International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(5s) 2026 pp. 154-164
https://doi.org/10.70917/ijcisim-2026-2682
Article

Competitive Multi-Class Alzheimer's Disease Classification Using a Hybrid GAN–DWT–CNN Model on MRI Data

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Abstract: To diagnose AD as it advances to a third pathological stage, MRI images of the brain still suffer from accuracy issues. Subtle structure changes occur even at such an early stage of the disorder that they can barely be detected with existing technology. In order to conduct multi-classification of Alzheimer disease cases from MRI images, this paper proposes an automatic diagnosis system of Alzheimer's based on Generative Adversarial Nets (GANs) and Discrete Wavelet Transform (DWT). Significantly as well as increasing the number of classes, has it been able to do this. In addition to the data imbalance problem and the classification quality of deep learning algorithms, GAN-based augmentation can tackle changed scale of the features. The DWT can also improve the discrimination power of multiresolution features extracted from MRI images classified by a deep learning model based on the four-class classification problem: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented subjects. The model achieved a precision of 92 percent for overall classification accuracy, and 91% when computing the macro-averaged F1-score across all classes. What should be borne in mind is that the proposed framework has high recall on early stage patients (where other methods are difficult to apply), which shows off its ability more. The stability of the convergence of the training process of the model, together with the results of the confusion matrices, confirms the robustness of the model's use. The stable process if training of the model together with analysis for the confusion matrices further confirms the stability of the proposed model and its training process. The results of the experiments show that for diagnosing Alzheimer's disease, GAN-based augmentation and DWT feature extraction can provide a very important performance improvement, and that, overall, we can therefore believe that it is feasible to use the proposed framework as a computer-helped diagnosis tool in the clinical care of sufferers from this dread disease.
Keywords: Alzheimer's disease (AD), Magnetic Resonance Imaging (MRI), Generative Adversarial Networks (GANs), Discrete Wavelet Transform (DWT), Deep Learning, Medical Image Classification, Early Diagnosis.

1.Introduction

Alzheimer's disease (AD) is a slowly degenerating disease and one of the most common forms of dementia in older adults worldwide. It is characterized by a progressive decline in cognition, a gradual loss of memory and changes in behavior that increase discomfort. Quality of life is highly affected for AD patients, and because AD has no cure, diagnosis at an early stage is important to control the disease and improve clinical effect [1].

Aqua blue is drawing attention to them with its stethoscope image to illustrate what we may expect from money off useless exercises of exertion and worry about cost effectiveness or time constraints The Deep learning in recent years, particularly convolutional neural networks (CNNs) have shown themselves quite capable of producing impressive results on many tasks in medical image analysis [2], Alzheimer's disease classification [3]. However, deep learning models still face class imbalance and insufficient training data even on the ad proxy image datasets used to test their effectiveness [4].

Generative Adversarial Networks (GANs) have been recently proposed for use in medical imaging due to the above drawbacks. GANs can generate synthetic MRI scans. These scans can be used to augment the dataset and improve the generalizability of the model, particularly in the later disease stages with less-data [5]. At the same time, Discrete Wavelet Transform (DWT) has been effective at extracting multi-resolution spatial and frequency features, which could provide a better representation of the subtle neurodegenerative patterns in brain MRI images [6].

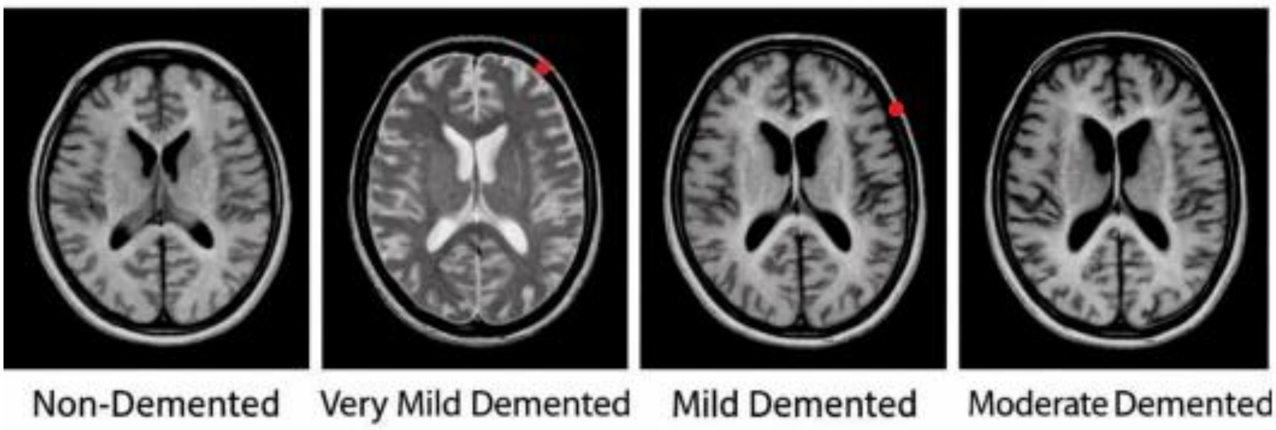

Figure 1. Alzheimer's disease stage

These observations motivate the development of the hybrid model proposed in this paper, which combines GAN-based data augmentation and DWT-based feature extraction for the early diagnosis of AD based on MRI images. The main contribution of this work is the combination of GAN-based augmentation, DWT-based feature extraction, and CNN-based classification into a single framework for multiclass diagnosis of AD. As existing studies have relied on GAN augmentation or CNN classification models in isolation, the proposed method introduces a data generation process with a multi-resolution feature extraction process in order to increase the robustness and accuracy for multi-stage classification in detecting early-stage AD as shown in Fig. (1) [7]. The proposed model seeks to raise the robustness and accuracy of classification throughout multi-stages.

2. Related Works

During the last decade, deep learning based methods have considerably increased the performance of automatic AD diagnosis. As reported in several recent surveys, the gold standard methods for MRI-based AD classification problems are CNNs, since they inherit the large spatial information of neuroimaging data while extracting early multi-grade features [8], [9]. Many works have been proposed with CNN architectures to classify multi-class Alzheimer's disease stages. For example, a deep learning model has been proposed by Sorour et al. [10] to classify AD stages from MRI images that demonstrated a higher accuracy in classifying AD than classical machine learning models. Deep CNN models were utilized by Bekhet et al. [11] on 4-class MRI datasets and showed that multi-class AD classification is possible, accurate, and efficient. Some architectures have been developed based on residual and attention-based CNNs to address network depth and consider only the brain regions relevant to diagnosis [12].

However, CNN models do not always generalize well to the test set, despite passing the inferencing task successfully. CNNs can get stuck in the small dataset and easy to tilt state. Various Data Augmentation Techniques have been proposed to address this issue in the medical imaging community. GANs can be used to create realistic representative artificial MRI data and balance classes, providing robustness against cases present and not present in training samples. Yuda et al [14] applied WGAN-GP data augmentation to MRI data sets of Alzheimer's disease and reported improved classification accuracy. They used combined CNNs and GANs for super-resolution which considerably improved the diagnostic test results and feature quality for small sample sizes. Oraby et al. [15] In this paper, a hybrid framework using a deep super-resolution GAN and a convolutional neural network (CNN) is introduced to classify four-stage AD MRI scans. The hybrid approach, through magnifying the MRI image for classification purposes, achieved very high accuracy and AUC scores. The results have shown that combining GAN-improved images with a CNN classifier improves the multiclass AD detection results compared to those of normal deep learning models. Wavelet feature extraction in the area of Alzheimer's III diagnosis continues to be an area of research. This approach produces good results and is supported by a combination of DWT and CNNs. Fayaz et al [16] increase the classification of the brain MRI images by having different, successively higher-resolution spatial and frequency characteristics of multilayer dominations. Lao et al [17] generalize the wavelet analysis to 3D images, showing the impact of multi-scale features on the classification of neurodegenerative disorders. Fusion methods have been employed, by combining deep features extracted from original MRIn images and the transitional domains such as t,DWT, with good results for AD classification as well18. As well as being encouraged for Alzheimer's disease classification research f o years, validation can be a solution to data leakage and statistical bias from splitting MRI study samples, which Young et al.[19] have argued leads to overly optimistic results. This leads to an increase in the use of standard validation methods, as well as the use of data tumble across divides, to obtain valid performance levels. Methods have been developed to ensure class distribution, detect small early structures, and to ensure the robustness of multiclassification performance. In that regard, this paper seeks to propose a GAN-DWT-CNN hybrid model that can extract GAN data augmentation based on FAIBIWAM both unfairness and dependability and DWT and CNN improvisation based features from FAIBIWAM in multiclass AD diagnosis [20]. Multi-feature fusion techniques have also been utilized to improve AD classification. In addition, Angkoso et al. [37] presented a multi-plane MRI feature fusion method to improve the classification by combining multiple feature representations. In Table I, we summarize the state-of-the-art methods for Alzheimer classification based on MRI data. It can be observed that most of the existing works focus either on improving classification accuracy or on feature extraction mechanism. In this way, CNN methods focus on hierarchical feature extraction while hybrid methods (e.g., DWT-CNN) focus on multi-resolution feature extraction. Nonetheless, problems remain with data imbalance and model robustness to real-world conditions. Table X shows that only a few studies set out to bring attention to these challenges. In contrast, GAN-DWT-CNN combines the data augmentation, feature extraction, and classification into a single end-to-end model for better robustness and generalization.

Table I. Comparison of state-of-the-art Alzheimer's disease classification methods

Ref.	**Proposed Method**	**Problem Addressed**	**Compared With**	**Limitation**
[6]	CNN-based AD classification (Suresha et al., 2020)	(i) Basic MRI classification (ii) Feature learning	Traditional ML methods	(i) Limited feature extraction (ii) No imbalance handling
[16]	DWT + CNN (Fayaz et al., 2021)	(i) Multi-resolution feature extraction (ii) Improved classification	CNN-based models	(i) No data augmentation (ii) Sensitive to dataset size
[10]	Deep CNN (Sorour et al., 2024)	(i) Multi-class classification (ii) Deep feature learning	Conventional CNN	(i) Overfitting risk (ii) Requires large dataset
[11]	DeepALZNET (Bekhet et al., 2025)	(i) Multi-modal learning (ii) High accuracy classification	MRI-based methods	(i) Requires clinical data (ii) High complexity
[37]	Multi-feature fusion (Angkoso et al., 2022)	(i) Feature fusion (ii) Improved representation	Single-feature methods	(i) High computational cost (ii) No imbalance handling
Proposed	GAN–DWT–CNN Framework	(i) Data imbalance (ii) Multi-resolution feature extraction	CNN, DWT-CNN, Deep models	(i) Slightly lower accuracy compared to some methods

		(iii) Multi-class classification		

3.Deep Learning with Discrete Wavelet Transform

Deep learning is a subfield of machine learning based on neural networks with multiple layers that can learn hierarchical feature representations from data. In recent years, CNNs have outperformed other machine learning methods in the classification of Alzheimer's disease from MRI data [21]. The application of DWT and deep learning classifier not only highlights the feature extraction but also improves the robustness of the classification as shown in Fig. (2).

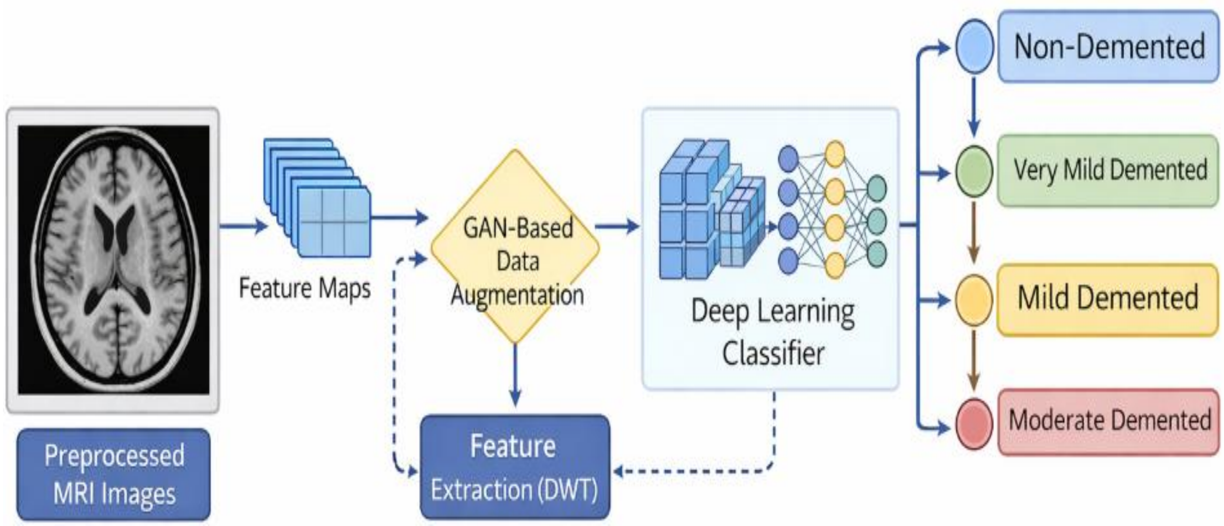

Figure 2. Deep learning architecture for multi-class classification of Alzheimer disease stages.

3.1 Convolutional Neural Network (CNN)

As a footnote to the medical uses of CNN (to which we will return), the more generic architectures-leNet, ZFNet, and GoogleNet-explain something else. Stories about databases such as Pacific Ecoin Exam and NEON, or about graphics and economics, say nothing of other topics-in other words their preconceptions these stories cultural critics miss for the most impressive achievements in this era of information infrastructure [22]. The continuing success of CNNs in analyzing medical images may well be because they automatically learn the spatial hierarchies of features. Rather than having to hand-craft features for the machine, as with customary machine learning, features can be learned directly from the input data [23].

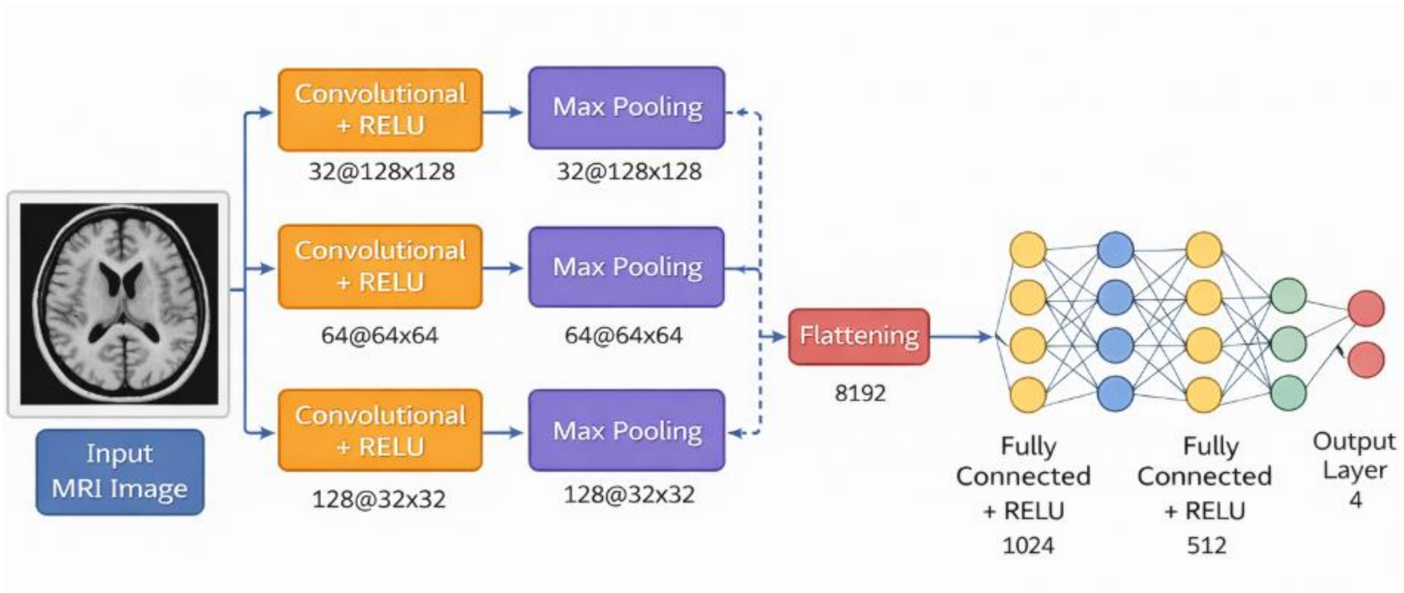

Figure 3. A Convolutional Neural Networks Architecture.

A CNN architecture consists of convolutional layers, pooling layers, and fully connected layers. The convolutional layers utilize learnable filters to extract local spatial features such as edges, textures, and shapes from the input. High-level reasoning and eventually classification are done by fully connected layers [24]. CNN has been widely used in the diagnosis of Alzheimer's disease and has been shown to be particularly successful at differentiating structural changes in MRI of the brain such as hippocampal atrophy, cortical thinning and ventricular enlargement. Other studies have demonstrated the efficacy of CNN over classical machine learning approaches in discriminating between stages of Alzheimer's disease. As an example, with Alzheimer's stage, CNN as a main classification module got discriminant features from the data after applying the DWT. as shown in Fig. (3).

3.2 Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a widely acceptable signal and image processing technique. The DWT decomposes an image while preserving its spatial character. Because of the natural frequencies and the localized spacetime of the DWT, it is computationally efficient. It is well suited for medical image analysis where morphological information localized in some level is required for diagnosis purposes [26]. Therefore, in this two-dimensional MRI image, the DWT breaks the input image into four sub-bands: LL, LH, HL and HH. These three high frequency detail sub-bands (LH, HL, HH) contain edges and texture changes, which are important for scanning fine brain abnormalities in the development of Alzheimer's disease [27]. Numeral studies and experiments proved that DWT also improved the classification accuracy when numerous machine learning algorithms or current deep learning algorithms are merged together, especially when we are diagnosing neurodegenerative diseases [28]. In this study, we use the DWT as a feature extractor before the classification stage with a CNN-based classifier. Our proposed model takes advantage of the multi-resolution property of DWT, so it can work well on the global brain structures and identify the variations of structures in high detail. Therefore, the proposed model improves the robustness and accuracy of the deep learning classification tasks as illustrated in Fig. (4).

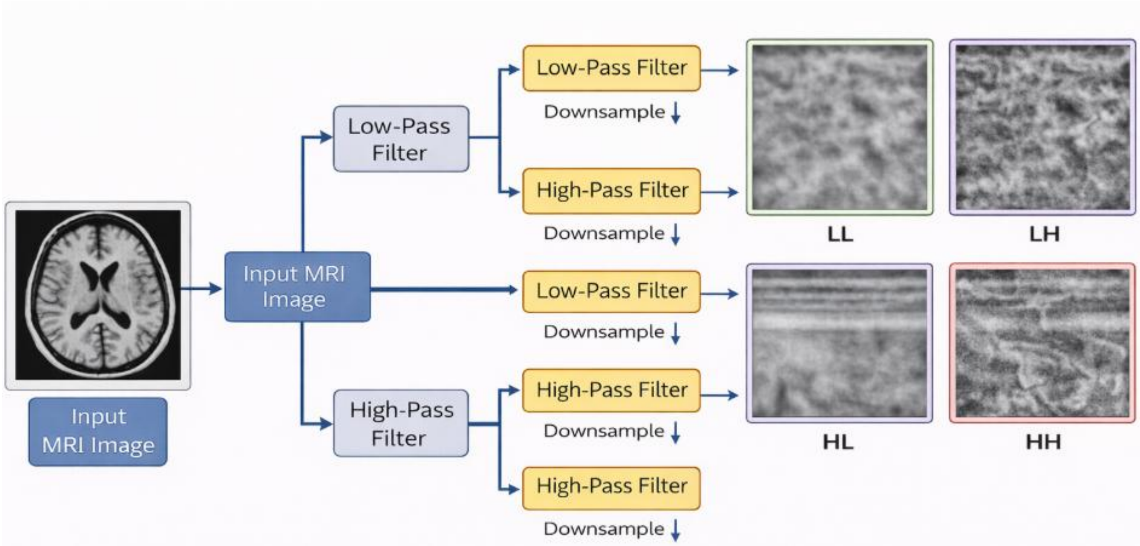

Figure 4. Block diagram of Discrete Wavelet Transform (DWT) showing how an MRI image is decomposed into four frequency sub-bands (LL, LH, HL, and HH) by low-pass and high-pass filtering.

3.3 Dataset Description

The experiments reported in this study used **the Alzheimer MRI 4-class** dataset available on the Kaggle website, which contains brain MRI images in four clinical stages of Alzheimer's disease. The four stages are Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. This dataset is widely used in other studies for classifying Alzheimer's disease because it is equally represented for each stage and is accessible for research purposes. The dataset is publicly available for researchers to promote reproducibility and transparency. All MRI images were preprocessed by resizing and normalizing so that each image has the same dimensions before training. This dataset was then divided into training and testing sets to evaluate the performance of the model and test the generalization of the proposed framework.

4.Proposed Method

This paper suggests a hybrid algorithm for the detection of AD from MRI images based on the combination of GANs, DWT and CNNs in order to accomplish a more stable and accurate process in case of a limited or an imbalanced data set, applying a method similar to that used by the aforementioned three methods [29]. The complete pipeline began with preprocessing the MRI images: resizing images to a standard input size and normalizing them to a common intensity. Since the datasets for Alzheimer's disease are knowledge-dense and intrinsically complex, data augmentation using GANs is used to generate MRI data for the classes with no real data. To avoid data leakage, the dataset is split into training and testing data before performing data augmentation. GAN data augmentation was applied only to training data to diversify the input data and address the class imbalance in the dataset. The model was not trained using the test data to provide a realistic evaluation of the generalization performance of the model on unseen data. It is been revealed that GANs have an important impact on deep learning. Both experimentally and theoretically, GANs can be used to improve the diversity of the data, and improve the generalizability of deep neural network models in medial image classification [30],[31]. After the GAN processing, DWT is applied to the medical images. The DWT then rearranges the input image frequency domains to spread multi-scale and redundant wavelet transforms features conveniently into a 2-measurement signal. Each image can be decomposed into poly phases which can reveal useful information. This decomposition has been shown in two of the most recent articles [32], [33] to be useful when differentiating between stages of neurodegenerative diseases such as Alzheimer's.

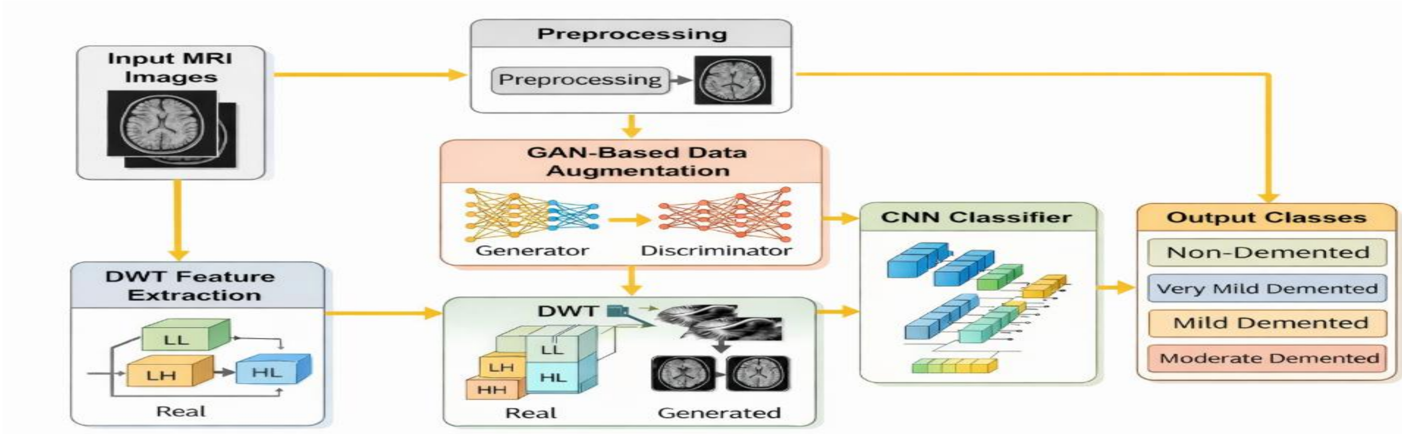

Figure 5. **Block diagram of the proposed GAN–DWT–CNN framework for Alzheimer's disease classification using MRI images.**

For classification, the extracted wavelet features are fed into a convolutional neural network (CNN), which learns hierarchical feature representations through the convolutional and pooling layers. CNNs have been found to be effective for recognizing morphological and structural changes associated with disease from MRI images, and have outperformed customary ML methods in classifying Alzheimer's disease. The proposed model employs a GAN for data augmentation, a DWT for feature extraction, and a CNN for classification [34], [35]. This achieves data balancing, feature representation and stable accurate multi-stage AD classification [36]. The overall framework of the proposed method is illustrated in Fig. (5).

5.Results and Discussion

Additional experiments have been conducted to analyze the learning process of the proposed GAN-DWT-CNN network model, including its convergence stability and generalization ability. For this experiment, the proposed network model was trained for 30 epochs. To measure the model performance, we used the training accuracy and the validation loss and accuracy metrics, usually used in deep-learning based classification tasks on medical images. Table II. Training and validation accuracy and loss between epochs. The accuracies for training and validation rapidly increase and the loss quickly reduces in the first stage of training between epochs 6 and 10, showing good feature learning and optimization.

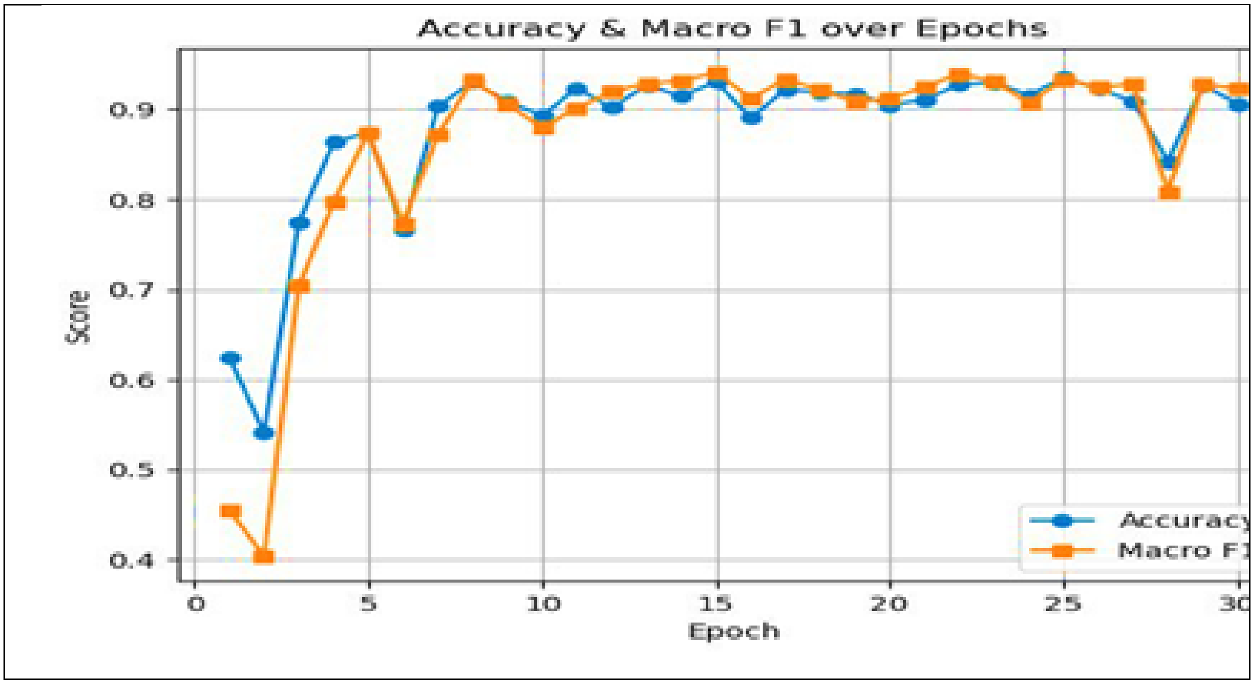

Figure 6. Training accuracy and macro F1-score evolution over epochs for the proposed GAN–DWT–CNN model.

The training and validation accuracies from epoch 11 to epoch 20 were above 90%. This indicates that the network is able to generalize well without overfitting to the training data, as the training and validation curves are almost similar with no important deviation from each other. This is mainly due to using the GAN-based data augmentation and the DWT-based feature extraction which captures more distinct features from the data, addressing the overfitting issue during the training process. This showed that these components contributed to the generalization capability of the CNN classifier. The convergence behavior in this study confirmed the robustness of the proposed framework and its effectiveness in improving classification stability under limited and imbalanced datasets using DWT-based features and GAN-based data augmentation methods. The effect of this was positive. The model's best performance was in between the 21st and 30th epochs when validation loss and accuracy stabilized (or were close to it) at about 0.15 and 92%, respectively. The performances of the experiments conducted and their validation proved that this classification method is valid. These multi-class Alzheimer disease classification fiftieths show the potential of its use in computer-helped diagnosis (CAD) systems. An analysis of the confusion matrix allows us to understand the proposed model's performance on the four stages of the AD. Most of the MRI images were classified correctly in their respective classes, showing the proposed framework's discriminative capability. The few misclassification results between Mild Demented and Moderate Demented classes were probably due to the fact that the structures of brain images between the Mild and the Moderate stage of the AD disease progression are quite similar. The confusion matrix shows that the proposed GAN-DWT-CNN model is capable of classifying the different stages of AD, as it can be seen in Fig. (6).

Table II. Details of Training Accuracy, Validation Loss, and Validation Accuracy

Epoch Range	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)
6 – 10	87.9	0.22	85.4
11 – 15	91.6	0.18	90.9
16 – 20	92.4	0.16	91.8
21 – 25	93.1	0.15	92.3
26 – 30	92.8	0.15	92.0

Table III: compares the performance of the proposed method with recent studies

Study	Dataset Type	Classes	Method	Accuracy (%)	Key Strength	Limitation
Suresha et al. (2020)	MRI	2–4	CNN	90.3	Baseline CNN model	Limited feature representation
Fayaz et al. (2021)	MRI	4	DWT + CNN	96.0	Multi-resolution feature extraction	No data imbalance handling
Sorour et al. (2024)	MRI	4	Deep CNN	94.5	Deep architecture	Sensitive to dataset size
Bekhet et al. (2025)	Clinical + MRI	4	DeepALZNET	96.2	Multi-modal learning	Requires clinical data
Proposed Method	Kaggle MRI	4	GAN + DWT + CNN	92.0	Handles imbalance + robust features	Slightly lower accuracy

In Table III, we summarize the results of AD classification of several previous works compared with that of the proposed method. While some previous works such as [11,16] outperformed the proposed method, they relied on additional preprocessing or clinical data. On the other hand, the proposed GAN-DWT-CNN model tackles class imbalance and feature representation problems in medical image analysis. The introduction of GAN for data augmentation addresses the class imbalance issue and improves the model's generalization capability. Furthermore, DWT extracts multi-resolution features, including both spatial and frequency features, from MRI images. Although achieving a 92% accuracy, which is lower than some other methods in the literature, the results are competitive for a more realistic and limited scenario. Therefore, the proposed model is a trade-off between accuracy, robustness, and usability for diagnosing Alzheimer disease in real-world applications.

6.Conclusion

This paper proposes a hybrid framework for the brain disease classification (Alzheimer's disease) into multiple classes using Magnetic Resonance Images (MRI) based on (DWT), (GANs), and (CNNs). The issues considered in developing the framework were: the well-known problems of medical image analysis in terms of data imbalances, the difficulty in obtaining the abnormalities of the images with normal datasets, and the calculation time required by image analysis techniques. The utility of our proposed GAN-DWT-CNN framework was confirmed with an overall correct rate of 92% and an average F1 score of over 0.91. The network yielded a good generalization behavior with strong convergence of training and a good discriminative power, for all AD stages analyzed. The high recall for early stage cases suggests that the model may be used not only for diagnosis at an early stage, but also for supporting decisions about the clinical course. Within the field, GAN-based image augmentations have alleviated the class imbalance problem. DWT-based feature extraction has provided more accurate spatial and frequency representations at multiple scales. These techniques, paired with hierarchical learning with CNNs, have increased classification accuracy and stability in comparison to more customary deep learning methods. hope that the above-revealed encouragements endure and a similar comfort reaches our posterity, too. In our view, in the long term, using 3D MRI volumes as large as possible, multi-modal neuroimaging data as diverse as conceivable and applying methods from the field of explainable Artificial Intelligence (XAI) could lead to better interpretability and explainability, and thus to higher clinical trust in the models. The GAN architecture is in its infancy and more advanced deep learning architectures have yet to be explored. In conclusion, however, the proposed framework is shown to make for a solid and efficient classification algorithm to bring the idea of AD detection automation one step closer to reality.

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