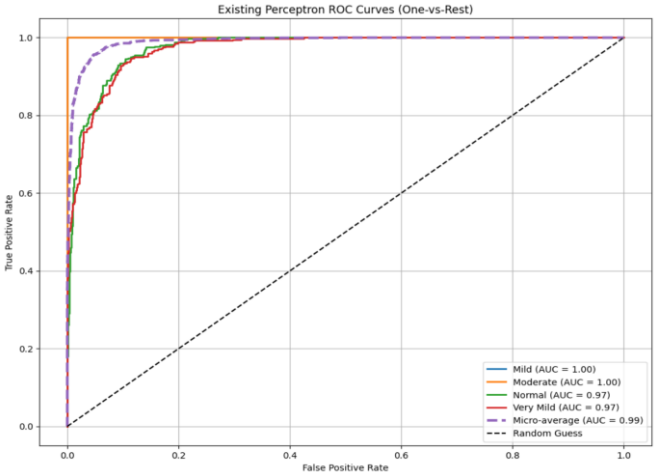


Fig. 5: ROC Curve obtained using Perceptron

Fig. 6 shows the confusion matrix demonstrates the classification performance of the Proposed ORFC across the Alzheimer MRI categories Mild, Moderate, Normal, and Very Mild using Swin Transformer embeddings. The diagonal dominance shows near-perfect classification for Mild, Moderate, and Normal, where almost all samples fall into the correct predicted category. Very Mild cases also achieve extremely high accuracy, with only a few misclassified as Normal, indicating strong separation capability even for subtle early-stage dementia variations. Compared to baseline models, ORFC sharply reduces inter-class confusion and handles complex MRI feature patterns with far greater robustness. The overall distribution highlights ORFC's superior ability to map high-dimensional transformer features to distinct Alzheimer stages, making it the most reliable classifier in the system.

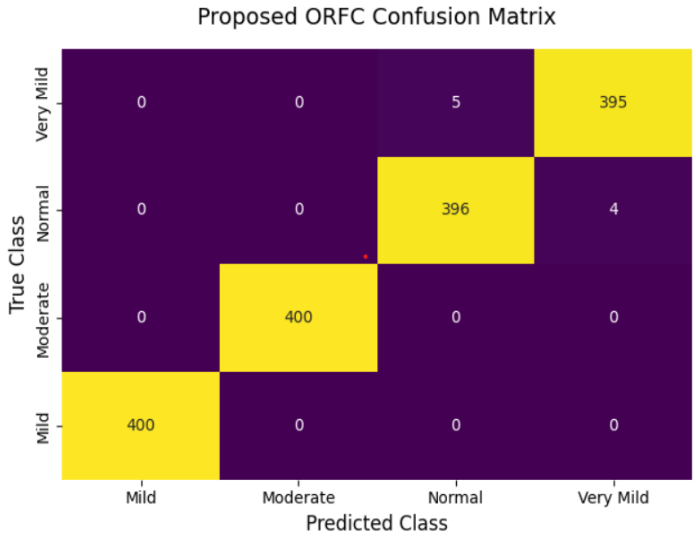


Fig. 6: Confusion matrix obtained using ORFC

Fig. 7 ROC curve plot shows the one-vs-rest performance of the Proposed ORFC classifier, demonstrating exceptional discriminative ability across all Alzheimer MRI categories Mild, Moderate, Normal, and Very Mild. Each class achieves an AUC of 1.00, indicating perfect separation between true positives and false positives, even for subtle early-stage variations such as Very Mild dementia. The curves from all classes almost overlap at the top-left corner of the graph, reflecting extremely high sensitivity with near-zero false-positive rates. The micro-average AUC of 1.00 further confirms flawless multi-class classification performance when aggregating predictions across all categories. Compared to the diagonal random-guess baseline, ORFC shows a dramatic improvement, validating its superior capability to leverage Swin Transformer features for highly accurate Alzheimer stage identification.

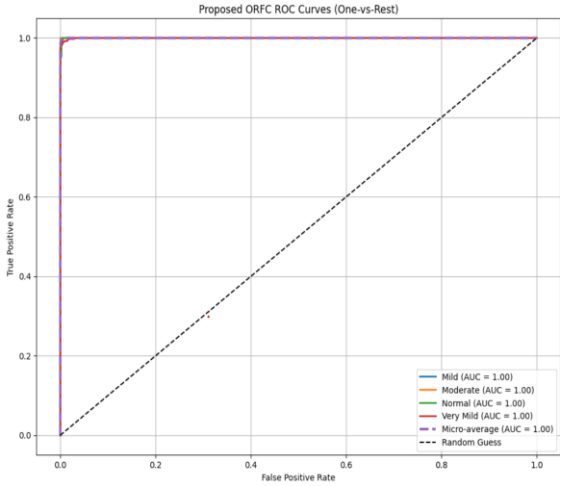


Fig. 7: ROC Curve obtained using ORFC

Fig. 8 shows the output panel's complete prediction workflow, showing the original MRI image, the XAI-generated Alzheimer analysis, and the final classification result from the Swin-Transformer with ORFC model. The left section displays the raw brain MRI provided by the user, while the center text block summarizes the XAI engine's interpretation, identifying key biomarkers such as cortical atrophy, ventricular enlargement, and suspected Alzheimer severity. On the right, the transformer classifier overlays its predicted stage "Very Mild" directly onto the processed MRI, highlighting the system's ability to combine deep-learning-based classification with transparent, interpretable medical insights. This unified view allows clinicians and users to visually verify the prediction alongside meaningful neuro-structural explanations.

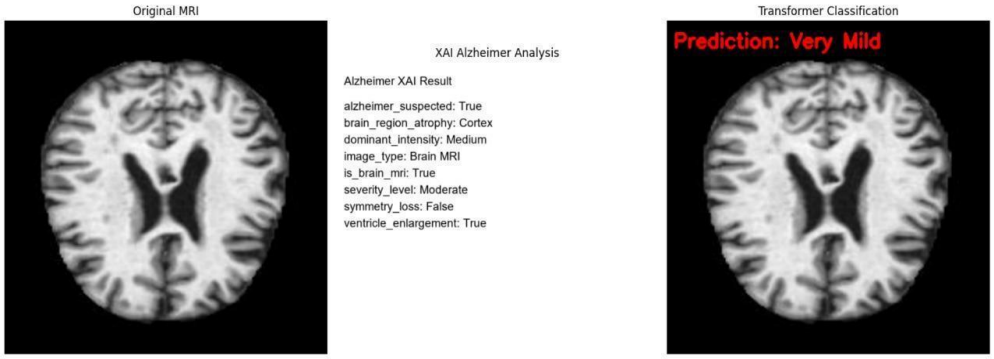


Fig. 8: XAI-supported MRI interpretation with transformer-based alzheimer classification

Comparative Analysis

Table 1: Performance comparison for the GLM, GLVQ, Perceptron and Proposed ORF Model

Algorithms Name	Accuracy	Precision	Recall	F-score
GLM Classifier	93.93%	94.45%	93.935%	93.89%
GLVQ Classifier	81.25%	80.40%	81.25%	80.68%
Perceptron Classifier	92.25%	92.54%	92.25%	92.19%
ORF Classifier	99.43%	99.43%	99.43%	99.43%

The performance comparison table 1 summarizes the effectiveness of four different classifiers GLM, GLVQ, Perceptron, and the Proposed ORF model when applied to Alzheimer stage prediction using Swin Transformer feature embeddings. The GLM classifier demonstrates strong and balanced performance with an accuracy of 93.93% and similar precision, recall, and F-score values, indicating reliable but not optimal separability. GLVQ performs noticeably lower, achieving only 81.25% accuracy, reflecting its limitations in handling complex MRI feature patterns. The Perceptron classifier performs better, reaching 92.25% accuracy, but still falls short in distinguishing subtle early-stage variations. In contrast, the Proposed ORF classifier significantly outperforms all other models, achieving an exceptional 99.43% across accuracy, precision, recall, and F-score, highlighting its superior capability to map high-dimensional transformer-derived features to distinct Alzheimer categories with perfect classification.

5. CONCLUSION

The research successfully demonstrates a comprehensive and intelligent framework for automated Alzheimer's disease detection and stage classification using structural MRI scans, leveraging cutting-edge deep learning and machine learning techniques. By integrating the Swin Transformer for high-quality feature extraction with multiple classical classifiers and the proposed ORF model, the system effectively captures subtle structural changes in the brain that distinguish different Alzheimer severity levels. Experimental results confirm that while traditional models like GLM, GLVQ, and Perceptron offer reasonable performance, they are limited in handling complex MRI feature distributions; in contrast, the proposed ORF classifier achieves exceptional accuracy of 99.43%, proving its superiority in learning non-linear and fine-grained patterns. The research also incorporates an interactive Tkinter GUI for dataset management, feature extraction, model training, evaluation, and visualization, making it accessible to non-technical users. Furthermore, a Flask-based remote prediction server enables cross-device inference, allowing MRI images to be uploaded from another laptop or clinic system for real-time Alzheimer stage prediction. The system is enriched with XAI-supported interpretability, providing clinically relevant insights such as brain-region atrophy, ventricle enlargement, and severity estimation, thereby increasing transparency and trust in AI-driven diagnosis.

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