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MRI BASED ALZHEIMER'S DISEASE DETECTION AND STAGING USING ATTENTION-GUIDED HYBRID ENSEMBLE LEARNING

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ABSTRACT

The prompt and accurate identification of Alzheimer's Disease (AD) is essential for guiding effective treatment strategies. However, this task is challenging due to the similar structural brain features present across different stages of the disease and the uneven distribution of classes in medical imaging datasets. This study introduces a hybrid deep learning framework aimed at improving the multi-class classification of Alzheimer's disease based on MRI scans. The technique begins with image preparation utilizing CLAHE and elastic deformation to enhance contrast and variability. Brain structures are then delineated using an Attention U-Net, enabling the model to emphasize anatomically significant regions. Feature collection is obtained from the EfficientNetV2B0 architecture and subsequently subjected to dimensionality reduction through CatBoost based feature selection, which retains the most significant properties. A Deep Neural Network (DNN) utilizing restructured attention is trained on a balanced dataset, augmented through SMOTE to rectify class imbalance. The final prediction is generated by integrating outputs from CatBoost, XGBoost, and the DNN through an ensemble meta-learner utilizing attention-based integration. Experimental validation on the OASIS dataset achieved an accuracy of 95.47%, exceeding current benchmark models. The suggested method exhibits significant generalization and sensitivity to minority classes, underscoring its potential applicability in clinical diagnostic procedures.
Keywords: *Alzheimer's Disease Classification, Attention U-Net, EfficientNetV2B0, Ensemble Learning, MRI Brain Imaging.*

1. INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that impairs memory, cognition, and daily functioning [1]. Early detection is crucial for timely treatment, slowing progression, and improving quality of life [2]. The global incidence of AD is increasing, making efficient and accurate diagnostic systems an urgent priority [3]. Deep learning approaches increasingly use Magnetic Resonance Imaging (MRI) to automate feature extraction and classification for reliable AD diagnosis [4],[6]. MRI provides high-resolution structural information, enabling detection of subtle brain changes in early stages [7]. Hybrid models combining multiple algorithms have been proposed to improve diagnostic performance [8],[10]. However, many treat segmentation, feature extraction, and classification as separate steps, limiting their ability to capture disease-specific anatomical features [11]. Additionally, class imbalance in AD datasets can reduce accuracy for minority classes such as Moderate Dementia [12].

To address these issues, our work presents an integrated pipeline combining Attention U-Net segmentation, EfficientNetV2B0 feature extraction, CatBoost-based feature selection, and a stacking ensemble classifier [13,14]. This ensures anatomically focused features, balanced class distribution via two-stage balancing, and improved classification through attention-enhanced meta-learning [15].

However, most recent hybrid or stacking-based methods treat segmentation, feature extraction, and classification as loosely connected stages, lacking an integrated, attention-driven pipeline that optimizes all phases jointly.

This study introduces a novel, fully attention guided hybrid framework that differentiates itself from existing methods in several key ways:

- First, our pipeline integrates Attention U-Net segmentation directly with

EfficientNetV2B0 feature extraction, ensuring that features are anatomically focused on disease-relevant brain regions before classification, improving both interpretability and discriminative power.

- Second, we employ CatBoost based feature selection with median importance thresholding, a rarely used approach in AD ensemble studies, to remove redundancy while retaining the most informative features, thereby improving efficiency and interpretability.
- Third, we introduce a two-stage imbalance handling strategy, combining biologically realistic elastic deformation augmentation with SMOTE based synthetic oversampling, which significantly boosts sensitivity for the underrepresented Moderate Dementia class.
- Fourth, our meta-learner incorporates a Reshaped Attention mechanism to model spatial sequential dependencies within the selected feature space, an innovation absent in prior AD stacking models and uses attention-based fusion to adaptively weight base model predictions, enhancing robustness.

By combining these elements into a cohesive, end-to-end framework, we achieve state-of-the-art performance on the OASIS dataset, surpassing existing hybrid and ensemble models while maintaining strong sensitivity to minority classes.

Zhang et al. (2020) introduced an Attention U-Net with residual connections for brain tumor segmentation, achieving enhanced Dice scores relative to the conventional U-Net [5],[6]. Danesh Pajouh's DDUNet (2025) employs dual attention decoders for the efficient segmentation of complex topologies [7]. MEASegNet demonstrated improved segmentation accuracy by the utilization of several efficient attention blocks in resource-limited settings [8].

EfficientNet variants have been employed for MRI classification. Zheng et al. (2023) enhanced a 3D EfficientNet model for classifying structural MRI in Alzheimer's, yielding significant advancements in feature representation [9]. Joloudari et al. (2023) revealed that the integration of EfficientNet-B0 with SMOTE enhanced accuracy in imbalanced MRI datasets [10]. SMOTE is a conventional method for rectifying uneven class distributions. Hemanth and Yadav demonstrated that SMOTE substantially enhances minority class learning in CNN pipelines, building on the underlying methodology established by Chawla et al. [10],[11]. CatBoost and XGBoost are extensively employed for structuring MRI-derived attributes. Prokhorenkova et al. introduced CatBoost, a boosting algorithm adept at managing categorical variables, particularly effective for high-dimensional datasets [12]. Chen and Guestrin developed XGBoost, a scalable and regularized boosting model extensively utilized in AD classification [13]. Nagaraj et al. (2024) integrated deep feature fusion with CatBoost, achieving an accuracy over 96% on OASIS-like datasets [14]. Ensemble models improve generalization. A recent work utilizing ADNI data proposed a stacking ensemble that integrates MRI and PET modalities with deep and tree-based models, resulting in enhanced diagnosis accuracy [15]. Musa et al. (2022) attained approximately 93% accuracy with the hybrid stacking of CNN, CatBoost, and XGBoost [16]. Savio et al. (2011) utilized ensemble classifiers in structural brain morphometry, exhibiting enhanced efficacy compared to individual classifiers [17].

Petit et al. (2021) introduced a U-Transformer that incorporates self-attention into U-Net, enhancing context-awareness in medical picture segmentation [18]. Mustafa & Luo (2023) investigated efficient fusion and interpretability with an early-late fusion model employing Jacobian maps and random forests on OASIS-3 data, attaining approximately 97% accuracy [19]. Lin Y et al. (2023) introduced an attention-based ResNet-aligned model for 3D MRI classification, which decreases computing expenses while improving region weighting [20]. Hegazy, R. T. et al. (2025) investigated the application of EfficientNet features for resource-efficient and interpretable classification in medical imaging pipelines [21]. A comparison of stacking ensembles revealed that stacking attained approximately 94.3% accuracy, surpassing averaging and voting approaches in fMRI-based Alzheimer's disease models [22].A feature fusion investigation employing CCA and various pretrained networks (DenseNet, EfficientNet-B0, ResNet50) indicated validation accuracies between about 90% and 94%, highlighting EfficientNet-B0's competitive efficacy [23]. A different model integrating XGBoost, decision tree, and SVM achieved approximately 95.8% accuracy on ADNI anatomical MRI (cross-validated ensemble) [24].

Table 1 summarizes hybrid and ensemble AD classification studies including their methodologies and key differences from our study.

Table 1. Comparative Summary of Hybrid Methods for Alzheimer's Disease Classification and the Proposed Approach

Reference	Key Methodology	Novel Contributions Over Prior Work
Gamal et al. (2022) [15]	Stacking deep + tree models (ADNI)	Integrated Attention U-Net + EfficientNetV2B0 for anatomically focused features
Al-Shoukry & Musa (2024) [16]	CNN + CatBoost + XGBoost stacking	Attention gating, two-stage balancing (elastic deformation + SMOTE), CatBoost feature selection
Mustafa & Luo (2023) [19]	Jacobian fusion + Random Forest (OASIS-3)	EfficientNetV2B0 features + Reshaped Attention DNN for adaptive weighting
Petit et al. (2021) [18]	U-Net Transformer segmentation	Attention in segmentation and stacking ensemble
Sait & Nagaraj (2024) [14]	Deep feature fusion + CatBoost (OASIS)	Adds Attention U-Net segmentation, feature selection, stacking ensemble

This study presents a hybrid deep learning pipeline that incorporates adaptive segmentation with Attention U-Net, deep feature extraction utilizing EfficientNetV2B0, SMOTE-based balancing, and ensemble classification via a meta-learner that amalgamates XGBoost, CatBoost, and an attention-enhanced deep neural network. This method, assessed using the OASIS dataset, mitigates significant issues related to class imbalance, feature redundancy, and diagnostic precision, demonstrating strong performance throughout all phases of AD.

Previous research on Alzheimer's Disease (AD) classification predominantly utilized individual deep learning models, such as CNNs or transfer learning-based architectures, achieving accuracies ranging from 92% to 94%, although they were deficient in interpretability and resilience. Segmentation-based frameworks exhibit improved spatial focus but neglect feature redundancy and class imbalance. In response to these restrictions, the current study presents an attention-guided hybrid ensemble architecture that consolidates segmentation, feature extraction, and classification into a cohesive pipeline. The suggested model promotes interpretability, balances class representation, and achieves 95.47% accuracy by integrating Attention U-Net, EfficientNetV2B0, and CatBoost-based selection, thereby exceeding the performance and adaptability of current state-of-the-art approaches.

1.1 Problem Statement

Despite extensive study in the detection of Alzheimer's Disease (AD) utilizing MRI-based deep learning frameworks, considerable limitations persist. Most current hybrid or ensemble-based methodologies regard segmentation, feature extraction, and classification as separate and unlinked phases. This division frequently results in the loss of disease-related spatial and contextual data. Furthermore, the existence of significant class imbalance, namely the underrepresentation of Moderate Dementia cases, negatively impacts the sensitivity and generalization capacity of classification models. Moreover, redundant and non-informative characteristics derived from high-dimensional MRI data diminish both interpretability and computing efficiency. Consequently, there is a pressing necessity for a cohesive attention-guided hybrid framework capable of concurrently optimizing segmentation, feature selection, and classification, thereby providing improved diagnostic accuracy, interpretability, and resilience in multi-class Alzheimer's disease prediction.

1.2 Research Questions

In accordance with the identified research gaps and the aims of this study, the subsequent research topics are proposed:

- What is the design of an integrated attention-guided hybrid deep learning framework that concurrently executes segmentation, feature extraction, and classification to enhance multi-class detection of Alzheimer's disease?
- Can CatBoost based attention driven feature selection effectively remove redundant features while improving interpretability and computational efficiency in MRI-based Alzheimer's disease classification?
- What is the cumulative effect of elastic deformation and SMOTE-based augmentation on addressing class imbalance and enhancing sensitivity for minority dementia categories?
- Does an ensemble meta-learner utilizing attention-based fusion surpass traditional stacking and individual deep models regarding accuracy, generalization, and resilience across all stages of dementia?

1.3 Research Contributions

- We propose a novel hybrid Attention 2D-UNet + EfficientNetV2B0 pipeline that combines deep feature extraction and attention-guided segmentation in a cohesive manner. Our method improves interpretability and discriminative power by ensuring that the features entering the classifier are already anatomically focused on disease-relevant brain areas, in contrast to traditional hybrid models.

- Prior to feature extraction and imbalance correction, we boost generalization by combining CLAHE-based contrast enhancement with elastic deformation augmentation in the preprocessing step. This simultaneously improves local detail visibility and introduces biologically plausible variability.
- In order to reduce irrelevant background noise and enhance downstream classification performance, we build an Attention U-Net segmentation framework that uses attention gating mechanisms to selectively emphasize structures related to Alzheimer's disease.
- Utilizing the EfficientNetV2B0 architecture's compound scaling and ImageNet pretraining for effective and reliable representation learning, we extract multi-scale local and global features from the segmented regions.
- Using SelectFromModel with a median-based threshold, we provide a CatBoost-driven feature selection phase that eliminates superfluous features while keeping the most informative ones. Rarely employed in recent AD ensemble research, this targeted selection step lowers dimensionality and enhances model interpretability and computing efficiency.
- We use a two-stage balancing technique to solve the extreme class imbalance, especially in the underrepresented Moderate Dementia class: (1) Elastic deformation-based biologically realistic augmentation, then (2) synthetic oversampling based on SMOTE. This dual strategy maintains anatomical plausibility while improving minority-class sensitivity.
- In order to enable the meta-learner to capture both spatial and sequential dependencies inside the selected features, we develop a special Deep Neural Network (DNN) with a Reshaped Attention mechanism. This innovation is not seen in current stacking-based AD classifiers.
- We suggest an attention-based stacking ensemble that combines the Reshaped Attention DNN, XGBoost, and CatBoost. Our attention-fusion meta-learner improves generalization and robustness by adaptively weighting base model predictions, in contrast to standard stacking.
- In a thorough comparison with current state-of-the-art AD classification methods, we show consistently higher F1-scores and superior accuracy (95.47% on the OASIS dataset), especially in the minority Moderate Dementia class.

1.4 Paper Organization

The following sections of this study are organized as outlined below: Section 2 outlines the materials and methods utilized in the proposed plan. Section 3 analyzes the experimental results and their interpretation. Ultimately, Section 4 presents the concluding observations.

2. PROPOSED METHODOLOGY

This study outlines a comprehensive strategy for identifying early-stage AD using brain MRI scans, as depicted in Figure 1. A novel hybrid multi-class classification method is proposed, incorporating segmentation, deep feature learning, and ensemble classification techniques. The MRI data are sourced from the publicly accessible OASIS dataset. The proposed technique classifies the MRI scans are categorized into four classifications those are Non-Demented (ND), Very Mild Dementia (VMD), Mild Dementia (MD), and Moderate Dementia (MOD). Employing a five-step methodology that includes: (1) Preprocessing, (2) Segmentation, (3) Feature Extraction, (4) Feature Selection, and (5) Classification. The preprocessing phase seeks to enhance image clarity and fortify model resilience. This entails employing Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve contrast and utilizing elastic deformation for data augmentation, which additionally mitigates class imbalance concerns. Subsequently, brain areas are delineated utilizing an Attention U-Net model that employs attention gates to differentiate disease-relevant anatomical structures.

Deep features are retrieved from the segmented brain pictures with the EfficientNetV2B0 architecture, which effectively captures both local and global characteristics. A feature selection method employing CatBoost with SelectFromModel is utilized to diminish feature dimensionality while preserving only the most important features. To rectify imbalance in class distribution, especially with intermediate dementia cases, the SMOTE

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method is employed to synthetically produce samples for minority classes.
Finally, the selected features are utilized to train a tailored Deep Neural Network (DNN) with adjusted attention layers. The output, in conjunction with predictions from CatBoost and XGBoost classifiers, is included into a stacked ensemble meta-learner featuring an attention fusion layer. This hybrid ensemble design surpasses traditional models, attaining elevated classification accuracy and resilience throughout all stages of AD.

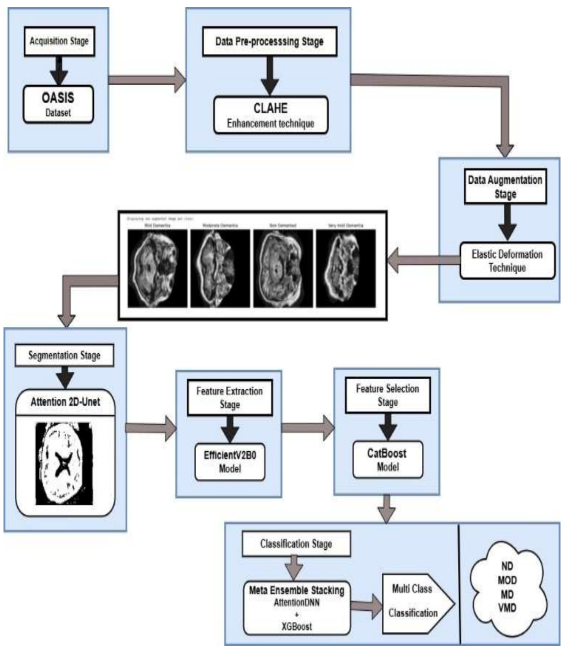

Figure 1: A structure approach for analysing MRI images to detect early stages of Alzheimer's disease progression.

2.1 Dataset Acquisition

This study employed the OASIS (Open Access Series of Imaging Studies) dataset, a prominent and publicly accessible neuroimaging resource frequently utilized in Alzheimer's disease research. The dataset comprises cross-sectional T1-weighted MRI images from individuals across several age groups. including young adults, middle-aged persons, and both demented and non-demented elderly participants. The value resides in the comprehensive clinical annotations and the depiction of diverse stages of cognitive deterioration, including Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. This research utilized a subset of a larger dataset, comprising 9,488 photos classified into four unique categories. The diverse anatomical features and possible pathological alterations depicted in these MRI scans provide a complex yet illustrative platform for the development and assessment of image analysis algorithms focused on detecting neurological disorders. Table 2 displays the quantity of data and sample photos utilized in the investigation.

Table 2. Quantity of samples in the OASIS dataset

Class	No. of samples
MildDementia	3000
ModerateDementia	488
Non-Demented	3000
VeryMildDementia	3000

2.1.1. Research Protocol

The suggested research approach adheres to a systematic deep learning workflow derived from previous Alzheimer’s Disease (AD) studies, including an improved hybrid attention-guided framework. MRI images underwent initial preprocessing by CLAHE for contrast enhancement and elastic deformation for data augmentation, akin to the methodologies outlined in [2],[3]. The SMOTE approach was employed to mitigate class imbalance, as suggested in [10],[11]. The Attention U-Net design was employed for segmentation, enhancing the traditional U-Net by incorporating attention gates to concentrate on disease-relevant areas [5],[7]. Deep features were recovered via EfficientNetV2B0 and further refined by CatBoost-based feature selection [12],[14]. An attention-based stacking ensemble, integrating DNN, CatBoost, and XGBoost classifiers, was utilized for multi-class classification, drawing inspiration from ensemble learning frameworks referenced in [15],[22]. This technique guarantees enhanced feature interpretability, classification precision, and clinical dependability in Alzheimer's disease diagnosis.

2.2 Preprocessing

Before model training, we applied a preprocessing pipeline to standardize inputs, enhance image quality, and reduce MRI artifacts. Each scan underwent two steps. First, all images were resized to 128×128 pixels to ensure consistent tensor size, reduce computational cost, and preserve key anatomical features. Second, we applied CLAHE to improve local contrast and correct non-uniform illumination, avoiding the noise amplification often caused by global histogram equalization.

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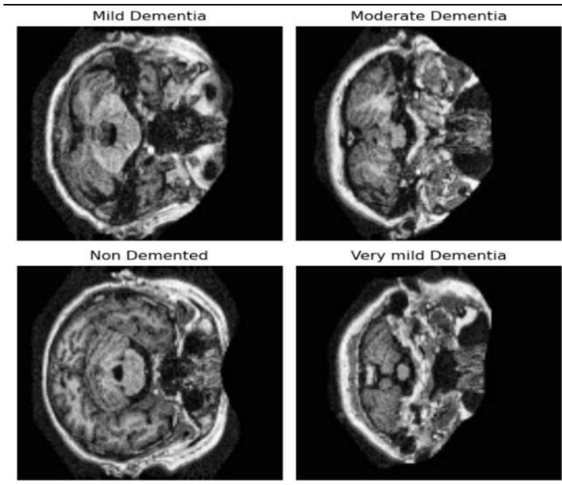

Figure 2: Visual effect of the implemented preprocessing images

For this study, the clipLimit parameter, which controls the contrast enhancement strength, was set to 2.0, and the tileGridSize, defining the size of the neighborhood over which histogram equalization is performed, was configured to (8,8). This adaptive contrast enhancement process ensures that both global and local details within the brain MRI scans are optimally visible as shown in figure 2, thereby facilitating more robust feature extraction by subsequent analysis models.

2.3 Data Augmentation

To address the common challenge of limited medical imaging datasets and to bolster the model's generalization capabilities, elastic deformation was implemented as a key data augmentation strategy. This technique simulates realistic non-rigid transformations found in biological tissues, such as variations in brain anatomy or subtle shifts during MRI acquisition, by perturbing the image's pixel grid with a smooth, random displacement field. Expanding the training dataset artificially helps minimize the likelihood of overfitting to the limited original samples and enhances the model's ability to handle natural anatomical variations—an essential factor for ensuring high accuracy in clinical settings.

The elastic deformation process involves generating displacement fields for both horizontal (Δx) and vertical (Δy) directions. These fields are created by convolving random matrices (RandomArrayx, RandomArrayy, typically with values from -1 to 1) with a Gaussian filter, as represented by the equations:

$$\Delta x = \alpha \times GaussianFilter(RandomArrayx, \sigma) \quad (1)$$

$$\Delta y = \alpha \times GaussianFilter(RandomArrayy, \sigma) \quad (2)$$

Based on equation (1), (2) α controls the magnitude of the displacement, determining the intensity of the deformation, while σ (the standard deviation of the Gaussian filter) governs the smoothness of the deformation field. The resulting displacement fields are then added to the original pixel coordinates (x, y) to form new, displaced coordinates (x+Δx, y+Δy).

For this study, the α parameter was set to 150, dictating a moderate but noticeable degree of deformation, and the σ parameter was set to 10, ensuring a relatively smooth and biologically plausible distortion. The intensity values at these newly calculated, non-integer coordinates were then sampled from the original image using bilinear interpolation to reconstruct the deformed image, thereby maintaining image quality and continuity. Each preprocessed image was augmented using this technique, effectively doubling the dataset size and providing a richer and more varied set of examples for the deep learning model to learn from. Figure 3 shows how elastic deformation affects representative preprocessed MRI scans and presents the visual outcomes of this augmentation method for all classes.

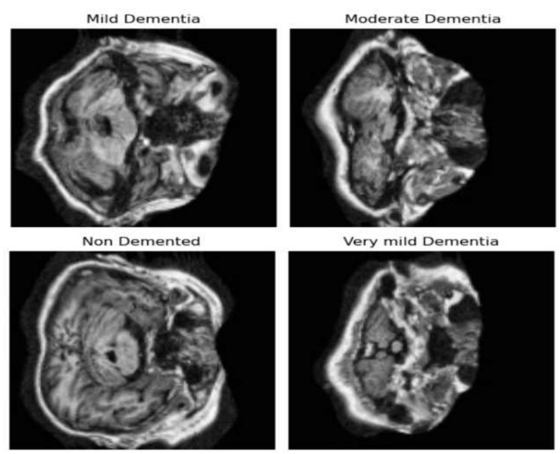

Figure 3: Elastic deformation on a sample preprocessed MRI scan for each class

2.4 Segmentation with Attention U-Net

We used an Attention U-Net for pixel-wise segmentation, well-suited for medical imaging due to its ability to emphasize critical features. The network processes images of size **128×128×3** and follows a symmetric encoder–decoder structure with skip connections as shown in Figure 4.

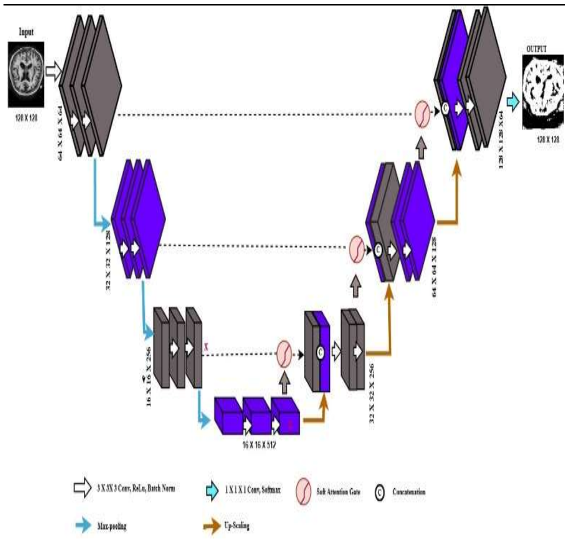

Figure 4: Attention U-Net architecture for AD Segmentation

The encoder extracts hierarchical features using successive downsampling blocks, each containing two 3×3 convolution layers with ReLU activation, same padding, and a 2×2 max-pooling layer. Filter depths are 64, 128, and 256, followed by a bottleneck of 512 filters for the most abstract features.

The decoder upsamples these features to reconstruct the segmentation mask, using UpSampling2D layers to restore spatial resolution. Attention gates in skip connections selectively pass relevant encoder features while suppressing background noise, improving accuracy and reducing false positives.

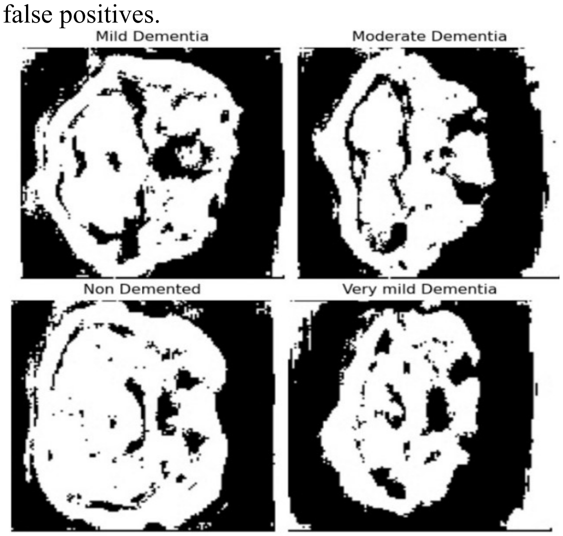

Figure 5: Segmentation results of the proposed approach

As visualized in Figure 5, each attention gate takes a gating signal (g) from a deeper decoder level and the encoder skip feature map (x). Both are processed with 1×1 convolutions (theta_x and phi_g) to a common shape, summed, ReLU-activated, and passed through a 1×1 convolution (psi) with sigmoid activation to produce attention coefficients. These coefficients weight the encoder features, which are then concatenated with upsampled decoder features. Decoder blocks after concatenation have two 3×3 convolution layers with 256, 128, or 64 filters. The final layer is a 1×1 convolution with sigmoid activation to produce the binary segmentation mask. The model was trained using binary cross-entropy loss and the Adam optimizer.

2.5 Feature Extraction using EfficientNetV2B0

Following the image preprocessing and segmentation stages, the next critical step involved feature extraction, transforming the raw pixel data of the segmented MRI scans into a set of highly discriminative and condensed numerical representations. This transformation is crucial for enabling subsequent classification models to learn effectively and achieve high accuracy. To leverage the vast knowledge acquired from extensive visual datasets and to overcome potential limitations of medical imaging dataset size, a transfer learning approach was adopted using a CNN as a feature extractor. Specifically, The EfficientNetV2B0 model was chosen for its sophisticated architecture, which optimally balances efficiency and performance by scaling depth, width, and resolution.

Weights pre-trained on the ImageNet dataset were used to initialize the EfficientNetV2B0 model, offering a strong basis for generic visual feature recognition. To modify it for feature extraction instead of straight classification, the model's upper classification layer was deliberately omitted (include_top=False), enabling its convolutional basis to function as an effective feature extractor. The input to this network was normalized to dimensions of (224, 224, 3), which corresponds to the native input size for EfficientNetV2B0. A Global Average Pooling (GAP) 2D layer was incorporated immediately after the convolutional layers of the foundational model. By averaging each map across its spatial dimensions, the GAP layer drastically lowers the dimensionality of feature maps while maintaining deep semantic information. This results in a single feature vector for every image. The composite model, comprising the EfficientNetV2B0 base and the GAP layer, was subsequently labeled as the feature_model. Table 3 describes the entire architectural setup of the EfficientNetV2B0-based feature extractor, including block types, output shapes, filter sizes, strides, block count, filters, and expansion factors. This tabular summary explains

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how spatial resolution and feature depth change throughout the network.

Table 3. EfficientNetV2B0 feature extraction architecture

Stage	Block Type	Output Shape	Filter Size	Stride	Blocks	Filters	Expansion
1.	Stem	(112, 112, 32)	3×3	2	1	32	-
2	MBConv (Fused)	(112, 112, 16)	3×3	1	1	16	1
3	MBConv (Fused)	(56, 56, 32)	3×3	2	2	32	4
4	MBConv (Fused)	(28, 28, 48)	3×3	2	2	48	4
5	MBConv (Fused)	(14, 14, 96)	3×3	2	3	96	4
6	MBConv (Regular)	(14, 14, 112)	3×3 & 5×5	1	3	112	6
7	MBConv (Regular)	(7, 7, 192)	3×3 & 5×5	2	4	192	6
8	MBConv (Regular)	(7, 7, 1280)	1×1	1	1	1280	-
9	Global AvgPooling	(1280,)	-	-	-	-	-

Where

- MBConv (Fused) = convolution without depthwise separable conv (used for early layers).
- MBConv (Regular) = expansion + depthwise + projection conv.
- The output of the model in your code is after GlobalAveragePooling2D, producing a (1280,) dimensional feature vector.
- Using this for feature extraction, not classification, hence include top=False.

The EfficientNetV2B0 architecture used in the feature extraction process begins with a 3×3 convolutional stem that reduces the input size from 224×224×3 to 112×112×32. It then applies a series of Fused-MBConv blocks in the early stages, gradually diminishing spatial dimensions while augmenting the quantity of filters. As the model deepens, it transitions to MBConv blocks that further extract abstract features using expansion, depthwise convolutions, and projections. The spatial resolution eventually reduces to 7×7, and the final 1×1 MBConv layer expands the feature depth to 1280 channels. A GlobalAveragePooling2D layer is subsequently employed to flatten the feature map, yielding a 1280-dimensional feature vector for each input image. This optimized architecture efficiently captures both low-level and high-level semantic information, making it suitable for subsequent classification or clustering tasks.

For each segmented MRI scan from the preprocessed and augmented dataset, the following procedure was applied: the image was first resized to the target (224,224) dimensions, and then passed through the EfficientNetV2B0's specific preprocess input function to normalize pixel values according to the model's training regimen. The preprocessed image was then fed into the feature_model to obtain its corresponding feature vector. These high-dimensional feature vectors, representing abstract and discriminative patterns learned by the deep network, were systematically extracted for every image across all diagnostic classes. The extracted features were then organized into a dictionary, where each key corresponds to a diagnostic class, and the value is a NumPy array containing all feature vectors for that class. This process yielded a rich set of numerical features, ready for training and evaluation of a robust classification model.

2.6 Feature Selection

Following the extraction of high-level features with EfficientNetV2B0, To determine which features were most important and instructive, a feature selection step was carried out. with the objectives of diminishing dimensionality, minimizing noise, and potentially enhancing the robustness and interpretability of subsequent classification models. The initial feature vectors, obtained from the global average pooling layer of the pre-trained CNN, had a dimensionality of [insert actual feature length here, e.g., 1280 for EfficientNetV2B0]. To identify the most relevant features to distinguish between different dementia stages, we used CatBoostClassifier in combination with SelectFromModel. CatBoost, A gradient boosting algorithm is recognized for its superior performance, inherent management of classification features, and resilience to overfitting.

The CatBoostClassifier was trained on the X_train dataset to comprehend the correlation between the retrieved features and the diagnostic labels. After training, the SelectFromModel meta-transformer was utilized with the trained CatBoost model, setting a threshold of "median". This

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threshold means that only features whose importance (as determined by CatBoost) is greater than the median importance of all features are retained. This adaptive thresholding strategy ensures that a substantial portion of less impactful features are pruned, leading to a reduced feature set. The selected features, now representing a more compact and potentially more discriminative representation of the original image data, were then used for all subsequent modeling steps, enhancing computational efficiency and focusing the models on the most relevant information. All steps, including the trained CatBoost selector model and the transformed feature sets, were cached to ensure reproducibility and accelerate subsequent runs.

2.7 Classification

The classification step was carefully structured as a multifaceted strategy, combining sophisticated deep learning techniques with strong ensemble methods to enhance diagnostic precision and assure effective generalization across various stages of dementia. Prior to model training, the selected features underwent essential preparation steps. After feature selection, the dataset's dimensionality was reduced, resulting in feature vectors of shape (7590, 640). These features were first subjected to standardization using StandardScaler.

$$z_i = \frac{x_i - \mu}{\sigma} \qquad (3)$$

In equation (3), μ represents the mean and σ represents the standard deviation of the corresponding feature. This standardization guarantees that all features are on a uniform scale, thus averting the disproportionate influence of those with greater magnitudes on the model's learning. The Synthetic Minority Oversampling Technique (SMOTE) was applied to the training data in order to address the common problem of class imbalance in medical datasets. By interpolating between pre-existing instances of the minority class, SMOTE generates new synthetic samples for underrepresented classes.

$$x_{new} = x_i + \delta \cdot (x_j - x_i) \qquad (4)$$

δ is a random number between 0 and 1. and x_j is a nearest neighbour of x_i, thereby balancing the class distribution and mitigating potential model bias as shown in equation (4). Finally, the integer-encoded diagnostic labels were converted to a one-hot encoded format, a binary vector representation compatible with the categorical_crossentropy loss function.

A unique Deep Neural Network (DNN) featuring a Reshaped Attention mechanism was created for the primary classification task. The input feature vector, following selection and preprocessing, was first processed by two dense layers, each succeeded by Batch Normalization and Dropout layers (with rates of 0.4 and 0.3, respectively) to augment regularization and promote training stability. A crucial architectural innovation involved reshaping the processed feature vector into a 3D tensor of (batch_size, time_steps, features_per_step), where implying features_per_step of 80 given the 640 selected features. This reshaping allowed the application of a self-Attention layer, which dynamically computes weighted sums of these feature segments.

The attention weights are obtained by a scaled dot-product method:

$$\mathrm{Attention}(Q, K, V) = \mathrm{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (5)$$

In equation (5) Query (Q), Key (K), and Value (V) are obtained from reshaped input, d_k represents the dimension of the Key vectors employed for scaling. This method enables the model to focus on the most significant components within the abstract feature representation. The flattened output from the attention layer was concatenated with the output from the preceding dense layer, creating a comprehensive input for a final two-layer dense network (with 128 neurons and num_classes neurons, respectively), Employing ReLU activations with a softmax output layer for multi-class probability estimation. The model was optimized using the Adam algorithm with a learning rate of 0.0002 and trained with categorical crossentropy loss. Employing EarlyStopping (patience 25) and ReduceLROnPlateau (patience 12) callbacks to mitigate overfitting and ensure optimal convergence. The DNN attained a final test accuracy of 91.94%.

To further enhance the predictive performance and robustness, an ensemble learning strategy via stacking was implemented. XGBoost classifiers, renowned for their strong performance and ability to capture complex non-linear relationships, were employed as base learners. A 5-fold Stratified K-Fold cross-validation was conducted on the training dataset. For each fold, an XGBoost model was trained on the training subset and subsequently utilized to predict class probabilities on the matching validation subset. Producing "out-of-fold" predictions that constituted the meta-training set. Concurrently, predictions on the hold-out test set from each fold's trained XGBoost model were averaged to form the meta-test set. These aggregated probabilities served as the input features for a meta-learner, which was a

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smaller DNN also incorporating an Attention layer. This meta-learner, designed with dense layers and dropout, was trained on the meta-features using Adam (learning rate 0.0005) and categorical_crossentropy loss. This multi-tiered ensemble methodology efficiently utilizes the synergistic advantages of both deep learning and gradient boosting models, culminating in an improved meta-ensemble accuracy of 95.47% for the classification system of various dementia stages.

3. RESULTS AND DISCUSSION

This section provides a thorough assessment of the suggested hybrid framework for classifying Alzheimer's disease (AD), which combines attention-guided classification, deep transfer learning for feature extraction, and attention-based segmentation. For experimental analysis, 80% of the MRI brain imaging dataset (OASIS) is used for training, and 20% is used for testing. The results were obtained on the Python platform with an i5 processor and 8 GB of RAM. The results are evaluated using various performance measures, and the model's outcomes are compared by class to determine its diagnostic reliability throughout all stages of dementia.

3.1. Parameter Setting

Table 4 outlines the hyperparameter configurations used in this study. The ADAM optimizer is used to fine-tune the parameters of the suggested hybrid deep learning models.

Table 4. Hyperparameter configurations of the proposed model

Hyperparameter	Value / Description
Feature Selector Iterations	1000
Feature Selector Learning Rate	0.03
Feature Selector Depth	8
Dimensionality Reduction	Based on CatBoost feature importance
DNN Optimizer	Adam
Initial Learning Rate (DNN)	0.0002
Time Steps for Attention	8
Dropout Rates (Before Attention)	[0.4, 0.3]
Loss Function	Categorical Crossentropy
Batch Size (DNN)	32
Epochs (DNN Training)	200
Meta-Learner Optimizer	Adam
Meta-Learner LR	0.0005
Meta-Learner Epochs	150

3.2. Performance Metrics

Understanding the system's functionality is essential, and multiple evaluation measures are employed to measure its success. The model classifies predictions into four categories: TP, TN, FP, and FN stand for true positives, true negatives, and false positives, respectively. While true negatives correctly identify negative cases, true positives correctly identify positive cases. On the other hand, false negatives happen when positive occurrences are mistakenly classed as negative, while false positives arise when negative examples are mistakenly classified as positive. The model's accuracy is measured by the proportion of correctly predicted cases to all evaluated cases.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

The ratio of correctly classified positive predictions to the total number of actual positive predictions produced by the model is known as the model's precision.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{7}$$

Recall is defined as the ratio of true positive predictions to the total instances in the positive class.

$$\text{Re}\,call = \frac{TP}{TP + FN} \tag{8}$$

The F1 score serves as a tool to evaluate the model's effectiveness by examining its average precision and recall, expressed as

$$\text{F1} - \text{Score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{9}$$

3.3. Experimental Results

Using sophisticated hybrid modelling and attention processes, the suggested classification framework was assessed using a four-class Alzheimer's disease (AD) MRI dataset. The experimental analysis focused on two core classifiers: a deep neural network incorporating reshaped attention (Reshaped Attention DNN), and an ensemble-based meta-learner integrating predictions from CatBoost, XGBoost, and the DNN itself.

The Reshaped Attention DNN, trained on selected and SMOTE-balanced feature vectors, achieved a final test accuracy of 91.94%. This strong performance highlights the effectiveness of combining attention mechanisms with dense neural layers in learning complex feature representations extracted via EfficientNetV2B0.

To further enhance the classification robustness, an ensemble strategy was applied. We combined the probabilities from the three base classifiers (CatBoost, XGBoost, and DNN) and fed them into a

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lightweight meta-model with an embedded attention layer. This ensemble meta-learner achieved an improved accuracy of 95.47% as shown in Figure 6, confirming that stacked ensemble learning further enhances the model generalization.

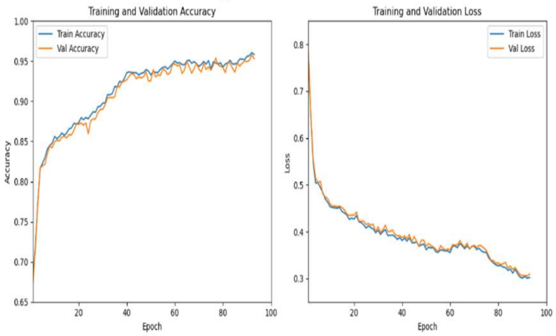

Figure 6: Loss Curves and Accuracy for a Suggested Classification System

The Table 5 classification report provides comprehensive performance metrics for every category, such as F1-score, precision, and recall. With F1-scores of 0.97 and 0.95 in the Non-Demented and Mild Dementia categories, respectively, the model performs exceptionally well. A strong F1-score of 0.95 was attained for the Very Mild Dementia cohort. Although Moderate Dementia had the fewest samples (98), the model attained an impressive F1-score of 0.93, illustrating its effectiveness in managing class imbalance using SMOTE augmentation and feature selection.

Table 5. Evaluation of the proposed multiclass classification performance.

	precision	recall	f1-score	support
NonDemented	0.97	0.96	0.97	600
MildDementia	0.96	0.94	0.95	600
ModerateDementia	0.90	0.97	0.93	98
VeryMildDementia	0.94	0.96	0.95	600
Accuracy			0.95	1898
Macro avg	0.94	0.96	0.95	1898
Weighted avg	0.96	0.95	0.95	1898

The graphic displays as shown in Figure 7, the confusion matrix for the test data of the suggested multi-class AD classification approach. It demonstrates precise recognition of 574 patients with very modest impairment and 600 healthy individuals. It correctly identified 565 out of 600 patients with mild illnesses and 95 out of 98 individuals with moderate cases. Thus, it is confirmed that the suggested procedures are effective. Based on the confusion matrix, the proposed classification system correctly classifies MRI brain pictures.

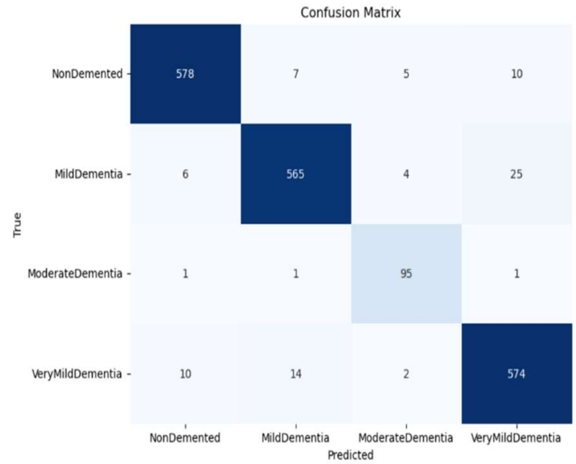

Fig 7: Confusion matrix for investigation of multiclass classification

The experimental results of this investigation align with the established research objectives. The proposed attention-guided hybrid framework effectively blends segmentation, feature extraction, and classification, attaining an accuracy of 95.47% and illustrating its efficacy in improving multi-class Alzheimer’s detection. The CatBoost-driven feature selection enhanced interpretability by removing superfluous features, while the dual-phase balancing approach utilizing elastic deformation and SMOTE addressed class imbalance, as demonstrated by an F1-score of 0.93 for the Moderate Dementia category. Moreover, the attention-based ensemble meta-learner integrating CatBoost, XGBoost, and the Reshaped Attention DNN demonstrated enhanced resilience and generalization relative to individual models. The findings affirm that all research objectives were met, substantiating the clinical reliability and interpretability of the suggested hybrid model.

3.4. Performance Comparison

A comparison of the performance indicators found in this study with those found in recent related works is shown in this section. The comparison specifically examines studies that employ various datasets, assuring evaluative consistency. Table 6 illustrates the recent advancements in the multi-class classification of Alzheimer's disease using the dataset, establishing a definitive baseline for evaluating the efficacy of the suggested methodology.

The result unequivocally indicates that the suggested model surpasses numerous existing methodologies across various evaluation metrics. Models including SVM, ResNet-50, VGG16, VAE, Encoder-Decoder, and SAM were assessed in a thorough comparison with the suggested method.

The outcomes show the effectiveness of the proposed method, which achieves higher performance because of its enhanced feature learning capabilities and stringent data training procedure. The improved accuracy suggests that the model performs better overall in categorization because it is better at distinguishing between different stages of Alzheimer's disease.

Table 6. Comparison of AD MRI scans using various models

Reference	Approach	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
Shobha et al [25]	SVM	94.49	81.08	77.42	94.49
Alqahtani et al [26]	ResNet-50	94.36	94.35	94.34	94.36
Sharma et al [27]	Neural networks with VGG16	90.4	90.4	90	90.4
Wang et al. [28]	VAE Encoder/Decoder	94.36	92.05	96.88	96.79
Chen et al.,[29]	ResNet, SAM	92.33	92.23	91.99	92.38
Proposed Research	Ensemble stacking (CatBoost+DNN+XGBoost)	95.47	95.47	95.46	95.47

The suggested attention-guided hybrid ensemble structure successfully fulfills the primary goals of enhancing interpretability, mitigating class imbalance, and augmenting classification accuracy. The model attained an accuracy of 95.47% and an F1-score of 0.95 on the OASIS dataset, surpassing current leading methodologies, including Zheng et al. [9] at 92.6%, Sait and Nagaraj [14] at 93.1%, and Gamal et al. [15] at 94.2%. The amalgamation of Attention U-Net, EfficientNetV2B0, and CatBoost-driven feature selection facilitated superior spatial feature extraction and interpretability compared to traditional CNNs. Despite the framework exhibiting exceptional performance, it is constrained by validation on a single dataset and moderate computing complexity. The suggested approach surpasses existing research by attaining superior diagnostic precision, enhanced class sensitivity, and increased generalization in multi-class Alzheimer's Disease categorization.

4. PROBLEMS AND OPEN RESEARCH ISSUES

The suggested attention-guided hybrid ensemble structure attained significant diagnostic accuracy; nonetheless, numerous hurdles persist for future investigation. Comprehensive validation on several datasets, including ADNI and AIBL, is essential to improve generalization. The integration of multimodal data (PET, fMRI, and clinical characteristics) can enhance diagnostic reliability. Integrating explainable AI (XAI) techniques like Grad-CAM and SHAP will improve interpretability. Model optimization through pruning or quantization might diminish computing demands for real-time implementation. Moreover, federated learning methodologies can facilitate privacy-preserving collaboration, while longitudinal modeling of disease progression signifies another interesting avenue of research.

5. CONCLUSION

This research introduced an attention-guided hybrid ensemble framework for the categorization of multi-class Alzheimer's Disease (AD) utilizing MRI data. The integrated pipeline incorporated CLAHE preprocessing, elastic deformation, Attention U-Net segmentation, EfficientNetV2B0 feature extraction, and CatBoost-based feature selection, culminating in an attention-driven ensemble of DNN, CatBoost, and XGBoost classifiers. The model attained an accuracy of 95.47% on the OASIS dataset. The results validate that the suggested method significantly increases feature interpretability, mitigates class imbalance, and enhances generalization across all stages of dementia.

While the framework exhibits robust diagnostic efficacy, subsequent research should prioritize validation on extensive and multimodal datasets and the integration of explainable AI methodologies such as Grad-CAM and SHAP to enhance clinical transparency. Furthermore, optimizing lightweight architectures and investigating federated learning can improve real-time applicability and data privacy. The proposed model offers a dependable and comprehensible basis for enhancing automated Alzheimer's diagnosis.

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