

AUTOMATIC DETECTION AND MULTI-CLASS CLASSIFICATION OF MANAGEMENT AND PREVENTION OF NEURODEGENERATIVE DISEASES STAGES USING PROGRESSIVE WASSERSTEIN GENERATIVE ADVERSARIAL NETWORK

R. Pavaiyarkarasi¹ and Dr.D.Paulraj²

¹Department of Electronics and Communication Engineering, R.M.K. Engineering College,
Kavaraipettai, Chennai, Tamil Nadu

²Department of Computer Science Engineering, Jeppiaar Institute of Technology, Sunguvarchathram,
Chennai, Tamil Nadu.

Corresponding mail id: pavaipanneer@gmail.com

Abstract

Alzheimer diseased (AD) is a neurodegenerative disease that impacts on the memory and cognitive capacity of a person [1]. It is a non-curable disorder, which advances continuously. Therefore, the proposed framework introduces an innovative framework for classifying AD stages effectively. The proposed scheme comprises multiple steps: data procurement, pre-processing, feature extraction (FE), and classification. At first, the input neuroimaging data is acquired from a familiar database on neurodegenerative illness. Once pre-processed, a procedure called normalized gamma-based contrast-limited improved histogram equalization (NG-CLiHE) is presented in order to eliminate data artefacts. Extended concise empirical wavelet transform (Ex-CEWT) is then fed with pre-processed data in order to extract features. The obtained feature vectors are further optimized by uniting Ladybug Beetle Optimizer (LBO) with Salmon migration optimizer (SMO) that are referred to as improved Ladybug Beetle Optimization algorithm (Imp-LBOA) to optimize weight parameter of Ex-CEWT. Finally, the Progressive Wasserstein generative adversarial network (PW_GAN) is provided with the optimized features to implement a classification of several stages of AD into the categories of CN, SMC, EMCI, LMCI, MCI and AD. The suggested algorithm is implemented in MATLAB and the performance measures such as accuracy, precision, sensitivity, F1-Score, and the consumption of the computational time (TC) are compared. The proposed framework achieves the overall accuracy of 96.51, precision of 96.95, sensitivity of 96.47, F-measure of 96.96 and 191.36s respectively.

Keywords: Alzheimer's Disease, Management and Prevention Neurodegenerative Disorder, Disease Diagnosis, Functional Magnetic Resonance Imaging, Dementia, Neuroimaging.

1. Introduction

Alzheimer's disease (AD) is a neurodegenerative illness that affects a person's memory and cognitive ability [1]. It is an incurable condition that progresses relentlessly. It is thought that hyperphosphorylation of tau and excessive production of amyloid- β ($A\beta$) cause AD pathogenesis [2]. As a result, tau neurofibrillary tangles and $A\beta$ plaques accumulate, interfering with nucleocytoplasmic transfer across neurons, and resulting in cell death [3]. Initially, the illness mostly affects the hippocampal area. Reminiscence loss is one of the earliest signs of AD as the hippocampal region is linked to learning and memory [4]. Although the precise origin of AD is uncertain, genetics may play a role in some situations. The memory-related neurological illnesses are all referred to as dementia, AD is the most prevalent kind of dementia [5]. The global Alzheimer's Report 2015 estimates that 70–80% of instances of dementia, which affects around 50 million people, are caused by AD [6]. According to estimates, 131.5 million individuals worldwide will have AD by 2050. The prevalence of AD is so high worldwide that one person gets AD every three seconds [7]. Additionally, AD ranks sixth amongst the top causes of death for the elderly population. In 2015, the projected global cost of fighting the illness was \$818 billion [8]. The symptoms of AD are minor at first and develop worse with time. It is a progressive condition [9]. According to research, AD brain alterations may start 20 years or more before AD symptoms manifest [10]. AD, cognitively normal (CN), early mild cognitive impairment (EMCI), MCI, late MCI (LMCI), and substantial. Some of the stages of the condition include memory concern

(SMC) [11]. CN individuals have typical aging symptoms; they do not exhibit dementia or depression [12]. The patient in SMC exhibits mild memory problems but otherwise displays normal cognitive functioning. Individuals struggle to create and maintain fresh memories, which makes them keep older ones [13]. EMCI, MCI, and LMCI are the stages of the disease when it has progressed and starts to disrupt day-to-day functioning [14]. The patient is experiencing the symptoms of loss of motor functioning, difficulty in speaking, memory problems, and difficulties in writing and reading [15]. The severity of MCI is determined by the use of a neuropsychological test known as the Wechsler Memory Scale (WMS) [16]. The advanced and last stage of AD is the illness that ultimately results in death [17]. Although there isn't a treatment for AD, the correct medicine and attention can help control symptoms [18]. In the early stages of the illness, cognitive decline can be slowed down even if AD cannot be cured [19]. Thus, diagnosing AD at an early stage is imperative to optimize patient outcomes and medication trial developments [20]. As neurodegenerative disorders like AD have grown in prevalence, researchers from all over the world have become increasingly interested in perusing the unreasonable issues connected to each phase of AD to develop highly effective methods for diagnosis, treatment, preventive therapies, and target drug discovery. Patients with AD advance at varied rates, and at different stages of the disease, different people may exhibit distinct symptoms. This makes it difficult to diagnose and prognose AD based on the stage categorization. Utilizing sophisticated diagnostic instruments and biomarker testing, AD may now be diagnosed due to recent advancements. For the diagnosis of AD, a variety of invasive and non-invasive neuroimaging techniques were used, including structural MRI (s-MRI), functional MRI (fMRI), Positron Emission Tomography (PET), computerized tomography (CT), electroencephalography (EEG), magnetoencephalography (MEG), and biomarkers found in cerebrospinal fluid (CSF). These technologies' neuroimaging data are utilized to enhance AD healthcare systems by enabling physicians and clinicians to make computer-aided diagnoses. Since the existing approaches don't provide sufficient accuracy in the prediction of AD the time consideration is higher. This motivates to do research in this area.

1.1. Novelty

The originality of the manuscript is shown in the following way, Progressive Wasserstein generative adversarial network (PWGAN) is suggested in this manuscript. This method has an enhanced generalization capacity thus reducing computing. Overhead and ensuring an efficient process for classifying the multiple neurodegenerative diseases like CN, SMC, EMCI, LMCI, MCI, and AD.

1.2. Contribution

1. The major contributions of the proposed methodology are provided as follows,
2. To suggest an innovative deep learning (DL) model (PW_GAN) to classify various neurodegenerative diseases using extensive features learning.
3. To pre-process the original neuro images with normalized gamma based contrast limited improved histogram equalization (NG-CLiHE) to improve the quality of the image. To extract the various diseased features using extended concise empirical wavelet transform (Ex-CEWT) for improving the learning capability of the model.
4. To tune the weight parameters of Ex-CEWT by integrating the Ladybug Beetle optimizer (LBO) with the Salmon migration optimizer (SMO) algorithm.
5. To present a new Progressive Wasserstein generative adversarial network (PW_GAN) to classify neurodegenerative diseases like CN, SMC, EMCI, LMCI, MCI, and AD.

To confirm the effectiveness of the framework that has been proposed using the conventional technique by comparing. Different measures of assessments such as accuracy, PPV, MCC, kappa coefficient, and time of computation. The following sections will be structured in the following way: Section 2 provides the outlay of the section about related work, Section 3. Discusses the proposed methodology, the results and discussion are given in Section 4, and the conclusion is found in Section 5. Expresses the end of the suggested framework.

2. Recent Research Work: A Brief Review

The current study is one of the many studies conducted on prediction of neurodegenerative diseases. Some of the recent research in this section, works are discussed.

Erdaş, et.al, [21] have introduced the use of the DL methods to identify and evaluate the brain in 2021 deformative diseases. Examples of these were Parkinson disease (PD), Huntington disease (HD) and

ALS. Neurodegenerative disorders (NDDs) which may bring about motor symptoms besides structural brain deterioration. The disease-specific effect of the motor symptoms on walking dynamics is possible; the latter frequently results in gait disturbance. The level of illness worsens the degree of walking capacity. Here examined the NDDs such as PD, HD, and ALS influenced gait and developed a technique of detecting neurodegenerative diseases and determining their. Severity based on ConvLSTM and three dimensional 3D CNN. In 2019, Rohini, et.al, [22] have suggested group ML classifiers for the classification of brain deformative disease phases. The goal of the suggested endeavor was to create a learning system for early AD prediction. Additionally, it categorizes the characteristics based on the possibility that a patient with MCI or Pre-MCI may acquire AD. A variety of ML methods were trained using an AD control dataset. The clinical cardiovascular index, brain atrophy ratio, neurological test results, demographics, social behaviour, and other initial data can also be utilized as extract predictors. A validation process was used to find a subset of relevant predictors. Only non-invasively and efficiently collecting predictors were used to determine the conversion to AD in MCI and Pre MCI individuals.

In 2023, Faisal, et.al., [23] have suggested a deep-learning algorithm that uses gait patterns to forecast neurodegenerative illnesses. To improve the analysis of walking gait patterns, both GRF signals and extracted characteristics were combined. The neural network architecture NDDNet was a special design to recognize three different neurodegenerative diseases (NDDs), and NDDNet is capable of analysing each of the two data simultaneously. Having tried numerous tests with the information collected concerning 64 individuals, could distinguish three types of NDDs with an average of 96.75 accuracy. The suggested approach may offer a technique to work with GRF signals more efficiently and aid in the more accurate diagnosis of patients with abnormal gait patterns. In 2022, Berke Erdaş, et.al, [24] have suggested CNN-based gait analysis for neurodegenerative disease severity prediction. The given approach assumes a deep learning-based methodology of developing a legitimate and proper disease severity grading system of neurodegenerative diseases, i.e. Parkinson, Huntington etc. addytrophic lateral sclerosis. It uses gait data represented by a Quick Response code. Using a unique representation technique, each 1D gait data of the individuals was converted to a Quick Response code, resulting in the creation of the two-dimensional Quick Response data set. The CNN-DL approach was used to regress this data set in an attempt to find a solution for the illness severity grading challenge. In 2023, Jing, et.al, [25] have presented model development and validation for DL-assisted gait parameter assessment for brain deformative diseases. The 41 different subjects (age between 25 and 85; mean 57.51, SD 12.93) were sampled with a motion sequence using the Microsoft Corp. Azure Kinet motion camera (3D, 30 Hz) and the data were obtained. Each walking frame was classified to be having a type of gait using SVM and Bi-LSTM classifiers trained on spatiotemporal variables that were obtained out of the raw data. After obtaining the gait semantics from the frame labels, all the gait parameters could be computed appropriately. A comparison was also made between the suggested algorithm and the earlier best heuristic approach. In 2022, Lan, et.a., [26] have suggested DL methods for prioritizing noncoding variants in neurodegenerative disorders. With an emphasis on applying DL to forecast the influence of genetic variations on disease pathogenesis, gather and examine the numerous novel model architectures, development ideas, and construal techniques that have surfaced. Here covers the current framework on neurodegenerative diseases, with a focus on Alzheimer 's-specific literature, as well as widely applicable genomic deep-learning techniques that may be tailored to disease-specific situations. Here wrap off with a summary of the field's prospects at the nexus of deep learning, genomics and neurodegeneration. In 2020, Lin, et.al, [27] have suggested classifications of neurodegenerative diseases using a machine-learning model based on multiplex blood biomarkers. Here create machine learning algorithms that would detect individuals with various neurodegenerative illnesses by utilizing multiplex blood-based indicators. Healthy controls, patients with AD spectrum, patients with PD spectrum with different cognitive severity, and patients with FTD were provided plasma samples. In comparison to the MCI and control groups, found that the AD group had higher levels of every biomarker except A β 40. In PDD, plasma α -synuclein levels were higher than in PD with normal cognitive function.

3. Proposed Methodology

The suggested method will be divided into several stages: data collection, pre-processing, FE and classification. The input brain images are first acquired and it is first pre-processed with normalized gamma-based contrast-limited improved histogram equalization (NG-CLiHE) to eliminate noise and artifacts in the images. The feature engineering process is then done on pre-processed images which are introduced to the extended concise empirical wavelet transform (Ex-CEWT). Initial and the resulting feature vectors are optimized upon a hybrid LBO and the SMO algorithm that is referred to as an Imp-LBO to adjust the weight parameter of Ex-CEWT. Finally, the Progressive Wasserstein generative adversarial network (PW_GAN) optimized features to the classification of multiple stages of Alzheimer disease as CN, SMC, EMCI, LMCI, MCI, and AD are presented to be accurately classified. The workflow of the proposed approach is deliberated in figure 1.

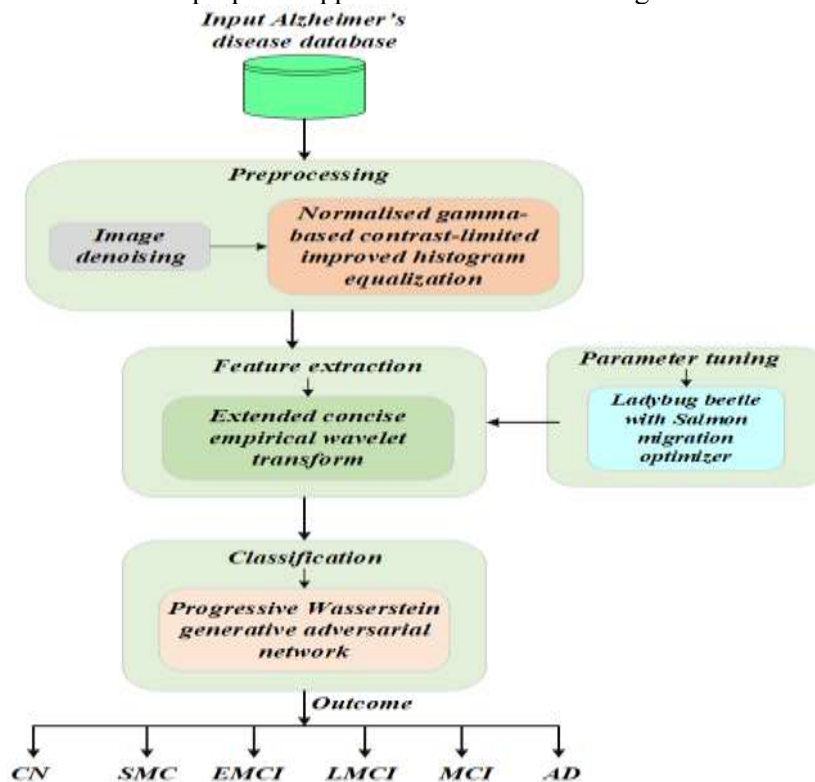


Figure 1: Workflow of the Proposed Approach

3.1. Data Acquisition

The raw neuroimaging data is obtained from the openly accessible AD Neuroimaging Initiative (ADNI) database [28] for AD classification. The ADNI is a widespread multisite framework planned for designing biological, neuroimaging, inherited, and medical biomarkers for detecting, predicting, and sensing ADs. This database consists of neurological images from different modalities like MRI, s-MRI, Diffusion tensor imaging (DTI), fMRI, and PET. For this framework, resting-state fMRI brain imaging is utilized and it is provided by ADNI. The simulation process is carried out with 138 fMRI images of five different classes such as CN (25 images), SMC (25 images), EMCI (25 images), LMCI (25 images), MCI (13 images), and AD (25 images). People with an age of more than 71 are considered for the experimentation process that detects and marks based on a value obtained in cerebral tests.

3.2. Pre-processing Stage

This is because the acquired images of the database are of high noises that cannot be directly fed on the proposed network model. The histogram equalization (HE) [29] tool nowadays is crucial in eliminating blurriness which is undesired and increasing the contrast of the image. But structural useful components are remained in the equalization process. To realize this problem, a normalized gamma-limited contrast-limited. A better histogram equalization (NG-CLiHE) method is provided which maintains relevant information and enhances the light of the neuro images. The gamma modification process is a grey-level alteration function implemented on images to improve the image contrast level. This can be

achieved by a power-law (PL) function that uses the spatial property for adjusting the image illumination level and it is formulated in equation (1)

$$X = zY^n \quad (1)$$

Here, X indicates the gamma-modified image, Y represents the actual image and it is in the range of 0 to 1, z represents the constant positive parameter, and n represents the constant positive parameter indicating gamma values. The parameter z is eliminated due to increased loss of essential details and vulnerable illumination in the image. Hence, the optimized PL is utilized and it can be formulated in equation (2),

$$P_l = Y^n \quad (2)$$

For altering the pixel intensities to a particular range, normalization is performed and it is implemented mainly in poorly contrasted images, and it can be expressed in equation (3),

$$norm = \frac{[K - \min(K)]}{[\max(K) - \min(K)]} \quad (3)$$

Here, K indicates the input image, and $norm$ indicates the normalized image, $\min$ and $\max$ operators are used to reduce and increase the pixel intensities. Here, an innovative normalized gamma function is used to minimize the illumination and improve the contrast of the image. It can be mathematically formulated in equation (4),

$$norm_{gamma} = \frac{[V - \min(V)]}{[\max(V) - \min(V)]} \quad (4)$$

Finally, the normalized gamma function is combined with CLIHE to enhance the contrast and brightness of the image. After applying CLIHE, the updated pixel value $\mathcal{Y}$ in quadrant 1 with the region (a, b) is mathematically expressed in equation (5),

$$\begin{aligned} y_{new} = & \frac{c}{c+d} \left(\frac{j}{i+j} f_{a-1,b-1}(y_{old}) + \frac{i}{i+j} f_{a,b-1}(y_{old}) \right) \\ & + \frac{d}{c+d} \left(\frac{j}{i+j} f_{a,b-1}(y_{old}) + \frac{i}{i+j} f_{a,b}(y_{old}) \right) \end{aligned} \quad (5)$$

Here, c , d , i and j manipulates the pixel distances, $f(\cdot)$ indicates the cumulative distribution function. The updated pixel values for quadrants 2, 3, and 4 with the region (a, b) can be evaluated using the above-mentioned procedure. It is to be noted that quadrants 1 and 3 are the same for the inner pixel region whereas quadrants 2 or 4 are different, then the updated pixel value $\mathcal{Y}$ in quadrant 2 with the region (a, b) can be mathematically formulated in equation (6),

$$y_{new} = \frac{d}{c+d} f_{a,b-1}(y_{old}) + \frac{c}{d+c} f_{a,b}(y_{old}) \quad (6)$$

However, quadrant 1 is completely different from other quadrants, and the updated pixel value $\mathcal{Y}$ in quadrant 1 with the region (a, b) is mathematically expressed in equation (7),

$$y_{new} = f_{a,b}(y_{old}) \quad (7)$$

Here the corner pixels are mapped in the same way and the updated values of pixels are recovered in the updated array size that is similar to the actual image to obtain the enhanced image.

3.3. Feature Extraction

The pre-processed images are then fed into the feature extraction (FE) stage for extracting disease features from the neuroimages. Nowadays, the empirical wavelet transform (EWT) technique [30] is highly effective in extracting features but it is time-consuming and error while selecting corresponding

scalar wavelets. To tackle this problem, an extended concise EWT (Ex-CEWT) is introduced in this framework that minimizes the complexity while scrutinizing larger neuroimages. The brief analysis of the proposed Ex-CEWT technique with its mathematical expressions is depicted as follows: Initially, the power spectral density (PSD) of the image is evaluated and split into different modes. The PSD

indicates the dissemination of power with frequency and the image $I(k)$, with its Fourier transform (FT) $I'(f)$ and average power ρ can be expressed in equation (8),

$$\rho = \lim_{K \rightarrow \infty} \frac{1}{2K} \int_{-K}^K I(k)^2 dk \quad (8)$$

The FT of the image in the interval $[0, K]$ can be mathematically deliberated in equation (9),

$$I'_K(f) = \frac{1}{\sqrt{K}} \int_0^K I(k) \exp(-x2\pi f k) dk \quad (9)$$

Then, the PSD can be mathematically expressed in equation (10),

$$z_{II}(f) = \lim_{K \rightarrow \infty} E \left[|I'_K(f)|^2 \right] \quad (10)$$

From the above equation (10), the PSD value is more than zero and is dependent on the frequency spectrum. The feature characteristics with its pulse information in the composed neuroimages are masked and it can be mathematically formulated in equation (11),

$$\begin{cases} z_{r_1} = 3 \cos(2\pi f_1 k) \cos(2\pi f_2 k) \\ z_{r_2} = 3 \cos(2\pi f_3 k) \\ z_{r_3} = \sum_{x=1}^N 4 \exp\left(-g \times 2\pi f_m^x k \sqrt{-g^2 - 1}\right) \\ z_1 = z_{r_1} + z_{r_2} + z_{r_3} \end{cases} \quad (11)$$

However, the number of decomposition levels and regularization parameters are highly non-linear due to complex interpretations in brain images.

3.4. Parameter Tuning using ILBO Technique

The proposed Ex-CEWT technique is highly sensitive to various parameters like regularization constants, and decomposition levels. While processing with larger databases, these parameters make the feature vectors ineffective for inputting into the proposed model. Hence, it is necessary to optimize these parameters thereby providing better scalability over feature subsets. In order to do this, combined Ladybug beetle (LB) [31] and salmon migration (SM) [32] are introduced and this leads to ILBO technique. In this case, the exploration phase of LBO is substituted with the exploitation stage of the SMO technique. The beetles are a wide family comprising of over 380K species one of which is LBs. According to the report, over 6K LB species are discovered that vary in body, shape, color, and size. It is divided into four phases i.e. ovum, grubs, cocoons and adults. Depending on their geographical location the ways of life were different and they gave birth to the same nutrition in cocoon and adult stages.. The LBs reproduce during the summer season and are completely inactive during winter time. LBs forage more than aphids and their major food sources are tiny insects, pest spawns, and lice. These animals are socialized because they relate and coordinate amongst themselves. Each stage can be expressed mathematically as discussed below in brief:

Step 1: Initialization Phase

The LB optimizer is stimulated by the synchronized movement of the LB to find the position with the most warmth. The initial population contains $M(0)$, and the final population $M(u_{\max})$ LBs with a

general condition $M(0) \geq M(u_{\max})$ is defined. Moreover, the best optimum objective function is also determined.

Step 2: Random Generation

Hausrung the most suitable solution randomly in the set of input parameters after the initialization process..

Step 3: Fitness Function

The changes in the iterative solution can be analysed using the fitness function and the optimal number of decomposition levels, and regularization parameters are chosen to enhance the normalization and scalability performance. The fitness function f is calculated using equation (12),

$$f = \lambda \times (1 - error) + \alpha \times (1 - |1 - N_d|) + \chi \times (1 - |1 - \eta|) \quad (12)$$

Here, $error$ indicates the mismatch between excerpted and ground truth features, N_d represents the decomposition level, η represents the regularization parameter. Moreover, λ , α and χ manipulates the weighting factors for determining each essential feature.

Step 4: Exploration Phase

In this phase, the location of LBs is combined and the best individuals are selected based on optimal function. Assuming the location of x^{th} LB in the y^{th} iteration is encompassed as $v(l)$ and this LB moves based on outcome vectors to enhance during $(l+1)^{th}$ iteration. Then, it moves towards l^{th} LB and the l^{th} move towards the $(y-1)^{th}$ iteration. The updated location of x^{th} LB is mathematically formulated in equation (13),

$$v_x(l+1) = v_x(l) + rand \times (v_y(l) - v_x(l)) \\ + rand \times (v_y(l) - v_{y-1}(l)) + rand \times |P_x|^{\frac{u}{N(u)}} \times v_y(l) \quad (13)$$

Here, P_x means the equality ratio of the LB cost to the total LB of the iteration of the proposed optimizer. The new solution of the LBO is however not more effective because it is susceptible to previous convergence issues and it does not provide a global optimum solution.

Step 5: Exploitation Phase

Since the exploration phase of the fox optimizer is not effective, the obtained solutions are updated in the exploitation phase using the SM optimizer. Salmon is one of the anadromous fish that propagates over streams and rivers. The water movements are highly sensitive to its lateral line system. It follows a water flow-oriented (WFO) mechanism to output the velocity matrix for the upcoming movements. Initially, monotonically reduced exponential expression is emphasized for analyzing the direction

matrix $L = [L_{xy}]_{m \times d}$ in complex dimensional space depicted in equation (14),

$$L_{xy} = \begin{cases} \alpha & f_{\min}(z_{xy} + \alpha) \leq f_{\min}(z_{xy}) \\ -\alpha & otherwise \end{cases} \quad (14)$$

Here, α indicates the self-enhanced parameter for the direction analysis, and it is expressed in equation (15),

$$\alpha = \left(1 - \frac{k}{K}\right)^c \quad (15)$$

Here, c indicates the exponential convergence and in this framework $c \geq 1$ is considered.

Step 6: Updation of LBO for SMO

For constructing the direction matrix L , the WFO uses a novel velocity matrix for different salmons and the updated position of salmon in terms of velocity matrix $V = [V_{xy}]_{m_1 \times d}$ is deliberated in equation (16),

$$v_x(l+1) = \left(\begin{array}{l} v_x(l) + rand \times (v_y(l) - v_x(l)) \\ + rand \times (v_y(l) - v_{y-1}(l)) + rand \times |P_x|^{\frac{u}{N(u)}} \times v_y(l) \end{array} \right) V_{xy}(k+1) \quad (16)$$

Here, $V_{xy}(k+1)$ indicates the updation function of LBO, and it is mathematically formulated in equation (17),

$$V_{xy}(k+1) = rand \times z_{besty} - z_{xy} / |z_{besty} - z_{xy}| \times dz_y + L_{xy} \times dz_y \quad (17)$$

Here, V_{xy} represents the vector velocity for the final iteration, $rank_x$ defines x^{th} salmon and it is arranged ascending in absolute difference value $|\Delta f_x|$, m_1 represents the number of salmon, and dz_y manipulates the step size in complex dimensional space. Moreover, z_{besty} indicates the y^{th} position of the salmon with the best value, and $|z_{besty} - z_{xy}|$ indicates the absolute value.

Step 7: Return the Best Optimal Solution

Step 8: Termination

Finally, the parameters of the Ex-CEWT technique are tuned using the ILBO, repeating step 3 until the $k = k+1$ stopping criteria are met.

3.5. Neurodegenerative Disease Classification using the PW_GAN Technique

The performance of the Progressive Wasserstein Generative Adversarial Network is then fed with the extracted optimal features. Application of (PW_GAN) to identify neurodegenerative disease capable of impacting the normal human physical activity. Yet, GAN [33] method has a high training instability to guarantee convergence during training complicated medical imaging information. The designed architecture consists of three significant steps: generator, weighted discriminator, anatomically delicate integrated loss function, and discriminator. The modern producer consists of the refined generator of several convolutional (Conv) layers which are trained on large volumes of data learning the abnormal condition. It has six various stages that train the corresponding features in the imparting with the classification process. Conv layers are added in each of the stages that receive model input. LSTM layers are applied and it is extended to six times in order to extract the features. Stacked network is offered to enhance the model parameters and balance the. Classification model. In addition, intra-phase iterative unfold residual block (RB) is used to minimize the network parameters. The elaborated analysis of the architecture developed is overcome below:

3.5.1. Generator CNN

There are 6 steps that are fused together in this step and they include Relu activation, ConvLSTM and RBs. The single RB is further projected five times hence reducing network parameters. The strides are 1 with three size of its kernel and a total of 32 filters are factored in ReLU at both the input and output. In addition to this, 32 filters are factored in Conv layers existing in LSTM and RB layers. Consequently, the last Conv layers take the result of RBs with 32 filters and output the resultant developed with a single filter.

3.5.2. Discriminator CNN

The discriminator blocks are fed with the result of the generator. In the discriminator block, there are 8 layers. Exist that offer adversarial results on the basis of the created result. The first six layers comprise of the fully connected (FC) layers may be found in conv layers and the last two. The kernel size of all the layers is set to three, and the initial two layers have 64 Conv kernels. In the following two layers, the Conv kernels have been folded as the 128th and fifth-sixth layer contains 256 Conv kernels in total. Otherwise, stride 1 will be used in all the Conv layers and the last layer will give the decision variable in the case of multiclass classification. The Leaky occurs in the discriminator block. The activation function is the application of ReLU function.

The PW_GAN architecture is shown in figure 2.

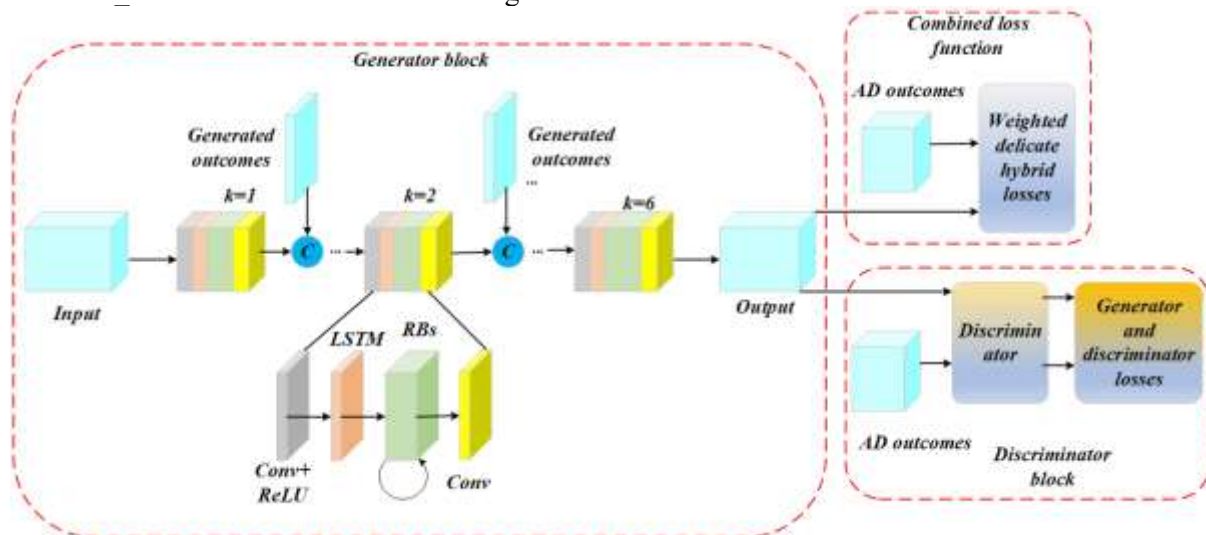


Figure 2: Architecture of PW_GAN technique

3.5.3. Weighted Anatomically Delicate Integrated Loss Function (WAD_LF)

To improve the performance of the accuracy, a WAD has LF is planned to be used in processing the generator phase. In this WADLF input, the normal and outcome of the generator are supplied into the input of the WADLF and the resultant error is obtained is reversed propagated to maximize the model parameters. The training of the network model is the complex that is in training the LF. Its influence on the strength and validity of the model developed. The neuroimaging results have large levels of unstructured correlated features, and specific interdependencies. The intention of reconstituting abnormal classes is to produce a more similar result to the ground truth. In the real process of adversarial, the generator intends to align the set classified outcomes with the actual outcome in a more similar way. The discriminator however, fails to. Distinguish between the generated outcome and the actual outcome because of poor learning of complex brain patterns. To address this challenge, the WADLF is proposed that takes into account successful LF to improve the precision performance. The stepwise discussion of the PW -GAN method is as follows:

L2 Loss: It is considered the default loss function that is caused due to data regularity, differentiability, and convexity. It can be mathematically determined in equation (18),

$$L_2 = \frac{1}{D} \|G(x) - x\|_2^2 \quad (18)$$

Here, D indicates the dimension of the data, and $G(x)$ represents the data generated during the training process. However, L2 LF inclines to be wedged at local minima and makes the outcome inaccurate.

L1 Loss: It is more operative than L2 LF in minimizing training error and the minimum value of L1 LF is lower than that of L2 LF. It can be expressed mathematically in equation (19),

$$L_2 = \frac{1}{D} |G(x) - x|_2^2 \quad (19)$$

The total LF for enhancing the PW_GAN model is formulated in equation (20),

$$L_{total} = L_1 + L_2 \quad (20)$$

Finally, from the SoftMax layer various neurodegenerative diseases like CN, SMC, EMCI, LMCI, MCI, and AD are accurately classified.

4. Results and Discussion

The proposed framework is processed and experimented with via the Python platform. The simulation process is carried out via the openly accessible ADNI database that consists of six different classes: CN, SMC, EMCI, LMCI, MCI, and AD. Various assessment measures like accuracy, precision, recall, F-score, and computation time (CT) are analyzed to analyze the performance of the proposed method. Several conventional techniques like 1-Channel ResNet-18 (1CR), fine-tuning (FT) model, off-the-shelf (OTS) transfer learning model, AlexNet, and integrated AlexNet with CNN [28] are compared with the proposed technique to prove the efficacy of the proposed scheme.

4.1. Assessment Metrics

Such performance metrics as Accuracy, recall, precision, F-score, and computation time are calculated to an improved extent appreciate the proposed approach.

4.1.1. Accuracy

It establishes the overall recognition accuracy of the model, which takes into consideration TP and TN. It is calculated as using equation (21),

$$Accuracy = \frac{w + x}{w + x + y + z} \quad (21)$$

4.1.2. Recall

Recall measures positive results which are correctly predicted model has been able to capture. This is calculated by use of equation. (22),

$$Recall = \frac{x}{x + y} \quad (22)$$

4.1.3. Precision

Precision is the proportion of the suggested model's positive recognition that are correct out of all the positive forecasts. It is computed using equation (23),

$$Precision = \frac{x}{x + z} \quad (23)$$

Here, w , x , y , and z indicates the true positive (TN), true positive, (TP), False negative (FN), and false positive (FP) respectively.

4.1.4. F-measure

The F-measure displays the consonant mean of recall and precision. It is computed using equation (24) as follows,

$$F1-score = 2 * \left(\frac{Precision * Recall}{Precision + Recall} \right) \quad (24)$$

4.2. Comparative Analysis of Suggested Method over Conventional Schemes

In this section, the results attained by the suggested method are examined through graphical representation. The comparison between the existing methods and the suggested one includes the calculation of different metrics such as accuracy, precision, recall, F-score and time consumption. The short-term reflection of the attained performances is presented below:

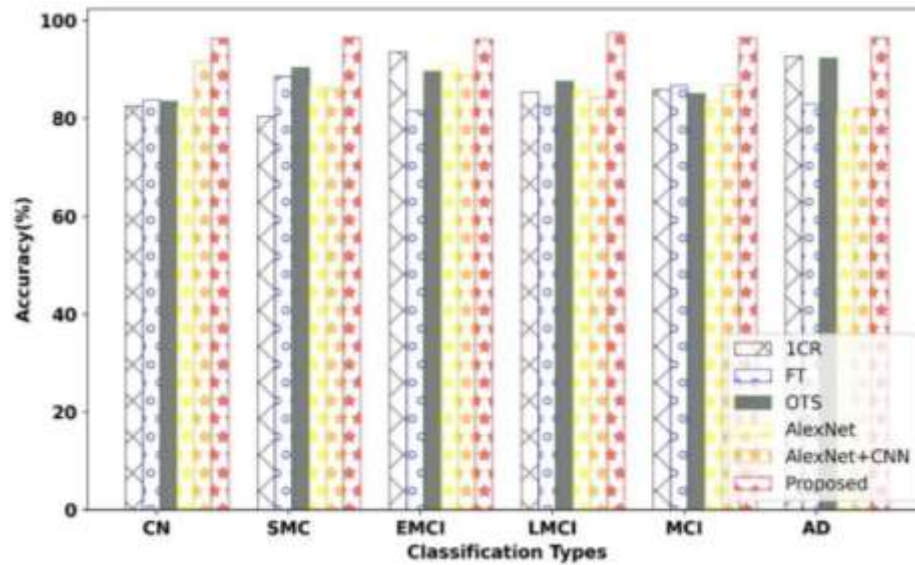


Figure 3: Accuracy Analysis for Varying Classes

Figure 3 represents the Accuracy analysis for varying classes with different conventional systems. From the graphical manifestation, it is clear that the developed PW_GAN technique outperforms greater accuracy compared with other techniques. The existing frameworks lack effective learning performance while processing complex brain imaging data. The proposed method achieved 9.84%, 12.16%, 8.47%, 11.38%, and 9.92% higher accuracy while comparing with existing 1CR, FT, OTS, AlexNet, and AlexNet with the CNN model. Table 1 tabulates the Accuracy performances under different techniques

Table 1: Accuracy performances under different techniques

Classification Types	1CR	FT	OTS	AlexNet	AlexNet + CNN	Proposed
CN	82.44	83.76	83.48	82.19	91.54	96.26
SMC	80.35	88.61	90.34	86.36	86.22	96.46
EMCI	93.51	81.58	89.55	91.07	88.81	96.10
LMCI	85.31	82.54	87.53	85.76	84.21	97.47
MCI	85.89	86.71	85.02	83.45	86.86	96.39
AD	92.57	82.91	92.32	81.26	81.95	96.43
Average	86.67	84.35	88.04	85.13	86.59	96.51

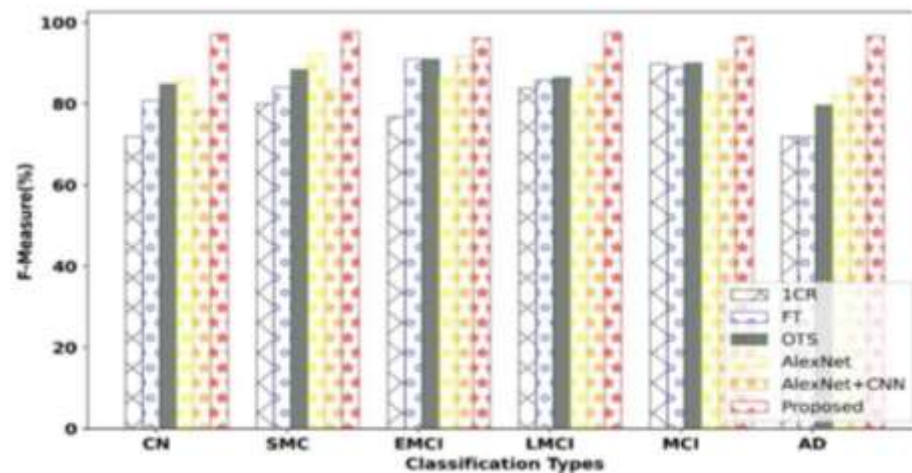


Figure 4: F-measure Analysis for Varying Classes

Figure 4 represents the F-measure analysis for varying classes with different conventional systems. From the graphical manifestation, it is clear that the developed PW_GAN technique outperforms greater F-score compared with other techniques. The existing frameworks lack effective learning performance while processing complex brain imaging data. The proposed method achieved 17.91%, 13.21%, 10.24%, 11.49%, and 10.22% higher F-measure performance while comparing with existing ICR, FT, OTS, AlexNet, and AlexNet with the CNN model. Table 2 tabulates the F-measure performances under different techniques. The tabulation shows that the suggested PW_GAN technique proved the best outcomes compared to other techniques.

Table 2: F-measure performances under different techniques

Classification Types	ICR	FT	OTS	AlexNet	AlexNet + CNN	Proposed
CN	71.90	80.78	84.77	85.82	78.36	97.06
SMC	80.07	84.08	88.31	92.18	83.47	97.78
EMCI	76.78	90.95	90.97	86.094	91.54	96.13
LMCI	83.84	85.79	86.51	84.31	89.62	97.64
MCI	89.81	88.97	90.05	82.32	90.77	96.46
AD	71.80	71.81	79.60	82.02	86.57	96.64
Average	79.03	83.73	86.70	85.46	86.72	96.95

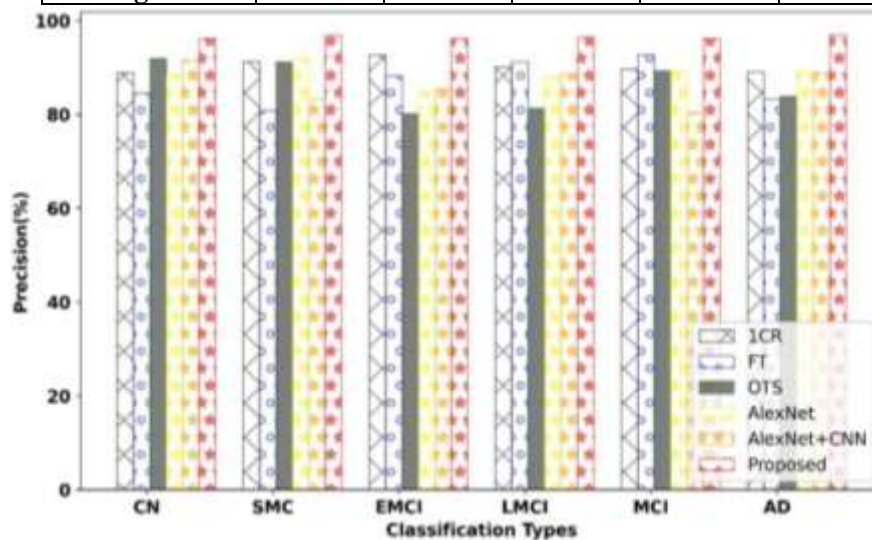


Figure 5: Precision Analysis for Varying Classes

Figure 5 represents the Precision analysis for varying classes with different conventional systems. From the graphical manifestation, it is clear that the developed PW_GAN technique outperforms improved precision compared with other techniques. However, the existing frameworks lack effective learning performance while processing complex brain imaging data. The proposed method achieved 6.21%, 9.68%, 10.19%, 7.84%, and 10.11% higher precision performance while comparing with existing ICR, FT, OTS, AlexNet, and AlexNet with the CNN model. Table 3 tabulates the Precision performances under different techniques. The tabulation shows that the suggested PW_GAN technique proved the best outcomes compared to other techniques.

Table 3: Precision performances under different techniques

Classification Types	ICR	FT	OTS	AlexNet	AlexNet + CNN	Proposed
CN	88.90	84.55	91.90	88.50	91.59	96.14
SMC	91.28	80.83	91.12	92.04	83.21	96.90

EMCI	92.61	88.23	80.10	84.74	85.49	96.17
LMCI	90.07	91.14	81.32	88.02	88.67	96.48
MCI	89.63	92.71	89.35	89.28	80.47	96.16
AD	89.07	83.29	83.88	89.18	88.75	96.99
Average	90.26	86.79	86.28	88.63	86.36	96.47

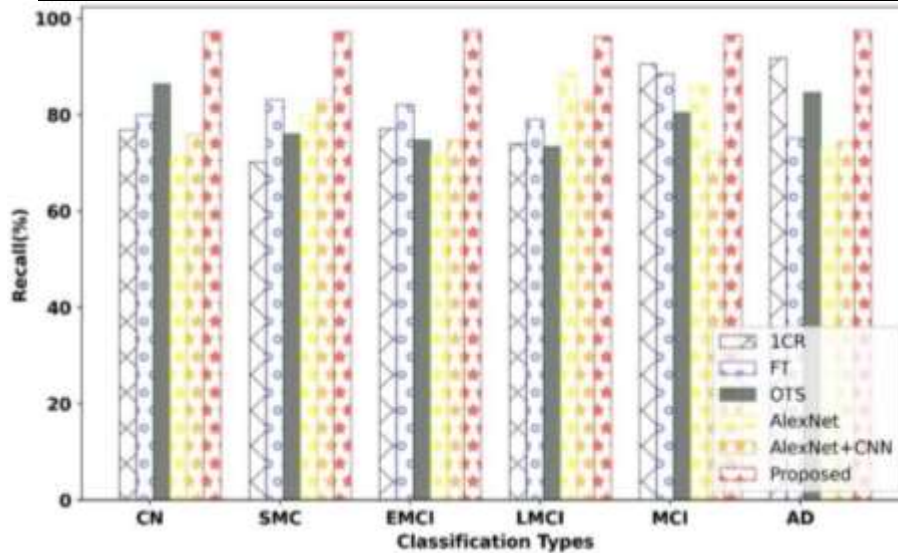


Figure 6: Recall Analysis for Varying Classes

Figure 6 represents the Recall analysis for varying classes with different conventional systems. From the graphical manifestation, it is clear that the developed PW_GAN technique outperforms improved recall performance compared with other techniques. The proposed method accurately learns complex brain patterns with optimal feature vectors and provides outstanding classification performance. The proposed method achieved 16.92%, 15.66%, 17.70%, 18.59%, and 19.8% higher recall performance while comparing with existing ICR, FT, OTS, AlexNet, and AlexNet with the CNN model. Table 4 tabulates the Precision performances under different techniques. The tabulation shows that the suggested PW_GAN technique proved the best outcomes compared to other techniques.

Table 4: Recall Performances under different techniques

Classification Types	1CR	FT	OTS	AlexNet	AlexNet + CNN	Proposed
CN	76.82	79.98	86.43	71.19	75.89	97.15
SMC	70.10	83.22	75.97	79.94	83.10	97.09
EMCI	77.05	82.06	74.72	71.83	74.63	97.49
LMCI	74	79.05	73.37	88.51	82.82	96.19
MCI	90.51	88.45	80.45	85.75	72.05	96.42
AD	91.75	75.04	84.59	72.96	74.42	97.43
Average	80.04	81.30	79.25	78.36	77.15	96.96

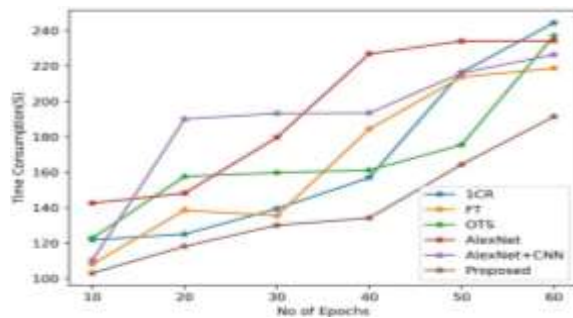


Figure 7: Time Consumption by Varying Epochs

Figure 7 encompasses the Time Consumption by varying epochs. The time by the proposed PW_GAN technique is much less than the other techniques. However, the existing techniques consume a high amount of training time to learn the complicated brain patterns. The proposed technique uses effective performance even when complex features are considered for the training process. For 60 epochs, the existing 1CR, FT, OTS, AlexNet, AlexNet with CNN, and the proposed PW_GAN technique consume time of about 244.2s, 218.67s, 236.92s, 234.14s, 226.3s, and 191.36s respectively.

5. Conclusion

The proposed framework introduced and investigated the new PW-GAN model for identifying AD stages effectively. The proposed PW-GAN model proved better performance and prevents training complexity in learning complex brain patterns. To assist the PW-GAN model, highly effective NG-CLIH and Ex-CEWT techniques are introduced in the pre-processing and FE stage to improve the accuracy performance. The NG-CLIH in the pre-processing stage uses an innovative Gamma function and provides superior image quality. Moreover, the metaheuristic ILBO technique that combines LB and SM optimizers provides the best optimum solution and tunes the weighting parameters of the Ex-CEWT technique efficiently. Finally, numerous stages of AD asCN, SMC, EMCI, LMCI, MCI, and AD are classified accurately with minimal error and time complexity. The scheme proposed is simulated in MATLAB and the performance parameters such as accuracy and precision are obtained. Sensitivity, F1-Score, and TC are performed and compared with other traditional methods. The overall precision 96.95, sensitivity 96.47, accuracy 96.51. In the future, a highly effective DL model will be introduced to determine the earlier prognosis of AD that can assist and resist the disease progression to improve the patient's condition.

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