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Transformer-Based Representation Learning with Explainable AI for Robust Alzheimer's Stage Prediction

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Abstract

Alzheimer's disease is the most prevalent form of dementia among the elderly and poses a significant global healthcare burden, with millions of new cases reported each year. It is characterized by progressive neurodegeneration, beginning with mild cognitive impairment and advancing to severe memory loss, behavioral changes, and reduced awareness. A pretrained Swin Transformer model is utilized to extract high-dimensional and discriminative features that capture subtle neuroanatomical variations across stages such as Mild, Moderate, Very Mild, and Normal conditions. The extracted features are evaluated using baseline classifiers including Generalized Linear Model (GLM), Generalized Learning Vector Quantization (GLVQ), and Perceptron. The proposed Optimal Rule Fit Classifier (ORFC) demonstrates superior performance by effectively modeling complex and non-linear relationships. To enhance usability, a Tkinter-based graphical interface supports dataset handling, preprocessing, training, and evaluation, while a Flask-based server enables real-time remote predictions. Additionally, Explainable Artificial Intelligence (XAI) techniques provide interpretable insights, such as brain-region atrophy and ventricular enlargement. Experimental results show that the proposed system achieves 99.43% accuracy, highlighting its effectiveness for early diagnosis and clinical decision support.

Keywords: Alzheimer's disease, classification, deep learning, magnetic resonance image, neuroimaging, explainable AI.

1. Introduction

With the global population aging at an unprecedented rate, the prevalence of Alzheimer's disease (AD) is rising significantly. It is estimated that nearly 9.9 million [1] new dementia cases are reported each year, meaning that a new patient is diagnosed approximately every 3.2 seconds. Projections indicate that the number of individuals affected by AD will surpass 100 million by the year 2050 [2]. Despite this alarming growth, an effective and definitive treatment for the disease has not yet been established.

In recent years, neuroimaging techniques have played a crucial role in understanding the progression of AD, enabling researchers to observe structural and functional brain changes. Additionally, substantial advancements [3] have been made in applying deep learning approaches to medical imaging, both in research and clinical practice [4]. One of the key macroscopic characteristics of AD identified through these studies is widespread brain atrophy, reflecting the gradual degeneration of neural tissue associated with the disease.

Problem Definition: AD is a progressive neurodegenerative disorder that leads to cognitive decline, memory loss, and ultimately, the inability to perform basic daily tasks. Early and accurate diagnosis of Alzheimer's, especially identifying its stages (mild, moderate, severe), is critical for effective treatment and care planning. However, traditional diagnosis relies heavily on manual interpretation of MRI scans

by specialists [5], which can be time-consuming, prone to human error, and subject to inter-observer variability. Moreover, in resource-limited settings, the availability of neurologists and radiologists is scarce.

Significance: The analysis of MRI images using advanced computational techniques plays an important role in improving the accuracy and efficiency of neurological disease diagnosis. Automated data analysis systems can help medical professionals process large volumes of imaging data quickly and identify patterns that may not be easily visible through manual examination. Such systems can support healthcare institutions by reducing diagnostic time, improving consistency in medical analysis, and assisting doctors in making more informed decisions. The integration of intelligent analysis methods in medical imaging also contributes to advancements in medical

2. Literature Survey

Many studies have investigated DL approaches for Alzheimer's disease detection, relying on neuroimaging data such as CT, PET, MRI, and fMRI [6]. Most existing studies are either unimodal, using a single data modality, or multimodal, adopting heterogeneous data types such as different neuroimaging types, genetic information, or clinical data, which are often challenging to obtain, costly, and not routinely collected [7]. However, some studies focused on generating other representations of the same data to catch underlying features [8]. In this study, we transform the selected 2D MRI slices into an audio form, enabling a multimodal framework that relies entirely on structural MRIs. Ref. [9] proposed a deep learning approach named Adaptive Hybrid Attention Network (AHANet), which consists of two attention modules for local and global feature extraction from brain MRIs. The first is for extracting contextual and spatial data for long-term dependencies; the second is for capturing local features. The results demonstrated an accuracy of 98.53; however, achieving this required 75 training epochs and used 73,400 AD slices, 77,520 Mild Cognitive Impairment (MCI) slices, and 43,180 HC slices, which can be considered highly time- and resource-consuming. Another study [10] proposed AlzheimerNet, a fine-tuned CNN designed to classify six classes, five AD stages, and one normal control. 23,805 MRI slices obtained from the ADNI dataset are used, achieving an accuracy of 98.67%. Their method relies heavily on extensive image augmentation to address data imbalance, yielding 60,000 images across the six classes, which can introduce certain dependencies and limitations [11]. Rekha Gangula et al. [12] proposed a methodology for early Alzheimer's disease detection using MRI. The system performed image preprocessing and feature extraction. The classification model improved early-stage disease identification. The authors in [13] introduce a deep learning model consisting of two stages for automatic AD diagnosis, utilizing MRI images. They introduced an enhanced 3D DenseNet for brain tissue segmentation and an improved MobileNetV3 for classification. Their method achieved 97.85% classification accuracy in distinguishing AD from Cognitive Normal (CN). While demonstrating high accuracy, it relies solely on MRI images, without exploring other data formats. Several studies investigated the use of PET scans for AD classification, as they provide valuable information regarding the disease. Deep learning and machine learning methods have been widely applied to PET data. For example, researchers in [14] introduced a multi-view separable pyramid network (MiSePyNet) that learns feature representations from multiple orientations of PET scans for AD classification. Their experiments yielded an accuracy of 83.05% for MCI prediction.

Ref. [15] employed a wavelet transform as a fusion technique of MRI and PET scans to incorporate the metabolic and structural information. Researchers in [16] proposed a multimodal approach that combines heterogeneous features obtained from PET and MRI scans in a shared space where data from those modalities are mapped. This shared space reveals common patterns that help AD prediction. Another study [17] integrates MRI, PET, genetic data, and clinical scores to capture different aspects. Auto-Encoders used for feature extraction from clinical and genetic data while CNN-based models for

feature extraction from imaging data. Although PET scans are valuable because they reflect cerebral metabolic activity and can reveal functional abnormalities earlier, they are expensive and require patients to receive radioactive tracers, making them less suitable for routine or repeated screening. Rekha Gangula et al. [18] proposed a diabetes prediction model using Logistic Regression. The framework analyzed clinical datasets for risk prediction. The model improved prediction accuracy and disease prognosis. Another study [19] employed a convolutional autoencoder (CAE) to classify AD and MCI versus healthy controls using a single 2D MRI slice per subject from the OASIS dataset. Their method achieved an accuracy of 74.66, showing a moderate improvement over the basic 2D CNN. Researchers in [6] proposed a DANMLP, a multimodal system that integrates MRI, clinical, and genetic data. It combines a dual attention CNN with a multilayer perceptron (MLP) for feature extraction and classification of AD and MCI. They achieved accuracies of 93% for AD vs. MCI and 82.4% for MCI vs. CN. A CNN-based model known as PINet is introduced in [20]. The model takes MRI images as input along with privileged information (PI), a data driven from previous clinical findings. The PI is used to guide the model to the desired direction. Pavankumar Nagapuri et al. [21] proposed a deep learning hybrid model for lung disease detection using CXR images. The model combined feature extraction and classification stages. The approach improved diagnostic accuracy in medical imaging. Rekha Gangula et al. [22] proposed an ensemble machine learning approach for dengue disease prediction. The framework utilized multiple classifiers for improved performance. The model enhanced prediction accuracy and reliability.

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 Figure 1, it utilizes a Tkinter-based administrative interface for secure data management, where a Swin Transformer replaces traditional Convolutional Neural Networks (CNNs) 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.

Proposed System Workflow

1. **Secure System Initialization and Data Management:** The system begins with a secure administrative layer designed to manage sensitive medical datasets. An administrator accesses the system via a Tkinter-based Graphical User Interface (GUI), protected by a high-performance LMDB authentication system. Once authenticated, the administrator uploads the structural MRI dataset. The system is designed to be agnostic to specific folder structures, automatically scanning directories to identify class labels (e.g., Non-Demented, Mild Demented, Moderate Demented) based on subfolder names, ensuring data is correctly ingested for the pipeline.
2. **Deep Feature Extraction using Swin Transformer:** The core innovation lies in the transition from traditional CNNs to the state-of-the-art Swin Transformer (Hierarchical Vision Transformer). After images are pre-processed (resized to 224×224 pixels and normalized), they are passed through the swin_base_patch4_window7_224 model. Unlike

standard CNNs that process images in a fixed grid, the Swin Transformer utilizes shifted windows to capture local details (tissue texture) and global dependencies (overall brain morphology) simultaneously. The model acts as a feature extractor, converting each MRI into a 768-dimensional numerical feature vector (embedding).

3. **Model Training and Classification:** Extracted features are split into training and testing sets using stratified sampling to maintain class balance. This phase involves benchmarking the proposed model against three distinct baselines:
    - **3.1 Baseline Model 1: GLM:** Utilizes an SGD Classifier to attempt to find a linear relationship between the 768-D vectors and target classes. It serves as a speed and simplicity benchmark.
    - **3.2 Baseline Model 2: Perceptron:** A simple artificial neural network used to test if the Alzheimer's features are linearly separable. Its performance typically highlights the non-linear complexity of the MRI dataset.
    - **3.3 Baseline Model 3: GLVQ:** A prototype-based algorithm that classifies data based on proximity to learned "class prototypes." While powerful, it serves to test how the system handles high-dimensional distance metrics.
    - **3.4 Proposed Model: ORFC:** The ORFC is the primary engine of the system. It overcomes the limitations of linear boundaries and pure distance metrics by identifying "optimal regions" in the high-dimensional feature space. By aggregating weak learners, it creates a robust, non-linear decision boundary tailored for complex transformer embeddings.
4. **Deployment via Flask (Client-Server Architecture):** To ensure clinical utility, the architecture decouples the training environment from the prediction service. The trained Swin Transformer configuration and the saved ORFC model (.pkl) are deployed on a Flask Web Server. This server exposes a REST API endpoint (/predict) that listens for incoming POST requests containing MRI images from remote client devices. This allows heavy computation to remain server-side while providing lightweight access to diagnostic tools.
5. **Explainable AI (XAI) Integration and Final Prediction:** The final step bridges the gap between "Black Box" AI and clinical interpretation. Upon receiving an image, the Flask server triggers an XAI module powered by the Gemini Large Multimodal Model. This layer performs a dual validation:
    - **Validation:** It confirms the uploaded file is a valid Brain MRI, rejecting non-medical or incorrect imagery.
    - **Feature Reasoning:** It extracts human-readable symptoms such as "Hippocampal Atrophy," "Symmetry Loss," or "Ventricle Enlargement." The local ORFC model then provides the definitive classification (e.g., Moderate Demented). The system returns a comprehensive Java Script Object Notation (JSON) response containing the technical label, the XAI-generated medical reasoning, and the confidence metrics.

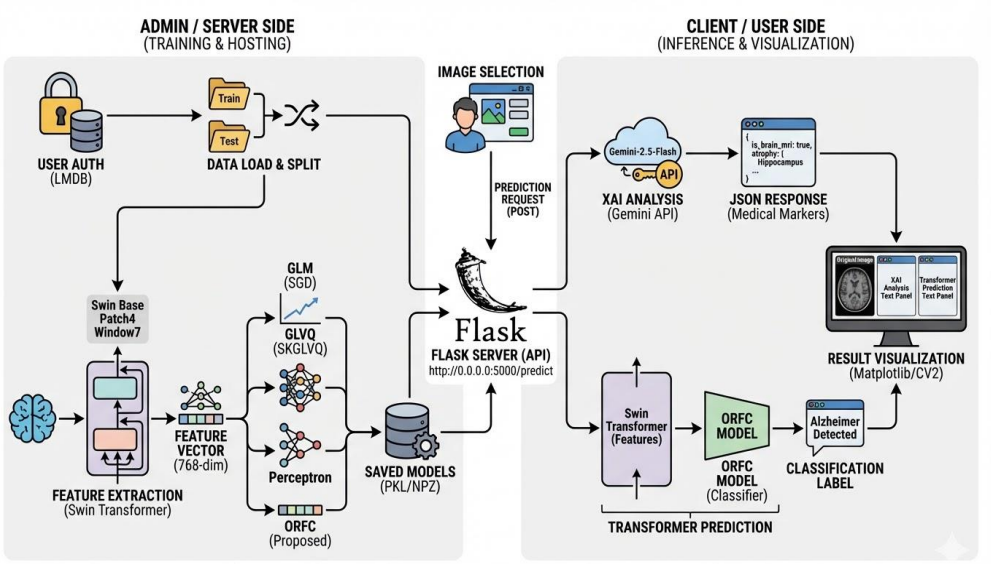


Figure 1: Proposed system architecture

3.1 Swin Transformer Feature Extraction

The Swin Transformer, specifically the Base model initialized with pre-trained weights, serves as the non-traditional, hierarchical feature extraction backbone for this Alzheimer's detection system, directly replacing a standard CNN. Its role is highly specific: by removing its original classification head, the model is utilized solely to process the preprocessed (224x224) MRI images and output a concise 768-dimensional feature embedding. As shown in Figure 2 the process leverages the Swin Transformer's shifted window mechanism to efficiently capture both fine-grained local structural anomalies (like early atrophy) and broad global context across the entire brain slice, providing a superior, highly descriptive input vector for the subsequent, lighter-weight ORFC, thereby improving diagnostic accuracy and efficiency over conventional deep learning models.

Step 1. Initialization and Weights Loading: The process begins by initializing the Swin Transformer Base model (swin_base_patch4_window7_224) using the timm library in PyTorch. Crucially, the model is initialized with pre-trained weights (likely from the large-scale ImageNet dataset) and configured with num_classes=0. This configuration is essential: it removes the final classification head, preventing the model from predicting ImageNet classes and instead forcing it to output the raw feature vector from its final pooling layer. The entire model is transferred to the available device, preferably Graphics Processing Unit (GPU) (cuda), for efficient processing.

Step 2. Image Preprocessing and Scaling

Before the MRI slice can be fed into the Swin Transformer, it must be standardized to meet the model's input requirements. This is handled by a defined transform. Compose pipeline:

- The raw MRI image is resized to a fixed input resolution of (224, 224) pixels.
- It is converted to a PyTorch Tensor and normalized using a specific mean and standard deviation (0.5 for all channels) which matches the standard pre-trained setup. This standardization ensures the input data falls within the optimal range the pre-trained weights were designed for.

Step 3. Feature Extraction (Forward Pass): The pre-processed image tensor is passed through the initialized Swin Transformer. The model performs its hierarchical processing, where feature maps are

generated across multiple stages, gradually capturing features from local patches to global spatial relationships:

- **Patch Partitioning:** The input image is first split into non-overlapping patches.
- **Shifted Window Attention:** This mechanism is the core innovation, calculating self-attention within local "windows" and then shifting the windows between layers. This allows the model to capture long-range dependencies (global context, crucial for identifying overall atrophy) while maintaining local details (like tissue density), which is often superior to the fixed local kernels used in traditional CNNs.
- **Vector Output**: The final stage aggregates the high-level features into a single 768-dimensional feature embedding.

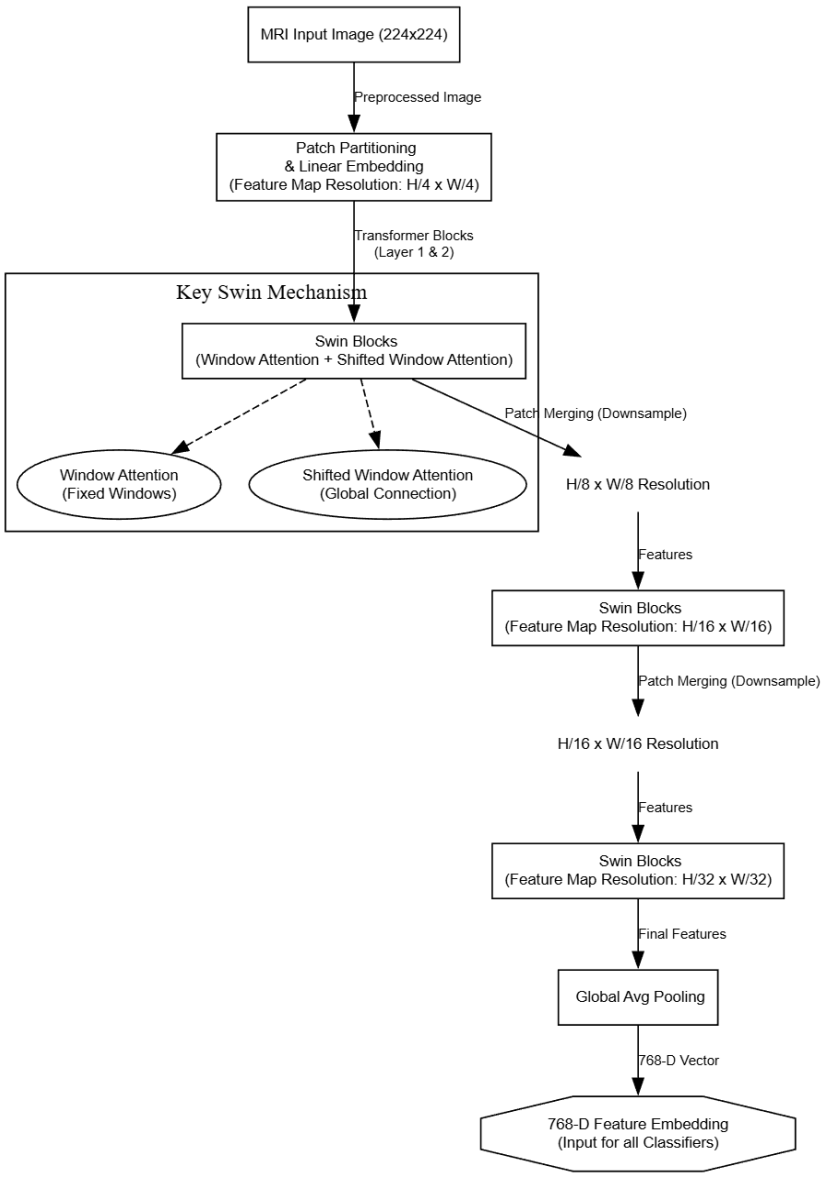


Figure 2: Internal workflow of swin Transformer.

4. Results and Discussion

Table 1 presents the distribution of MRI samples used for Alzheimer's disease classification across four categories: Mild, Moderate, Normal, and Very Mild. The dataset is well-balanced, with a total of 5776 samples, including 4621 training samples and 1155 testing samples. Specifically, Mild contains 1133 training and 283 testing samples (1416 total), Moderate includes 1131 training and 283 testing samples (1414 total), Normal has 1157 training and 289 testing samples (1446 total), and Very Mild comprises 1200 training and 300 testing samples (1500 total). This balanced distribution ensures unbiased model training and improves generalization across different Alzheimer's stages.

Figure 3 illustrates the initialization of the Alzheimer prediction server developed using a Flask-based framework. It shows the successful deployment of the backend system where trained models, including the proposed ORF classifier, are loaded into memory for inference. This stage confirms that the server is ready to accept incoming MRI data for prediction. The initialization process ensures efficient model loading, reduced latency, and readiness for real-time remote access, enabling seamless integration between clinical systems and the prediction engine.

Table 1. Dataset Distribution.

Class	Train Data	Test Data	Tota l
Mild	1133	283	1416
Moderate	1131	283	1414
Normal	1157	289	1446
Very Mild	1200	300	1500
Total	4621	1155	5776

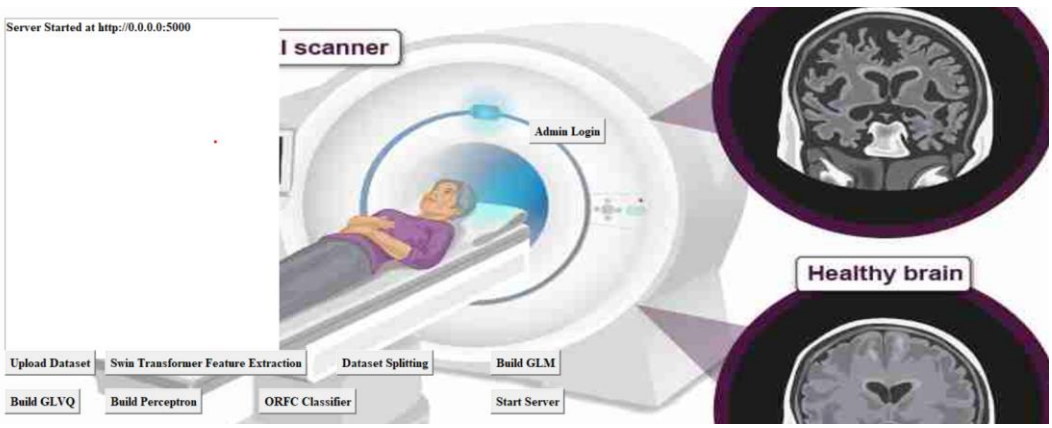


Figure. 3: Alzheimer Prediction Server Initialization.

Figure 4 depicts the remote user interface through which MRI images are uploaded and Alzheimer's predictions are received. The interface allows users, such as clinicians or researchers, to submit MRI scans from external systems and obtain instant classification results. The output typically includes the predicted Alzheimer stage along with supporting details, ensuring usability and accessibility. This interface demonstrates the system's capability for real-time, cross-device deployment, making it suitable for practical healthcare environments.

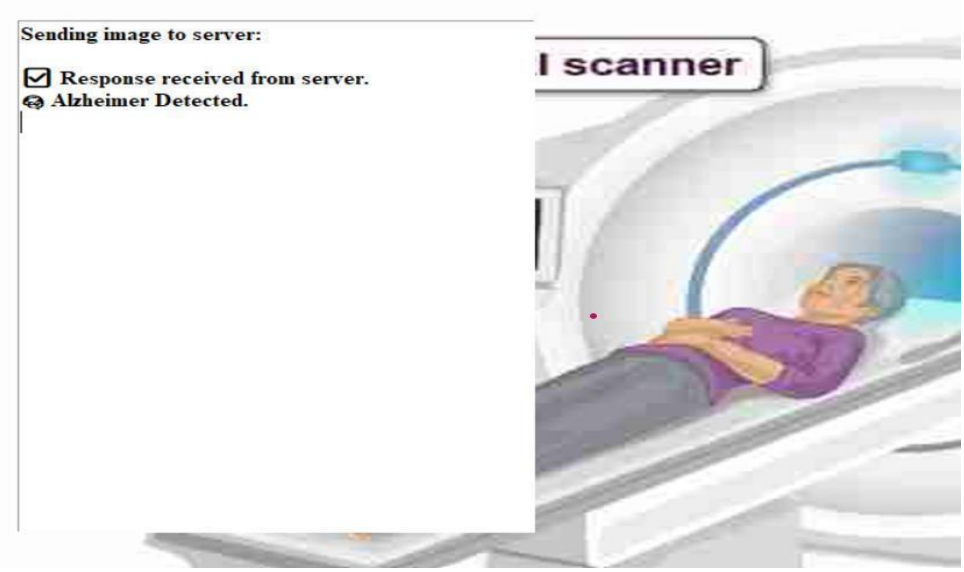


Figure 4: Remote User Alzheimer Prediction Response Interface.

Figure 5 shows the confusion matrix of the proposed Optimal Random Forest (ORF) classifier, highlighting its classification accuracy across all Alzheimer categories. The matrix exhibits strong diagonal dominance, indicating that most MRI samples are correctly classified into their respective classes. Misclassifications are extremely minimal, reflecting the model's robustness. This observation is supported by the quantitative results, where the ORF model achieves 99.43% accuracy, 99.43% precision, 99.43% recall, and 99.43% F-score, demonstrating near-perfect classification performance.

Figure 6 presents the explainable AI (XAI)-based interpretation of MRI scans using a transformer-based Alzheimer classification model. The visualization highlights critical brain regions contributing to the classification decision, such as areas exhibiting atrophy or ventricle enlargement. By providing these visual explanations, the system enhances transparency and clinical trust, enabling healthcare professionals to understand the reasoning behind predictions rather than relying on a black-box model.

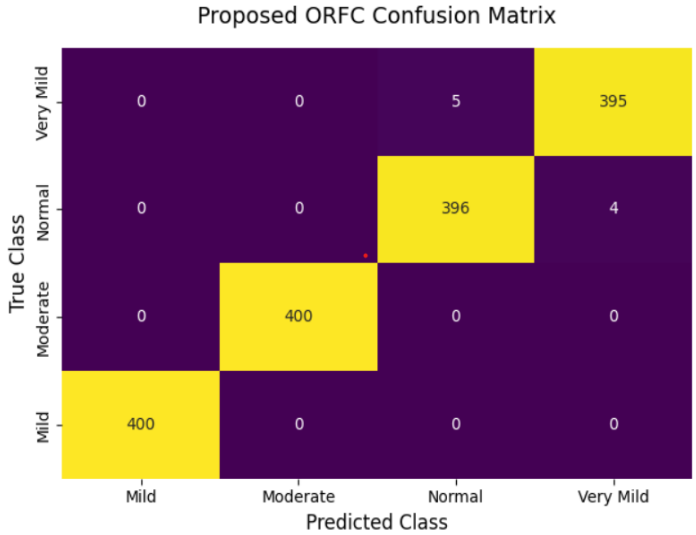


Figure 5: Confusion matrix obtained using ORFC.

Table 2 compares the performance of different classifiers, including GLM, GLVQ, Perceptron, and the proposed ORF model. The GLM classifier achieves 93.93% accuracy, 94.45% precision, 93.935% recall, and 93.89% F-score, while the GLVQ classifier shows lower performance with 81.25% accuracy

and 80.68% F-score. The Perceptron model performs moderately well with 92.25% accuracy and 92.19% F-score. In contrast, the proposed ORF classifier significantly outperforms all others, achieving 99.43% across all metrics, demonstrating its superior ability to handle complex MRI feature patterns and accurately classify Alzheimer stages.

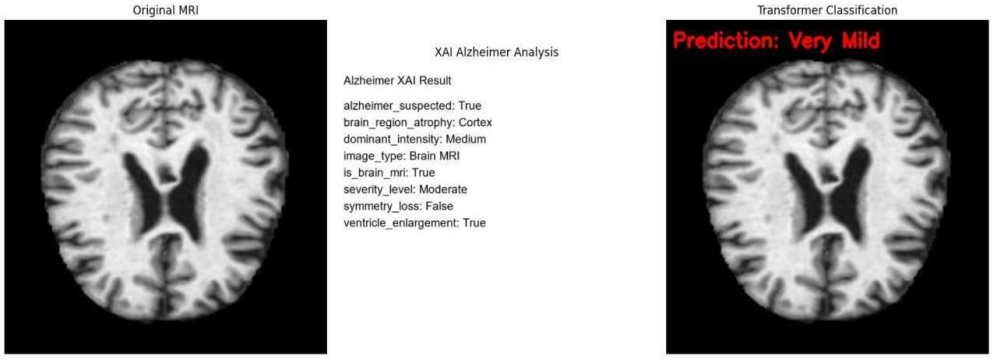


Figure 6: XAI-supported MRI interpretation with transformer-based alzheimer classification

Table 2: 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%

5. Conclusion

This research presents a robust and intelligent framework for automated Alzheimer's disease detection and stage classification using structural MRI scans, integrating advanced deep learning and machine learning techniques. The use of the Swin Transformer enables effective extraction of high-dimensional and spatially rich features, capturing subtle structural variations in the brain associated with different stages of Alzheimer's disease. The experimental analysis demonstrates that while traditional classifiers such as GLM, GLVQ, and Perceptron provide satisfactory performance, they are limited in modeling complex, non-linear MRI data distributions. In contrast, the proposed ORF classifier achieves outstanding performance with 99.43% accuracy, precision, recall, and F-score, highlighting its effectiveness and reliability. The system is further enhanced by an interactive Tkinter-based graphical interface that simplifies dataset handling, model training, and evaluation, making it accessible to users without deep technical expertise. Additionally, the Flask-based remote prediction server enables real-time, cross-platform inference, allowing MRI scans to be analyzed from remote clinical setups. The integration of XAI-based visualization adds a critical layer of interpretability by highlighting clinically relevant brain regions such as atrophy zones and ventricle enlargement, thereby increasing trust and transparency in AI-assisted diagnosis. Overall, the proposed framework offers a scalable, accurate, and interpretable solution that can significantly support early diagnosis, clinical decision-making, and improved management of Alzheimer's disease in real-world healthcare environments.

References

[1] How Is Alzheimer's Disease Diagnosed? Available online: https://www.nia.nih.gov/health/alzheimers-symptoms-and-diagnosis/how-alzheimers-disease-diagnosed

[2] Zhou, Q.; Wang, J.; Yu, X.; Wang, S.; Zhang, Y. A Survey of Deep Learning for Alzheimer's Disease. Mach. Learn. Knowl. Extr. 2023, 5, 611–668.

[3] Arafa, D.A.; Moustafa, H.E.-D.; Ali, H.A.; Ali-Eldin, A.M.T.; Saraya, S.F. A Deep Learning Framework for Early Diagnosis of Alzheimer's Disease on MRI Images. Multimed. Tools Appl. 2024, 83, 3767–3799.

[4] Purmani, S. S. R. (2025). Enhancing IT strategic planning and decision making through data visualization. International Journal of Enhanced Research in Management & Computer Applications, 14(4), 75–81.

[5] Chiroiu, V.; Munteanu, L.; Ioan, R.; Dragne, C.; Majercsik, L. Using the Sonification for Hardly Detectable Details in Medical Images. Sci. Rep. 2019, 9, 17711.

[6] Qiang, Y.-R.; Zhang, S.-W.; Li, J.-N.; Li, Y.; Zhou, Q.-Y. Diagnosis of Alzheimer's Disease by Joining Dual Attention CNN and MLP Based on Structural MRIs, Clinical and Genetic Data. Artif. Intell. Med. 2023, 145, 102678.

[7] Gionfrida, L.; Roginska, A. A Novel Sonification Approach to Support the Diagnosis of Alzheimer's Dementia. Front. Neurol. 2017, 8, 647.

[8] Barrass, S.; Kramer, G. Using Sonification. Multimed. Syst. 1999, 7, 23–31.

[9] Illakiya, T.; Ramamurthy, K.; Siddharth, M.V.; Mishra, R.; Udainiya, A. AHANet: Adaptive Hybrid Attention Network for Alzheimer's Disease Classification Using Brain Magnetic Resonance Imaging. Bioengineering 2023, 10, 714.

[10] Shamrat, F.M.J.M.; Akter, S.; Azam, S.; Karim, A.; Ghosh, P.; Tasnim, Z.; Hasib, K.M.; De Boer, F.; Ahmed, K. AlzheimerNet: An Effective Deep Learning Based Proposition for Alzheimer's Disease Stages Classification from Functional Brain Changes in Magnetic Resonance Images. IEEE Access 2023, 11, 16376–16395.

[11] Pattilachan, T.M.; Demir, U.; Keles, E.; Jha, D.; Klatte, D.; Engels, M.; Hoogenboom, S.; Bolan, C.; Wallace, M.; Bagci, U. A Critical Appraisal of Data Augmentation Methods for Imaging-Based Medical Diagnosis Applications. arXiv 2022, arXiv:2301.02181.

[12] Rekha Gangula et al. [1] proposed a methodology for early Alzheimer's disease detection using Brain Magnetic Resonance Imaging (MRI). The system performed image preprocessing and feature extraction. The classification model improved early-stage disease identification.

[13] Jin, Z.; Gong, J.; Deng, M.; Zheng, P.; Li, G. Deep Learning-Based Diagnosis Algorithm for Alzheimer's Disease. J. Imaging 2024, 10, 333.

[14] Pan, X.; Phan, T.-L.; Adel, M.; Fossati, C.; Gaidon, T.; Wojak, J.; Guedj, E. Multi-View Separable Pyramid Network for AD Prediction at MCI Stage by 18F-FDG Brain PET Imaging. IEEE Trans. Med. Imaging 2021, 40, 81–92.

[15] Goel, T.; Sharma, R.; Tanveer, M.; Suganthan, P.N.; Maji, K.; Pilli, R. Multimodal Neuroimaging Based Alzheimer's Disease Diagnosis Using Evolutionary RVFL Classifier. IEEE J. Biomed. Health Inform. 2025, 29, 3833–3841.

[16] Ning, Z.; Xiao, Q.; Feng, Q.; Chen, W.; Zhang, Y. Relation-Induced Multi-Modal Shared Representation Learning for Alzheimer's Disease Diagnosis. IEEE Trans. Med. Imaging 2021, 40, 1632–1645.

[17] Venugopalan, J.; Tong, L.; Hassanzadeh, H.R.; Wang, M.D. Multimodal Deep Learning Models for Early Detection of Alzheimer's Disease Stage. Sci. Rep. 2021, 11, 3254.

[18] Rekha Gangula. proposed a diabetes prediction model using Logistic Regression. The framework analyzed clinical datasets for risk prediction. The model improved prediction accuracy and disease prognosis.

[19] Yagis, E.; de Herrera, A.G.S.; Citi, L. Convolutional Autoencoder Based Deep Learning Approach for Alzheimer's Disease Diagnosis Using Brain MRI. In Proceedings of the 2021 IEEE 34th International Symposium on Computer-Based Medical Systems (CBMS), Aveiro, Portugal, 7–9 June 2021; pp. 486–491.

[20] Tang, Z.; Zhang, T.; Song, Q.; Su, J.; Yang, B. PINet: Privileged Information Improve the Interpretablity and Generalization of Structural MRI in Alzheimer's Disease. In Proceedings of the 14th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics, Houston, TX, USA, 3–6 September 2023; ACM: Houston, TX, USA, 2023; pp. 1–9.

[21] Pavankumar Nagapuri et al. [3] proposed a deep learning hybrid model for lung disease detection using Chest X-Ray (CXR) images. The model combined feature extraction and classification stages. The approach improved diagnostic accuracy in medical imaging.

[22] Rekha Gangula et al. [4] proposed an ensemble machine learning approach for dengue disease prediction. The framework utilized multiple classifiers for improved performance. The model enhanced prediction accuracy and reliability.