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# Deep generative adversarial networks with marine predators algorithm for classification of Alzheimer's disease using electroencephalogram

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A R T I C L E  I N F O

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A B S T R A C T

Alzheimer's disease (AD) is a neurological disorder characterized by cognitive decline and memory loss. An early and precise diagnosis of Alzheimer's disease is critical for effective therapy and management. The electroencephalogram (EEG) has shown promise as a non-invasive and cost-effective tool for Alzheimer's disease (AD) categorization. The capacity to diagnose Alzheimer's disease at an early stage is one of the benefits of EEG (electroencephalogram) over other methodologies in Alzheimer's disease research. Traditional EEG analysis approaches, such as estimating coherence between various pairs of electrodes, necessitate a significant amount of human labor. We introduce a novel strategy for AD classification based on EEG by combining deep generative adversarial networks (GANs) and the Marine Predators Algorithm (MPA). GANs are powerful deep-learning models that can be trained to generate realistic samples via negative generator and discriminator training. MPA is a nature-inspired optimization method well-known for its ability to solve complicated optimization problems. The proposed system generates synthetic EEG samples using GANs' ability to learn meaningful representations from raw EEG data. The MPA is then employed to enhance classification performance by optimizing the discriminative features extracted by GANs. The MPA simulates the hunting behavior of marine predators, facilitating the exploration of the feature space and identifying significant characteristics for AD categorization. We evaluated the efficacy of the proposed strategy using a publicly accessible EEG database of AD patients and healthy controls. The results of classification precision, sensitivity, and specificity demonstrate that deep GANs with MPA are superior to state-of-the-art techniques.

## 1. Introduction

The most prevalent type of dementia, Alzheimer's disease, is a severe public health issue today. More than 1 % of people worldwide are predicted to develop Alzheimer's disease or a condition comparable to it by the year 2050, prompting the need for comprehensive care for a sizable portion of this population. Although Alzheimer's disease typically manifests as a chronic neurodegenerative condition in middle-to-old age, early-onset Alzheimer's disease can occasionally strike persons between the ages of 45 and 64. Memory loss, language problems, cognitive and judgment impairment, and other cognitive decline symptoms are signs of Alzheimer's. Depending on the stage at which a patient's sickness progresses, a symptomatic person may need light to ongoing assistance with daily activities. These symptoms negatively impact patients' quality of life (QOL) and their families. According to studies on the expense of Alzheimer's and dementia, the growing need for aged care is leading to a significant rise in overall social and economic stress. Dementia and Alzheimer's disease significantly decrease both patients' and their families' overall quality of life. Patients experience cognitive decline, loss of self-sufficiency, communication difficulties, challenging behaviors, and social isolation. Families, who often provide care for others, deal with mental stress, financial pressure, time limits, social isolation, and the emotional disruption of seeing their loved ones' health deteriorating. Seeking assistance and preparation

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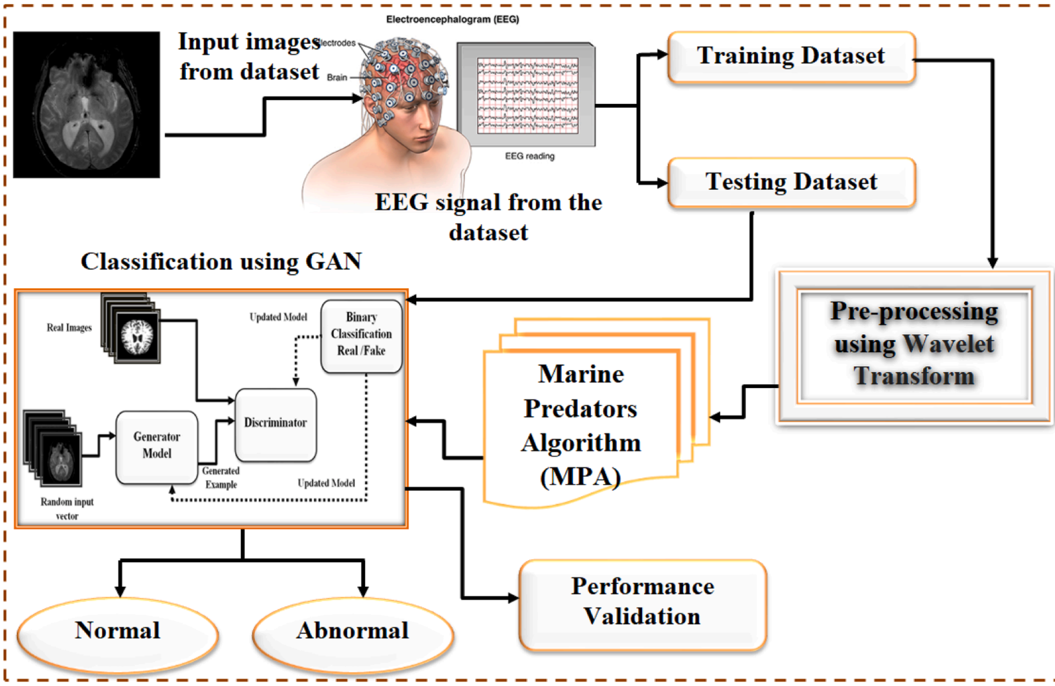


**Fig. 1.** Proposed model of GAN - MPA method.

**Table 1**
Dataset coherence.

| Class label | Class ID | Number of subjects | Number of observations |
|---|---|---|---|
| AD | 1 | 7 | 154 |
| HS | 2 | 6 | 129 |
| Total | | 13 | 283 |

ahead of time may help minimize these issues and improve the general well-being of the individuals.

A neurological condition known as Alzheimer's disease (AD) is considered by forgetting and diminished analytical skills (Metz and Pavlov, 2021). This is mainly caused by an unusual rise in the protein surrounding brain cells. A common misconception about AD is that it is an inevitable part of aging that disproportionately affects older individuals. Alzheimer's disease risk is affected by several variables, including genetics, lifestyle choices, and underlying medical disorders, in addition to age. While age is a major risk factor, other variables such as family history, smoking, and certain medical problems also play a role. Most Alzheimer's instances occur in persons 65 and older, although the disease's effect on mortality is greater in those 85 and older. Meantime, Alzheimer's disease is not a natural component of the aging process. While certain changes to the brain are unavoidable as age, substantial memory difficulties are not. Alzheimer's disease, according to scientists, is caused by a combination of hereditary, behavioral, and environmental factors that damage the brain over time. The impact of these variables in raising or lowering the chance of acquiring Alzheimer's disease varies by individual (Martınez-Negro et al., 2021). Alzheimer's disease symptoms in people include worsening confusion and a loss of memory and learning abilities. AD can be broadly categorized into three stages based on its symptoms and indications. The most prevalent symptom of mild Alzheimer's disease (AD) is amnesia, which does not significantly affect daily life. During this phase, the sufferer becomes more dependent on others (Ferrari et al., 2021). The severe third phase of Alzheimer's disease renders the patient helpless (Nguyen et al., 2021). Early detection is crucial in situations with mild and severe Alzheimer's disease (Toe et al., 2021). Identifying this signal processing technology, integrated into the digital device to quantity the spectrum of Alzheimer's disease severity, becomes especially difficult given that symptoms like amnesia are frequently considered as usual signs of aging. Additionally, support from imaging and artificial intelligence (AI). Numerous neural models and classifiers were created. Consequently, estimate the severity rate of AD in its early stages without using many resources (Jayamohan et al., 2021).

Diseases are often diagnosed through comprehensive testing and eliminating other disease incidences (Khurana et al., 2021). Alzheimer's disease can be analyzed using blood tests, physical and psychological evaluations, and neurological tests. Perform brain scans such as magnetic positron emission tomography (PET), resonance imaging (MRI), or confirm or computed tomography (CT) to rule out other possible causes of symptoms. To identify AD, visual approaches based on AI and psychological tests like the mini-mental state assessment have been developed (Zhao et al., 2021). However, they have certain drawbacks, such as an incorrect classification of diseases, a high mistake rate, and others. However, the researchers focused on AD diagnosis strategies based on EEG signal analysis. 10–20 electrode systems directly record the brain's reading using electrodes. Early identification and accurate disease classification are made possible by EEG-based AD diagnosis (Gao et al., 2021).

Recent studies on the early diagnosis of Alzheimer's disease have focused on changes in the synchronization of EEG signals (Geng et al., 2022). However, in a single synchrony, the diagnosis needs to be revised. Several brain samples are collected from a person to gauge the severity of Alzheimer's disease (AD) based on EEG signals (Guerrero et al., 2021). This has simplified forecasting how brain neurons respond to different behaviors and emotions. Many people use the EEG-based AD detection method to get an early diagnosis of AD. Our research offered a very effective and precise AD detection method based on EEG signals to address the flaws of existing approaches (Woodbridge et al., 2021). The best way for determining illness range has also been incorporated into a unique deep network. Additionally, the secret stages of the developed model run the noise removal function, which has increased the ability to watch for and ignore noise features. The classification score improved, and the algorithm's complexity was suggestively concentrated due to

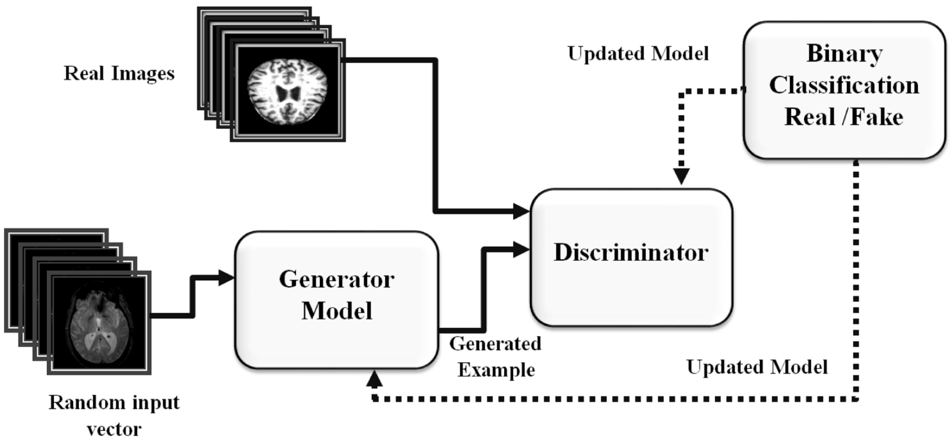


**Fig. 2.** Generative Adversarial Network general block diagram.

**Table 2**
Particulars of the execution settings.

| Parameter Specifications | |
|---|---|
| **Dataset type** | **Specifications** |
| Version R | 2020b |
| Operating system | Windows 10 |
| Programming language | MATLAB |
| Signal | AD Signal |
| Objective | Severity range prediction |
| Signal type | EEG |
| Total EEG signals | 11,500 |

**Table 3**
Precision Analysis of the GAN-MPA Technique Using Existing Systems.

| Number of data from the dataset | SCNN | KNN | LSTM | CNN | GAN-MPA |
|---|---|---|---|---|---|
| 100 | 73.78 | 84.98 | 79.12 | 89.45 | 92.67 |
| 200 | 74.11 | 85.12 | 80.45 | 89.13 | 93.21 |
| 300 | 76.34 | 86.45 | 81.34 | 90.56 | 94.19 |
| 400 | 77.34 | 87.56 | 82.34 | 91.45 | 95.78 |
| 500 | 78.55 | 88.34 | 83.67 | 91.87 | 96.19 |

the effective noise removal during the filtering stage. Finally, a comparative assessment (Murugan et al., 2021) was performed to ascertain the level of improvement across various AD severity levels.

However, re-identifying anonymized data in a large dataset becomes impossible due to its extreme complexity and laborious nature. This problem has a solution in the form of synthetic medical data production, viewed as applicable when actual data is challenging or expensive to obtain. For training, education, the creation of machine learning models, and software testing, synthetic data may be used independently or in combination with accurate data. Although many methods exist for creating artificial data, generative adversarial networks (GAN) are one of the best frameworks for creating fake medical data. Understanding physiological signals and creating synthetic biological signals requires much work and time. Each biomedical signal has a distinct morphology depending on the organ source, independent features, noise, electrode placement, and pathological events. Additionally, the quality of biological signals is diminished by external equipment, which causes too much noise to obscure them.

The proposed method has important implications for Alzheimer's disease diagnosis and tracking at an early stage. By adequately analyzing EEG data with Deep GANs and the MPA, clinicians and researchers can identify AD biomarkers and develop practical, time-sensitive intervention strategies. The model's ability to create synthetic EEG signals also allows for data augmentation, improving AD classification algorithms' resilience.

The Contribution of the paper is

- Using GANs' capacity to learn meaningful representations from raw EEG data, the proposed method generates synthetic EEG samples.
- Following that, the MPA is used to improve classification performance by optimizing the discriminative features extracted by GANs.
- The MPA simulates marine predator hunting behavior, allowing for easier exploration of the feature space and identification of significant traits for AD categorization.
- Using a publicly available EEG database of AD patients and healthy controls, we assessed the efficacy of the proposed method.
- The classification precision, sensitivity, and specificity findings show that deep GANs with MPA outperform state-of-the-art approaches.

The organization of the current study is as surveys. The existing works are discussed in great length in Section 2. Section 3 explores the suggested action plan and how the current issue will be solved. The conclusion drawn from the proposed model is further discussed in Section 4, and the research grounds are briefly summarized in Section 5.

## 2. Literature survey

Hajamohideen et al. (2023) suggested a triplet-loss function with a Siamese Convolutional Neural Network (SCNN) architecture to represent MRI images as k-dimensional embedding. The photos were mapped into the embedding space using pre-trained and untrained CNNs, respectively, by the researchers. A four-way classification strategy was used to diagnose Alzheimer's disease based on these embeddings. The proposed model was evaluated using the ADNI and OASIS datasets, with accuracy rates of 91.83 % and 93.85 %, respectively. These consequences indicated the model's potential as a classification tool for Alzheimer's disease.

The combination of Hjorth parameters with other frequently used features was emphasized to improve the accuracy of early-stage Alzheimer's disease (AD) detection from EEG data in a study by Safi and Safi (2021). The researchers also examined the effectiveness of several signal decomposition techniques, such as brain frequency band filtering, discrete wavelet transform (DWT), and empirical mode decomposition (EMD). The effectiveness of additional methods, including support vector machines (SVM), K-nearest neighbours (KNN), and regularized linear discriminant analyses (RLDA), was also assessed.

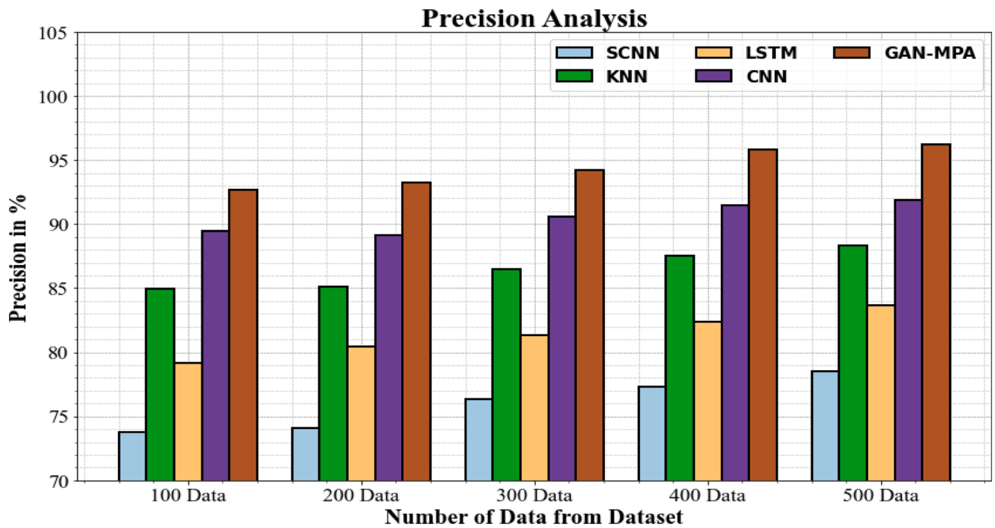


**Fig. 3.** Precision Analysis of the GAN-MPA Technique Using Existing Systems.

**Table 4**
Recall Analysis for the GAN-MPA approach using existing systems.

| Number of data from the dataset | SCNN | KNN | LSTM | CNN | GAN-MPA |
|---|---|---|---|---|---|
| 100 | 81.64 | 84.19 | 89.45 | 92.18 | 94.19 |
| 200 | 81.34 | 85.55 | 89.19 | 92.87 | 94.66 |
| 300 | 82.19 | 86.19 | 90.45 | 93.19 | 95.98 |
| 400 | 83.98 | 87.23 | 91.34 | 93.34 | 96.12 |
| 500 | 83.99 | 88.34 | 91.23 | 93.44 | 97.23 |

Including a novel deep feature is recommended to be the most efficient method for evaluating EEG data and determining the severity of Alzheimer's disease (AD) in Swarnalatha's study (Swarnalatha, 2023). A particular recurrent neural system (RNS) model has been explicitly created for forecasting AD severity, and the actions of voracious sandpipers inspired it. The severity levels are separated into three categories—low, medium, and high—and the data is correctly filtered—all to improve the predictability of results. Utilizing the filtered data, feature analysis—the suggested method's input—is then carried out. This method is implemented using the MATLAB system, and critical metrics, including precision, recall, specificity, accuracy, and misclassification score, are used to gauge how well the model works.

Zhou et al. study (Zhou et al., 2023) investigated the most recent developments in the field, including generative models, graph-neural networks, and recurrent neural networks. Classifying the fundamental kinds of unsupervised, supervised, and semi-supervised algorithms advanced for specific applications in this discipline was necessary. In addition, they offered a comprehensive analysis of the various data capture, cleaning, training, and grading strategies. This data offers crucial direction for further deep-learning studies on Alzheimer's illness. Despite achieving remarkable results in various study domains and applications, deep learning still needs to improve with interpretation and generalization.

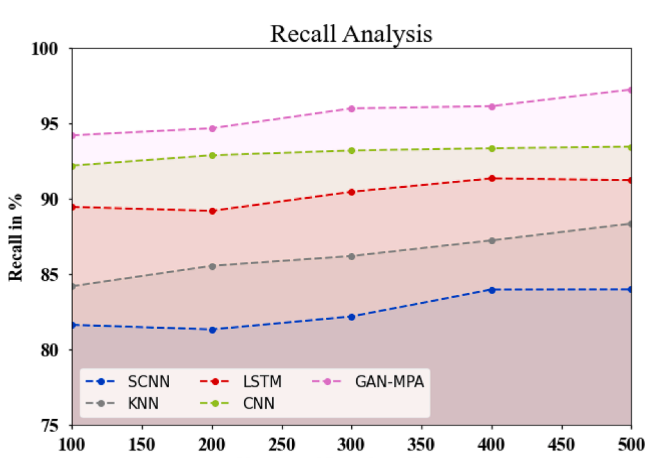


**Fig. 4.** Recall Analysis for the GAN-MPA approach using existing systems.

To accurately classify Alzheimer's disease, Chitra Devi and Prabha (2020) used a segmentation technique to partition the brain into different subregions. The segmented data is then supplied to machine learning classifiers to help them recognize Alzheimer's disease. The Grey-Wolf optimization technique achieved a 98 % success rate for this project. To make precise predictions about the course of illness, Ostertag et al. (2020) suggested using multi-modal data for training. Baseline and 12-month MRI images from the Alzheimer's Disease Neuroimaging Initiative dataset were used. This method has a remarkable accuracy rate of 92.5 %.

Using the ADNI dataset, Mehmood et al. (2021) suggested a transfer learning-based CNN classification method for identifying early Alzheimer's disease. With accuracy scores of 98.37 % and 83.72 %, respectively, the authors classified their 2-way classification (AD vs. CN and EMCI vs. LMCI) using this technique. The AlexNet model was suggested for extracting characteristics from brain MRI data in a study by Nawaz et al. (2021). Several methods were used to categorize the pictures, including Random Forest, Support Vector Machine, k-nearest Neighbor, and others. The proposed method produced findings for classifying Alzheimer's disease that were pretty accurate.

In their study, Arifa et al. (Shikalgar and Sonavane, 2020) outline a state-of-the-art hybrid technique for incorporating MRI and EEG recording data into a deep neural network. This strategy's core tenet is to train the classifier with multimodal data. Chitra Devi and Prabha (2020) proposed a technique for segmenting brain sub-regions in a separate study to enhance Alzheimer's disease categorization. With the segmented output and the Grey-Wolf optimization technique, machine learning classifiers can diagnose AD with an astounding 98 % accuracy.

Kelwin et al. (Fernandes et al., 2018) developed a deep Siamese learning model for cervical cancer diagnosis using a biopsy and other patient-specific medical data. Their method operated in a low-dimensional domain and intended to lessen data dimensionality. Their approach produced more accurate predictions compared to denoising autoencoders. The use of binocular fundus images to train conventional neural networks (CNN) in a Siamese-like form was also suggested by

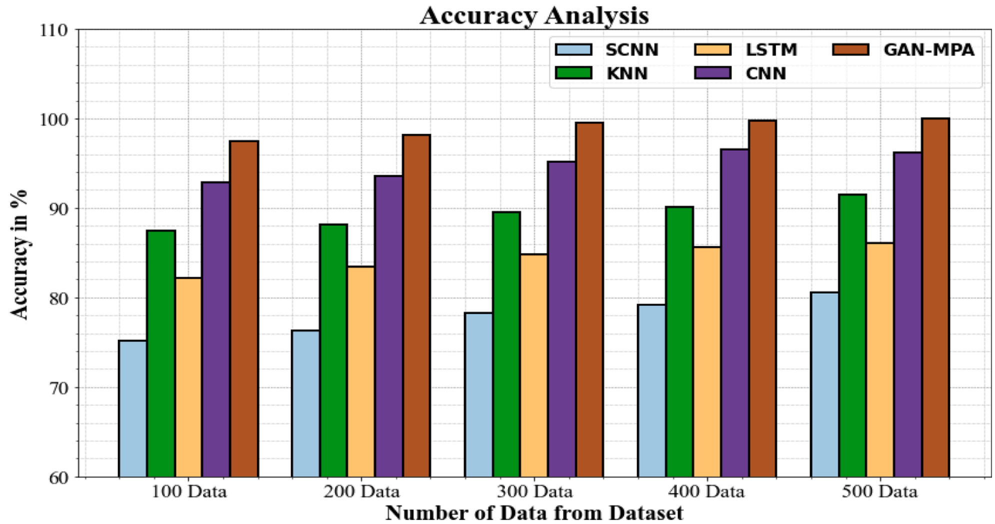


**Fig. 5.** Accuracy Analysis for GAN-MPA technique with existing systems.

**Table 5**
Analysis of GAN-MPA technique accuracy with existing systems.

| Number of data from the dataset | SCNN | KNN | LSTM | CNN | GAN-MPA |
|---|---|---|---|---|---|
| 100 | 75.16 | 87.45 | 82.19 | 92.87 | 97.45 |
| 200 | 76.34 | 88.12 | 83.45 | 93.56 | 98.13 |
| 300 | 78.23 | 89.56 | 84.78 | 95.19 | 99.56 |
| 400 | 79.14 | 90.13 | 85.67 | 96.56 | 99.78 |
| 500 | 80.56 | 91.45 | 86.11 | 96.19 | 99.96 |

Xianglong et al. (Zeng et al., 2019). By achieving an improved area under the curve (AUC) accuracy of 0.951 instead of the present monocular model's 0.940, their method exceeded it.

The automated EEG-based AD detection method was introduced by Cassani et al. in their paper (Cassani et al., 2017). It is based on the automatic artifact removal algorithm with a low-density EEG setup. Next AAR, amplitude-modulation characteristics and standard EEG metrics like spectral power and coherence are calculated. The features that have been gathered are categorized using an SVM. The most fantastic accuracy of the proposed diagnostic system was 91.4 %.

By examining resting-state EEG waves, Xia et al. (2023) suggested a novel method to recognize Alzheimer's disease (AD) in their work. They wanted to differentiate between those with AD, people with healthy controls (HC), and mild cognitive impairment (MCI). The initial dataset they employed, which included one-dimensional EEG data collected from 100 patients, comprising 49 patients with AD, 37 patients with MCI, and 14 persons with HC, had some drawbacks. The deep learning models utilized in the study had overfitting issues. The researchers investigated the usage of overlapping sliding windows to enhance the dataset to overcome these issues. The improved EEG data was categorized using the revised Deep Pyramid Convolutional Neural Network (DPCNN). After five 5-fold cross-validations were accepted, a confusion matrix was created to evaluate the model's performance.

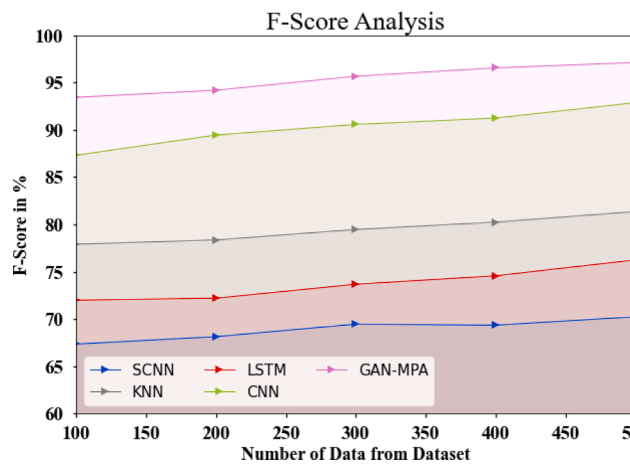


**Fig. 6.** F-Score Analysis for GAN-MPA technique with existing systems.

### 2.1. Limitations of existing system

- Various factors, such as arousal level, drugs, and other underlying medical disorders, influence EEG signals. Because of this lack of specificity, it is challenging to assign EEG patterns purely to Alzheimer's disease. Similar EEG patterns could exist in various neurological illnesses or healthy people.
- Analyzing and interpreting EEG data for Alzheimer's disease classification necessitates experience and specific knowledge. EEG pattern interpretation can be subjective and vulnerable to inter-rater variability, making developing a consistent and effective diagnostic tool challenging.
- EEG provides data on brain electrical activity but lacks precise spatial precision. It measures the summed electrical activity of enormous populations of neurons, making it difficult to pinpoint the source of Alzheimer's disease-related anomalies. This constraint makes it difficult to identify specific brain regions affected by the condition.
- Standardized procedures for collecting, processing, and interpreting EEG data are not yet available in Alzheimer's disease research. This results in methodological differences across studies, making it difficult to compare and combine results from different study organizations. The need for established standards complicates the creation of practical and globally applicable categorization models.

### 2.2. Problem identification of existing system

- The absence of standardized data collection and analysis methods is another challenge in the organization of Alzheimer's disease using EEG. Standardized guidelines are required for electrode location, recording duration, and pre-processing techniques. It isn't easy to compare results across studies and build a meaningful classification framework without defined procedures.

**Table 6**
F-Score Analysis for GAN-MPA technique with existing systems.

| Number of data from the dataset | SCNN | KNN | LSTM | CNN | GAN-MPA |
|---|---|---|---|---|---|
| 100 | 67.34 | 77.89 | 71.98 | 87.31 | 93.44 |
| 200 | 68.12 | 78.34 | 72.19 | 89.45 | 94.18 |
| 300 | 69.45 | 79.45 | 73.67 | 90.56 | 95.67 |
| 400 | 69.34 | 80.23 | 74.55 | 91.23 | 96.55 |
| 500 | 70.23 | 81.34 | 76.23 | 92.87 | 97.12 |

- Accurate classification models require vast, diverse datasets with correctly annotated EEG recordings. However, such datasets for Alzheimer's disease classification are in short supply. Due to privacy and ethical problems, obtaining EEG data from patients with established Alzheimer's disease, healthy controls, and pertinent clinical information can be difficult. The need for annotated datasets makes creating and validating robust classification algorithms difficult.
- EEG signals can vary significantly between people and even within the same individual over time. Because of this inter- and intra-subject variability, it is challenging to develop broad categorization models for Alzheimer's disease using EEG. The classification algorithms must account for these variations, which must be robust enough to manage individual differences while maintaining high accuracy and dependability.
- Integrating EEG data with other modalities such as neuroimaging (e.g., MRI or PET scans) or clinical assessments may be advantageous in improving the accuracy of Alzheimer's disease categorization. However, effectively fusing multimodal data and extracting complementing information poses additional challenges for feature selection, model integration, and data fusion.

## 3. Proposed system

This section suggests a brand-new method for categorizing AD using EEG. GANs are powerful deep-learning models that can train a generator and a discriminator in an adversarial fashion to produce realistic examples. The MPA optimization algorithm, which draws inspiration from nature, is well known for its ability to solve challenging optimization issues. It is based on how predatory sea animal's forage. The proposed system generates synthetic EEG samples using GANs' ability to learn meaningful representations from raw EEG data. GAN-generated synthetic EEG samples provide significant benefits in neuroscience and related fields. They supplement limited EEG datasets, maintain privacy, allow algorithm testing, and assist in training and education. These synthetic samples can be designed to simulate specific EEG features and correct data imbalances. They also make cross-modality research, hypothesis testing, and benchmarking of EEG analysis techniques possible, while potentially reducing data collection costs. The MPA is then employed to enhance classification performance by optimizing the discriminative features extracted by GANs. The MPA simulates the hunting behavior of marine predators, facilitating the exploration of the feature space and identifying significant characteristics for AD categorization. The GAN-MPA (Generative Adversarial Network for Multi-Modal Pattern Analysis) approach for Alzheimer's disease classification presents several challenges when compared to other methods. These include difficulties in obtaining diverse multi-modal data, high computational demands, complex model structures, the risk of mode collapse limiting data representation, potential overfitting, limited interpretability, ethical concerns around data privacy, the need for rigorous validation across different populations, and a lack of standardized benchmarks and metrics for performance evaluation. Fig. 1 displays the Block diagram of the GAN-MPA method.

### 3.1. Dataset

Both persons with Alzheimer's disease and those in good health can benefit from understanding the electroencephalographic signals used in this investigation. The signs were obtained in the "raw" data forms of European data format (EDF) (Biagetti et al., 2021), DAT, and GNT from an unnamed source. The information was then split into two folders with names that mirrored the two distinct classes, i.e.

- AD: employing the EEG information gathered from AD-diagnosed individuals.
- HS: made up of EEG data taken from healthy individuals.

Thirteen patients were involved in the study, 7 of whom were in the AD class and the other six in the HS class. Each subject's continuous EEG signals were captured between 21 and 23 times, totalling 283 observations. Table 1 displays the number of available words for each class. Each statement has had its length reduced to 148,096 samples (predictors) at a sampling rate of 128 Hz to maintain consistency. Several different formats were considered for the data before settling on the EDF format. Then it was converted to MAT format. EEG data is typically converted from EDF to MAT format to ensure seamless compatibility with MATLAB, a widely used software for EEG analysis. Through MATLAB's extensive capabilities and specialized toolboxes, the MAT format streamlines data manipulation, supports integration with other

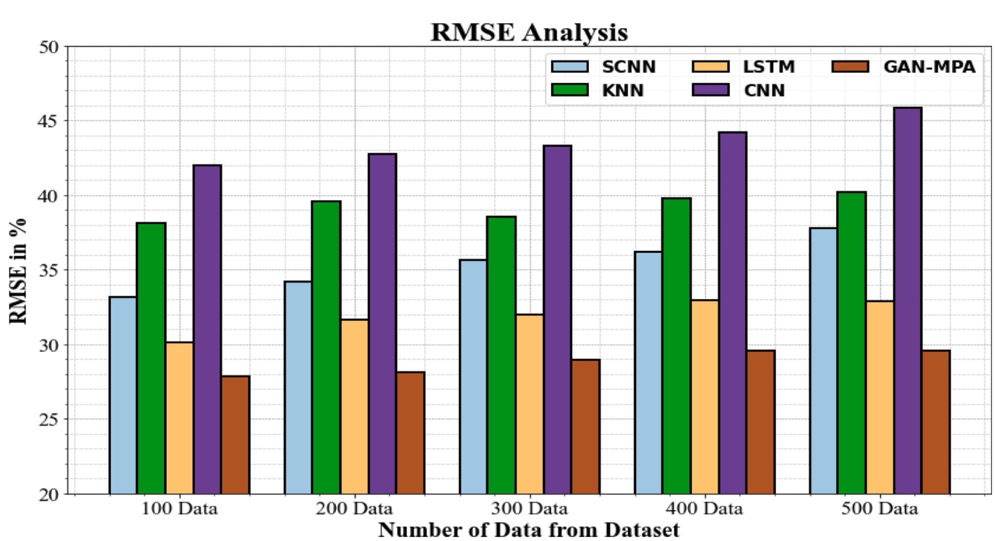


**Fig. 7.** RMSE Analysis of the GAN-MPA Technique Using Existing Systems.

**Table 7**
RMSE Analysis of the GAN-MPA Technique Using Existing Systems.

| Number of data from the dataset | SCNN | KNN | LSTM | CNN | GAN-MPA |
|---|---|---|---|---|---|
| 100 | 33.17 | 38.12 | 30.13 | 41.98 | 27.87 |
| 200 | 34.19 | 39.56 | 31.65 | 42.76 | 28.13 |
| 300 | 35.67 | 38.56 | 31.98 | 43.33 | 28.98 |
| 400 | 36.19 | 39.77 | 32.98 | 44.19 | 29.56 |
| 500 | 37.77 | 40.21 | 32.87 | 45.88 | 29.55 |

data types, simplifies custom analysis, and provides convenient visualization and collaboration tools. It also provides efficient data storage, facilitates metadata organization, and allows for simple data export to other formats, making it a versatile option for researchers working with EEG data. There were 13 matrices of varied sizes due to this method being applied to every subject for both semesters.

The MATLAB scientific computer environment (Matrix Laboratory) was used for the data conversion, feature extraction-based data matrix building, and classification processes. The edfbrowser1 tool was used to get a more accurate depiction of the EEG traces for each subject. Specifically, files with the correct extension can be opened by this software. A free and open-source reader and toolkit, edfbrowser1, is available everywhere. EEG, EMG, ECG, and Bio-Impedance are just a few file types that can have time-series data from which it is designed to analyze. The time scale was compressed by the software to match the length of the recording interval, and the amplitude was changed to fit within the window's boundaries. In MATLAB, techniques such as interpolation, resampling, and time warping can be used to control the time scale of recorded data to match a specified recording interval. Load the data first, then specify the desired time scale and select the appropriate time scaling method: interpolation keeps the original data points, resampling changes the sampling rate and time warping provides nonlinear scaling. Next, apply the selected method to the data, and then visualize and analyze the results to ensure that they are in line with the intended recording interval. As a result, it could show 21–23 traces from each patient within a single window, with each fraction lasting, on average, 24 min and, at the very least 19 min.

### 3.2. Data pre-processing

In addition to artifacts from the equipment and other sources, such as muscular movement, EEG readings also contain electrical activity from the brain (Shoka et al., 2019; Kim, 2018). It is essential to prepare the signals before evaluating them as a result. The most often used technique for excluding undesired information from specific EEG frequencies is digital filtering. Digital filtering is an important step in EEG data analysis because it allows the extraction or exclusion of specific frequency components. It involves collecting EEG data, converting it into discrete samples, analyzing its frequency content, designing filters (e.g., low-pass, high-pass, band-pass, or band-stop), applying these filters to the data, adjusting filter parameters and interpreting the filtered EEG data for research or clinical purposes. This process improves EEG data quality by isolating relevant brainwave patterns while reducing unwanted noise and frequencies, resulting in more accurate and meaningful insights (Bansal and Mahajan, 2019). After establishing the signal's spectrum, the Discrete Fourier Transform (DFT) is a valuable technique for creating digital filters. The intensity of each frequency band is shown together with the frequency domain reflection of the original signal in the spectrum. The Inverse Fourier Transform can eliminate a particular frequency band's effect on spectra and bring them back into the time domain. The inverse Fourier Transform is the method of transforming a signal from the frequency domain to the time domain that is the inverse of the Fourier Transform. It extracts the original signal from its frequency spectrum. It is important in many signal-processing applications. To filter a frequency domain signal, first calculate the DFT of the input, multiply the result by the sampled frequency response, and then compute the inverse DFT of the product. When dealing with non-stationary signals like the EEG, the DFT has drawbacks. The Discrete Fourier Transform (DFT) has limitations in analyzing non-stationary signals due to fixed time and frequency resolution, poor time localization, and over-representation of high frequencies. Wavelet transforms, such as the Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT), address these limitations by delivering variable time and frequency resolution, improved time localization, multiresolution analysis, and reduced computational complexity, making them more appropriate for non-stationary signal analysis. When statistics like mean, variance, and covariance are tracked over time within a sample of the input data, they remain constant in stationary signals. The use of DFT has been made possible by the development of wavelets. Wavelets are mathematical techniques that use convolutional operations to divide a call into several time–frequency scales. In EEG data analysis, the wavelet selection and signal decomposition processes are critical factors influencing the accuracy and fidelity of results. Selecting the appropriate wavelet, by considering its frequency and time characteristics, and adjusting its parameters to match the EEG signal can improve accuracy. The decomposition method used, such as wavelet transform or ICA, also affects the results, with factors such as artifact removal and data interpretation being critical. Proper consideration and sensitivity analysis are required to produce meaningful results from the analysis of EEG data without misunderstanding or distortion of neural activity data. Coefficients that preserve signal information are obtained by using wavelets for signal decomposition. The signal can then be recreated using these coefficients and the inverse operation. For signal analysis, wavelets have advantages over methods such as the Discrete Fourier Transform (DFT) provide time and frequency localization, signal change adaptability, efficient handling of sparse signals, and control over time and frequency trade-offs. Wavelets are especially useful for non-stationary signals because they eliminate edge effects and provide clear time-domain interpretations. Image processing, denoising, compression, and biomedical signal analysis are among their applications.

**Table 8**
Analysis of the GAN-MPA technique's execution time with existing systems.

| Number of data from the dataset | SCNN | KNN | LSTM | CNN | GAN-MPA |
|---|---|---|---|---|---|
| 100 | 11.672 | 9.114 | 7.765 | 4.198 | 1.543 |
| 200 | 12.442 | 9.346 | 7.345 | 4.567 | 1.876 |
| 300 | 12.876 | 10.456 | 8.119 | 5.987 | 2.567 |
| 400 | 12.554 | 10.677 | 8.678 | 6.345 | 2.689 |
| 500 | 13.335 | 11.673 | 8.654 | 6.117 | 3.765 |

Many experts consider the segmentation of various EEG components helpful since each identified EEG rhythm is linked to distinct phases of the brain and may be utilized to examine how medicines, stimuli, and illnesses alter neuronal dynamics (Sharma et al., 2020). Previous research has shown that individuals with Alzheimer's disease have greater levels of low-frequency activity and decreased levels of high-frequency activity. The researchers extracted the beta (15–30 Hz), alpha (8–15 Hz), theta (4–8 Hz), and delta (0–4 Hz) frequency bands from the EEG signals for analysis. This was done using the Daubechies-4 wavelet transform approach. The Daubechies wavelet transform is a discrete wavelet transform defined by computing running averages and differences with scalar products and wavelets. The Daubechies wavelets are a type of orthogonal wavelet with compact support and approximate wavelet expansion properties. They can be identified by the maximum number of vanishing moments for a given support. It is crucial to emphasize that during the pre-processing stage of this inquiry, the Wavelet Transform was the only approach employed. The Wavelet Transform approach is used in various applications during the pre-processing stage because it provides multiresolution analysis, supports feature extraction, enables data compression, helps in denoising,

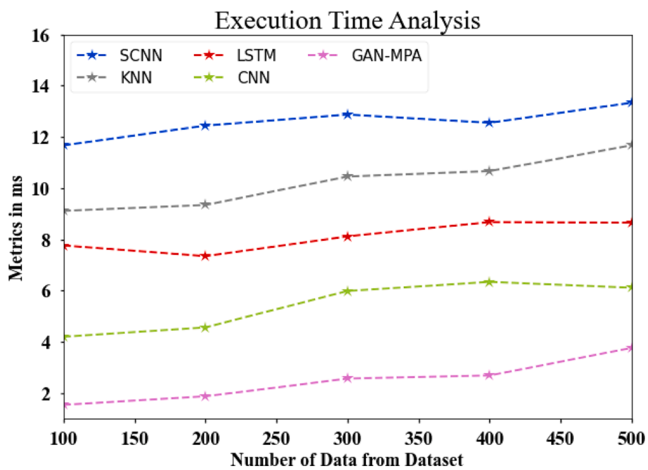


**Fig. 8.** Analysis of GAN-MPA technique execution time with existing systems.


**Fig. 10.** Model loss Analysis for the GAN-MPA technique.

supports anomaly detection, provides time–frequency analysis, and is useful in image processing, biomedical signal analysis, and more. It improves data features, reduces noise, and prepares data for subsequent analysis or compression, making it a versatile and powerful data processing and analysis tool.

### *3.3. Marine predators algorithm (MPA)*

In (Faramarzi et al., 2020), the MPA was first implemented. The movements of biological ocean predators stimulated it. The Marine Predators Algorithm (MPA) is a nature-inspired optimization algorithm that follows the criteria that naturally regulate optimum foraging strategy and experience rate policy in marine habitats.

The following are the primary MPA steps:

**Starting up the MPA:** Equation (1) illustrates the initialization phase of the MPA, like that of all population-based algorithms.

$$Y_0 = v + rand(l - v) \tag{1}$$

Where the lower and upper boundaries, respectively, are denoted by v and l. A random vector of the range [0, 1] is known by the term Rand. The Elite matrix E, as shown in Equation (2), is constructed using the best response, $Y_i$. The elite matrix has dimensions for a problem with n search agents and d total dimensions [n, d].

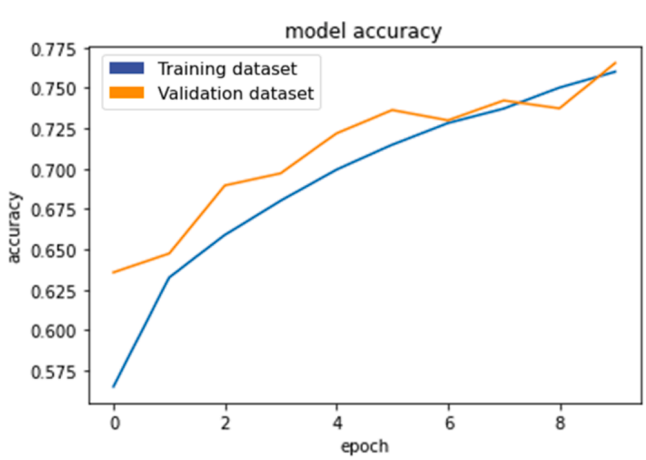


**Fig. 9.** Model Accuracy Analysis for GAN-MPA technique.

$$E = \begin{bmatrix} Y^I_{1,1} & Y^I_{1,2} & \cdots & Y^I_{1,d} \\ Y^I_{2,1} & Y^I_{2,2} & \cdots & Y^I_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ Y^I_{n,1} & Y^I_{n,2} & \cdots & Y^I_{n,d} \end{bmatrix}_{n \times d} \tag{2}$$

Equation (3) states that the Prey matrix P is constructed with the Elite matrix's dimensions in mind.

$$P = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,d} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ Y_{n,1} & Y_{n,2} & \cdots & Y_{n,d} \end{bmatrix}_{n \times d} \tag{3}$$

The MPA process divides the speed gap between a predator and its prey into three categories.

The predator's most excellent strategy is to stay still when it is faster than the prey (during the exploring phase). In the first third of iterations, exploration becomes increasingly essential. A step size produced using Equation (4) updates the prey's location.

$$\overrightarrow{stepsize_i} = \overrightarrow{Rn}_C \otimes \left( \overrightarrow{E_i} - \overrightarrow{Rn}_C \otimes \overrightarrow{P_i} \right), i = 1, 2, ...., n \tag{4}$$

Where $Rn_c$ is a vector of haphazard quantities. Equation (5) demonstrates how to update the new prey position.

$$\overrightarrow{P_i} = \overrightarrow{P_i} + 0.5.\overrightarrow{N} \otimes \overrightarrow{stepsize_i} \tag{5}$$

The vector N is arbitrarily chosen between [0, 1].

Exploration vs. Exploitation: Prey and Predator Moving at Equal Speeds.

Both the predator and the prey actively pursue their own goals when moving at the same speed. The early exploratory attempts briefly change into targeted exploitation efforts throughout this phase of the optimization procedure. It is an important stage for both extraction and exploration objectives. Therefore, exploration and extraction comprise half of the population (Ewees et al., 2022). During this time, the prey is responsible for carrying out the exploitation, while the predator guides the exploration. In optimization, the transition from exploratory to exploitation phases involves broad exploration of the solution space, evaluation of potential solutions, adaptation of the search based on learning, and shifting to targeted efforts once predefined performance thresholds or convergence criteria are met. During the exploitation phase, the emphasis shifts to promising regions for more precise optimization, intensifying efforts and iterating between exploration and exploitation as needed, with dynamic adjustments to prevent local optima. The objective of this strategic shift is to efficiently converge on optimal solutions. Equations (6) and (7) show the first half of the populations' new positions, showing support for exploitation.

$$\overrightarrow{stepsize_i} = \overrightarrow{Rn}_L \otimes \left(\overrightarrow{E_i} - \overrightarrow{Rn}_B \otimes \overrightarrow{\mathrm{P}_i}\right) i = 1, \ldots n/2 \tag{6}$$

$$\overrightarrow{\mathrm{P}_i} = \overrightarrow{\mathrm{P}_i} + 0.5.\overrightarrow{N} \otimes \overrightarrow{stepsize_i} \tag{7}$$

Equations (8) and (9) show the revised population placements for the second half, based on the vector $\mathrm{Rn}_\mathrm{L}$, which comprises random integers created by the Levy distribution. The goal of this change is to stimulate interest and encourage more research.

$$\overrightarrow{stepsize_i} = \overrightarrow{Rn}_B \otimes \left(\overrightarrow{Rn}_B \otimes \overrightarrow{E_i} - \overrightarrow{\mathrm{P}_i}\right) i = n/2, \ldots, n \tag{8}$$

$$\overrightarrow{\mathrm{P}_i} = \overrightarrow{E_i} + 0.5.\overrightarrow{B} \otimes \overrightarrow{stepsize_i} \tag{9}$$

Equation (10) was used as a reference to derive the control parameter B.

$$B = \left(1 - \frac{Iter}{MaxIter}\right)^{\left(2\frac{Iter}{MaxIter}\right)} \tag{10}$$

With incredible speed, the predator is outpacing its prey (exploitation).

This situation develops after the optimization process has been completed effectively and is frequently associated with a significant potential for exploitation. Equations (11) and (12) illustrate how the prey positions are updated.

$$\overrightarrow{stepsize_i} = \overrightarrow{Rn}_L \otimes \left(\overrightarrow{Rn}_L \otimes \overrightarrow{E_i} - \overrightarrow{\mathrm{P}_i}\right) i = 1, \ldots, n \tag{11}$$

$$\overrightarrow{\mathrm{P}_i} = \overrightarrow{E_i} + 0.5.\overrightarrow{B} \otimes \overrightarrow{stepsize_i} \tag{12}$$

Fish Aggregating Devices (FADs) have been proposed to continue the quest. Equation (13), a depiction of FADs mathematically, is provided. The MPA's pseudo code is displayed in Algorithm 1.

$$\overrightarrow{\mathrm{P}_i} = \begin{cases} \overrightarrow{\mathrm{P}_i} + CF\left[Y_{\min} + \overrightarrow{Rn} \otimes (\overline{Y}_{\max} - \overline{Y}_{\min})\right] \otimes \overrightarrow{V} \\ \quad if\ rn \leq FADs \\ \overrightarrow{\mathrm{P}_i} + [FADs(1 - rn) + rn](\overline{p1} - \overline{p_{r2}}) \\ \quad if\ rn > FADs \end{cases} \tag{13}$$

Algorithm 1 pseudocode for MPA

```
initialize populations. t=1.
while (t <= Tmax) do
Calculate the fitness and form the Elite matrix.
if t < Tmax/3 then
Update the prey position based on Equation (5) .
else if Tmax/3 < t < 2 * Tmax/3 then
For the first half of the populations, update prey position based on Equation (6).
For the other half, use Equation (7) to update the position.
else if t > 2 * Tmax/3 then
Update prey position using Equation (9).
end if
Apply memory saving and Elite update
Apply FAD effect using Equation (10)
Apply memory saving and Elite update
t = t + 1
end while
return the best position.
```

### 3.4. Image classification

Two alternative approaches—imaging-based or patient-based—can be used to classify images of Alzheimer's disease. On the one hand, an imaging-based strategy would only allow for collecting image data from a single Alzheimer's patient, which could then be utilized for training and testing. In Alzheimer's disease research, an imaging-based strategy involves gathering brain images from a single Alzheimer's patient to train and test machine-learning models for disease diagnosis. The collected data undergoes preprocessing and serves as the training set. The models learn patterns indicative of Alzheimer's and are evaluated on separate datasets. However, this approach has limitations due to the disease's variability among individuals, making larger and more diverse datasets essential for robust research. Classification of Alzheimer's disease using imaging techniques provides objectivity, early detection, and biomarker discovery, but they are expensive, expose users to radiation, and provide only a limited amount of functional data. Although patient-based assessments are less expensive, provide clinical insight, and allow for longitudinal tracking, they are subjective, detect symptoms later, and may not reveal underlying brain pathology. Combining the two approaches improves diagnosis accuracy and provides a more comprehensive understanding of the disease, improving both patients and healthcare providers.

#### 3.4.1. Deep generative adversarial networks

Two essential parts make up a Generative Adversarial Network (GAN): a Discriminator Neural Network (Dis) and a Generator Neural Network (Gen) (Goodfellow et al., 2014; Ali et al., 2023; Lakshmana Kumar et al., 2022). The discriminator in a GAN serves as an authority to distinguish between real and generated data. The generator and discriminator compete during the adversarial training process. The discriminator is required to maximize its accuracy in distinguishing between real and fake data, whereas the generator is required to generate data that manipulates the discriminator. Despite the generator's attempts to deceive it, the discriminator adapts to maintain its accuracy. The general layout of a GAN used to produce random images is shown in Fig. 2's diagram. Differentiating between images created by the generator (Gen) and actual photographs is the discriminator's job (Dis) job. On the other hand, the generator attempts to produce random images (Gen(n)) that closely resemble the real image dataset (y) by using random noise (n) as input. The discriminator determines the likelihood that a sample comes from the actual image collection instead of being created by the generator. As a result, the discriminator is taught to recognize and accept input from both created and authentic images.

When it believes a picture to be accurate, the discriminator will give a probability estimate of 1. When considering the image to be random, it will provide a probability estimate of 0. The discriminator's main goal is to maximize the number of correct classifications when faced with various input image types, even when the generator tries to trick it and lower its accuracy. As a result, both networks are competing against one another to see which is better at attaining their objective. As a result, the discriminator is taught to increase the likelihood that it correctly distinguishes between genuine and random images, while the generator is educated to reduce the possibility that the random images it generates will be mistaken for random images by the discriminator or to minimize $1 - Dis(Gen(z)$. Thus, both networks engage in a minimax game, which may be mathematically described as the following value function as shown in (14)

$$\min_{Gen}\max_{Dis} V(Dis, Gen) = F_{y\sim p_{data}(y)}[\log Dis(y)] + F_{n\sim p_n(n)}[\log(1 - Dis(Gen(z))] \tag{14}$$

Where $p_{data}(y)$ is the data distribution of real images (y) and $p_n(n)$ is the noise(n) distribution.

After completing the required training successfully, the creator can use noise signals n to generate random images that seem realistic and natural. This ability to discern between real photos and those affected by Alzheimer's disease will also noticeably improve.

## 4. Result and discussion

### 4.1. Experimental setup

On the Windows 10 platform, the MATLAB programming environment is utilized to run and process the model mentioned above. MATLAB is an ideal choice for classifying Alzheimer's Disease using Electroencephalogram (EEG) data due to its robust signal processing capabilities, specialized toolboxes, extensive machine learning and statistical functionalities, and strong support for data visualization. Its interactive nature, parallel computing capabilities, and integration options with other languages like Python make it a versatile environment for EEG data analysis. Windows 10 is a viable platform for EEG signal processing in MATLAB because it provides compatibility, usability, hardware options, and driver support. However, it has limitations, such as resource demands, occasional instability, costs, security risks, and limited customization when compared to Unix-based systems. The reference site's EEG signal for AD is first collected and used as the MATLAB system's input. Table 2 has a description of the parameters. The training-to-testing ratio for the EEG signal processing framework is 75:25, or 75 % for training and 25 % for testing. The severity classes considered include low, medium, and high. The k-nearest Neighbor (KNN) conventional neural networks and Siamese Convolutional Neural Networks are a few examples of current systems employed in this study. K-Nearest Neighbor (KNN) analysis is a critical tool in Alzheimer's disease diagnosis, allowing for the analysis of complex patient data and the identification of patterns that may assist in early detection and personalized risk assessment. Its accessibility and adaptability in integrating separate data sources make it useful for healthcare professionals. The ability of KNN to continuously learn from new data contributes to staying current on the latest research findings. However, it should be used in combination with other methods to overcome its limitations and improve Alzheimer's diagnosis accuracy, ultimately benefiting patient care and our understanding of the disease. Siamese Convolutional Neural Networks (Siamese CNNs) perform well in Alzheimer's disease diagnosis compared to traditional neural networks. They demonstrate remarkable performance when assessing collections of medical images, effectively managing limited labelled data, generating interpretable image embeddings, and adapting to evolving diagnostic criteria. Siamese CNNs are susceptible to image variations, effectively tackle class imbalance, and provide uncertainty estimates, thus holding significant promise for precise and dependable Alzheimer's disease diagnosis and monitoring.

### 4.2. Evaluation metrics

Patients who had Alzheimer's disease and were correctly diagnosed were classified as true positives (TPs). In contrast, those who did not have the condition were classified as true negatives (TNs), while those who did not have the infection were classified as false negatives (FNs), and those who did not have the disease were classified as false positives (FPs). The most dangerous projections in medicine end in a false negative. In medicine, a false negative occurs when a test incorrectly indicates that a patient is healthy or does not have a disease when they do. This is extremely concerning because it can result in missed diagnoses, delayed treatment, and even public health issues in the case of contagious diseases. Patients may experience emotional distress, and healthcare providers may face legal consequences. It also wastes resources and erodes trust in the healthcare system, making it a risky medical outcome. Accuracy was calculated using correctly detected occurrences (Acc). The formula for calculating accuracy was provided in

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{15}$$

Precision is instrumental when analysing a suggested Model utilizing expected and actual outcomes. It is a solid evaluation criterion for determining the percentage of expected positives that are positives. Precision largely relies on True Positives and False Positives values when calculating the count of accurately projected positives.

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

Another relevant evaluation indicator is recalled, representing the fraction of appropriately categorized positives. The TP and FP values are used to compute recall.

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{17}$$

A classifier that optimizes recall and precision is called F-Score. The F-score, which varies from zero to 1, represents measurements for precision and recall that are statistically significant.

$$F - Score = 2*\frac{precision*recall}{precision + recall} \tag{18}$$

The averaged error between the actual and anticipated data is squared using the Root-Mean square Error calculation (RMSE). An equation can be used to determine its value (19) Table 3.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(predicted_i - actual_i)^2}{n}} \tag{19}$$

#### 4.2.1. Precision analysis

In Fig. 3 and Table 3, the precision of GAN-MPA methodology is contrasted with that of other frequently employed techniques. The graph illustrates how the precision has risen with the deep learning approach. For example, the precision values for the SCNN, KNN, LSTM, and CNN models are 73.78 %, 84.98 %, 79.12 %, and 89.45 %, respectively, while the GAN-MPA model has a precision of 92.67 % for 100 data. In comparison to the SCNN, KNN, LSTM, and CNN models, which have precision values of 78.55 %, 88.34 %, 83.67 %, and 91.87 % respectively, the suggested GAN-MPA model has a precision of 96.19 % with 500 data Table 4.

#### 4.2.2. Recall analysis

In Fig. 4 and Table 4, the recall of the GAN-MPA technique is compared to that of other popular methods. The graph establishes how the deep learning method performs better in terms of recall. In comparison to the SCNN, KNN, LSTM, and CNN models, with recall values of 81.64 %, 84.19 %, 89.45 %, and 92.18 % for 100 data respectively, the GAN-MPA model has a recall value of 94.19 %. Consequently, the suggested GAN-MPA model has a recall value of 97.23 % for 500 data, which is higher than the recall values of the SCNN, KNN, LSTM, and CNN models, which are 83.99 %, 88.34 %, 91.23 %, and 93.44 %, respectively.

#### 4.2.3. Accuracy analysis

In Fig. 5 and Table 5, the accuracy of the GAN-MPA method is compared to that of other common methodologies. The graph shows how the deep learning technique has improved accuracy. For example, the GAN-MPA model has an accuracy of 97.45 % for 100 data, while the SCNN, KNN, LSTM, and CNN models have accuracy values of 75.16 %, 87.45 %, 82.19 %, and 92.87 %, respectively. Like this, the suggested GAN-MPA model has an accuracy of 99.96 % under 500 data, compared to 80.56 %, 91.45 %, 86.11 %, and 96.19 % for the SCNN, KNN, LSTM, and CNN models, respectively.

#### 4.2.4. F-score analysis

The f-score of the GAN-MPA approach is compared to that of other frequently used methods in Fig. 6 and Table 6. The graph demonstrates how the deep learning method performs better with the f-score. For instance, the f-score value for 100 data for the GAN-MPA model is 93.44 %, while it is 67.34 %, 77.89 %, 71.98 %, and 87.31 % for the SCNN, KNN, LSTM, and CNN models respectively. Like this, the suggested GAN-MPA model has an f-score value of 97.12 % under 500 data, compared to 70.23 %, 81.34 %, 76.23 %, and 92.87 % for the SCNN, KNN, LSTM, and CNN models, respectively.

#### 4.2.5. RMSE analysis

Fig. 7 and Table 7 displays an RMSE comparison of the GAN-MPA strategy with other well-known methods. The machine learning technique has an enhanced performance while reducing RMSE, as shown in the graph. For example, the GAN-MPA model's RMSE value for 100 data is 27.87 %, while the RMSE values for the SCNN, KNN, LSTM, and CNN models are 33.17 %, 38.12 %, 30.13 %, and 41.98 %, correspondingly. However, the GAN-MPA model has proven to perform well across various data sizes with low RMSE values. In a similar vein, for 500 data, the MSE value for the GAN-MPA is 29.55 %, whereas, for the SCNN, KNN, LSTM, and CNN models, it is 37.77 %, 40.21 %, 32.87 %, and 45.88 %, respectively Table 8.

#### 4.2.6. Execution time analysis

The execution times of the proposed GAN-MPA methodology and those of existing methods are contrasted in Table 8 and Fig. 8. The information unequivocally shows that the GAN-MPA approach has outperformed all the other methods. The suggested GAN-MPA approach, for example, took only 1.543 ms to execute 100 data, whereas other current methods such as SCNN, KNN, LSTM, and CNN methods have taken 11.672 ms, 9.114 ms, 7.765 ms, and 4.198 ms, respectively for execution. Similarly, the suggested GAN-MPA approach takes 3.765 ms to execute 500 data, while existing techniques like SCNN, KNN, LSTM, and CNN methods took 13.335 ms, 11.673 ms, 8.654 ms, and 6.117 ms, respectively as their execution time.

#### 4.2.7. Model accuracy analysis

Fig. 9 shows the model accuracy analysis of the GAN-MPA method. The GAN-MPA model uses a training dataset and a validation dataset. According to the data, the proposed GAN-MPA method outperformed the other techniques in every way with maximum accuracy.

#### 4.2.8. Model loss analysis

Fig. 10 shows the model loss analysis of the GAN-MPA method. The GAN-MPA model uses a training dataset and a validation dataset. According to the data, the proposed GAN-MPA method performed well with minimum loss.

## 5. Conclusion

Electroencephalogram (EEG) classification of Alzheimer's disease offers enormous potential as a non-invasive and economical technique for early disease identification and monitoring. EEG-based techniques have shown substantial promise in identifying people with Alzheimer's disease from those who are healthy or have other cognitive abnormalities. Researchers can uncover specific EEG biomarkers associated with Alzheimer's disease by studying the brain's electrical activity patterns, providing vital insights into the underlying neurophysiological alterations. While more research and validation are needed, EEG-based classification is a crucial tool in the fight against Alzheimer's, perhaps allowing for earlier therapies and better disease management. This research describes a novel EEG strategy for classifying Alzheimer's disease. GANs are powerful deep-learning models that can be trained to generate realistic samples via adversarial training of a generator and a discriminator. Complex optimization issues are well-suited for MPA, a well-known natural-inspired optimization method. Its basis is the imitation of the foraging techniques used by marine predators. The proposed system generates synthetic EEG samples using GANs' ability to learn meaningful representations from raw EEG data. The MPA is then employed to enhance classification performance by optimizing the discriminative features extracted by GANs. The MPA simulates the hunting behavior of marine predators, facilitating the exploration of the feature space and identifying significant characteristics for AD categorization. We evaluated the efficacy of the proposed strategy using a publicly accessible EEG database of AD patients and healthy controls. Model accuracy was measured against the datasets and found to be 99.96 %, respectively. Enhance the model's decision capacity to be understood and explained. Develop strategies for visualizing and comprehending the GAN model's learned properties and the significance of varied EEG patterns in Alzheimer's disease classification. Expanding the training and assessment dataset improves model generalizability and robustness. Larger and more diverse EEG datasets of Alzheimer's disease patients would help classify the disease. Integrating the proposed strategy into clinical practice would make a difference. This would require legal and ethical considerations, user-friendly interfaces, and compatibility with existing healthcare systems.

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## Code availability

Not applicable.

## Data availability statement

No datasets were generated or analyzed during the current study.

## Authors' contributions

All author is contributed to the design and methodology of this study, the assessment of the outcomes and the writing of the manuscript.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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