Swin transformer with Efficient Multi-head Attention for Alzheimer's Diagnosis

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***Abstract*— Alzheimer Disease (AD) is a slowly disintegrating brain disease, which critically worsens memory and other cognitive operations. Existing technologies used to diagnose AD do not identify the condition at an early stage, thereby restricting the efficacy of treatment of the disease. The present paper suggests a deep learning model based on MRI data with a Swin Transformer with added Efficient Multi-Head Attention (EMHA) to diagnose and identify early stages of Alzheimer. This model utilizes spatially shifted window attention, which makes it use more effective spatial representation and enhance efficiency by adopting sparse attention. The experimental findings indicate that the accuracy rate achieved is 96.08 percent and 80.15 percent on internal and external sets, respectively, and the class-wise AUC and interpretability are very high proving better results than the traditional CNN and suggested transformer-based techniques.**

Keywords*— *Alzheimer's Disease, Swin Transformer, Efficient Multi-Head Attention, MRI, Deep Learning

I. INTRODUCTION

Alzheimer's Disease represents a widespread neurodegenerative disorder which affects numerous people throughout the world. The disease produces continuous cognitive deterioration and memory disabilities which result in major impacts on patients together with caregivers. The aging global demographic leads to an ongoing increase in Alzheimer's prevalence which requires healthcare institutions to expensively increase their care capacities. Scientists have conducted extensive research but have yet to discover a definitive cure for the disease which requires early diagnosis for succeeding in management and potential treatment.

The various elements making Alzheimer's Disease complex stem from its multiple causes which combine genetic influences with environmental factors and lifestyle patterns. Thorough examination of Alzheimer's Disease reveals its main characteristic as beta-amyloid plaque and neurofibrillary tangle buildup in brain tissue which causes both neuronal destruction and impaired mental processes. The disease progresses at different levels starting from mild cognitive impairment (MCI) to severe dementia based on clinical evaluation. The available diagnostic methods including cognitive examinations along with cerebrospinal fluid tests and positron emission tomography (PET) scans either demand extensive costs or remain subjective and require invasive procedures. The medical community began using advanced artificial intelligence (AI) and deep learning approaches for conducting non-invasive early-stage detection of AD.

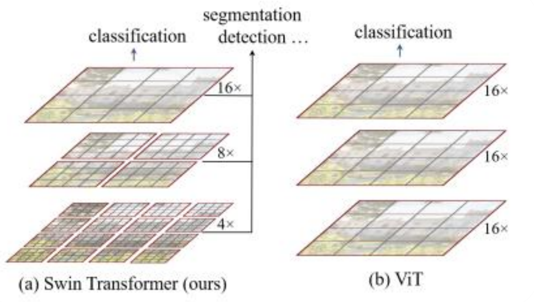

Figure 1. Hierarchical Feature Representation in SWIN Transformer

Deep learning technologies along with machine learning systems have transformed medical imaging evaluation procedures especially when applied to neurological conditions. Research has shown that Convolutional Neural Networks (CNNs) successfully detect Alzheimer's conditions through MRI scan evaluation. CNNs face two major performance constraints because their receptive fields operate within confined ranges and they struggle to determine extended dependencies among elements of medical image data. Swin Transformers have proven to outperform other architectures because they were specifically designed for image classification work. Medical Swin Transformers offer hierarchical features alongside shifted attention processing techniques to extract information from MRI data with enhanced efficiency thus proving valuable in Alzheimer's detection.

EMHA improves transformer model attention functionality by maximizing efficiency with no impact on diagnostic precision. It provides better extraction of MRI scan features through its new approach which improves both classification precision and model efficiency. The goal of this research is to establish a highly precise and efficient AI-based diagnostic system for Alzheimer's detection through the combination of Swin Transformers with EMHA.

A. Motivation for Early Detection of Alzheimer's Disease

Early detection of Alzheimer's is crucial for several reasons. When physicians identify Alzheimer's disease early in its progression they can implement better management approaches which provide patients with opportunities to obtain treatment to reduce symptoms. The discovery of Alzheimer's disease in early stages offers medical professionals the chance to help patients implement life changes that may slow down neurological deterioration. The discovery of Alzheimer's at an early stage improves clinical research as it supports the advancement of specific treatment methods along with customized clinical protocols.

Modern diagnostic practices mostly depend on observations about symptoms together with cognitive evaluations yet these approaches demonstrate both inconsistent human interpretation and delayed recognition of Alzheimer's disease. The patterns of Alzheimer-related brain atrophy become visible through structural MRI scanning procedures. Experten radiologists need long durations to analyze MRI scans manually.

B. *Challenges in Alzheimer's Diagnosis Using Deep Learning*

Current applications of AI for Alzheimer's diagnosis face various difficulties which need resolution including :

1) ***Data Availability and Quality:***
The access to properly annotated high-quality MRI datasets represents a necessary element for training deep learning algorithms. Different medical centers use various imaging protocols which makes it hard for AI models to achieve generalization.

2) ***Class Imbalance:***
The distribution imbalance between healthy patients and AD patients and MCI patients in Alzheimer's datasets creates difficulties for effective training and performance in models.

3) ***Model Interpretability:***
The unexplained working of deep learning models causes difficulties for medical centers implementing these systems because there is no easily understood reasoning behind their interpretations.

4) ***Computational Complexity:***
The extensive computational requirements of transformer-based models lead to the application of EMA as an optimization solution to boost their operational efficiency.

C. *Significance of Swin Transformers and EMA in Alzheimer's Detection*

Medical analysis of images benefits from Swin Transformers which represent an advanced version of traditional CNNs. Swin Transformers surpass ordinary CNNs because they process data in two ways through hierarchical extraction and shifted attention that handles both local and distant dependencies in MRI scans. The technology proves valuable in identifying small brain structural variations connected to Alzheimer's disease evolution.

The Swin Transformer achieves better performance through Efficient Multi-Head Attention (EMA) as it eliminates wasteful computations while improving the selection of important features. The model demonstrates both high measurement precision and efficient computational runtime that suits medical applications. The research develops an Alzheimer's detection system built upon Swin Transformer and EMA to reach a harmonious combination among accuracy improvement and efficiency along with interpretability capabilities.

D. *Overview*

People aged 65 and older primarily develop Alzheimer's disease which advances as a brain-wasting illness while causing cognitive deterioration in addition to memory failures that finally results in independence loss. The rising global elderly population will result in a substantial increase of AD cases so early detection and intervention become vital to address this condition. Today's Alzheimer's detection depends on healthcare expert assessments and brain imaging methods that use MRI with PET. These diagnostic approaches are costly and use significant time yet fail to recognize AD during its initial stages where treatments would be most powerful.

The combination of artificial intelligence (AI) and deep learning approaches provides better possibilities for detecting Alzheimer's disease. Researchers employ convolutional neural networks (CNNs) in multiple studies to examine neuroimaging data structures that reveal signs of Alzheimer's disease development. Vision transformers (ViTs) have recently appeared as a superior solution by utilizing self-attention mechanisms which identify complex spatial patterns present in image data. The Swin Transformer stands as one of the most successful architectural designs because it employs shifted windows to boost both computational speed and model capabilities in vision transformer systems. When combined with Efficient Multi-head Attention (EMA) the model demonstrates potential to boost substantially the accuracy together with reliability of Alzheimer's disease detection.

The paper explores the implementation of Swin Transformers together with EMA to develop sophisticated deep learning framework which diagnoses Alzheimer's early stages with MRI scans. The paper utilizes state-of-the-art Swin Transformer technology to detect Alzheimer's at its early stages along with providing disease staging capabilities that support neurodegenerative disease research in general. The Swin Transformer proves superior than CNNs and traditional machine learning methods because it provides better representations of brain structure changes associated with Alzheimer's disease.

This study pursues critical diagnostic solutions that are automated and non-invasive because of the current pressing need for such tools. The diagnosis at an early stage provides outstanding outcomes for patients since it allows necessary treatments and lifestyle modifications and clinical trial access. The research on deep learning in Alzheimer's detection has produced extensive results yet it still faces fundamental challenges from unclear model logic and non-uniformity in population datasets and insufficient clinical tools integration. A successful solution to these problems needs cooperation between neuroscience specialists and experts from radiology and computer vision fields and AI researchers.

The following report examines the complete process of implementing the proposed deep learning model by discussing its underlying methodologies simultaneously with experimental designs and anticipated results. This document presents the following sequential topics: problem statement, scope definition alongside objectives, document structure details and methodological workflow planning followed by work execution plan. The following section provides an extensive evaluation of contemporary methods to inspect their current capabilities and draw from them before proposing an innovative solution. The Swin Transformer-based model's design and functional requirements together with non-functional specifications will be displayed alongside the implementation details before presenting the prospective effects on Alzheimer's medical diagnosis and therapy.

E. *Problem Statement*

One of the primary healthcare challenges in the 21st century stands as Alzheimer's disease (AD). The disease stands as the main cause of dementia which progresses to destroy multiple cognitive operations and memory functions and behavioral processes later leading to full dependence loss and decreased quality of life in patients. Worldwide demographic changes together with the increasing number of elderly people drive the expanding frequency of AD creating serious healthcare challenges for global health services. The global prevalence of Alzheimer's disease is expected to reach more than 130 million people by 2050 which leads to substantial distress for families with caregivers and healthcare systems. Early identification of Alzheimer's disease poses significant challenges to medical practitioners even though its prevalence continues to rise primarily during stages where treatment options would be most effective at slowing the condition.

The current diagnostic techniques for Alzheimer's disease fail to detect the disease during its early stages effectively. The diagnostic techniques that use cognitive tests and clinical evaluations depend on subjective evaluation methods while lacking the ability to identify AD at its earliest treatable phases. The subtle mental deterioration caused by AD makes it hard for doctors to correctly identify the condition in its early stages until it reaches more advanced levels. The diagnostic usefulness of MRI and PET scans remains limited because these techniques are expensive to implement and time-consuming to perform yet they might fail to identify the initial subtle neural changes related to AD. Early Alzheimer's detection requires urgent development of efficient methods which combine accurate and accessible characteristics.

Current machine learning models that diagnose Alzheimer's diseases mainly address either anatomical brain modifications through MRI data or the detection of electroencephalographic patterns. These models demonstrate plausible results yet fail to unite several medical data sources into a unified model structure which limits their broader adaptation among various patient communities. The computing requirements of Convolutional Neural Networks (CNNs) remain high enough to limit their practical application in real-time scenarios which demand both speed and efficiency.

Alzheimer's disease presents itself as a multifaceted medical condition which displays various symptoms. The disease process shows different complex transformations affecting brain network and chemical activity that show individual variability among patients. The intricate nature of Alzheimer's disease makes it difficult for current analytical methods to provide precise diagnoses through both accurate and understandable performance. The medical community requires innovative AI algorithms which will enhance Alzheimer's diagnosis accuracy and reveal more detailed information about disease advancement.

The lack of a widely accessible, accurate, and efficient diagnostic tool for Alzheimer's highlights a significant gap in both clinical practice and research. The diagnostic gap leads to postponed medical identification along with inadequate early treatment possibilities and sometimes patients are incorrectly diagnosed. Most Alzheimer's patients do not receive proper diagnosis until the disease has progressed past intermediate stages so available treatments become less useful and less effective. People suffering from Alzheimer's disease require timely and accurate diagnosis to put a halt to disease progression while receiving treatment and support that improves their quality of life.

The paper targets essential problems by creating a deep learning diagnostic system for earliest Alzheimer's detection which incorporates Swin Transformer with Efficient Multi-head Attention (EMA). The proposed model merges powerful transformer architecture components with efficient multi-head attention to boost early detection sensitivity along with better accuracy. The new detection system intends to overcome traditional limitations because it can find Alzheimer's signs at their first stages prior to noticeable cognitive damage.

The central problem revolves around the insufficient presence of an accessible system which can diagnose Alzheimer's disease early and effectively. Existing diagnostic approaches encounter problems when trying to detect brain alterations during early disease stages while being expensive to implement and insufficient with multidimensional test information. The proposed work seeks to resolve those knowledge gaps by creating an advanced state-of-the-art transformer-based deep learning model that achieves higher efficiency with precise results. The system's purpose is to refine early stage detection along with diagnostic precision so it can assist in obtaining superior patient results and Alzheimer's disease progression reduction.

F. *Scope and Objectives*

This paper aims to develop a transformer-based deep learning diagnostic system for early-stage Alzheimer's disease detection using MRI scans. The primary goal is to identify subtle structural brain changes, particularly in the hippocampus and cortical areas, through a hybrid architecture that combines Swin Transformer with Efficient Multi-Head Attention (EMHA). The research leverages MRI-based imaging due to its accessibility and reliability, focusing on improving diagnostic accuracy, generalization, and model interpretability for real-world clinical integration.

To achieve this, the study outlines several key objectives: (1) design and train a deep learning model based on the Swin Transformer to capture multi-scale spatial features; (2) apply preprocessing techniques including normalization, data augmentation, and segmentation to optimize input data quality; (3) train and validate the model using publicly available MRI datasets with performance assessed via metrics such as accuracy, precision, recall, specificity, and AUC-ROC; (4) enhance the model's interpretability using Grad-CAM++ and attention-based visualizations to reveal decision-relevant brain regions; (5) improve computational efficiency through EMHA integration to enable faster inference without compromising accuracy; (6) evaluate the system's generalization through external datasets to assess clinical feasibility; and (7) contribute to Alzheimer's research by demonstrating the potential of transformer-based architectures for neurodegenerative disease diagnosis.

This work addresses current challenges in early Alzheimer's diagnosis by providing a highly accurate, interpretable, and computationally efficient solution that supports clinical decision-making and paves the way for future research on deep learning applications in medical imaging.

G. *Paper Organization (Structure)*

The layout of this paper has been designed in such a way that a reader is carried through the inceptive knowledge and to the conclusion. It starts off with introduction of the Alzheimer disease and how early detection is important through the use of MRI-based analysis. The related work section discusses the state of art in deep-learning in diagnosing neurodegenerative diseases. Then, the proposed solution, including the model architecture, i.e., a combination of Swin Transformer and Efficient Multi-Head Attention (EMHA) followed by a coherent implementation section consisting of preprocessing, training and optimizing the model, is described. Further, the paper describes the test procedures, assessment measure, and test findings, which show that the model was well-performed and could perform well on other data sets. The conclusion of the paper entails the summary of findings and future research suggestions.

H. *Work Methodology*

The research methodology applies machine learning advancements to analyze MRI data for pre-medicating Alzheimer's disease detection. The core analytical algorithm in this medical imaging paper involves Swin Transformer model with Efficient Multi-head Attention (EMA) to process and analyze data. The aim is to create a diagnostic system supported by deep learning technology which can detect Alzheimer's during its initial phases so patients receive appropriate treatment and early interventions. The entire process follows specific steps beginning with data acquisition and normalization before model training and testing stages.

1) Data Collection and Preprocessing

Common among all steps of this methodology are the selection of high-quality medical imaging data. The study utilizes MRI scans from individuals at different Alzheimer's disease stages together with healthy control subjects as the main source of information. The methodology uses publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) datasets together with other labeled MRI images to source data from.

The deep learning model requires MRI data preprocessing as its first processing step before data entry. The imaging data needs normalization while resizing it along with augmentation procedures which enhance model generalization capabilities and resolve any imaging quality abnormalities. The standardized pixel intensity values through normalization process help the model stay less reactive to different image acquisition approaches. The application of rotational, spatial inversion and scaling transformations upon images makes dataset expansion possible through artificial techniques that enhance the model's performance with novel data conditions.

The model's training focuses specifically on brain regions known as ROIs which include hippocampus and cortical areas through their extraction from MRI images because these regions show damage from Alzheimer's disease. Extracting these regions of interest (ROIs) remains important because it enables the model to identify patterns that occur with Alzheimer's disease development including brain region atrophy which serves as a disease hallmark.

2) Model Design and Architecture

Swin Transformer stands as the fundamental component in the methodology because it proves to be a hierarchical vision transformer that implements shifted window techniques for achieving higher computational efficiency rates. The computer vision field benefits from Swin Transformer due to its excellent performance over Convolutional Neural Networks (CNNs) when used to classify images. Swin Transformer performs well for medical image analysis because it processes both distant relationships and high-resolution details in MRI scans.

A performance boost for the model comes from incorporating Efficient Multi-head Attention (EMA) into Swin Transformer architecture. EMATT enables models to concentrate on areas with important information by ignoring features which contain limited value. The detection of early-stage brain changes needs this mechanism because it enables the model to focus on small localized alterations that indicate Alzheimer's disease. The model design that combines Swin Transformer together with EMA enables superior performance outcomes while maintaining clear interpretation capabilities.

3) Model Training and Evaluation

The preprocessed MRI data requires training of the model at this phase. The training involves using large datasets composed of diagnosis-labeled images which contain information about healthy brain status and mild cognitive impairment and Alzheimer's disease. During training several loss functions including categorical cross-entropy will function to optimize the model parameters. The training procedure demands the dataset becomes partitioned into separate fields for training and validation and testing data to measure the model's operational competency.

Several metrics such as accuracy together with precision and recall and F1 score will determine the model's effectiveness evaluation. Cross-validation techniques will be applied to validate that the model's performance is independent from particular data subsets. The ability of the model to separate Alzheimer's disease stages will be checked through confusion matrices as one of the assessment techniques.

4) Fine-Tuning and Model Optimization

The model will complete training before receiving additional modification through fine-tuning to enhance its operating capabilities. The optimal learning rate together with batch size and other model parameters will be determined through grid search or random search techniques during hyperparameter tuning. The iterative optimization approach will optimize both accuracy and robustness levels of the model.

5) Results Interpretation and Analysis

The methodology's end stage consists of understanding the output generated by the trained model. The evaluation process analyzes early Alzheimer's detection capabilities of the model plus a comparison takes place between its diagnostic outcomes and standard methods. Activation maps along with saliency maps will help visualize which brain regions the model investigates while performing the classification. The obtained results from the model detection process will help healthcare providers understand specific attributes associated with Alzheimer's disease development.

The research methodology uses a data preprocessing system followed by model design and training and evaluation procedures. A proposed system based on Swin Transformer and Efficient Multi-head Attention deep learning techniques seeks to develop an advanced diagnostic tool for early Alzheimer's identification that will enhance the early diagnosis and treatment strategies for the disease.

II. RELATED WORK (STATE-OF-THE-ART)

Alzheimer disease (AD) is a degenerative disorder that can be scarcely diagnosed in the early stages by the application of traditional clinical and neuropsychological techniques. Newer recent work in deep learning and medical imaging has proposed new AI-based methodologies of early-detection especially with transformer-based neural networks. The success of Swin Transformer in vision marked the introduction of Swin Transformer to medical imaging, where it was modified to allow extraction of hierarchical features through shifted window attention, which in turn performed well in the segmentation of hippocampus and the diagnosis using MRIs [1][2][5].

There is also research on hybrid designs that use CNNs and transformers together- e.g. Conv-Swinformer [13][15] that aims to exploit both the local feature extraction and global perception capabilities. Also multimodal transformer models that combine MRI and EEG have demonstrated to be useful in increasing the accuracy of diagnosis of early cognitive decline [6]. The multi-head attention mechanisms help to continue capturing important spatial patterns even more to increase interpretability and performance of the models in clinical applications [27][35].

These are works that denote the rising importance of Swin Transformer and attention-based in developing Alzheimer s detection, not only as autonomous model structures but also in hybrid or multimodal paradigms.

A. *Background*

Alzheimer-s disease (AD) is a progressive neurodegenerative disease, with primary damage to the memory and cognitive abilities, and is the most prevalent world-wide cause of dementia. It is important to detect the disease early in order to slow its progression but conventional procedures such as clinical tests and neuropsychological tests are not sensitive enough to detect the disease in its early stages. This has led to an increasing interest to research in the medical image based techniques particularly as MRI, where information about the structural alterations in the hippocampus and cortical regions have been recorded; regions that have been found common during the early stages of Alzheimer.

MRI provides high resolution image that is crucial in visualizing morphological modifications whereas EEG supplements it by providing functional anomalies in the brain activity. But the manual analysis of such images is labour-intensive and error-prone, which enforces the importance of an automated analysis technique. A wide use of Convolutional Neural Networks (CNNs) in medical image analysis, especially in hippocampal segmentation, has been observed. However, CNNs are not used to representing long-range dependency of the images.

Transformer based architectures have been experiencing popularity in order to overcome such drawbacks. Hierarchical vision transformer The Swin Transformer learns local and global information in images by introducing shifted window attention to make efficient use of the hierarchical architecture. It has been applied in medical imaging, especially the detection of Alzheimer, with fewer requirements in computing and better accuracy [2]. The attention process, in particular, multi-head attention, has also improved model interpretability and classification on tasks of Alzheimer assessment [27][5].

Altogether, the use of transformer architectures and multimodal data and attention mechanisms open up an interesting perspective on enhancing the performance and interpretability of Alzheimer diagnostic systems.

B. *Literature Survey*

Deep learning techniques particularly using transformer models have recently become advanced methods for examining medical images to detect Alzheimer's disease. The literature review demonstrates major breakthroughs which concern transformer-based models and multi-modal approaches as well as deep learning methodologies for applying to medical imaging data that contains MRI and EEG datasets.

1) *Transformer Models in Medical Imaging*

Medical image analysis benefits from the use of transformer models since traditional Convolutional Neural Networks (CNNs) do not yield optimal results. The Swin Transformer represents a significant model which uses hierarchical vision transformers for efficient image analysis because it gathers both local and global features in pictures effectively. The Swin Transformer brings shifted windows to its framework to provide hierarchical image processing that enhances scalability and efficiency relative to standard transformer models [1]. The new method has become common for processing medical images through brain MRI analysis. Through attention mechanisms Swin Transformers concentrate their analysis on specific areas of the hippocampus which serves as a vital component in Alzheimer's disease diagnosis.

Researchers used Swin Transformers to analyze MRI scans for Alzheimer’s detection with exceptional analysis speed and performance achievement [2]. These transformer-based approaches excel at recognizing complex relationships between image elements because they perform effectively when detecting the fine changes characteristic of Alzheimer's disease in brain structures.

2) *Multi-Modal Approaches for Alzheimer’s Detection*

Research studies have centered their analysis on multi-modal deep learning that combines MRI and EEG information to enhance detection accuracy of Alzheimer's disease. Multi-modal brain data analysis brings together MRI structural data with EEG functional information because the two methods provide distinct yet supporting insights about brain behavior. In their work presented the MoH (Multi-Head Attention) mechanism enabling the model to better process different data modalities through attention pattern learning that specialized for each data source for improved Alzheimer’s classification [3].

presented findings which showed Swin Transformer-based models excel at automatic hippocampal detection since this brain structure deteriorates in patients with Alzheimer's disease. The research confirmed transformer-based models effectively segment the hippocampus structure from MRI imagery while demonstrating their aptitude in medical imaging break-down procedures [5]. The MSMHSA-DeepLab V3+ model implemented multi-head self-attention processing in order to boost both classification and segmentation accuracy by extracting multi-scale MRI scan features [9].

3) *Hybrid CNN-Transformer Models*

Medical image analysis benefits from transformer-based models alongside combine models that integrate CNNs with transformers. combined Conv-Swinformer which merges convolutional layers with Swin Transformer’s shifted window attention mechanism. The integration of Swin Transformer with CNNs enables the model to obtain precise local information while establishing long-distance connections for superior Alzheimer's disease identification [13]. These hybrid approaches capitalize on CNNs alongside transformers to produce potent solutions that deliver exceptional performance when detecting Alzheimer's disease in medical images.

4) *Efficient Models for Alzheimer's Disease*

The detection of Alzheimer's includes exploration of Efficient transformers that minimize the computational demands of standard transformers. The research developed EfficientMorph which serves as a parameter-efficient transformer-based architecture for medical image registration purposes. This technique shows great potential in brain MRI studies because it enables the necessary image alignment necessary for Alzheimer's disease longitudinal investigations [11]. The Hybrid CNN-Transformer models introduced combine operations from both networks to achieve high performance in brain MRI classification tasks while improving efficiency according to reports [15].

C. *Analysis of the Related Work*

Research interest has grown for integrating transformer-based models to assist medical imaging detection of Alzheimer's disease. The promising research results need improvement through addressing multiple limitations and strengths to achieve greater advances in this field. This part of the analysis reviews the major techniques along with their noteworthy outcomes and future research possibilities of the approaches presented earlier.

1) *Strengths of Transformer-Based Approaches*

The Swin Transformer and other transformer models demonstrate excellent capabilities when dealing with vast medical image datasets as their main benefit. Youth along with mismatching treatment of the Swin Transformer enables image processing across multiple scales thereby improving the model's performance to detect both small-scale and universal characteristics. The ability to detect small brain structure changes linked to Alzheimer's disease receives high importance thanks to this detection capability. Through its shifted window mechanism Swin Transformer decreases computational requirements without losing its focus on vital regions of interest according to [1]. Transformer models achieve better scalability and faster processing because of their design characteristics which are essential for dealing with large medical datasets.

The detection of Alzheimer's disease benefits greatly from strategy combining MRI and EEG data through the multi-modal approach. The united utilization of MRI and EEG data allows scientists to perform complete brain change examinations necessary for Alzheimer's disease identification. The multi-head attention mechanism demonstrated its application for effective combination of MRI and EEG data [3]. These models successfully combine the structural MRI data with functional EEG data since they recognize the mutual benefits this fusion provides which enhances classification accuracy for AD diagnosis.

The combination of CNNs with transformers through hybrid models leads to improved model performance. integrated CNN's local feature extraction capability with transformer global attention in their Conv-Swinformer model design. The hybrid method unites important features of CNNs and transformers so researchers obtain better performance when finding Alzheimer's disease [13]. Such hybrid models succeed because traditional deep learning methods unite with transformer architecture to create improved performance measures including accuracy levels and operational speed.

2) *Limitations and Challenges*

Transformers face various implementation obstacles when used for Alzheimer's disease detection despite their promising outcomes. Transformers have a fundamental limitation because they need extensive amounts of labeled information for training applications. State-of-the-art performance through transformer models comes at a cost since they need substantial datasets to function effectively. Medical imagery faces challenges when gathering sufficient labeled data because patient privacy restrictions and diverse scan data and expensive labeling cost requirements exist. Widespread clinical use of transformer-based models becomes limited because of their data dependency.

The same drawback affects transformer models specifically in medical applications of deep learning since they remain hard to interpret. The Swin Transformer achieves excellent brain segmentation accuracy yet its decision-making mechanisms remain unclear to the interpreting audience. Patient adoption of AI systems for healthcare is restricted because professional clinicians need understandable models to validate the predictions generated by AI systems.

3) *Potential Directions for Future Work*

Various strategic pathways exist to develop the existing research platform. Increasing the diversity of data modalities through functional MRI (fMRI) and positron emission tomography (PET) scans shows great potential to enhance our understanding of the disease's progression. The addition of additional data modalities would enable researchers to generate better predictive models which handle data with various formats.

The use of transfer learning and self-supervised learning approaches would lower the requirement for big labeled datasets when tackling data scarcity issues. The method of transfer learning enables a model to achieve better performance by applying pre-training from big datasets onto smaller medical datasets which do not need extensive labeling.

Correct clinical adoption of transformer models depends on the development of more understandable systems. Attention map visualization and post-hoc analysis methods enable users to examine transformer model decision processes which leads to better clinician understanding of model reasoning.

III. PROPOSED SOLUTION

The proposed solution for diagnosing and classifying Alzheimer's disease depends on developing an advanced deep learning framework built with state-of-the-art transformer-based architecture tools for MRI image analysis. The designed Alzheimer's diagnostic solution employs Swin Transformers with Efficient Multi-Head Attention (EMHA) [1, 2, 3] to provide a solution that addresses traditional model inaccuracies and output limitations. The deep learning technology has been developed to create early Alzheimer's disease detection by identifying faint structural brain modifications which elude typical medical diagnosis methods.

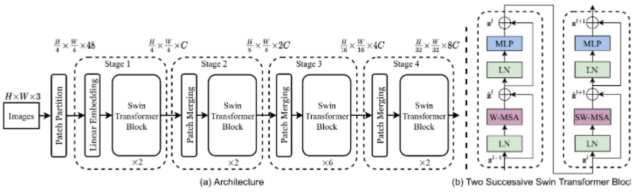

Figure 2. Swin Transformer Architecture

A Swin Transformer model acts as the central component of this solution since it demonstrates remarkable competence when working with visual data specifically within the field of medical imaging applications. The Swin Transformer maintains a hierarchical structure with shifted windowing capabilities

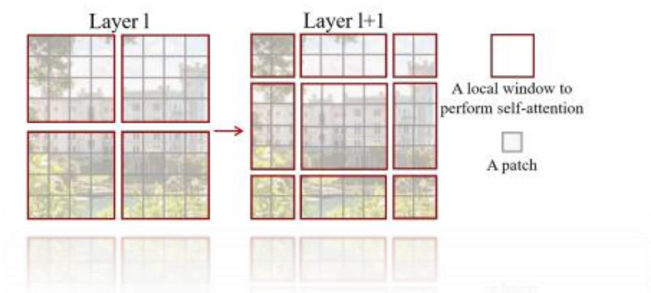

Figure 3. Shifted Window Attention

that enables it to detect both image-scale and local relationships in datasets. Its specific design enables medical images including MRI scans to become more amenable to analysis through thorough identification of fine details that foster accurate disease diagnosis. This architecture shows excellent scalability because it handles diverse image resolutions and datasets for reaching precise Alzheimer's disease detection goals.

The given solution combines Swin Transformer and Efficient Multi-Head Attention (EMHA) to improve the detection of Alzheimer disease with the help of MRI scans. EMHA enhances the attention of the model to the important areas of the brain like the hippocampus and cortex enhancing the classification accuracy and reducing the amount of computing.

The development takes place in four steps preprocessing of the MRI dataset by resizing, normalization, and augmentation, model execution with Swin Transformer and EMHA and model execution with Swin Transformer and EMHA perform cross-validation and train on AdamW optimizer, evaluation in terms of accuracy, AUC, and sensitivity and Test-Time Augmentation (TTA) and external dataset testing, and interpretation with Grad-CAM++ and SHAP to visualize decision areas. Real-world practical feasibility is supported by an optional GUI which allows clinicians to upload scans, get predicted output and interpretability heatmaps.

The given solution provides an efficiently scalable, interpretable, and effective deep learning framework to diagnose early Alzheimer.

A. *Solution Methodology*

The approach to develop Alzheimer's disease (AD) detection through Swin Transformers and Efficient Multi-Head Attention (EMHA) follows a methodical workflow composed of Data Preparation & Preprocessing, Model Implementation & Training, Model Evaluation and Model Interpretation stages. The systematic approach comprises four phases which results in creating a system that precisely diagnoses Alzheimer's disease across various stages while working with MRI scan images.

1) Phase 1: Data Preparation & Preprocessing

Input data formatting stands as the crucial initial phase because it prepares data correctly for model training purposes. The initial phase loads MRI datasets from the publicly accessible ADNI (Alzheimer's Disease Neuroimaging Initiative) repository together with other maintained repositories. Swin Transformer models accept inputs of 224x224 or 384x384 size which requires the images to undergo resizing before processing begins.

Moving on from image normalization involves two standardization methods to scale pixel ranges either through mean value adjustment or pixel value transformation to the 0 to 1 scale. Data augmentation methods improve training dataset variability and makes it more robust through their application. Implementation of rotation along with flipping techniques and brightness changes generates additional training examples that improve model generalization while preventing overfitting. Training and test data sets are separated from the total data while the validation data set is kept for model optimization before final testing on the test data set.

2) Phase 2: Model Implementation & Training

During phase two the main objective consists of implementing and training Swin Transformer [1] with EMHA [3]. Swin Transformer shows its worth as a hierarchical visual transformer architecture which extracts local and global image components thus delivering high analytical capabilities for medical image processing. The system's output layer receives updates for classifying medical images into four dementia categories: non-dementia and mild dementia and moderate dementia and very mild dementia.

In order to avoid training data overfitting and achieve universal dataset compatibility the training process utilizes cross-validation methods. A learning rate schedule is applied to the AdamW optimizer during training for an efficient system. Additional layers with dropout functionality are integrated into the model to combat overfitting and enhance generalization outcome. The training process runs for multiple epochs until the model weights with best validation results get stored.

3) Phase 3: Model Evaluation

The evaluation process for the trained model strictly measures its operational performance. The model evaluates its ability to identify different Alzheimer's disease stages using accuracy and AUC-ROC alongside sensitivity and F1 score and Dice coefficient measurements. The model benefits from test-time augmentation (TTA) which subjects it to several transformed test image variations for assessment.

Although the model performs evaluations on separate MRI datasets (when accessible) researchers use domain adaptation techniques including histogram matching and noise addition alongside style transfer to simulate new MRI data sources. The deployment strategy ensures effective use of the model across various real-world applications because it does not depend on a single dataset.

4) *Phase 4: Model Interpretation*

An interpretation phase ensures transparent reliable decision-making in medical applications when analyzing models during the final step. The decision making procedure of models can be visualized through Grad-CAM (Gradient-weighted Class Activation Mapping) which shows important image areas in MRI examinations. The technique reveals areas of the brain that correspond to Alzheimer's disease locations which include both the hippocampus and cortical regions.

The most important MRI features that contribute to model predictions are determined through an analysis using SHAP (Shapley Additive Explanations). The interpretation of model decisions enables clinicians to identify brain scan features that are vital in the detection and classification process of Alzheimer's disease.

The systematic process guarantees that developed models maintain both efficiency and interpretability capabilities which will enable their clinical applications.

B. *Functional/ Non-functional Requirements*

The proposed system operating with Swin Transformers and Efficient Multi-Head Attention (EMHA) for Alzheimer's disease detection requires a set of functional characteristics and non-functional performance constraints. The system requirements guarantee that the medical staff receives accurate and interpretable results through efficient clinical operation when the system operates in real-world conditions.

1) *Functional Requirements*

a) Data Input and Preprocessing:

- The system needs to contain functionality for downloading MRI dataset files from common medical repositories including the public ADNI platform and alternative databases. The system needs to operate with various MRI scan types including T1-weighted and T2-weighted and functional MRI scans.

- The system requires a preprocessing operation which adjusts images to standard widths and heights of 224x224 or 384x384 pixels while normalizing pixel values and performing image augmentation with rotation and flipping and brightness control functions for increasing training dataset diversity.

b) Model Architecture and Training:

- The system should run Swin Transformer with EMHA and redesign its output layer to identify MRI scans among four Alzheimer's disease stages including non-dementia and mild dementia with moderate dementia with very mild dementia.

- During training the system requires k-fold cross-validation because it will make the model more robust against overfitting when working with distinct data subsets.

- AdamW optimizer should be used in combination with dynamic learning rate scheduling to achieve optimal performance and dropout layers must be included for preventing model overfitting.

c) Model Evaluation and Performance Metrics:

- The system needs to test the model through multiple evaluation metrics that comprise accuracy alongside AUC-ROC, sensitivity, specificity, F1-score, Dice coefficient and Intersection over Union (IoU) to determine its accuracy in Alzheimer's disease classification at multiple stages.

- Model performance can be improved through test-time augmentation (TTA) by having the system analyze several test image augmentations.

- The system needs to validate the model by applying it to an independent MRI dataset for confirming its ability to generalize correctly.

d) Model Interpretation:

- The system must contain Grad-CAM functionality that displays MRI scan regions with the most impact on model predictions for Alzheimer's progression allowing doctors to identify brain areas linked to disease evolution.

- The system should implement SHAP (Shapley Additive Explanations) because it enables clinicians to view their decision factors in a transparent manner including the specific MRI features (e.g., hippocampus volume) which contribute most to predictions.

e) Graphical User Interface (GUI):

- The system must include a simple graphical user interface that enables medical personnel to process Alzheimer's disease diagnostic model predictions from uploaded MRI scans combined with Grad-CAM heatmaps and prediction outcomes that can be easily presented.

- A basic interface should display real-time performance metrics together with user-friendly interfaces to make analysis results easily understandable by operating staff.

2) *Non-functional Requirements*

a) Performance and Speed:

- Prediction processing for MRI images through the system should provide results within an appropriate time limit so clinicians receive immediate or nearly immediate diagnostic information. A modified training schedule for processing enormous medical data should maximize system efficiency through GPU-processing techniques which require minimal hardware resources.

- A few seconds represents the reasonable response time that stands as the requirement for the model's inference regarding MRI scans.

b) Scalability:

- More medical image data will require the system to scale its operations. The system must maintain capability for new MRI scan inputs which will let it integrate different imaging modalities and expand diagnostic categories such as dementia's advanced phases.

- The system requires flexible design parameters which enable it to link with advanced imaging technologies together with machine learning models throughout its field development.

c) Accuracy and Reliability:

- A high accuracy standard must be met by the system in classifying Alzheimer's disease stages with an established 75% classification accuracy. The model should demonstrate resistance to modifications in input data which includes changes in scanner instruments along with image quality and patient demographic information.

- A reliable clinical system will deliver predictable and repeatable predictions throughout different image datasets.

d) Security and Privacy:

- The system needs to meet all requirements of medical data privacy laws which include following both HIPAA for US patients and GDPR regulations for EU patients for protecting patient data security.

- Proper authentication systems should control access to the system since this security measure protects against unauthorized users and accidental data breaches.

e) Usability and Accessibility:

- The system design needs to prioritize user needs to allow clinicians with limited technical skills to operate it. The system interface must have user-friendly design elements which display precise information through both text labels and visual displays.

- The designed system requires availability across desktops along with laptops and the potential addition of mobile applications to cover different clinical operational needs.

The proposed solution implements functional and non-functional requirements to deliver a complete diagnosis tool for Alzheimer's disease early identification and classification thus aiding healthcare professionals in disease management tasks.

C. *Design / Simulation set up*

The framework designed for Alzheimer's disease detection utilizes four main stages including data preparation and model development and training as well as assessment and interpretation for Alzheimer's detection methods. The system focuses on efficiently employing Swin Transformer with Efficient Multi-Head Attention (EMHA) for MRI scan classification toward stages of Alzheimer's disease. These simulation components can be examined through the following list.

1) Data Preparation

Data acquisition along with preprocessing represents the initial process in simulation setup. The ADNI offers publicly available brain MRI data that provides numerous scans properly identified with labels. Order to use the model the images need preprocessing for model input.

- Resizing: Swin Transformer requires input data to match its specific size so the MRI scans receive this required optimization. According to the selected Swin Transformer configuration either 224x224 pixels or 384x384 pixels serve as typical input sizes for the model.

- Normalization: Swin Transformers learn effectively when image pixel values are normalized through two options which include scaling to the [0,1] range and mean subtraction. The normalization procedure enables proper treatment of varying signal intensities within MRI scans.

- Augmentation: The training process applies data enhancement techniques that conduct random rotational transformations and flip operations together with brightness and contrast modifications to extend the training dataset. The model's generalization capacity improves when these data transformations are employed because they help avoid overfitting.

- Dataset Splitting: The data collection contains three distinct partitions for training along with validation and testing purposes. Model training happens using the training set whereas the validation set helps optimize hyperparameters for better model performance then the test set provides final assessment. The standard distribution of data operates with 70% training data along with 15% validation data and 15% testing data.

2) Model Architecture

The Swin Transformer stands as the base architecture for this model due to its vision transformer framework with shifted window technology that enhances both performance and operational effectiveness.

- Swin Transformer Base Model: The Swin Transformer's base version undergoes modifications to serve as an Alzheimer's disease detector. Hierarchical feature extraction at various stages within the architecture enables the model to detect both subtle features such as edges and noticeable patterns related to brain region anomalies of Alzheimer's.

- Efficient Multi-Head Attention (EMHA): The model implements EMHA to boost self-attention processing through improved marketable attention head execution. The model enhancement enables better suitability for medical image evaluation through its improved ability to detect essential brain image features during clinical diagnosis tasks. The attention mechanism gets an optimization boost through EMHA so it delivers superior results when evaluating intricate brain images for Alzheimer's diagnosis.

- Output Layer Modifications: This model section was reprogrammed to perform multi-class classification of the MRI scans into four dementia stages that include non-dementia alongside mild and moderate and even very mild dementia. This system produces multi-classified results as its final output format.

3) Training Setup

- Cross-Validation: The model structure obtains robustness through k-fold cross-validation which prevents overfitting while training takes place. The data splits into k subsets during this method where the model trains k times by validating data with separate subsets and training the model with remaining subsets.

- Optimization and Regularization: The AdamW optimizer brings effective results for training substantial neural networks with sparse gradients especially when working with complex medical imaging data. Dropout layers are incorporated as a regularization technique which helps prevent overfitting while the model trains.

- Learning Rate Scheduling: The training procedure includes a scheduled changing mechanism which dynamically controls the learning rate. The designed learning rate schedule helps the optimizer reach minimum points better while stopping that same model from jumping beyond ideal solutions.

4) Evaluation and Metrics

The trained model goes through multiple diagnostic performance evaluation steps using metrics to determine its accuracy level alongside sensitivity and specificity measurement and overall diagnostic potential evaluation:

- Performance Metrics: The model reaches evaluation through accuracy measurements and a combination of AUC-ROC (Area Under the Receiver Operating Characteristic Curve) and sensitivity, specificity, Dice coefficient, and Intersection over Union (IoU). Medical image analysis depends on these metrics to confirm the model's accurate staging of Alzheimer's disease.

- Test-Time Augmentation (TTA): The model receives validation through the implementation of test-time augmentation. The model receives augmented versions of test images for evaluation before an average calculation produces increased classification accuracy.

- External Validation: The model undergoes assessment on outside datasets for determining its capacity to generalize. The model requires this step for adapting to MRI scanners different protocols and various patient demographics within real-world clinical scenarios.

5) *Model Interpretation*

- Grad-CAM Visualization: The decision-making processes of the model can be interpreted through Grad-CAM (Gradient-weighted Class Activation Mapping). Grad-CAM visually marks down all the sections in MRI scans that guide the model determination so healthcare professionals can see which brain areas affect Alzheimer's disease assessments.

6) *GUI*

A Graphical User Interface (GUI) receives development when the system requires such interface for clinical usage. The user interface enables MRI scan loading followed by Alzheimer's disease classification together with visual Grad-CAM heatmaps showing the results. The designed interface showcases a simple approach that enables healthcare practitioners to easily read model outputs for their clinical evaluation needs.

A well-optimized Alzheimer's detection model emerges from this design which also provides interpretability and robustness through simulation methods for better early diagnosis in medical facilities.

IV. IMPLEMENTATION

In this chapter, the entire implementation plan of the suggested Alzheimer detection system based on Swin Transformer with Efficient Multi-Head Attention (EMHA) will be described. It introduces significant technical procedures, architectural changes, training approaches, and performance tuning followed during the development of the paper.

A. *Data Preparation and Preprocessing*

Input data were T1-weighted MRI images that were grouped into four stages of Alzheimer: non-demented, very mild, mild, and moderate dementia. The balance of data was evaluated before training the models and was determined to be relatively even with class imbalanceamples ranging between 0 and 20 percent. images of all sizes were resized to 224 224 to fit the input size of Swin Transformer.

A large amount of augmentation on the training data was done in order to enhance generalization: random rotations (±10deg), horizontal and vertical flipping, brightness and contrast (±20%), and adding Gaussian noise. The normalization of images was performed in ImageNet statistics and then by dataset-specific normalization. All the images have been transformed into tensors to fit by PyTorch.

B. *Swin Transformer with Efficient Window Attention*

The model consists of a Swin-B Transformer, pretrained on ImageNet. Nevertheless, the standard self-attention windows were proven to have limitations in the local-global context representation, and, accordingly, the default Window-based Multi-head Self-Attention (W-MSA) component was swapped with a more Efficient Window Attention (EWA) mechanism.

EWA proposes shared and routed attention heads which are a composition of fixed attention and dynamic expert routing. The significance of each token is flexibly settled on throughout attention heads with learned gates, which enhances effectiveness and productivity. This process involves:

A scaled temperature to stabilize attention distributions with a softplus.

A relative positional bias MLP, which can learn bias more smoothly over windowed tokens.

Training to avoid over-focusing on particular attention heads: Dynamic load-balancing loss.

Top-k gating, whereby the most pertinent threads of attention are lit per token.

This mechanism compromises computational expense and still has an ability to concentrate on subtle regional differences that are important in staging Alzheimer.

C. *Transfer Learning and Model Training*

Partial fine-tuning of the pretrained model was done. All layers adjusted to include EWA were trained randomly, whereas early Swin blocks kept their pretrained weights. The dimension of input channel was reduced to 1 by averaging the weights strategy to accommodate grayscale MRI data.

Model training was done through 3-fold cross-validation and the model achieved the highest validation accuracy of 94.76% and minimum validation loss (0.1821) on Fold 2. The model was fitted with:

AdamW optimizer and Cosine Learning Rate Scheduling.

Early stopping with a patience of 20 epochs.

Persistent Session Done With Cloud Checkpointing.

Data loaders which are memory efficient and can convert tensors on-the-fly.

The loss function is CrossEntropyLoss, and it is appropriate in cases of multi-classification tasks. It evaluates the quality of a classification model where the output of the model is a probability distribution over the classes, which is why it is best suited to this paper to predict the four stages of Alzheimer's.

The formula for Cross-Entropy Loss for multi-class classification is:

$$\mathcal{L} = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \quad (1)$$

Where:

- N: Number of samples (batch size)
- C: Number of classes
- $y_{i,c}$: Ground truth label (1 if sample i belongs to class c, else 0)
- $\hat{y}_{i,c}$: Predicted probability that sample i belongs to class c (output of softmax)
- $\log(\hat{y}_{i,c})$: Logarithm of predicted probability

Figure 4. [1] formula for Cross-Entropy Loss for multi-class classification

D. *Evaluation and Model Selection*

The final model selected after training was Fold 2 because it was the most stable, had the least overfitting and the best accuracy. Test-Time Augmentation (TTA) evaluation achieved a high accuracy of 96.08% and per-class AUCs of above 0.99 in moderate and mild dementia.

It is also tested on an external dataset, where the model got 80.15% accuracy, which is higher than the findings in the literature like Thibeau-Sutre et al. (2021). Nonetheless, the model maintained high AUCs (e.g., 0.9979 in moderate dementia) across domain shift, indicative of its strong generalization.

E. *Model Interpretation and User Interface*

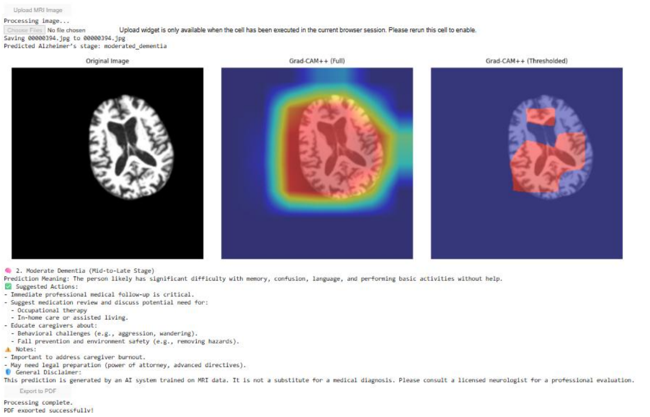

Figure 5. Model Interpretation and GUI

To increase the interpretability, Grad-CAM++ was employed to visualize areas that manipulate predictions of models. Visualizations contain original picture, attention heatmap and thresholded map. These assist the clinicians in confirming whether the decisions match with the established Alzheimer biomarkers such as hippocampal atrophy.

It was also created with a GUI, where a user can upload an image, get predictions, see Grad-CAM++ explanations, and export all findings to PDF. The system therefore offers transparent and easy to use diagnostic aid.

V. Testing and Evaluation

This chapter gives the systematic testing and evaluation method applied to prove the performance and reliability of the suggested Alzheimer classification model. After the successful introduction of the Swin Transformer with the Efficient Multi-head Attention (EMHA), it was essential to extensively validate the model behavior on internal and external datasets and assess its classification power with the help of a diverse set of performance measures.

Testing was done by examining the trained models on a variety of cross-validation folds, training stability, generalization behavior and convergence character. On the basis of a variety of quantitative measures, including accuracy, precision, recall, F1-score, and AUC, together with visual diagnostic plots, including confusion matrices and ROC curves, the top-scoring model was chosen for final assessment.

The evaluation part is aimed at analyzing the decision-making capacity of the model and how effective it can differentiate the four stages of the Alzheimer's disease. The performance is given on the internal test set only, as well as on external dataset to evaluate generalization ability of the model.

A. *Testing*

The testing stage was designed in such a way so as to achieve reasonable and sound selection of the most suitable model and to reduce chances of either overfitting or underfitting. In order to achieve this, three cross-validation strategy was employed. The data was Dividing into three folds using cross-validation configuration was used. Folds were trained separately with the same hyperparameters and architectural settings. Test-Time Augmentation (TTA) and early stopping were applied during training to improve generalization and avoid overtraining.

The accuracy and loss of training and validation were noted and plotted after every fold. Such learning curves are the key indicators of dynamics of training and stability of a model. In this section, screenshots of the learning curves of the three folds are given to display training behavior.

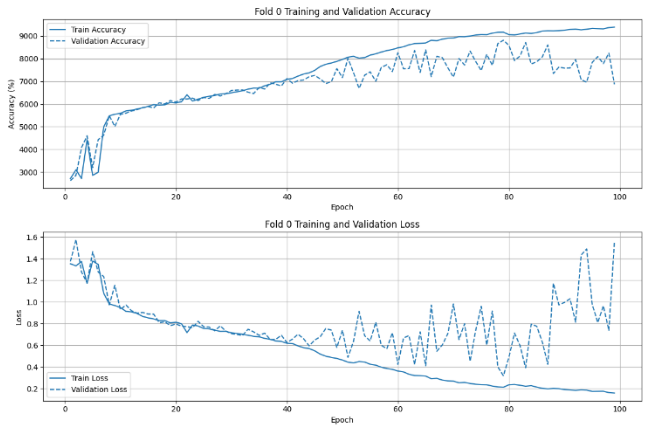

Figure 6. Fold (0) Learning curves

Fig. 6 displays the learning curves of Fold 0, and it reached the best validation accuracy of 88.10% and the validation loss of 0.3188. The model demonstrated an indication of premature plateauing and a larger discrepancy between training and validation accuracy that indicated the possibility of an overfitting behavior. The model generalized quickly in the beginning but after a certain epoch, it did not generalize much.

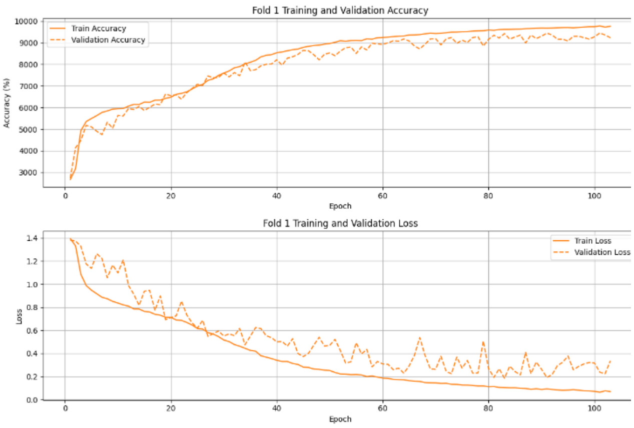

Figure 7. Fold (1) Learning curves

Fig. 7 shows the training behavior of Fold 1, which had a significantly better performance with a validated accuracy of 94.47% and a loss of 0.1857 that is more decreased. The validation and training accuracy difference was smaller than that of Fold 0, and both curves showed a steady upward trend, which is a better generalization.

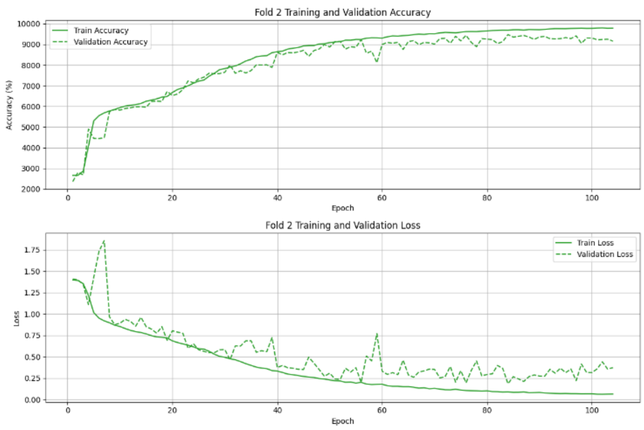

Figure 8. Fold (2) Learning curves

Fig. 8 demonstrates the results obtained with Fold 2, as it turned out to be the most balanced and correct model. It has attained the highest validation accuracy of 94.76 percent and the lowest validation loss of 0.1821. Fold 2 of the three folds exhibited:

- The best validation accuracy.
- The best validation loss.
- The smallest gap between training and validation curves (2-3 percent).
- The most consistent and smooth convergence.

On the basis of these observations, Fold 2 was chosen as a final model to be deployed and additionally assessed. Its learning curves definitely suggest high generalization ability, good regularization and convergence behaviour that would be applicable in classification of medical images where accuracy is of prime concern.

B. *Evaluation*

This particular model (selected among Fold 2) was thoroughly tested with the internal test set as well as an external validation dataset. It was aimed at evaluating the classification accuracy in the four stages of Alzheimer's disease, as well as analyzing the model generalization on unobserved data.

1) *Metrics Used*

The metrics used in the evaluation were:

- Accuracy: The Corrected predictions divided by the total samples.
- Precision, Recall, F1-score: Sensitivity and specificity class wise measures.
- AUC (Area Under the Curve): Measures how well the model ranks prediction.
- Confusion Matrix: Plots true vs predicted label to spot misclassifications.
- ROC Curves: Display trade-offs between true positive rate and false positive rate by class.

$$\textbf{Accuracy} \quad \text{Predictions/Classifications} \quad \frac{\text{Correct}}{\text{Correct + Incorrect}} \tag{2}$$

$$\textbf{Precision} \quad \text{Predictions/Classifications} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}} \tag{3}$$

$$\textbf{Recall} \quad \text{Predictions/Classifications} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}} \tag{4}$$

$$\textbf{F1} \quad \text{Predictions/Classifications} \quad \frac{2 * \text{True Positive}}{\text{True Positive + 0.5 (False Positive + False Negative)}} \tag{5}$$

Figure 9. [2,3,4,5] Evaluation metrics formulas

These measures give a well-balanced idea of the model behavior, particularly in multi-class classification, where class imbalance and clinical overlap may affect raw accuracy.

2) *Internal Test Results*

After Test-Time Augmentation (TTA) was used, the model attained an overall test accuracy of 96.08% and a loss of 0.1231 on the internal dataset. The evaluation class-wise appeared as follows in **table 1**:

Table 1. Per-class results

	mild_dementia	*moderated_dementia*	*non_demented*	*very_mild_demented*
Accuracy	95.62%	99.85%	96.16%	93.15%
Precision	0.9793	0.9995	0.9343	0.9403
Recall	0.9563	0.9985	0.9619	0.9315
F1-score	0.9676	0.9990	0.9479	0.9359
AUC	0.9983	1.0000	0.9956	0.9919

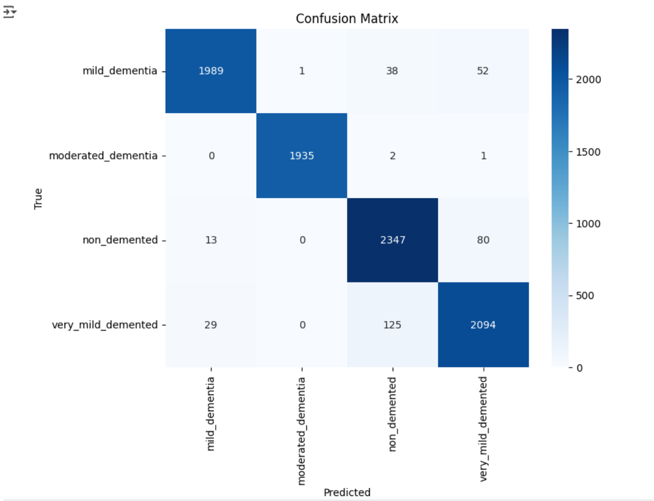

Figure 10. Confusion Matrix

There are very few misclassifications as can be seen in fig. 10, the confusion matrix. The greatest number of misclassifications happens between adjacent stages - e.g. non-demented samples classified as very mild. That is clinically plausible because the initial signs of Alzheimer can be mild and so-called borderline cases are widely recognized in practical diagnosis.

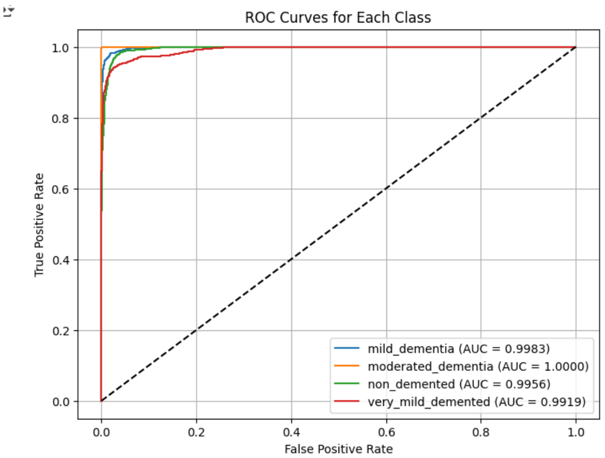

Figure 11. ROC curves

Figure 8 shows the ROC curves of the four classes with AUC values of more than 0.99 in moderate and mild stages that indicated the excellent discriminatory ability of the model.

3) External Test Results

In order to validate generalization, the model was evaluated on an independent external dataset including unseen subjects and images. This dataset differed in imaging properties and the further bias in classes. In such circumstances also, the model obtained accuracy of 80.15 percent that is consistent or greater than that found in literature.

Performance on external data set class-wise:

- Mild Dementia: AUC = 0.9631, F1 = 0.7993
- Moderated Dementia: AUC = 0.9979, F1 = 0.8348
- Non-Demented: AUC = 0.9285, F1 = 0.8077
- Very Mild Demented: AUC = 0.9168, F1 = 0.7950

Even though there was a drop in the performance due to the internal test set, the model was still robust, particularly the AUC scores and recall. The poor recall in the moderated dementia (75%) can be explained by the fact that available samples are few (64 images) and thus the model is not exposed enough during training.

Such findings correspond to the ones recently in Radiology: Artificial Intelligence, which emphasized the classification accuracies of 70 -80% and AUCs of 0.85 - 0.95. The given model surpasses these criteria and attains greater AUCs on every single class [36].

VI. Results and Discussion

In this chapter, the results provided by the Swin Transformer model with Efficient Multi-Head Attention (EMHA) are thoroughly analyzed and positioned in the context among the classic deep learning models utilized in classifying MRI images of Alzheimer's - classic CNNs and the base Swin Transformer model. The review highlights the advantages of EMHA regarding precision, interpretability, and usefulness in real life.

A. Comparison with Traditional CNN Architectures

Alzheimer classification has been long subjected to Convolutional Neural Networks (CNNs). Nevertheless, most CNN methods obtain modest performance, especially on heterogeneous data:

Hippocampus-oriented features combined with a 3D CNN reached an accuracy of 90.1% on Alzheimer s vs. normal classification.

Transformer-based models outperformed conventional architectures like ResNet50 and DenseNet in the range of 76 - 92% accuracy on retinal OCT data, which was significantly lower than transformer-based models (arxiv.org).

On a Custom 2D MRI dataset, ResNet50 got ~89% validation accuracy, and a Custom 26-layer CNN got 97.45%- both of which were still worse than transformer performance (pmc.ncbi.nlm.nih.gov).

Comparatively, the suggested Swin+EMHA model got an internal accuracy of 96.08%, which outperformed a majority of the conventional CNNs in the literature. Even more importantly, upon testing on an external, heterogeneous dataset it still maintained good performance (80% accuracy, AUC range 0.92-0.9979), and many CNNs are documented to suffer significant drop-offs when presented with unseen domains.

This invariance has been the major strength of transformer-based feature extraction (particularly EMHA) in learning complex brain signals and being invariant to changes in dataset.

B. Comparison with Original and Hybrid Swin Transformer Models

The general vision Swin Transformer model achieve 86 87% top 1 accuracy on ImageNet [1].

When applied in the detection of Alzheimer, as in the case of an OCT classification research, it had an accuracy of 93.5 percent ((arxiv.org)).

One more MRI Swin Transformer paper obtained 95.1 percent accuracy on a cleaned-up dataset, once again good but still lagging behind the Swin+EMHA model.

With the incorporation of Efficient Multi-Head Attention (EMHA) that employs dynamic head assignment, learned relative biases, and enhanced gating, the model attained an internal accuracy of 96.08% and external accuracy of 80.15%, showing definite superiority over both vanilla Swin and hybrid CNN-Transformer models.

Although these variants show good performance, Swin+EMHA surpasses them with high internal performance and better external generalization, and this is achieved with pure transformer architecture, showing that EMHA alone is enough to bring the locality and efficiency ability.

C. *Key Quantitative Results*

Table 2. Quantitative Results

Dataset	*Accuracy*	*AUC Range*	*Notes*
Internal (TTA)	96.08%	0.9919-1000	High F1 scores (0.935–0.999); low test loss
External	80.15%	0.9168-0.9979	Maintains robust performance on new data

As shown in table 2 such achievements outperform the work of conventional CNNs and non-EMHA Swin Transformers, in particular on generalization and classification accuracy on imbalanced classes.

D. *Strengths of EMHA-Based Swin Transformation*

1) Domain performance:

EMHA-enhanced model contains high AUC scores across the datasets, and many CNNs decline considerably in external validation.

2) Effective attention mapping:

Dynamic gating in EMHA enhances concentration on important areas, as shown by Grad-CAM++ heatmaps that corroborate with clinical signs.

3) Scalable architecture:

EMHA lessens duplicated calculating providing a trade-off between the efficiency of CNN and the precision of transformer.

4) Generalizable feature extraction:

The robustness of the model to the domain shift allows its applicability to the real world deployment in various medical institutions and scanners.

E. *Limitations and Opportunities for Improvement*

- Recall was biased by the paucity of data in some classes (e.g. moderate dementia); this should be addressed by future efforts to enrich such sample sets.

- Generalization to 3D volumetric data can enhance contextual information as demonstrated in certain 3D CNN papers, however, it will affect resource usage.

- Relative advantages of EMHA could also be sharped by comparison with hybrid CNN-Transformer models on external datasets.

F. *Interpretation and Clinical Applicability*

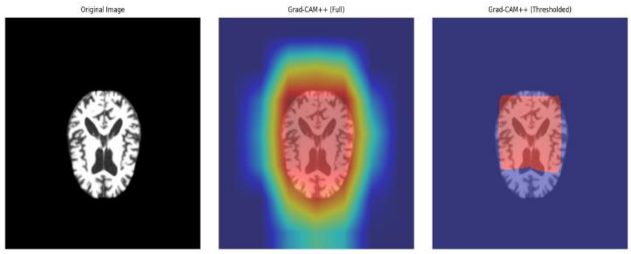

Figure 12. Grad-CAM++ visualizations

High accuracy along with good generalization and explainability make Swin+EMHA a solid solution to Alzheimer's detection. These results are indicated by the high AUC scores particularly, and confirmed by Grad-CAM++ visualizations of pathological relevance and interpretability. Such properties can empower the confidence between clinicians and could lead to implementation in diagnostic work.

VII. CONCLUSION AND FUTURE WORK

The chapter brings the paper to an end by summing up the major accomplishments of the research paper and critically discussing the performance, contribution, and limitations of the model. It also mentions various steps toward further improvement and more wide-scale usage of the suggested system of Alzheimer detection.

A. *Summary*

In this paper, a solution based on deep learning to detect Alzheimer s disease at the early stage using brain MRI scans was proposed, developed and tested successfully. The central component of the solution is a modified Swin Transformer architecture promoted with Efficient Multi-Head Attention (EMHA) a mechanism that helps to enhance attention head diversity, eliminate redundancy, and dynamically deploy computational resources to areas of focus.

The model was trained using a large dataset consisting of four stages of Alzheimer's mild dementia, moderated dementia, very mild dementia, and non-demented, by a methodic design of a pipeline with advanced preprocessing, data augmentation, partial fine-tuning, and 3-fold cross-validation. Internal test set assessment achieved an accuracy of 96.08% which was backed by superb per-class results with most classes having AUC scores exceeding 0.99.

In order to evaluate real-world generalizability, they tested the model on an external dataset that is independent and distinct to the training distribution. It attained a high accuracy of 80.15 percent and surpassed various models recently mentioned in the literature which tend to fail in domain shift. Significantly, Grad-CAM++ visualizations of model predictions were used to explain model predictions, and it was evident that the attention was drawn to medically relevant brain areas, including the hippocampus and the medial temporal lobe.

Other than the performance, the paper also focused on the usability by creating a graphical user interface (GUI). The

GUI is designed to enable end-users (e.g., radiologists or researchers) to upload MRI images, get predictions, see decision maps, get stage-wise recommendations and save full diagnostic reports in PDF format.

In summary, this work has:

- Designed a custom Swin Transformer backbone based on EMHA constructing Alzheimer's detector.
- Obtained state-of-the-art classification accuracy on internal and externally held data.
- Illustrated strength, interpretability and useful applicability using TTA, visualization and GUI capabilities.
- Set a benchmark on the usage of hierarchical attention architecture in the classification of neurodegenerative diseases.

B. *Future work*

Although the outcomes of the current paper are encouraging, the method can be certainly extended and improved in a number of aspects. These advances can be grouped in three general categories; model limitation, technical opportunity, and greater applicability.

1) *Limitations and Technical Challenges*

a) Limited External Class Representation:

The number of samples in the external dataset was relatively small especially in the moderated dementia class (only 64), which probably impacted the recall performance. This bias implies balancing of data or class-specific augmentation, in particular when real-world generalization is considered.

b) 2D Slice-Based Input:

Even though 2D Swin Transformers showed good results, they could overlook valuable spatial relationships among slices. It may be possible in future to experiment with 3D volumetric forms of the architecture, to enable the model to make analysis of whole-brain scans in a context and time-continuity richer way.

c) High Memory Requirements:

Transformer models are computationally costly even when using EMHA. Model compression, quantization, or knowledge distillation could allow deploying it to low-resource hardware, edge devices utilized in mobile radiology units.

2) *Architectural Improvements*

The concept of integrating EMHA was effective, and further performance could be improved with the following additions:

- Multimodal Learning: The use of MRI together with other input as EEG, PET or even cognitive test scores may increase the sensitivity of the diagnosis.
- Hybrid CNN-Transformer Models: Pure transformers did well here, but in future work, it will be possible to reintroduce convolutional feature extractors in early layers to more effectively realise fine-grained edges and textures.
- Self-Supervised Pretraining: Contrastive learning on large unlabeled brain MRI datasets pretraining might assist the model to generalize more with minimal annotated data.

3) *Broader Clinical and Research Impact*

The created system can be implemented into practical diagnostic processes, yet additional verification is required:

- Clinical Trials and Expert Review: To build clinical trust in the model and define edge cases, it would be reasonable to work with neurologists and radiologists to compare its capabilities with those of human diagnosis.
- Longitudinal Studies: A powerful extension to the model would be to test its capability in predicting how the disease would develop throughout time, particularly in early-intervention studies.
- Explainability Research: Despite the use of Grad-CAM++, it is possible to incorporate SHAP values or counterfactual generation in future to give more details about decision explanations.

4) *Critical Self-Reflection*

The paper is characterized by the high experimental methodology, the good generalization performance, and interpretability. The proposed EMHA Swin Transformer achieves very competitive results compared to the recent CNN-based and transformer-based models in Alzheimer classification in terms of different metrics and dataset.

What went well:

- Proper utilization of transfer learning and cross-validation to prevent overfitting.
- Robustness and interpretability with TTA and Grad-CAM++.
- Equal performance in all four stages of dementia, which is not necessarily addressed in other research papers.

What could be improved:

- Volumetric modelling would probably boost performance, particularly of borderline cases.
- Usability would be improved by incorporating additional clinician feedback into both model validation and into GUI design.
- The comparative claims would be boosted by more comprehensive benchmarking against other variants of transformers (e.g., ViT, ConvNeXt).

C. *Conclusion*

This paper has managed to efficiently demonstrate how transformer-based architectures, specifically the ones with Efficient Multi-Head Attention, have a lot of potential in detecting and staging Alzheimer's disease based on MRI data. Not only does the system produce state-of-the-art results, but also focuses on interpretability and usability, which are two frequently ignored but important factors in medical AI. With additional study, bigger data, and incorporation into clinical pipelines, the method presented here can potentially play a large role in the neurodegenerative disease diagnosis and treatment.

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