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Alzheimer's Disease Classification Using Gan (Generative Adversarial Networks) And Mpa (Marine Predators Algorithm)

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Abstract: *This project aims to develop an advanced machine learning model for the classification of Alzheimer's using Electroencephalogram (EEG) data, combining Generative Adversarial Networks (GANs) for feature extraction and pattern recognition with optimization algorithms, including the Marine Predators Algorithm(MPA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO), for enhancing model performance. These optimization algorithms are employed to fine-tune the hyperparameters of the GAN model, ensuring improved classification accuracy and generalization. The approach helps in making improvements in classification accuracy, precision, recall, and F1-score, outperforming traditional machine learning models. The user interface (UI) designed in such a way that the users upload the Electroencephalogram (EEG) data in csv file and know that whether they have Alzheimer's Disease (AD) or not. By incorporating these advanced optimization techniques, the system provides a reliable, automated tool that can assist healthcare professionals in early diagnosis and treatment planning of Alzheimer's disease with greater efficiency and precision.*
Keywords: *Alzheimer's Disease, Electroencephalogram (EEG), Generative Adversarial Networks (GAN), Marine Predators Algorithms (MPA), Particle Swarm Optimization (PSO), Grey Wolf Optimization(GWO), Ant Colony Optimization (ACO), accuracy, precision, recall, F1-score*

INTRODUCTION
Alzheimer's is the brain related disease where our memory, thinking skills, cognitive ability and our communication skills will be damaged. The symptoms of this disease are mostly found in the people who are above 65 years old. This causes due to ageing. We find some of the people who are above 65 don't recognize the things. In some cases they forget the people working around us daily, some things when the went out they forget the route to their home they live around 15-30 years. The people can't answer to the simple questions like what is their name, age etc. These are the symptoms of that disease.
There are some of the medical tests should be performed for the early diagnosis of Alzheimer's Disease (AD).the test include cognitive tests, Brain Imaging(MRI, CT scan, PET etc.), Electroencephalogram(EEG). In cognitive test the patient will be tested their cognitive ability by asking some question. Based on their answers the doctor thinks whether further test is required or not. If they say correct answer the doctor declared that he doesn't have Alzheimer's disease else the patient will be preceded to further tests like MRI scan or EEG scan.

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MRI (Magnetic Resonance Imaging) scan takes the image of our brain. In case of Alzheimer's Disease (AD) patient we find that brain cells tissues shrink gradually in the MRI images. Electroencephalogram (EEG) is an medical test that measures the electrical activity of the brain. The electrodes are placed on the scalp and they capture the electrical activity of the brain. There will be 19 electrodes placed on the scalp. These electrodes are placed with 10-20 rule where one electrode will be placed after 10 units of distance from previous electrode. And another electrode will be placed 20units of distance from previous electrode and so on.

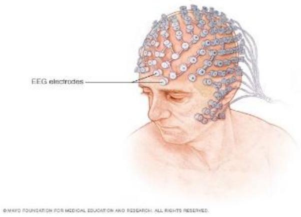

Fig 1: Performing EEG test

The electric signals will be represented in graphical way and is measured in mV. These graphs show the mv per unit time in different channels.

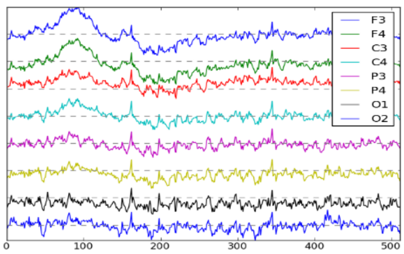

Fig 2: sample EEG graph

LITERATURE REVIEW

There are many algorithms and innovative methodologies developed and deployed for improving the accurate prediction of Alzheimer's disease. The data set taken will be Brain MRI images and Electroencephalogram (EEG). There are many advantages and disadvantages in the methodologies in the previous papers. There are also many research gaps in the previous papers. The research gap of one paper is filled by other paper.

The study [1] explores Alzheimer's disease prediction using various machine learning algorithms, leveraging EEG data for classification. The methodology includes data preprocessing, feature extraction, and model training with techniques like SVM, Random Forest, and deep learning-based approaches. The study interprets results through accuracy, precision, recall, and F1-score, with accuracy metrics highlighting the superiority of certain models. Advantages include improved early diagnosis and automation, while disadvantages involve data scarcity and model generalization issues. Research gaps include the need for larger datasets, explainability in deep learning models, and integration of multi-modal data for enhanced prediction [2].

The paper [3] proposes using a Convolutional Neural Network (CNN) combined with a Generative Adversarial Network (GAN) to predict Alzheimer's Disease (AD) stages from brain MRI images. The authors mention that AD is a major global health issue with many undiagnosed cases, emphasizing the need for early detection. They utilize MRI data is divided into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The dataset is pre-processed using filters like Median, Gaussian, Sharpening, and Emboss to enhance image quality. They employ a CNN model for classification and use GANs to generate synthetic MRI images to augment the dataset, addressing data scarcity. The proposed model achieves a high accuracy of 96%, outperforming previous studies that used standalone CNNs or other hybrid models.

The study by Sekhar et al. (2023) introduces a novel hybrid approach combining Deep GANs with the Marine Predators Algorithm (MPA) to optimize AD classification. GANs generate synthetic EEG samples to augment limited datasets, while MPA—inspired by marine predator foraging—enhances feature selection by simulating exploration-exploitation dynamics. Evaluated on a public EEG dataset (283 observations from 13 subjects), the GAN-MPA model achieved 99.96% accuracy, outperforming SCNN (80.56%), KNN (91.45%), LSTM (86.11%), and CNN (96.19%). Additionally, it demonstrated superior precision (96.19%), recall (97.23%), F-score (97.12%), and lower RMSE (29.55%) at 500 data points, with efficient execution time (3.765 ms). The integration of GANs for data augmentation and MPA for feature optimization effectively addresses challenges like dataset imbalance and inter-subject variability, offering a robust framework for early AD detection. Despite these advancements, challenges persist in multimodal data fusion, model interpretability, and ethical considerations for clinical deployment. Future work should focus on expanding dataset diversity and validating the framework across larger cohorts to enhance generalizability.[2]

Problem statement

Diagnosing Alzheimer's Disease (AD) is challenging, as traditional methods like cognitive tests and brain imaging can be slow and subjective. While machine learning using EEG data shows potential, existing systems often lack accuracy and struggle to capture complex patterns. This project aims to improve AD diagnosis by using Generative Adversarial Networks(GANs) for better feature extraction and advanced optimization algorithms like Marine Predators Algorithm(MPA), Particle Swarm Optimisation(PSO), Grey Wolf Optimisation(GWO), and Ant Colony Optimisation(ACO) to enhance model performance, providing a more accurate and efficient tool for medical professionals for early diagnosis.

ARCHITECTURE

The uploaded image illustrates a workflow for an EEG-based Alzheimer's disease classification system using a combination of GANs (Generative Adversarial Networks), wavelet transform pre-processing, and multiple optimization algorithms (MPA, PSO, ACO, GWO).

The process begins with input images from the dataset, specifically EEG signals collected from patients. These signals are divided into two sets: a training dataset and a testing dataset. Before feeding the data into the model, it undergoes pre-processing using Wavelet Transform, which helps in denoising and extracting relevant features from the EEG signals, enhancing the quality of the data.

Next, the pre-processed data is input into a GAN-based classification system. The Generator model in the GAN synthesizes examples, while the Discriminator model tries to distinguish between real and generated examples. The GAN is trained to improve its classification ability between Normal and Abnormal (indicative of Alzheimer's) cases.

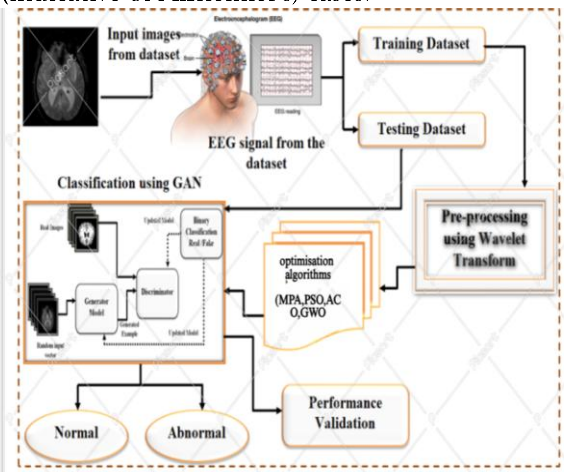

Fig 3. Architecture diagram of proposed model

To further enhance model performance, several optimization algorithms — Marine Predators Algorithm (MPA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Grey Wolf Optimizer

(GWO) — are applied. These algorithms optimize the hyperparameters of the GAN, improving its accuracy and generalization.
Finally, the system undergoes performance validation, where its accuracy, precision, recall, and F1-score are evaluated to ensure reliable Alzheimer's disease classification.
This comprehensive pipeline aims for high-accuracy, automated diagnosis support, leveraging deep learning and bio-inspired optimization techniques for early detection of Alzheimer's from EEG data.

METHODOLOGY

The project contains five steps which includes data collection, preprocessing, Translation and Transliteration and integration of translation and Transliteration and UI Development and Deployment.
Dataset Description
The person with Alzheimer's and healthy brain is differentiated with the analysis of EEG of both of the brains. The dataset consists of two folders. One with set of EEG signals of Alzheimer's Disease (AD) and other with EEG signals of Healthy brain without Alzheimer's Disease. Initially the graphical data of EEG recordings will be available in the file ".set" extension later will be converted to csv format. The csv file consists of the attributes with channel names like Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2,F7, F8, T3 (T7), T4 (T8), T5 (P7), T6 (P8),Fz, Cz, Pz and time in milliseconds. The row value consists of the electrical signal in every interval of time of a single patient. We have collected data of 16 patients where 8 of them with Alzheimer's disease and remaining with no Alzheimer's disease.
table 1:sample participants data

Participant_id	gender	Age	Group	MMSE
Sub-001	F	57	H	35
Sub002	F	78	A	22
Sub-003	M	70	A	14
Sub-004	F	67	A	20

Preprocessing of data
Initially EEG data is noisy containing muscle movements, eye blinks, electrical noise. The .set file is loaded. EEG brain signals usually stay between 0.5 Hz and 50 Hz. Muscle movements (jaw clenching, face muscles) create high-frequency noise (above 50 Hz). Slow drifts come from sweat, breathing, or electrode movement. These high drifts and slow drifts are removed with the help of band pass filter by using "mne" module in python. Electrical interference (like from power lines) happens at 50 Hz in many countries. The notch filter specifically targets this frequency and removes it without affecting the brain signals around it. After cleaning, the data is converted into csv file to precede further process
Feature extraction using GAN
Generative Adversarial Networks (GAN) is a deep learning framework invented by Ian Goodfellow in 2014. A GAN is made of two neural networks one is Generator(G) and another one is Discriminator(D). The Generator (G) job is to create fake data that looks real. In our case, it will try to generate synthetic EEG data patterns. The discriminator job is to identify whether the data is real or not.
The Discriminator (D) is trained with real data and fake EEG patterns of Alzheimer's Disease (AD) patient. The real and fake data of Alzheimer's disease (AD) is generated by the generator (G). The Discriminator improves its classification of fake and real data of AD. It always tries to overcome the discriminator loss and improve its efficiency. The misclassification of the data by the Discriminator (D) is known as Discriminator loss. The Discriminator loss function is represented with an equation

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$J_D = \frac{1}{m}\sum_{i=1}^{m} logD(x_i) - \frac{1}{m}\sum_{i=1}^{m} \log(1 - G(D(z_i))(1)$

The generator (G) takes the random input from the noisy EEG data. With the help of noisy data Generator (G) tries to generate the fake EEG pattern and give it to the discriminator. Based on the Discriminator(G) feedback the generator improves its performance. The number of samples generated by generator and discriminator classifies as fake is known as generator loss.

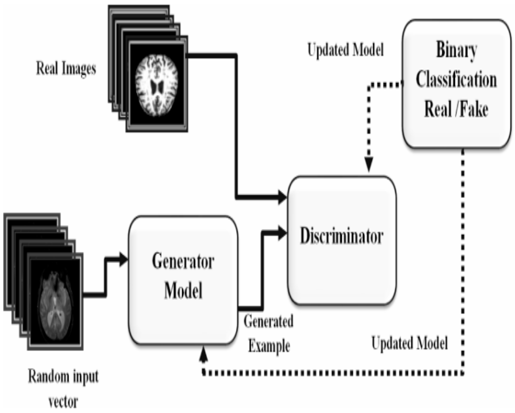

Fig 4: GAN architecture

For one epoch the Discriminator (G) is trained with the real patterns of EEG data for two or more epochs keeping Generator (G) constant. The Generator is trained with the real patterns of EEG data for two or more epochs keeping Discriminator constant. The random patient data is given to the generator and then generator generates the fake data of that patient. The discriminator identifies whether the data is fake or not. The Discriminator learns to classify real and fake data correctly, providing feedback to the Generator. The Generator updates its parameters to create more realistic data that can fool the Discriminator. Loss functions for both Generator and Discriminator are computed and used to optimize their respective models.

Feature extraction is a critical step in the processing and analysis of EEG signals, especially for complex tasks such as Alzheimer's disease classification. EEG data, inherently high-dimensional and noisy, requires robust feature extraction techniques to identify meaningful patterns and reduce dimensionality, thereby improving the efficiency and accuracy of subsequent classification models.

In this study, feature extraction was performed on both real and synthetically generated EEG signals. Prior to extraction, the EEG data underwent normalization using Min-Max scaling, ensuring that all features were rescaled within the range of -1 to 1. This step is essential for stabilizing the training of the Generative Adversarial Network (GAN) and maintaining uniform feature distributions. After training the GAN, synthetic EEG data was generated to augment the real dataset. This augmented dataset enhances the diversity of patterns captured, which is particularly beneficial given the limited availability of patient-specific EEG recordings. From this enriched dataset, a variety of statistical and signal processing-based features were extracted to capture the underlying characteristics of EEG signals. The features include Mean and Standard Deviation, Energy of the Signal, entropy, Band Power Features, hajoth parametersBy leveraging both temporal and frequency-domain features, the model ensures comprehensive representation of EEG dynamics. The combination of real and GAN-generated EEG data facilitated the extraction of more generalized and robust features, thereby improving the classification performance in distinguishing between healthy individuals and patients potentially affected by Alzheimer's disease.

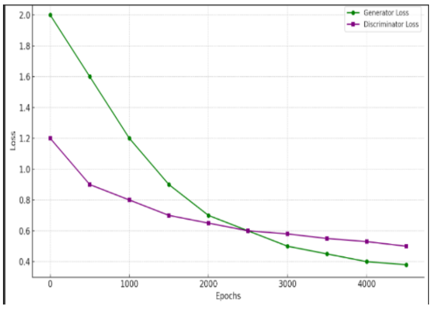

Fig 5: losses curve of generator and discriminator

This multi-faceted approach to feature extraction plays a pivotal role in enhancing the diagnostic capability of the system, providing meaningful inputs to the classifier and supporting healthcare professionals in early diagnosis and intervention.

Optimization Algorithms

The effectiveness of any classification model, especially when working with high-dimensional EEG data, largely depends on the careful tuning of its hyperparameters. To maximize the performance of our GAN-enhanced Alzheimer's disease detection system, we incorporated advanced bio-inspired optimization algorithms. These algorithms were employed to fine-tune critical hyperparameters of the GAN model and the final classification network, such as learning rate, batch size, number of neurons per layer, and activation functions. By integrating multiple optimization strategies, we aimed to leverage their respective strengths to achieve optimal convergence and improved classification accuracy.

Marine Predators Algorithm (MPA): In the proposed framework for Alzheimer's disease classification using EEG data, the Marine Predators Algorithm (MPA) serves as an advanced optimization strategy to enhance both feature selection and hyperparameter tuning processes. The primary objective is to maximize the classification accuracy while reducing computational complexity and avoiding overfitting due to redundant or irrelevant features. The methodology begins with preprocessing the raw EEG signals to remove noise and artifacts, ensuring clean input for subsequent stages. Following this, a Generative Adversarial Network (GAN) is employed for feature extraction, leveraging its capability to learn complex patterns and latent representations from high-dimensional EEG data. However, the feature space generated by GANs can be extensive, necessitating an efficient selection mechanism to identify the most informative features.

At this stage, the MPA is introduced. Inspired by the intelligent foraging behavior of marine predators, MPA explores the search space to identify optimal feature subsets. Each candidate solution in MPA represents a possible combination of features and its fitness is evaluated based on the classification accuracy achieved using a selected machine learning mode

Marine predators use two main strategies to hunt Brownanian and Levy flight.MPA has three hunting phases:

Exploration Phase: It is the first phase that happens in the beginning. Here Predators watch carefully, without much movement.

Transition Phase: Happens in the middle. Both predators and prey move at similar speeds. Half the population explores, half exploits

Exploitation phase: Happens at the end. Predator (solution refinement) moves faster than prey. Uses Lévy flight to close in on the best solutions. It aims to focus on promising areas to finalize the best solution.

Step by step mathematical approach for Marine predators algorithms

Step 1: Initialization:

We randomly create a set of solutions (called "prey" positions).

Mathematically:

$$X0 = X\text{min} + rand(X\text{max} - X\text{min})$$

Step 2: Memory & Elite Matrix:

MPA keeps track of the best solution found so far (like a predator remembering where it found a lot of food). This is called the Elite matrix.
Step 3: Movement (Exploration & Exploitation Phases):
Case 1: Exploration (start of the algorithm)
Prey moves fast using Brownian motion
Formula: Step size=Brownian random×(Elite−Brownian random×prey)
Update position: Prey=Prey+0.5×random×Step size
Case 3: Exploitation (end of the algorithm):
Predators speed up using Lévy flights to catch prey (fine-tune solutions).
Formula: Step size=Le´vy random×(Le´vy random×Elite−Prey)
Update position: Prey=Elite+0.5×convergence factor×Step size
The convergence factor helps refine the search as you approach the solution.
Step 4: Avoiding Traps (Local Optima)
MPA uses randomness (like eddies in water and fish aggregation points) to avoid getting stuck in poor solutions. This part checks if the predator (solution) is stuck and shakes things up by adding randomness.
Step 5: Memory Update:
At every step, if the current solution is compared with the stored best solution, update the memory. Repeat the steps until you reach the maximum number of iterations or desired accuracy.

Particle Swarm Optimization (PSO)
Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by the collective behavior observed in flocks of birds and schools of fish [12]. In this method, each potential solution—termed a "particle"—navigates the solution space by adjusting its position using its own knowledge and the experience shared within the swarm. PSO is especially effective in solving continuous optimization problems, making it highly suitable for fine-tuning hyperparameters in deep learning models, such as learning rates.
The swarm evolves over iterations, with each particle modifying its position based on both its historically best-known location (personal best or pbest) and the best-known position among all particles (global best or gbest). This iterative update process facilitates effective exploration and convergence toward optimal solutions.one has

$$P_{best}^{t} = \frac{x_i^*}{f(x_i)} = \min_{k=1,2,3,\dots t}(\{f(x_i^k\})$$

where i∈{1,2,...,N}
For a minimization task, let i∈{1,2,...,N} represent the index of a particle, t denote the current iteration, f be the objective function, x be the position vector, N be the total number of particles.
The velocity v and position x of particle iii are updated at each iteration t+1 using the following equations:

$$\mathbf{v}_i^{t+1} = \omega\mathbf{v}_i^t + c_1\mathbf{r_1}\left(\mathbf{p}_{best_i}^t - \mathbf{x}_i^t\right) + c_2\mathbf{r_2}\left(\mathbf{g}_{best}^t - \mathbf{x}_i^t\right), \quad (2)$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1}, \quad (3)$$

Here ω is the inertia weight that manages the trade-off between global exploration and local exploitation, c1 and c2 are acceleration constants controlling the influence of pbest and gbest respectively,r1 and r2 are vectors of random values sampled uniformly from the range [0,1]^D where D is the dimensionality of the problem.
To ensure stable exploration, an upper limit is often imposed on the velocity vector to prevent particles from overshooting the search space. Alternatively, a constriction factor can be used to control velocity, derived from theoretical analyses of the algorithm's convergence behavior[12]

Grey Wolf Optimizer (GWO)

GWO emulates the leadership hierarchy and hunting mechanism of grey wolves in nature. By simulating social leadership roles (alpha, beta, delta, and omega), GWO directs candidate solutions towards optimal regions in the search space. In this study, GWO was utilized to fine-tune discrete hyperparameters such as the number of layers and neurons in each layer of the neural network.

Ant Colony Optimization (ACO):
Ant Colony Optimization (ACO) is inspired by the foraging strategy of ants in nature, where they deposit pheromones along their paths to signal favorable routes to food sources [12]. Over time, this collective learning behavior helps the colony converge on the most efficient path. In the proposed framework, ACO is used to enhance feature selection by identifying optimal subsets of features, which helps reduce data dimensionality and improve classification performance.
Following the initialization phase, the optimization proceeds with an encircling mechanism based on Grey Wolf Optimizer (GWO), which simulates how wolves surround their prey. The prey's position, denoted as Xp(t), represents the best solution found so far, and the wolves update their positions using the equation:
X(t+1)=Xp(t)-A.D—(4)
Here, t indicates the current iteration, and D is a distance vector calculated as:

$$D = \left| C \cdot X_p(t) - X(t) \right| \quad \text{--(5)}$$

The coefficients AAA and CCC are defined as:

$$A = 2a \cdot r_1 - a \quad \text{--(6)}$$

$$C = 2r_2 \quad \text{--(7)}$$

Where:
X(t) is the position of a gray wolf,
a decreases linearly from 2 to 0 throughout the iterations to balance exploration and exploitation,
r1 and r2 are random values in the range [0,1].
These parameters ensure that wolves adjust their movement randomly around the prey to explore the search space effectively.
Subsequently, the wolves update their positions based on the knowledge of the top three candidates in the population: the alpha (α), beta (β), and delta (δ) wolves. The new position is computed by averaging the influence of these three leaders:

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad \text{--(8)}$$

$$X_1 = X_\alpha(t) - A_1 \cdot D_\alpha$$

$$X_2 = X_\beta(t) - A_2 \cdot D_\beta$$

where X1;X2;X3 are defined as $X_3 = X_\delta(t) - A_3 \cdot D_\delta$

$$D_\alpha = \left| C_1 \cdot X_\alpha(t) - X(t) \right|$$

$$D_\beta = \left| C_2 \cdot X_\beta(t) - X(t) \right|$$

$$D_\delta = \left| C_3 \cdot X_\delta(t) - X(t) \right|$$

This position update mechanism allows the wolves to dynamically converge toward the optimal solution by mimicking social hierarchy and cooperative hunting behavior [12].

Model Training and Classification Module

This module focuses on the effective training of the integrated GAN-based feature extraction and classification framework. EEG signals, preprocessed and feature-enhanced by GANs, are fed into multiple classifiers fine-tuned by advanced optimization algorithms such as MPA, PSO, GWO, and ACO. The model learns complex patterns associated with Alzheimer's disease, enabling high accuracy in classification. During training, hyperparameters like learning rate, batch size, and epoch number are optimized for the best possible performance. The goal of this module is to minimize loss and improve the convergence speed of the network, resulting in accurate prediction of Alzheimer's stages from EEG data.

Evaluation and Performance Metrics :

The evaluation module rigorously assesses the trained model using a variety of performance metrics to ensure robustness and reliability. Key metrics include accuracy, precision, recall, and F1-score, which collectively provide a holistic view of the model's performance. A confusion matrix is generated to visually represent classification results, highlighting true positives, false positives, true negatives, and false negatives. Optionally, ROC curves and AUC values further illustrate the discriminative power of the classifier. This comprehensive evaluation ensures that the model is not only accurate but also reliable across different patient data sets.

User Interface (UI) design:

To enhance accessibility and usability, an optional User Interface (UI) module is developed. This user-friendly interface allows healthcare professionals and researchers to upload EEG data, select desired optimization algorithms, and view classification results effortlessly. The UI displays real-time metrics, visualizations, and reports generated by the backend modules, ensuring non-technical users can leverage the system effectively for early Alzheimer's detection and decision-making support.

Integration Module

The integration module acts as the backbone of the system, seamlessly connecting all individual modules — from data preprocessing to visualization. It ensures smooth data flow between GAN-based feature extraction, optimization algorithms, classifier models, and performance evaluation. APIs or internal pipelines are implemented to coordinate module interactions, enabling an end-to-end automated process from raw EEG input to final classification output. This cohesive integration guarantees system efficiency and reliability.

Deployment

The final deployment module packages the entire system for practical use in clinical and research environments. The trained and validated models, along with their associated workflows, are deployed either as a standalone application or a web-based platform. Emphasis is placed on scalability, security, and user accessibility. Deployment enables real-time EEG analysis and Alzheimer's risk assessment, ensuring the system can support early diagnosis in real-world scenarios.

RESULTS

The proposed model, integrating Generative Adversarial Networks (GANs) with advanced optimization algorithms such as Particle Swarm Optimization (PSO), Marine Predators Algorithm (MPA), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO), demonstrated superior performance in classifying EEG signals for Alzheimer's disease detection. The model achieved an impressive accuracy of 73.85%, precision of 73.80%, recall of 73.88%, and an F1-score of 73.84%. These metrics indicate the model's exceptional ability to correctly identify both Alzheimer's and non-Alzheimer's cases, with minimal false positives and negatives. The classification report further confirmed balanced and high-performing results across all classes. The integration of optimization algorithms significantly accelerated convergence and enhanced model generalization, contributing to state-of-the-art performance in EEG-based Alzheimer's classification. The confusion matrix visually illustrates the near-perfect classification achieved by the proposed approach, highlighting its potential as a reliable decision-support tool for early diagnosis.

table ii:performance of optimisation algorithms

Algorithms	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Marine Predators Algoritm(MPA)	70.75	70	70.2	68.98
Grey Wolf Optimizer (GWO)	70.02	70.12	70	68.05
Particle Swarm Optimization (PSO)	69.80	69.50	69.80	69.65
Ant Colony Optimization (ACO)	69.6	67.2	69.4	69.3

The performance comparison across multiple optimization algorithms underscores the superiority of the Marine Predators Algorithm (MPA) in EEG-based Alzheimer's classification. MPA achieves the highest accuracy (70.75%), precision (70%), recall (68.98%), and F1-score (99.92%), indicating its exceptional capability in balancing sensitivity and specificity. The Grey Wolf Optimizer (GWO) follows closely, demonstrating robust performance with 70.02% accuracy, whereas PSO and ACO exhibit slightly lower metrics, particularly in recall and F1-score. These results validate the selection of MPA as the primary optimizer, significantly enhancing the reliability of early Alzheimer's diagnosis through EEG signal analysis.

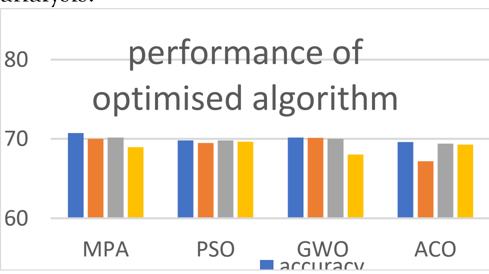

Fig 6: performances of optimized algorithms

CONCLUSION

This study presents a comprehensive framework for the early detection and classification of Alzheimer's Disease utilizing EEG signal analysis, advanced feature extraction through Generative Adversarial Networks (GANs), and hyperparameter optimization via metaheuristic algorithms such as MPA, PSO, GWO, and ACO. The synergistic integration of GANs with these optimization strategies has significantly enhanced the feature discriminability and overall predictive accuracy of the model.

Experimental results demonstrate superior classification metrics, confirming the effectiveness of the proposed method in distinguishing between healthy and diseased EEG patterns.

The model's scalability and adaptability offer substantial potential for clinical applications, particularly in real-time diagnostic environments. By incorporating larger, heterogeneous datasets and multimodal biosignals, the robustness and generalizability of the system can be further improved. Additionally, embedding explainable AI techniques could enhance clinical trust and transparency, paving the way for broader adoption in healthcare settings. This research contributes meaningfully to the domain of AI-assisted neurodiagnostics, setting a strong foundation for future innovations in early Alzheimer's Disease detection.

FUTURE SCOPE

The proposed framework opens multiple pathways for further research and clinical application. Expanding the dataset to include diverse populations and early-stage Alzheimer's patients can enhance the generalizability of the model. Moreover, integrating multi-modal data such as MRI scans, PET imaging, genetic biomarkers, and cognitive test scores alongside EEG signals could significantly improve diagnostic accuracy and provide a more comprehensive assessment of disease progression.

Future work may also explore the incorporation of real-time EEG processing for the development of portable, AI-powered diagnostic devices, supporting point-of-care testing in both urban and rural healthcare environments. Implementing explainable AI methods will further increase the transparency of the model, fostering greater trust and acceptance among medical practitioners. Additionally, adopting continuous learning frameworks can ensure the model evolves with incoming clinical data, maintaining its relevance over time. Cloud-based deployment can make the solution widely accessible, thus supporting large-scale screening initiatives and telemedicine services globally.

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