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ConvMix: An Improved Anatomical Features Based Model for Alzheimer's Disease Detection

Pawan Kumar Singh[1], Pawan Kumar Upadhyay[2]

[1,2]Jaypee Institute of Information Technology, Noida

Abstract

Progressive anatomical variation in the brain MRI plays an important role in the early detection of Alzheimer's disease. These structural changes modify anatomical characteristics and provide discriminative information. However, detection of multi-stage Alzheimer's disease remains challenging due to subtle inter-class variations and class imbalance in datasets. To address these issues, pre-processing techniques are employed to improve image quality and consistency. Furthermore, it is necessary to balance the Alzheimer's dataset using borderline-SMOTE. The proposed model uses the convolutional network as the backbone feature extractor. It learns a hierarchical representation of anatomical features from brain MRI images by progressively extracting information through multiple stages of successive downsampling. By increasing its receptive field, it captures both local and global contextual information. The motivation for combining this Cross-Scale Feature Fusion is to further enhance these representations by integrating feature maps from multiple stages, thereby preserving fine grained anatomical information while incorporating global contextual features. This multi-level feature fusion improves the discriminative capability of the proposed model, resulting in multi-stage Alzheimer's disease detection. This proposed approach effectively detects the four stages of Alzheimer's disease while providing interpretable attention-region visualizations. The results obtained by this model achieve an accuracy of 98.75%.

Keywords: Alzheimer's Disease Neuroimaging Initiative Dataset, Borderline-SMOTE, Adaptive Moment Estimation, Cross Scale Feature fusion.

1. Introduction

In recent years, Alzheimer's Disease (AD) has attracted intense research efforts to understand its intrinsic complexities and to address its many diagnostic and prognostic challenges. It is predicted that the prevalence of dementia will increase to 75 million by 2030, from 47 million in 2020. The hippocampus region is key to the formation, organization, and storage of new memories, as well as to linking experiences and emotional states to these memories. In Alzheimer's disease, the hippocampus is one of the regions affected, followed by gray matter volume loss and cortical thinning in the cerebral cortex. As a result, degeneration of white matter integrity and ventricular enlargement are followed by neuronal loss. It is a major biomarker of the progression of Alzheimer's disease in the brain. This is a major bio-signature for assessing this disease. A series of small changes occurs in the brain before it undergoes a significant change. Current clinical magnetic resonance imaging (MRI) resolution is sufficient to identify these changes. Figure 1 depicts protein deposits in the brain; the image shows a healthy brain compared with an affected brain in Alzheimer's disease, characterized by the accumulation of amyloid plaques [1].

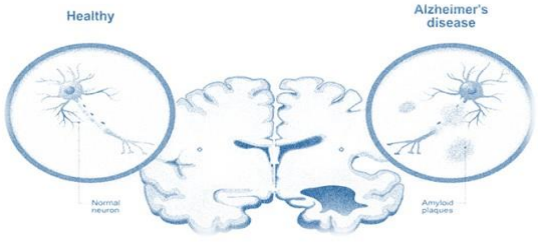

Figure 1: Left side Normal brain and Right side Alzheimer's brain showing amyloid plaques [1].

In previous research, texture-based classifications are more accurate than volume-based classifications [2]. Early detection of Alzheimer's disease has led to the greatest loss of tissue in the hippocampus, which is the major cause of short-term memory loss. This condition is primarily caused by hippocampal atrophy [3]. As a result,

structural MRI provides high-resolution images that enable assessment of variations in hippocampal atrophy, cortical thinning, and other neuroanatomical alterations, thereby supporting early detection. Various analytical procedures are employed to better segment brain MRI data in cross-sectional and longitudinal settings from the Alzheimer's Disease Neuroimaging Initiative (ADNI). In addition, for structural changes in the brain caused by neurodegenerative diseases, MRI is preferred over other methods [4]. Among non-invasive diagnostic approaches, MRI is considered more robust [5]. To improve the detection of Alzheimer's disease, large-scale tissue changes derived from secondary features such as atrophy have been used as biomarkers. An MRI is also used for texture analysis based on biomarkers to identify small-scale neurodegenerative changes. Medical imaging helps develop crucial procedures that facilitate advances in recognition, analysis, and enhancement techniques. The workflow of the proposed model is shown in Figure 2.

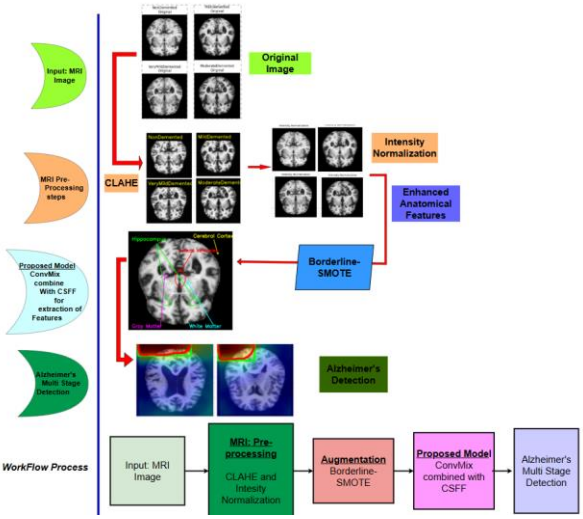

Figure 2: Proposed workflow of Alzheimer's multi stage detection

In this paper, the dataset is collected from ADNI, which consists of 6400 samples across four classes. To improve the quality and consistency of MRI images, pre-processing techniques are employed, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), which enhances local contrast and reduces noise, followed by intensity normalization of MRI pixel values to reduce scan variability and improve feature extraction. It is also observed that the Alzheimer's dataset is imbalanced, which raises concerns about overfitting. To address this issue, borderline-SMOTE is used to balance class samples across the various classes in the Alzheimer's dataset. Moreover, the ConvMix model is used to extract anatomical features such as gray and white matter, hippocampal reduction followed by shrinkage of the cerebral cortex, and ventricular enlargement to show the progression of disease. Furthermore, the purpose of Cross Scale Feature Fusion (CSFF) is to combine these features from successive stages of the ConvMix model to enhance anatomical feature representation, thereby preventing the loss of essential information. The dataset is split into two sets, i.e., training and testing. 80% is allocated to the training set, and 20% to the testing set. The results were evaluated on these splits; the model improved detection by reducing misclassification. This paper is organized as follows. Sect. 1: Introduction to Alzheimer's disease. Sect. 2 extends the related work related to anatomical features. Sect.3 Description of Alzheimer's Disease Neuroimaging Initiative dataset. Sect. 4 Discuss the proposed approach for Alzheimer's disease multi stage detection. Sect.5 Discuss obtained results of Alzheimer's disease. Sect. 6 summarizes the paper as conclusion and highlights promising opportunities for the future in this area.

2. Related work

This section describes the role of various deep learning models for detecting Alzheimer's disease and its severity. The researcher [6] mainly focuses on 3D brain MRI data and transforms it using wavelet transforms; for this purpose, Gray Level Co-occurrence Matrix (GLCM) and Haralick texture descriptors were employed to extract the region of interest (ROI). This proposal discusses the histogram distribution of wavelet coefficients for extracting the Gabor features. In the context of extracted descriptors, feature sets such as GLCM, Haralick, and Gabor wavelet–based Haralick. Categorization was implemented using a backpropagation neural network trained on each set of feature vectors. During the analysis of results, it was found that the integrated Gabor–Haralick features achieved the best average accuracy (approximately 97%), compared to 90% for Haralick features and 86% for GLCM features. Moreover, in

another paper, the author [7] proposed a novel classification technique that fused features derived from voxel-based morphometry and texture analysis to distinguish Alzheimer's disease from normal samples. They demonstrated greater discriminative capability and feature subset selection by combining SVM-RFE with covariance analysis to model inter-feature relationships. This approach was evaluated on MRI data from the ADNI database. As a result, the experimental results demonstrate that the combined feature set outperforms individual morphometric. After feature extraction, the next step is multi-stage severity detection. Another article is also connected; the author [8] proposes a transfer learning-based ensemble convolutional neural network model for Alzheimer's disease classification using pre-processed T1-weighted MRI images. The author's approach is to combine various models, such as VGG-19, Wide ResNet-50-2, GoogleNet, and Inception V3, with a Gompertz-function-based fuzzy ranking ensemble. The model classifies the four stages of Alzheimer's disease with 99.22% accuracy, demonstrating high diagnostic effectiveness. In continuation, another article connects to identifying (AD) at three levels, such as cognitively normal, mild cognitive impairment, and severe class, using sMRI [9]. To perform this classification, a discrete wavelet transform of sMRI images has been used, along with texture features, and the co-occurrence matrix has been analyzed for various statistical parameters, including contrast, correlation, energy, homogeneity, entropy, variance, and standard deviation. The best features were identified for training classical machine learning (cML) and convolutional neural networks (CNNs). As a result of the experiments, the classical ML achieved classification accuracies of 95.3% for AD vs. CN, 87.7% for AD vs. MCI, and 75.3% for CN vs. MCI. Furthermore, another related paper proposed an Inception model for feature extraction and a ResNet50 for classification [10]. In addition, adaptive Rider Optimization (ARO) further optimizes network parameters to improve detection performance. During the experimental evaluation on a benchmark dataset, the model achieved 96.6% accuracy, 98% precision, 97% recall, and 98% F1-score, outperforming state-of-the-art approaches. An ensemble learning model has drawn a performance comparison [11] that combined five deep learning architectures-VGG-16, VGG-19, ResNet-50, Inception-V3, and EfficientNet-B7 to enhance the detection of Alzheimer's disease in MRI scans. In the proposed model, 3,714 images were used for training and categorized into three classes: mild dementia (1,824), severe dementia (1,056), and non-dementia (834). The proposed voting ensemble achieved a diagnostic accuracy of 99.32% on the primary dataset. External validation on the OASIS and ADNI datasets yielded accuracies of 86.6% and 99.5%, respectively. In continuation of this, the author [12] proposed two novel approaches: in the first approach, a self-augmented CNN was used, and in the second approach, a modified ResNet model was used for the classification task, focusing on the segmentation of the brain into two sub-regions, such as grey matter, white matter, and cerebrospinal fluid, followed by AD classification. The segmentation model achieved higher similarity scores, i.e., 99.53% for Dice similarity and 99.09% for Intersection over Union. Furthermore, for multi-classification, the accuracy obtained with segmented features is 98.75%. Another related paper, authors [13] proposed deep learning models for classifying Alzheimer's disease (AD) using the ConvNeXt architecture. This model is a convolutional neural network inspired by Vision Transformers. The authors used AlzaSet, a carefully curated dataset comprising expertly labelled axial, coronal, and sagittal MRI views from AD patients and cognitively normal individuals. In this paper, the authors utilized three ConvNeXt variants (tiny, small, and base) and evaluated and compared them with established CNN models, including VGG16, VGG19, InceptionV3, and DenseNet121. As a result, ConvNeXt-Base achieved the best performance, particularly on coronal MRI slices, obtaining 98.37% classification accuracy and an AUC of 0.992. This work also finds coronal views as the most diagnostically informative due to their clear visualization of the medial temporal lobe. Finally, one more article related to Alzheimer's detection: the author [14] proposes a hybrid CA-ConvNeXt model for the early diagnosis of Alzheimer's disease, enabling patients to receive early and effective treatment and improve their condition for survival. This proposed model effectively solves the

problems of early Alzheimer's disease classification and the classification of common MCI, AD, and NC cases. They employ the latest ConvNeXt network, which has a simpler topology and better performance than other models such as ResNet and Swim Transformer. This model improves performance, achieving 96% accuracy on the public ADNI dataset by adding Coordinate Attention to the ConvNeXt network.

3. Results

In this section, the Alzheimer's dataset is collected from [15-17], which includes 2D MRI slice images of size (176 × 208) from the ADNI [18]. To assess the severity of Alzheimer's disease, a scale ranges from 0 to 3 (0 = no impairment, 1 = very mild, 2 = mild, and 3 = moderate) [19]. This dataset includes 6,400 MRI images, which are divided into four classes: very mild dementia (2,240 samples), mild dementia (896 samples), moderate dementia (64 samples), and non-demented (3,200 samples). The distribution of the Alzheimer's dataset is illustrated in Figure 3.

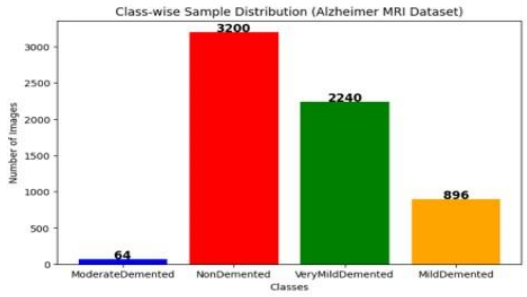

Figure 3: Distribution of Alzheimer's dataset

4. Methodology

In this section, the proposed model effectively detects the various stages of Alzheimer's disease. To enhance model performance, it is necessary to improve the quality of class samples through pre-processing techniques such as CLAHE and intensity normalization. Furthermore, the Alzheimer's dataset is imbalanced; it is necessary to balance the classes using Borderline-SMOTE. This combined effect shows clearer structural boundaries and more discriminative feature representations. In addition, the proposed ConvMix model extracts anatomical features at different stages, thereby improving multi-stage Alzheimer's detection by combining the CSFF. As a result, the performance of this proposed model is enhanced, leading to better detection of Alzheimer's disease across its multi-stage progression.

4.1. Pre-processing

To improve the quality of balanced samples, pre-processing techniques such as CLAHE are used to enhance the contrast of disease-related anatomical features and reduce intensity variation before feature extraction, as shown in Figure 4.

- CLAHE is used to enhance local contrast in MRI images, making subtle anatomical structures more distinguishable while preventing excessive noise amplification, as described in Equation 1.

$$\beta = \alpha * \frac{N_{pixels}}{N_{bins}} \qquad (1)$$

Where, α is user defined clip range to (0,1), N_{pixels}= Total pixel in contextual pixel and N_{bins} = Number of gray levels bins in the histogram.

- Finally, normalization is applied to adjust the pixel intensity values of an MRI image to the (0,1) range to improve image contrast, using equation 2.

$$I_n = I_{ss} - \frac{I_{min}}{I_{max} - I_{min}} \qquad (2)$$

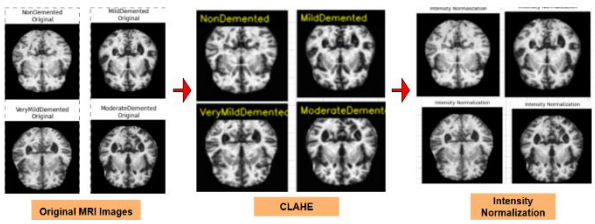

Figure 4: MRI images pre-processing by using CLAHE and intensity normalization.

4.2. Data Balancing

In this subsection, the goal is to increase sample uniformity in the existing dataset by using borderline-SMOTE to balance the dataset by augmenting minority-class samples while keeping the majority class unchanged. This change does not affect the convolutional network because convolution is invariant to rotation, color, and image size during augmentation. It focuses on samples near the decision boundaries between classes, such as between the very mild, mild, and moderate demented classes, where anatomical differences are subtle and overlap. These regions correspond to areas where a clear hard margin

cannot be achieved due to class overlap. By balancing samples in these critical boundary regions, the method effectively refines the decision boundary and improves class separability, as depicted in Algorithm 1.

Algorithm 1: Borderline-SMOTE for balancing the AD classes

Input: Minority set = T_min, Majority set =T_maj, neighbors = k

Output: Augmented dataset T_aug

1: Initialize T_aug ← T_min ∪ T_maj

2: for each sample x ∈ T_min **do**

Find k-nearest neighbors of x

Let N_maj be the number of majority samples among the k neighbors

if 0 < N_maj < k **then** ▷ Borderline situation

3: Randomly select a minority neighbor x_nn

4: Augmented λ ~ U (0,1)

5: Balanced sample:

x_new = x + λ (x_nn − x)

6: T_aug ← T_aug ∪{x_new} ▷ randomseed (10720)

7: **end if**

8: **end for**

9: **return T_aug**

4.2.1 Distribution of balanced class samples

The number of samples before SMOTE in the mild demented class is (717 samples), the moderate demented class is (51 samples), the very mild demented class is (1792 samples), and the non-demented class is (2560 samples). The number of samples balanced after SMOTE for each class is as follows: very mild demented (2560 samples), mild demented (2560 samples), moderate demented (2560 samples), and non-demented (2560 samples). The test set for each class is as follows: very mild demented (448 samples), mild demented (179 samples), moderate demented (13 samples), and non-demented (640 samples). The distribution of class samples is shown in Figure 5.

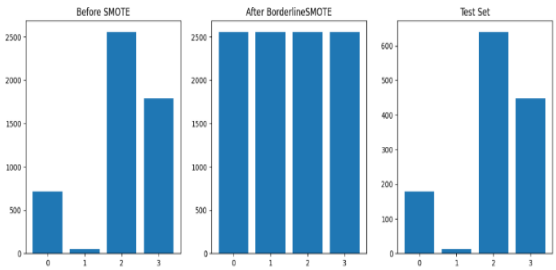

Figure 5: Distribution of class samples before, after borderline-SMOTE and Test set

4.3. Detection of multi stage Alzheimer's disease

The proposed approach is divided into three modules: ConvMix model for feature extraction, the cross-scale feature fusion for integrating feature maps, and the final classification head for Alzheimer's detection as follows:

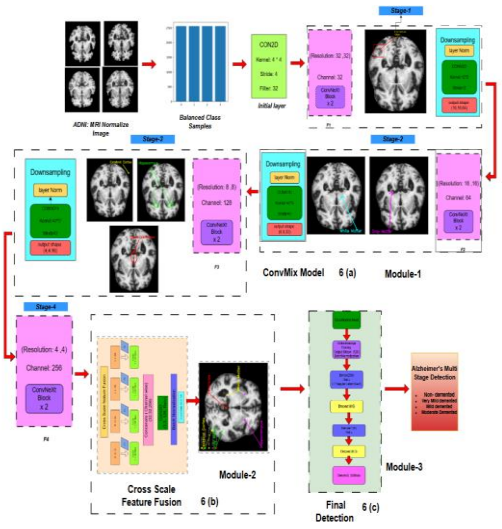

Figure 6: (a) ConvMix model is used to extract the features, (b) CSFF is incorporated to preserve the fine grained features, (c) Final classification head for Alzheimer's multi stage detection.

In Figure 6, initially, the normalized images are balanced using borderline-SMOTE of size (128 × 128 × 3), provided as input, and passed through a stem layer consisting of a 4 × 4 convolution with a stride of 4 and 32 filters, which performs initial feature extraction, such as edge detection. while reducing the spatial resolution from (128 × 128 x 3) to (32 × 32× 32) and decrease the computational complexity. Subsequently, the feature maps are processed through four hierarchical ConvMix stages, each containing two ConvMix blocks followed by a down-sampling operation. At Stage-

1, it extracts fine-grained anatomical details, including cortical edges and local brain textures. Now, proceed to Stage-2, which learns mid-level structural representations, such as gray-matter and white-matter characteristics that indicate neuronal loss and highlight degeneration.

Furthermore, Stage-3 captures disease-relevant anatomical structures indicating reductions in the hippocampus and cerebral cortex and enlargement of ventricular regions, which are strongly associated with Alzheimer's disease progression. Finally, Stage-4 learns high-level semantic representations that represent global disease-related patterns such as brain atrophy and show the progression of Alzheimer's disease. Due to downsampling, a transition layer is placed between consecutive stages of the ConvMix model to reduce spatial resolution and increase the number of channels, thereby increasing computational cost. To address the issue, the CSFF module is introduced to effectively utilize these complementary disease-related patterns learned at different network depths; the outputs of all four ConvMix stages (F1–F4) are forwarded to the cross-scale feature fusion module. Within this module, feature maps are first resized to a common spatial resolution and projected to a uniform channel dimension using 1 × 1 convolutions. The projected feature maps are then concatenated and refined using a 3 × 3 convolution followed by batch normalization, generating a unified multi-scale feature representation. Now, the fusion of features enables the model to preserve fine-grained anatomical patterns extracted from shallow layers while integrating high-level semantic information learned by deeper layers, thereby providing a more comprehensive representation of Alzheimer's disease-related structural alterations. Finally, these fused feature maps are processed through a Global Average Pooling layer, followed by two fully connected layers with 256 and 128 neurons, interleaved with dropout layers (0.5 and 0.3) to reduce overfitting. A final Softmax classifier predicts one of the four Alzheimer's disease stages: non-demented, very mild demented, mild demented, and moderate demented. This proposed architecture effectively combines hierarchical feature extraction with cross-scale feature integration, improving the model's discriminative capability for detecting multi-stage Alzheimer's disease.

5. Results and Discussion

This section effectively describes the experimental results obtained from the proposed ConvMix model combined with the CSFF module for multi-stage Alzheimer's disease. The experimental results analysis includes a confusion matrix, a performance assessment, and, finally, a comparison of various existing works.

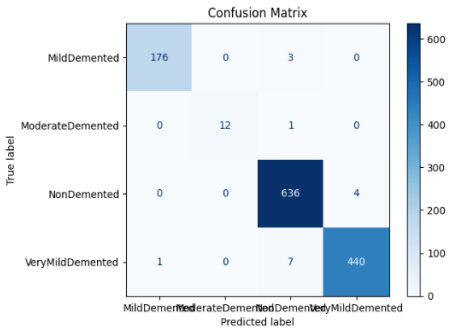

Figure 7: Confusion Matrix

In the analysis of the confusion matrix shown in Figure 7, misclassification was determined by comparing true and predicted labels. This confusion matrix presents the classification results for four classes: non-demented, very mild demented, mild demented, and moderate demented. The mild demented class consists of 179 samples, and the model makes 176 correct predictions. As a result, only 3 samples are assigned to the non-demented class. The prediction of this class is good, with an accuracy of 98.36%. Furthermore, the moderate dementia class consists of 13 samples, of which 12 are correctly classified, and 1 belongs to the non-dementia class. As a result, the samples are classified, and the achieved prediction score is 92.31%. Now, moving to the non-demented class, 636 samples are correctly classified, and 4 samples belong to the very mild demented class. This means that the model predicts an excellent score of 99.36%. Finally, in the very mild class, 440 samples are correctly classified; 7 are misclassified and assigned to the non-demented class, while 1 belongs to the mild demented class. Based on the confusion matrix analysis, the largest number of samples is classified as the non-demented class. This means the proposed model discriminates well among other classes.

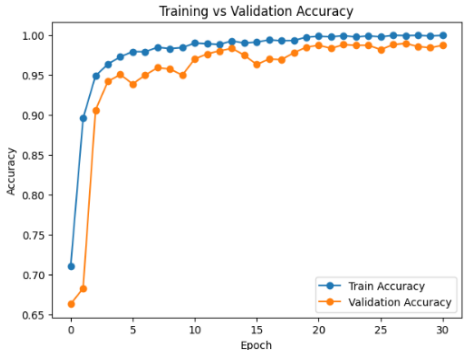

Figure 8: Performance assessment

This performance curve, as shown in Figure 8, indicates that both training and validation accuracy increase rapidly because the ConvMix model effectively learns low-level features. As training progresses, at stages 2 and 3, they learn more discriminative anatomical features, such as gray matter, white matter, hippocampal reduction, cortical contraction, and ventricular enlargement. At stage 4, the model learns more disease-specific patterns. With the addition of the CSFF module, the model preserves fine-grained anatomical features. Consequently, both training and validation accuracy gradually converge and stabilize at approximately 99%, with only a small gap between the curves. This minimum gap between the training and validation curves indicates that the model learns stably and generalizes well, demonstrating its effectiveness in detecting multi-stage Alzheimer's disease. The computational time taken by this model is 10.96 sec, with an average time per image of 0.0085 sec. The total parameters are 2,1014,820. The trainable parameters are 2,1014,564; the non-trainable parameters are 256; and the obtained test accuracy is 98.75% using equation 4.

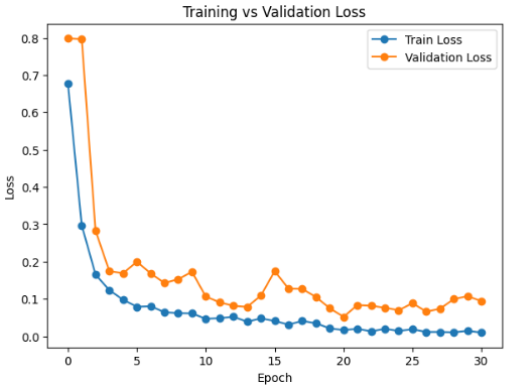

Figure 9. Loss assessment

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

The analysis of Figure 9 shows that both the training and validation curves decrease sharply during the initial epochs, suggesting that the model learns anatomical features more effectively and converges more quickly. As a result, the training loss continuously declines steadily, while the validation loss stabilizes with minor fluctuations, suggesting good generalization. This behaviour indicated that most class samples were correctly classified into their respective Alzheimer's disease stages, with only a few misclassifications. The consistently low validation loss demonstrates the robustness and reliability of the proposed model for multi-stage Alzheimer's disease detection. The classification summary of the proposed model, as shown in Table 1, is evaluated in terms of precision, recall, and F1_score by using equations 5, 6, and 7.

Table 1. Classification summary of proposed model

Class	Precision	Recall	F1_score	Class wise accuracy (%)
Mild Demented	0.99	0.98	0.99	98.36
Moderate Demented	1.00	0.92	0.96	92.34
Non Demented	0.98	0.99	0.99	99.38
Very Mild Demented	0.99	0.98	0.99	98.21

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1_{Score} = 2 * \frac{precision*recall}{precision+recall} \quad (7)$$

True positive and true negative are the two others measures used to assess the effectiveness of the proposed model in terms of sensitivity and specificity by using borderline SMOTE, it achieves a good balance, maintaining high sensitivity and specificity, and making it effective for correctly detecting Alzheimer's stages with minimal false positives, such as mild demented (sensitivity=0.98, specificity=0.99), moderate demented (sensitivity=0.99, specificity=0.98), non-demented (sensitivity=0.98, specificity=0.99), and very mild demented (sensitivity=0.99, specificity=0.99) by using equation 8 and 9. The interpretation of the obtained measures as shown in Table 2.

Table 2: Sensitivity and Specificity

Class	Sensitivity	Specificity
Non demented	0.98	0.99
Very mild demented	0.99	0.99
Mild demented	0.98	0.99
Moderate demented	0.99	0.98

$$Sensitivity = \frac{TP}{TP+FN} \quad (8)$$

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

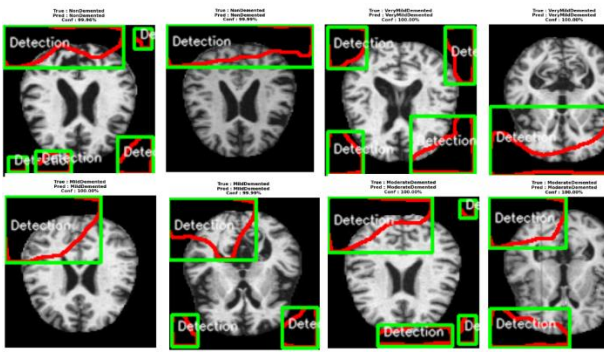

Figure 9: Predicted class samples.

Figure 9 shows the CSFF-based detection of MRI images from the four classes. For each image, the true class, predicted class, and prediction confidence are visualized. In the non-demented class, it is slightly more difficult for the model to detect, so it assigns a low probability to the other classes. The other images have more distinctive features, making the model more confident in its predictions and achieving close to 99-100% accuracy, indicating that the proposed CSFF-ConvMix model detects MRI images with high reliability. Furthermore, the color boxes, such as green bounding boxes and red contours, indicate the attention regions identified in the CSFF feature maps and mostly contribute to the model's classification decision. These highlighted regions across the various stages of the disease indicate that the model learns more distinct anatomical patterns of Alzheimer's disease progression. The CSFF technique integrates these features from multiple ConvMix stages, rather than from a single local region, enabling the model to leverage both fine anatomical details and high-level semantics, thereby improving feature representation, enhancing model interpretability, and contributing to multi-stage Alzheimer's disease detection. Finally, the last comparison of the proposed model with other existing work is shown in Table 3.

Table 3. Comparison drawn between proposed model with other existing work

References	Dataset	Model	Accuracy (%)
Author [6]	OASIS 3D Brain MRI Dataset	Backpropagation Neural Network using GLCM, Haralick, and Gabor–Haralick features	Gabor–Haralick: 97%, Haralick: 90%, GLCM: 86%
Author [7]	ADNI Dataset	SVMclassifier with SVM-RFE + Covariance-based feature selection (Voxel-Based Morphometr	Combined feature set outperformed individual morphometric or texture features and conventional methods

		y + Texture features)	
Author [8]	ADNI Dataset	VGG-19, Wide ResNet 50-2, GoogleNet, and Inception v3 + Gompertz function	Accuracy= 99.22%, Recall= 99.53%, Precision = 99.69%, F1-score = 99.61%, AUC = 98%
Author [9]	Structural (sMRI)	Classical ML (Wavelet + GLCM features) and CNN	cML:93.3% (ADvs CN), 87.7% (AD vs MCI), 88.2 % (CN vs MCI), 75.3% (Multiclass) CNN: 82.2%, 75.4%, 83.8%, 64%
Author [10]	Benchmark Dementia MRI Dataset	InceptionV3 (Feature Extraction) + ResNet50 (Classification) with Adaptive Rider Optimization (ARO)	Accuracy: 96.6% Precision:98 % Recall: 97% F1-score: 98%
Author [11]	MRI Dataset (3,714 images, Iraq clinics); External validation on OASIS and ADNI	Ensemble model (VGG16, VGG19, ResNet50, InceptionV3, Efficient-NetB7 – Voting Ensemble)	99.32% (Primary dataset) 86.6% (OASIS) 99.5% (ADNI)
Author [12]	ADNI Dataset	Two approaches: Self-Augmented CNN and Modified ResNet	99.53%
Author [13]	AlzaSet curated MRI dataset	ConvNeXt variants and other models: VGG16, VGG19, InceptionV3, and DenseNet121	Accuracy: 98.37% ConvNeXt-base model perform better than others
Author [14]	ADNI Dataset	CA-ConvNeXt	Accuracy=96 %
Proposed Model	ADNI dataset	borderline-SMOTE +ConvMix combined with CSFF + Anatomical Features	Accuracy=98. 75% Improved: other measures such as: precision, recall, f-score, sensitivity and specificity across various classes

6. CONCLUSION AND FUTURE SCOPE

In this paper, a ConvMix is proposed for multi-stage detection of Alzheimer's disease. The ADNI dataset comprises 6400 MRI images across four classes. The MRI dataset underwent comprehensive pre-processing steps, including CLAHE followed by intensity normalization, to improve image quality and consistency while preserving disease-relevant anatomical information. To address the class imbalance problem, borderline-SMOTE is used to balance the class samples for minority classes, resulting in a more balanced training dataset and reducing bias. The proposed approach, a ConvMix model combined with the Cross-Scale Feature Fusion module, effectively integrates multi-level feature representations, enhancing the extraction of both fine-grained anatomical details and high-level semantic information. The evaluated experimental results show that the proposed model achieves better detection performance across the four Alzheimer's disease stages while providing interpretable attention region visualizations that highlight the image regions contributing to the classification decisions. The proposed model achieves 98.75% accuracy and improves other measures, including precision, recall, and F1_Score. These findings suggest that the proposed model is an effective and reliable approach for detecting multi-stage Alzheimer's disease. In future, other deep learning models can be applied to assess global cerebral atrophy.

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