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REVIEW ARTICLE

Detection of brain disorders using artificial neural networks

Shaikh Abdul Hannan[1], Pushparaj[2,*], Mohammed Junaid Khan[3], Anil Kumar[4], Taranpreet Kaur[5]

[1] *Department of Computer Science and Information Technology, AlBaha University, AlBaha 65526, Kingdom of Saudi Arabia*

[2] *Department of Electronics and Communication Engineering, National Institute of Technical Teachers Training and Research, Chandigarh 160019, India*

[3] *Department of Electrical and Electronics Engineering, Mewat Engineering College (Waqf), Nuh 122107, Haryana, India*

[4] *Govt. Millennium Polytechnic, Chamba, H.P 176310, India*

[5] *P.G. Department of Computer Science Mata Gujri College, Fatehgarh Sahib, Punjab, 140406, India*

*** Corresponding author:** Pushparaj, pushprajpal@gmail.com

ABSTRACT

A utilitarian model of artificial neural networks (ANNs) is proposed in this paper to assist with existing determination procedures. In the space of radiology, cardiology, and oncology specifically, ANNs are as of now a "hot" concentrate on point in medication. The use of ANNs in the clinical field was endeavoured in this exploration. To distinguish and order the presence of brain cancers as per attractive reverberation (MR) imaging, a personal computer PC helped finding (computer aided design) framework utilizing ANNs was fabricated. This framework then distinguished which sort of ANNs and actuation capability for ANNs is great for picture acknowledgment. PCs and other generally open or made electronic contraptions assume a part in improving exhibition and bringing down intricacy in the division cycle. This study utilized brain single photon emission computed tomography information to show how helpful artificial neural networks are at distinguishing Alzheimer disease (promotion) Single Positron Emission Computed Tomography (SPECT).

Keywords: brain disorders; artificial neural networks; detection; Alzheimer's disease

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1. Introduction

Artificial neural networks (ANNs) have a crucial objective of handling data in a manner similar to how individuals perceive humor. ANNs are particularly employed in scenarios where advanced computational capabilities and brain-like abilities are desired[1–3]. The benefits of neural network data processing stem from their ability to detect and demonstrate nonlinear relationships among various types of data. Nonlinear interactions and data classification occur more frequently in natural systems compared to purely linear ones. While traditional statistical methods can demonstrate nonlinear interactions, doing so often requires extensive and complex mathematical modeling. In contrast, neural networks provide a simpler approach to perform the same type of analysis. When presented with new data beyond their training set, a properly designed and trained neural network can make decisions with a level of accuracy comparable to that of a human expert[4,5].

There are various helpful imaging methods accessible today as

Figure 1, shows including X-beam, CT, and X-ray sweeps of the brain to search for anomalies including Alzheimer's disease, drain, and growths. The run of the mill methodology for identifying these irregularities is having the sweeps inspected by the specialists. In the drive we've illustrated in this paper, we've made things a stride further as far as innovation by utilizing artificial knowledge to modernize the most common way of distinguishing irregularities in the brain. The brain is the most vital part of a body's working since it controls the whole body. The brain growth is a condition that can influence the brain and is basically a mass improvement of deviant brain cells. There are a wide range of types of brain cancers; some are harmless while others are threatening, making the disorder incredibly perilous[6,7]. They can likewise be named dangerous, which is malignant growth, and harmless, which is non-destructive. They commonly happen in the brain, and in light of the fact that they are so risky, they start to spread to different region of the brain. The essential issue is that the sensory system's capacity to work really relies on how rapidly the cancer might develop. A portion of the side effects and marks of this growth incorporate equilibrium issues, discourse issues, feeling very depleted subsequent to performing even straightforward errands, trouble following what is being said, and so on. There are many situations when the reason for the growth is obscure, hence a portion of the manners in which it can happen are through radiation openness or on the other hand on the off chance that there is a family background of brain growths and it is gone down through the qualities. Current mechanized approaches **Figure 2**, like Artificial Intelligence (AI) and profound learning have a vital impact in distinguishing the disease and help in the forecast at a beginning phase where the brain growth can be forestalled and kept to be a harmless one. Subsequently, detection is currently basic[8–10].

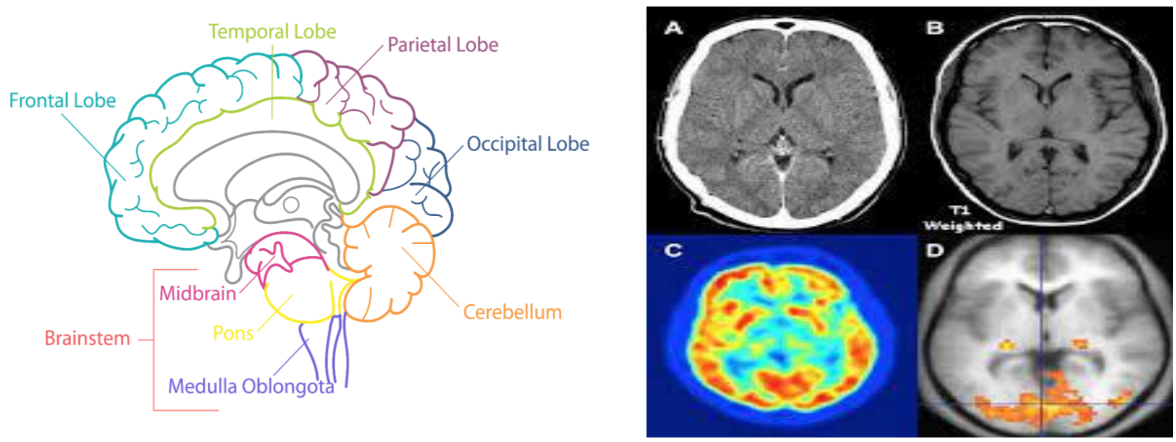


Figure 1. Brain structure and magnetic resonance imaging CT scan of brain shows disorders[1–5].

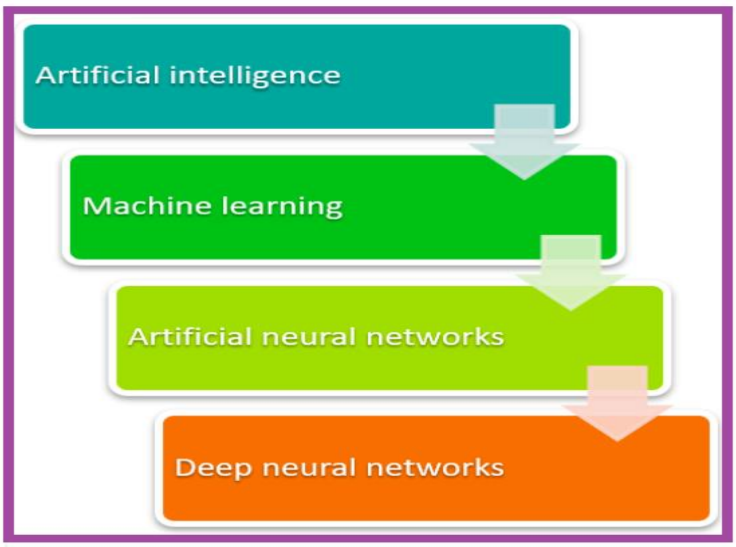


Figure 2. Evolution of neural networks.

1.1. Brain and its disorders

The brain is a complex organ that plays a critical role in the functioning of the human body. It controls various cognitive and physiological processes, including movement, perception, memory, and emotions. However, the brain can be susceptible to disorders that can impact its normal functioning. Understanding why these disorders occur and how they can be treated is of great importance. Brain disorders[11,12] can arise due to a variety of factors, including genetic predisposition, environmental influences, traumatic injuries, infections, tumors, and neurodegenerative processes. Some common brain disorders include:

1) **Neurodevelopmental disorders:** These disorders, such as autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD) are typically present from early childhood and affect brain development, resulting in challenges in social interaction, communication, and behavior.
2) **Neurodegenerative disorders:** Conditions like Alzheimer's disease, Parkinson's disease, and Huntington's disease fall under this category. They involve the progressive degeneration and loss of neurons in specific regions of the brain, leading to cognitive decline, movement difficulties, and other debilitating symptoms.
3) **Psychiatric disorders:** Mental health disorders like depression, anxiety disorders, bipolar disorder, and schizophrenia affect brain function and can significantly impact a person's thoughts, emotions, and behaviour. These disorders often arise from complex interactions between genetic, environmental, and biochemical factors.
4) **Stroke:** Strokes occur when the blood supply to the brain is disrupted, leading to the death of brain cells. They can result from a blocked blood vessel (ischemic stroke) or a ruptured blood vessel (hemorrhagic stroke). Strokes can cause severe neurological deficits, including paralysis, speech impairments, and cognitive impairments.
5) **Brain tumors:** Brain tumors are abnormal growths of cells in the brain. They can be benign (non-cancerous) or malignant (cancerous). Tumors can exert pressure on the surrounding brain tissue, leading to neurological symptoms such as headaches, seizures, changes in cognition, and motor impairments.

Treatment approaches for brain disorders depend on the specific condition and its underlying causes. They can include a combination of medication, surgery, radiation therapy, physical therapy, occupational therapy, and psychotherapy. In recent years, advancements in medical research and technology have opened up new possibilities for treatment. For example, targeted drug therapies and immunotherapies are being developed for certain brain tumors. Deep brain stimulation has shown promise in managing symptoms of movement disorders. Additionally, emerging fields like neuroplasticity and brain-computer interfaces offer potential avenues for enhancing brain function and restoring lost abilities[13–15].

1.2. Neural networks

1.2.1. Artificial neural networks (ANN)

Artificial neural networks (ANNs) are a class of machine learning models that aim to mimic the behavior of the human brain. They are composed of interconnected nodes, also known as artificial neurons, organized in layers. The structure of ANNs consists of an input layer, one or more hidden layers, and an output layer. Each artificial neuron receives inputs, applies a mathematical transformation to them, and produces an output that is passed to the next layer. The strength of the connections between neurons, called weights, is adjusted during the training process to optimize the network's performance. This training is typically done using labeled data, where the desired output is known, allowing the network to learn patterns and make predictions on new, and unseen data.

One of the strengths of ANNs is their ability to learn complex patterns and extract meaningful features from raw data. They are highly effective in tasks such as classification, regression, pattern recognition, and data clustering. ANNs have been successfully applied in various fields, including computer vision, natural language processing, speech recognition, finance, healthcare, and many others. There are different types of ANN architectures, each suited to different problem domains. Feed forward neural networks are the most common type, where information flows in one direction from input to output. Recurrent neural networks (RNNs) have feedback connections, allowing them to process sequential and time-dependent data. Convolutional neural networks (CNNs) are widely used for image and video analysis, utilizing specialized layers for spatial feature extraction. Other architectures, such as long short-term memory (LSTM) networks and generative adversarial networks (GANs), have also gained significant attention for their unique capabilities.

ANNs have some notable advantages, including their ability to handle large amounts of data, their adaptability to different problem domains, and their capacity for parallel processing. However, they also have challenges, such as the need for extensive computational resources, the potential for over fitting, and the difficulty of interpreting their internal decision-making processes. Despite these challenges, ANNs have demonstrated remarkable performance in various complex tasks, surpassing traditional methods in many domains. Their widespread use and continuous advancements contribute to the progress of artificial intelligence and its application in solving real-world problems[14].

1.2.2. Neural network

A deep neural network (DNN) is a type of artificial neural network shown in **Figure 3** that is designed to mimic the structure and functioning of the human brain. It consists of multiple layers of interconnected nodes, known as neurons, which are organized in a hierarchical manner. What sets deep neural networks apart from other types of neural networks is the presence of multiple hidden layers. These hidden layers allow the network to learn and represent complex patterns and relationships in data. Each layer learns progressively more abstract features as information passes through the network, leading to a hierarchical representation of the data.

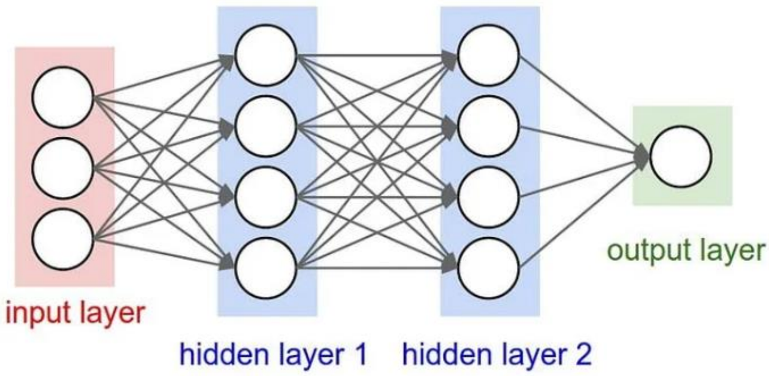


Figure 3. Architecture of deep neural network (DNN)[13–15].

Deep neural networks have shown remarkable performance in various domains such as image and speech recognition, natural language processing, and many more. This is because the multiple layers allow the network to learn and extract high-level representations of the input data, capturing intricate and nuanced patterns that would be difficult for shallow networks to discern.

Training a deep neural network involves iteratively adjusting the weights and biases of the neurons using a method called back propagation. This process enables the network to learn from labeled training data and refine its predictions over time. The depth of the network enables it to learn complex and intricate patterns, leading to more accurate predictions and better performance on challenging tasks. Overall, deep neural networks have revolutionized the field of artificial intelligence by enabling the development of highly sophisticated models that can tackle complex problems and learn from vast amounts of data. Their ability to learn hierarchical representations has proven invaluable in various applications, making them a powerful tool in the field of machine learning.

1.3. Importance of ANN in brain tumor detection comparison to other techniques

Artificial neural networks (ANNs)[16–18] play a crucial role in brain tumor detection, and their importance can be highlighted by comparing them to other techniques commonly used in this domain. Here are some key reasons why ANNs are valuable for brain tumor detection compared to other techniques:

1) **Pattern recognition capabilities:** ANNs excel in recognizing and learning complex patterns from input data. In the context of brain tumor detection, ANNs can analyze the features and characteristics of medical images, such as Magnetic resonance imaging (MRI) or CT scans, to identify subtle patterns associated with tumors. This ability to identify intricate patterns is particularly advantageous in detecting small or early-stage tumors that may be challenging for other techniques to identify.
2) **Non-linear relationship modeling:** Brain tumor detection often involves capturing non-linear relationships between different features or variables in medical images. ANNs are well-suited for modeling and capturing these complex relationships, allowing them to detect subtle connections and markers indicative of tumors. Traditional techniques, such as statistical methods, may struggle with capturing and modeling non-linear relationships effectively.
3) **Automated feature extraction:** ANNs have the capability to automatically extract relevant features from input data, eliminating the need for manual feature engineering. In the case of brain tumor detection, ANNs can learn to extract meaningful features from medical images, such as the shape, size, and texture characteristics of tumors. This automated feature extraction process reduces the burden on human experts and can potentially uncover subtle tumor markers that might be overlooked by manual analysis or other techniques.
4) **Adaptability and generalization:** ANNs can adapt and learn from examples, allowing them to generalize their knowledge to new, unseen data. This adaptability is especially important in the medical field, where new cases and variations of brain tumors continually arise. ANNs can be trained on diverse datasets of labeled brain scans, enabling them to learn from a wide range of tumor cases and improve their performance over time. This ability to generalize and handle new cases makes ANNs valuable in real-world clinical settings.
5) **Integration with other AI techniques:** ANNs can be combined with other artificial intelligence techniques, such as deep learning and computer vision, to enhance brain tumor detection. Deep learning architectures, such as convolutional neural networks (CNNs), can be utilized within ANNs to provide even more robust and accurate detection capabilities. This integration allows for more comprehensive analysis of medical images and can improve the overall performance of brain tumor detection systems.

Other techniques, such as support vector machines (SVMs) and traditional statistical methods have also been employed in brain tumor detection, ANNs offer distinct advantages in terms of their ability to handle complex patterns, model non-linear relationships, automate feature extraction, adapt to new data, and integrate with other AI techniques. These factors contribute to the importance and effectiveness of ANNs in brain tumor detection[19–22].

1.4. Tumor detection using different techniques and methods

Tumor detection[23] can be done using convolutional neural networks (CNNs) and deep neural networks (DNNs), along with the use of long short-term memory (LSTM) as a classifier, offers several key advantages over other techniques and methods. Here are some relevant points:

1) **Hierarchical feature extraction:** CNNs are particularly effective in extracting hierarchical features from medical images, such as MRI or CT scans. The hierarchical architecture of CNNs allows them to learn low-level features like edges and textures, and then progressively learn higher-level features relevant to tumor detection. This capability enables CNNs to capture intricate patterns and subtle details

that might be missed by other techniques.

2) **Spatial relationship modeling:** CNNs excel in capturing spatial relationships within images. By utilizing convolutional layers with filters, CNNs can learn spatial patterns and localize tumor regions accurately. This spatial modeling ability is crucial in tumor detection, as tumors can have diverse shapes, sizes, and locations within the brain. Other techniques, such as traditional machine learning algorithms or manual feature engineering, may struggle to capture such complex spatial relationships effectively.
3) **Deep learning for end-to-end learning:** DNNs, including CNNs, allow for end-to-end learning, eliminating the need for manual feature extraction. Instead of relying on handcrafted features, DNNs can automatically learn relevant features directly from the input data. This reduces the dependency on domain expertise and potentially uncovers latent tumor markers that may not be easily identifiable through traditional methods.
4) **Temporal modeling with LSTM:** In cases where sequential data is available, such as time-series data from brain scans, LSTM networks can be employed as classifiers. LSTM networks are a type of recurrent neural network (RNN) that can capture long-term dependencies and temporal patterns in sequential data. By incorporating LSTM layers into the network architecture, temporal information and context can be effectively utilized in tumor detection. This is particularly useful when analyzing dynamic changes or growth patterns of tumors over time.
5) **Improved accuracy and performance:** CNNs, DNNs, and LSTM classifiers have demonstrated state-of-the-art performance in tumor detection tasks. Their ability to extract intricate features, model complex relationships, and leverage temporal information leads to improved accuracy in identifying and classifying tumors.

Advancements in hardware, such as Graphics Processing Units (GPUs) and specialized accelerators, have made it feasible to train and deploy these deep learning models efficiently, further enhancing their relevance and practicality. It's important to note that while CNNs, DNNs, and LSTM classifiers offer significant benefits, they are not the only approaches to tumor detection. Other techniques, such as support vector machines (SVMs), random forests, or traditional image processing algorithms, can still be valuable depending on the specific requirements, available data, and computational resources. The choice of technique or method should be carefully considered in the context of the problem at hand[24,25].

2. Literature review

The study[1] presents a computer-aided detection system (CAD) that utilizes magnetic resonance imaging (MRI) and artificial neural networks (ANN) for brain tumor detection. By combining these technologies, the system achieves a remarkable accuracy of 99% and a sensitivity of 97.9% in accurately classifying MRI images as either tumor or non-tumor. This CAD system reduces dependence on human specialists, mitigates the potential for errors, and improves the efficiency of brain tumor diagnosis. Overall, the study demonstrates the effectiveness of using MRI and ANN in enhancing the detection and classification of brain tumors.

This work[3] provides an overview of the use of artificial intelligence (AI) in brain care. It highlights the applications of AI techniques in diagnosis, treatment planning, and outcome prediction. The study identifies 155 relevant studies that utilize AI algorithms, with artificial neural networks being prominent. Brain imaging data is commonly used. The practical implementation of AI in brain care requires addressing challenges and developing explainable algorithms. Overall, AI has the potential to enhance decision-making in neuroscience applications.

This survey[6] provides an overview of the applications of artificial neural networks (ANNs) in real-world scenarios. It highlights the strengths and benefits of ANNs, such as learning power, fault tolerance, and information processing capabilities. The study covers a wide range of application areas and proposes hybrid ANN models for improved performance. ANNs are recognized as valuable tools for addressing complex problems in diverse fields.

This article[9] explores the dynamics of dendritic spines in the brain and compares them to artificial intelligence (AI) counterparts. Unlike AI memory elements, spines not only store information but also implement algorithms for learning and adaptation. The spines exhibit structural changes influenced by synaptic plasticity and intrinsic dynamics, which are modulated by neuromodulator factors like dopamine. The review emphasizes the significance of intrinsic dynamics for memory management and adaptation and discusses the potential impact of disrupted spine dynamics on mental disorders. The article also highlights the algorithmic aspects of spine dynamics that could be relevant for future AI advancements.

This article[13] focuses on the diagnosis of epilepsy using electroencephalogram (EEG) signals. Neurologists traditionally rely on qualitative visual analysis to identify patterns associated with epilepsy. However, the article proposes a quantitative approach using Fourier signal analysis to differentiate between epileptic and non-epileptic patients. The EEG signals are analyzed to extract features, and classification techniques such as logistic regression, artificial neural networks, support vector machines, and convolutional neural networks are trained on these features. Based on the results, artificial neural networks were found to be the most effective technique, achieving an accuracy of 86% in characterizing epileptic patients.

This research[17] proposes a machine learning approach to assess the health of cotton plants by analyzing images of their leaves. The main objective is to detect diseases and assess the quality of the cotton plant using artificial neural networks. The approach involves image pre-processing to highlight the affected portion of the leaf based on color changes. By analyzing the data, the specific type of disease can be detected. The use of machine learning techniques offers a more accurate and efficient method for disease detection in cotton plants.

Artificial intelligence (AI), particularly artificial neural networks (ANN), has been recognized as a powerful tool for predicting disease outcomes in various clinical scenarios. The potential of ANN for predicting cancer progression and prognosis is highlighted. The limitations of conventional statistical methods in handling complex medical data are discussed. The study[21] analyzes the predictive ability of cellular markers, DNA plaids, cell-cycle profiles, as well as molecular markers such as tumor promoter and suppressor genes, growth factors, and hormone receptors in breast cancer management. The successful application of ANN in evaluating microRNA profiles to understand their impact on cancer progression and prognosis is also emphasized. It explores future improvements in ANN, including hybrid systems with fuzzy logic and artificial immune networks. The findings highlight the significant analytical support provided by ANN in predicting disease outcomes and the potential for further advancements in this field.

Modular neural networks (MNNs) have emerged as a promising approach to scaling and tackling complex machine learning problems. However, there is a lack of systematic analysis and comprehensive taxonomy of MNNs in existing surveys. In the paper, the authors[23] aim to establish a solid taxonomy that captures the essential properties and relationships of different MNN variants. They investigate the various levels at which modularization techniques operate and provide a universal framework for theorists studying MNNs. It also emphasizes the strengths and weaknesses of different modularization approaches, providing guidance for neural network practitioners. The study addresses the need for a more modular approach as learning problems become larger and more complex, offering insights and best practices for scaling ANNs effectively.

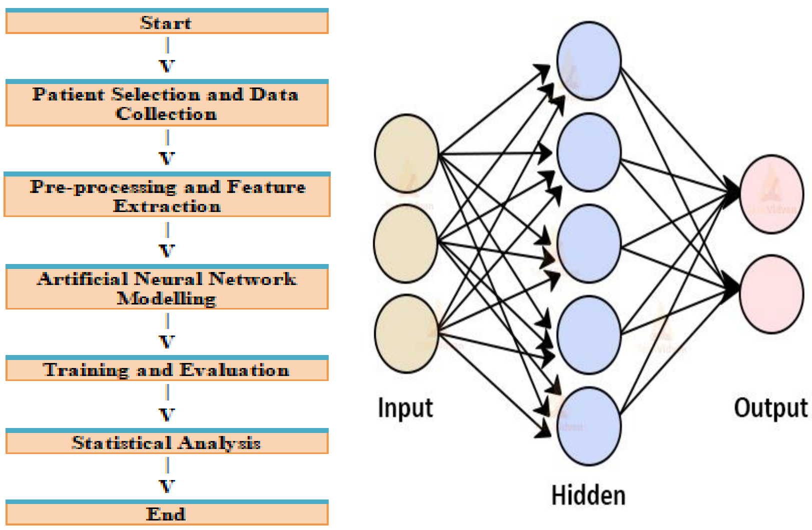
In recent years, there has been a significant increase in the use of statistical methods by psychologists to analyze human relationships. However, analyzing complex concepts using mathematical or statistical approaches can be challenging. The practical approach is based on artificial neural networks (ANN) is demonstrated as a useful tool for analyzing data in the field of cognitive psychology. To illustrate the method, a psychology problem involving five questionnaires was designed, and the questionnaires were randomly filled using MATLAB. The errors of the neural network were visualized using a surface function, confirming the reliability of the proposed method. The study[25] showcases the effectiveness of ANN in analyzing complex psychological data and provides a practical example to support its application in cognitive psychology research. Overall comparative of selected literature with common parameters findings is shown in the **Table 1**.

Table 1. Comparison of literature with some common reported parameters.

References	Main focus	Methodology	Key findings
[1]	Brain tumor detection using MRI and ANN	CAD system utilizing MRI and ANN	Accuracy of 99%, sensitivity of 97.9% in tumor classification. Reduces dependence on human specialists and improves efficiency.
[3]	Applications of AI in brain care	Overview of AI techniques in diagnosis, treatment planning, and outcome prediction	AI algorithms, with ANN being prominent. Potential for enhancing decision-making in neuroscience applications.
[6]	Applications of ANNs in real-world scenarios	Overview of ANNs' strengths and benefits	Wide range of application areas, hybrid ANN models proposed for improved performance. Valuable tools for addressing complex problems.
[9]	Comparison of spine dynamics and AI	Study of intrinsic dynamics of dendritic spines	Importance of intrinsic dynamics for memory management and adaptation. Potential impact on mental disorders. Relevance to future AI advancements.
[13]	Epilepsy diagnosis using EEG signals	Quantitative analysis using Fourier signal analysis and classification techniques	Artificial neural networks achieve 86% accuracy in characterizing epileptic patients. Promising approach for differentiation between epileptic and non-epileptic cases.
[17]	Disease detection in cotton plants using ANN	Analysis of leaf images for disease detection	ANN-based approach achieves more accurate and efficient disease detection in cotton plants. Pre-processing and color change analysis improve accuracy.
[21]	Prediction of cancer progression and prognosis using ANN	Potential of ANN for predicting disease outcomes	Cellular and molecular markers analysed for breast cancer management. ANN shows promise in predicting disease outcomes. Future improvements explored.
[23]	Modular neural networks for scaling and complex problems	Taxonomy and analysis of MNN variants	MNNs as a promising approach for scaling and complex problems. Taxonomy and framework established. Insights and best practices provided.
[25]	AI-based analysis of human relationships in cognitive psychology	ANN-based approach for analyzing complex psychological data	Practical approach using ANN demonstrated for analyzing cognitive psychology data. Reliability confirmed through error visualization. Effective tool for analyzing complex concepts.

3. Methodology

Figure 4a,b shows the methodology used for this work along with ANN 3-structured layered.



(a) **(b)**

Figure 4. (a) Processing flowchart; **(b)** 3-layer ANN structure representation.

3.1. Patients' population

The Clinical College of India's Division of Atomic Medication did the brain SPECT examination. There were 134 patients with clinical determinations in the review populace. Ages in the Alzheimer bunch went from 55 to 87 years (mean (SD): 71.9 (12.2)), while those in the ordinary gathering went from 54 to 82 years (mean (SD): 67.1) (12.0). Every patient's brain SPECT study was evaluated. The Diagnostic and Statistical Manual of Mental Disorders (DSM)-IV for dementia, created by the American Mental Affiliation, was utilized to analyze promotion[17]. To preclude further reasons for dementia, like a growth, stroke, or hydrocephalus, attractive reverberation imaging (X-ray; n = 49 patients) or a computed tomography assessment (CT; n = 5 patients; because of X-ray contraindications) were done on all patients.

3.2. Input signals for artificial neural network

SPECT filter picture information was utilized by an artificial neural organization. We made an assortment of 36 mathematical qualities for every patient. Every one of these numbers related a particular brain district to a brain profile (**Figure 5**). There were 12 regions in all of the brain profiles (parietal, ventricular, and thalamus). These factors filled in as the neural organization's feedback signals.

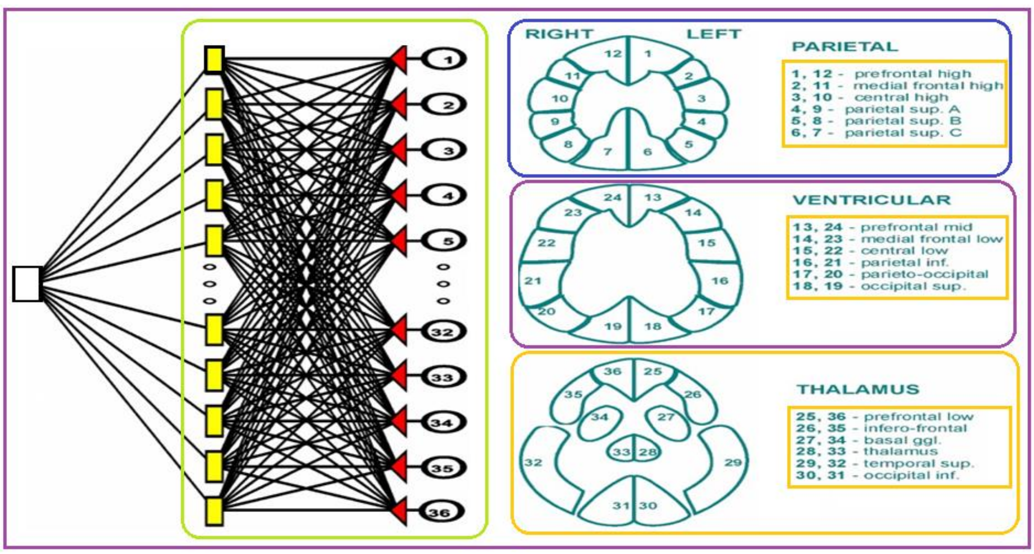


Figure 5. Artificial neural organization's engineering.

3.3. The architecture of the artificial neural network

In our exploration, we used a multi-facet perceptron network. Three layers made up the artificial neural organization: the info, stowed away, and yield layers, which had 36, 21, and 1 neurons, respectively as shown in **Figure 5**. We constructed artificial neural networks utilizing a product test system, and we utilized them to perform relapse issues that included assessing the quantity of revisions. Each experiment's artificial neural organization reaction went from 0 to 1 concerning numbers. To diminish misfortunes, the trigger of artificial neural networks naturally picked the initiation and dismissal levels for the result neuron. The blunder back-engendering procedure was utilized to change the weight linkages between the neurons during the learning stage. The blunder capability for the artificial neural not entirely settled to be the amount of squared contrasts between the qualities that were provided deduced and the genuine qualities at the result neuron. The initiation capability was a sigmoid (strategic capability). There were laid out to be 1000 ages, with every age having an unmistakable request for the neural organization's introduced cases.

The profiles of the 12 regions in each brain are displayed in the right board. The loads of the neural organization were initialized utilizing an irregular Gaussian procedure. We haphazardly isolated each of the patients into the preparation and testing bunches to decide the indicative nature of the artificial neural organization. The testing bunch had 34 occasions (18 promotion, 16 typical), while the preparation bunch had 100 cases (55 promotion, 45 ordinary).

3.4. The software simulation of ANN and the statistical analysis

The TIBCO Programming Inc. Factual (information examination programming framework), variant 13 programming emulator of artificial neural networks was utilized for all estimations. The Information Bus Company (TIBCO Programming Inc.) was utilized to assess the responsiveness and explicitness as well as the receiver operating characteristic ROC examination and discriminant investigation for the conclusion of Alzheimer disease. The ROC bend was utilized to survey how well the neural networks and discriminant investigation performed. The exhibition of the artificial neural organization and discriminant examination were estimated utilizing the region under the ROC bend. A discriminant investigation classifier was utilized. We utilized cross-approval testing with the L-technique for the re-enactments we present here. Both adroitly and computationally, discriminant examination and investigation of change are profoundly like each other. In this factual cycle, factors single photon emission computed tomography (SPECT counts) that had typical qualities that were different between the gatherings under assessment (the Promotion bunch and the control) were pursued. These factors are essential since they empower forecast of the appropriate task of new cases to the gatherings. Two stages of discriminant investigation were finished. In the first, to more readily catch the change of the informational index and decrease its dimensionality, discriminant capabilities, which are a straight blend of info factors, were laid out. The cycle amplified the contrast between the mean upsides of discriminative capabilities in specific subgroups. The making of order capabilities—likewise straight mixes of autonomous factors—occurred in the subsequent stage. These recipes showed the probability that a given occurrence had a place with either the Promotion or control bunch, which were the two broke down classifications. We isolated the total review bunch into the accompanying classifications for the discriminant examination, similarly as for neural networks: testing gathering and preparing bunch (45 typical, 55 promotion) (18 advertisements, 16 ordinary). A ROC district was given by the discriminant investigation classifier. The benchmark group and the Promotion bunch each got six count numbers after investigation of six areas from each piece of the brain (parietal, ventricular, and thalamus). Factual examination was completed utilizing statistical programming, including one-way and two-way analysis of variance (ANOVA). The acknowledged degree of importance was $p < 0.05$.

4. Results and discussion

The software simulation parameters and Quality of services (QoS) metrics is shown in the **Tables 2** which help to assess the accuracy, sensitivity, specificity, precision, recall, and overall performance of the proposed methodology. They also ensure statistical significance, validation, computational efficiency, and the potential for future research. Including these parameters and metrics in the paper can enhance its quality, reliability, and scientific value.

Table 2. Software simulation parameters and quality of service (QoS).

Software simulation parameters	QoS metrics
Simulation tool (e.g., TIBCO Software Inc.)	Accuracy
Simulation model (e.g., Artificial Neural Network)	Sensitivity
Input data (e.g., SPECT counts, brain region measurements)	Specificity
Pre-processing techniques (e.g., data normalization, feature extraction)	Precision
Network architecture (e.g., multi-layer perceptron, number of layers/neurons)	Recall
Training algorithm (e.g., back propagation, genetic algorithms)	F1 score
Performance evaluation method (e.g., ROC analysis, cross-validation)	Area under the curve (AUC)
Statistical analysis software (e.g., Statistical software)	Statistical significance (*p*-value)
Validation dataset (e.g., testing group)	Concordance (agreement between predicted and actual values)
Computational efficiency (e.g., training time, memory usage)	Execution time
Generalization capability (e.g., performance on unseen data)	Robustness
Comparative analysis with other methods or models	Benchmarking
Reproducibility of results (e.g., availability of code, data)	Transparency
Discussion of limitations and future scope	Research implications

A factual examination uncovered a massive distinction between the benchmark group and promotion patients in the mean glimmer signals (SPECT counts) in unambiguous districts of the brain shown in **Tables 3–5**.

Prefrontal high, average front facing high, focal high, parietal sup. (predominant) A, parietal sup. B, and parietal sup. C zones of the parietal region were incorporated into a two-way ANOVA examination, which uncovered a significant diminishing in the count number of the Advertisement bunch contrasted with the control (p=0.0001). The quantity of counts (SPECT counts) in the parietal region was not altogether impacted by the side of the brain ($p > 0.05$).

The count number of the advertisement bunch was altogether lower than that of the benchmark group ($p = 0.0001$) in the two-way ANOVA consolidated examination of the six zones of the parietal region (prefrontal mid, average front facing low, focal low, parietal inf. (sub-par), parieto-occipital, and occipital sup.). The **Figure 6**, shows the counts for AD. The quantity of counts (SPECT counts) in the parietal region was not essentially impacted by the side of the brain ($p > 0.05$).

Table 3. Alzheimer's disease (AD) patients and the control group were compared in terms of parietal area count in the brain (mean and SD).

Parietal area	Right		*p*-value	Left		*p*-value
	AD	Control		AD	Control	
Prefrontal high			0.0003			0.0005
Mean	127.24	178.50		126.65	176.05	
(SD)	(53.34)	(93.48)		(53.76)	(90.90)	
Medial frontal high			0.0003			0.0003
Mean	127.92	184.17		129.59	183.99	
(SD)	(57.12)	(94.13)		(55.13)	(94.41)	
Central high			0.0010			0.0005
Mean	131.66	183.69		130.62	182.85	
(SD)	(58.24)	(99.17)		(56.03)	(96.44)	
Parietal sup. A			0.0003			0.0003
Mean	128.16	183.19		126.62	180.97	
(SD)	(57.28)	(97.59)		(56.05)	(94.80)	
Parietal sup. B			0.0003			0.0003
Mean	126.16	185.62		125.74	184.34	
(SD)	(57.46)	(95.38)		(57.29)	(94.39)	
Parietal sup. C			0.0004			0.0004
Mean	132.53	188.14		133.51	187.25	
(SD)	(57.30)	(99.48)		(57.29)	(97.82)	

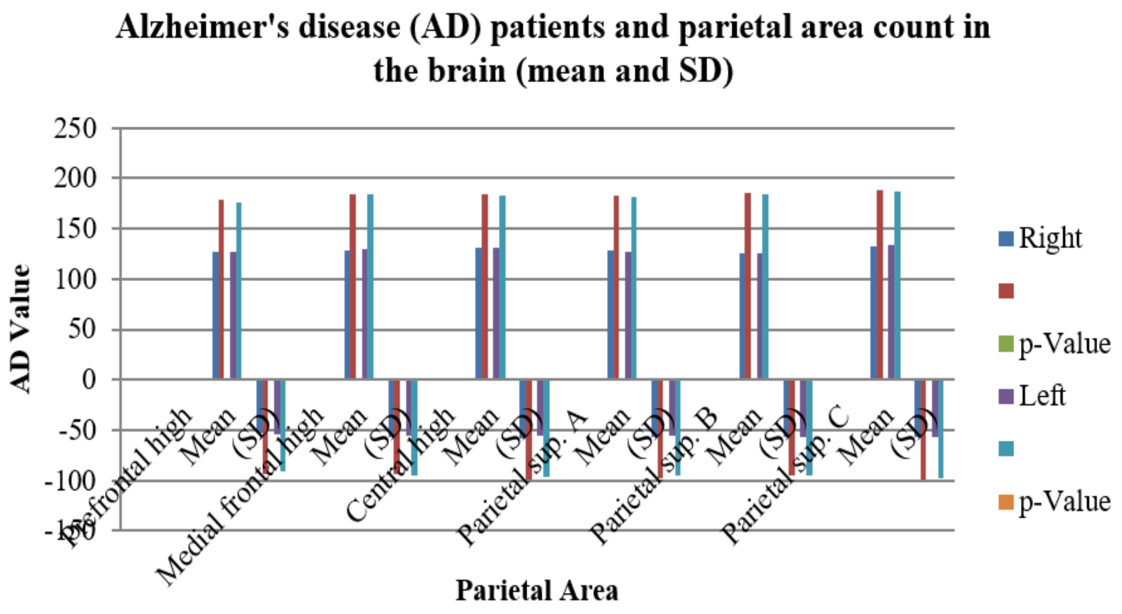


Figure 6. Mean and SD count for Alzheimer diseases

The two-way ANOVA consolidated assessment of the basal ggl. (ganglia), thalamus, fleeting sup., and occipital inf., six zones of the parietal region, uncovered a significant diminishing in the count number of the advertisement bunch contrasted with the control (p= 0.0001). The parietal region's SPECT counts were not altogether impacted by any side of the brain ($p > 0.05$).

Table 4. Comparison of the brain's ventricular region's count numbers in AD patients and the control group (mean and SD).

Ventricular area	**Right**		***p*-value**	**Left**		***p*-value**
	AD	**Control**		**AD**	**Control**	
Prefrontal mid			0.0003			0.0005
Mean	127.45	178.29		127.90	176.82	
(SD)	(53.35)	(89.73)		(53.94)	(90.45)	
Medial frontal low			0.0003			0.0003
Mean	125.81	180.29		126.96	180.99	
(SD)	(54.51)	(94.52)		(53.67)	(92.34)	
Central low			0.0009			0.0005
Mean	126.78	173.89		124.83	174.05	
(SD)	(54.15)	(93.71)		(52.99)	(92.60)	
Parietal inf.			0.0003			0.0003
Mean	125.91	180.65		123.56	178.20	
(SD)	(55.43)	(96.04)		(53.21)	(94.60)	
Parieto-occipital			0.0003			0.0003
Mean	128.28	182.24		126.12	182.17	
(SD)	(57.07)	(90.30)		(56.15)	(92.80)	
Occipital sup.			0.0010			0.0013
Mean	139.51	191.69		139.06	190.99	
(SD)	(60.09)	(99.53)		(59.47)	(99.67)	

SPECT cerebral brain stream tests demonstrated that promotion patients had extensively lower upsides of glimmer computations in every one of the regions of the brain in contrast with the benchmark group. The least mean worth of sparkle computations for both review bunches in both cerebral sides of the equator was tracked down in the thalamus region (**Figure 7**). Artificial neural networks' awareness for diagnosing promotion was 96.0% (standard deviation, 6.5%), while its explicitness was 102% (0.3%). The learning gathering's awareness was 100.3% (9.6%), while their explicitness was 102% (0.3%). They were, respectively, 88.3% (8.11%) and 97% (7.9%) in the separating examination.

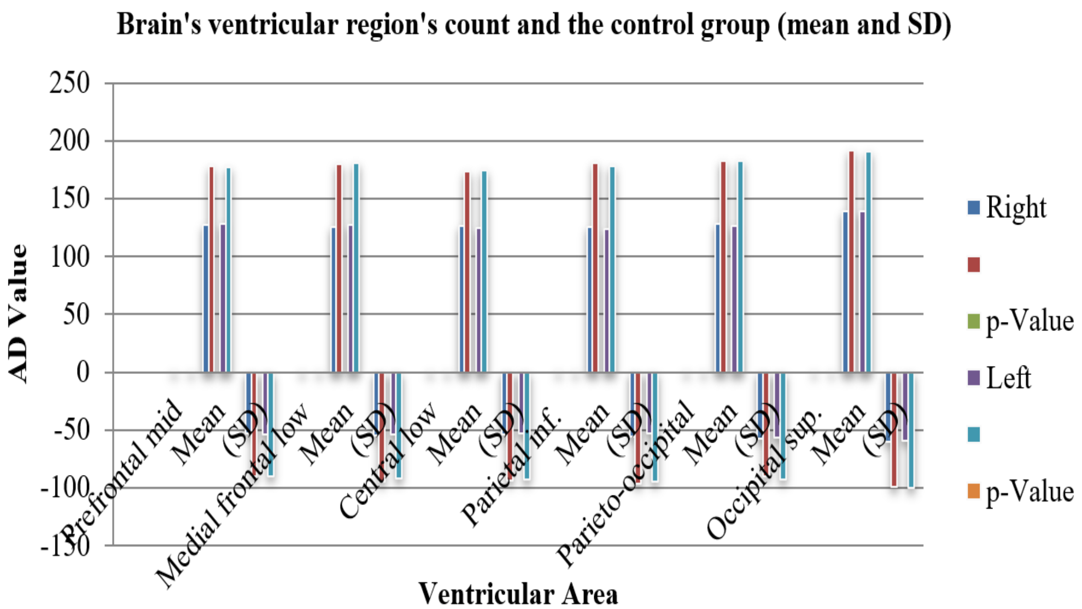


Figure 7. Brain's ventricular cunts and control group.

Table 5. Comparison of the brain's thalamus area's count numbers in AD patients and the control group (mean and SD).

Thalamus area	**Right**		***p*-value**	**Left**		***p*-value**
	AD	**Control**		**AD**	**Control**	
Prefrontal low			0.0013			0.0013
Mean	63.45	86.55		62.91	86.44	
(SD)	(28.31)	(46.56)		(27.87)	(46.47)	
Infero-frontal			0.0004			0.0004
Mean	65.06	91.24		64.88	91.15	
(SD)	(28.53)	(48.36)		(28.05)	(49.32)	
Basal ggl.			0.0011			0.0010
Mean	66.65	90.89		66.71	91.22	
(SD)	(29.64)	(49.73)		(28.73)	(49.67)	
Thalamus			0.0013			0.0021
Mean	69.78	93.84		69.70	93.69	
(SD)	(30.78)	(49.23)		(31.03)	(48.46)	
Temporal sup.			0.0063			0.0055
Mean	77.10	102.50		76.58	102.74	
(SD)	(37.68)	(56.38)		(38.22)	(57.54)	
Occipital inf.			0.0026			0.0022
Mean	67.70	90.02		67.02	90.62	
(SD)	(29.86)	(47.41)		(29.92)	(47.73)	

As indicated by a few examinations, recognizing occipital and parie to temporal hypoper fusion might assist with recognizing Alzheimer's disease from dementia with Lewy bodies (DLB). Regardless, both fron to temporal dementia and DLB patients' brains have been found to have hypoper fusion in the parie to temporal curve, and brain perfusion SPECT in a few psychotic diseases can look like that in promotion. Rather than ordinary factual strategies, an artificial neural organization is a device that, in the occasions referenced, uses the growing experience. In our work, the information from 134 patients' SPECT cerebral blood stream tests was utilized as the ANN's feedback. A bunch of 36 whole numbers was made for every patient, every one mirroring the calculation of shine in an alternate locale of the brain. There were no genuinely massive contrasts between the biased examination and ANN used to analyze advertisement (chi-square = 0.9, p = 0.6).

Rather than different tests where the region under the ROC bend ran somewhere in the range of 0.93 and 0.95, the created neural organization was better at segregating between promotion patients and solid members and the count can be seen in **Figure 8**. The writing to date has an extremely different scope of neural organization inputs. Four information sources make up the least number of ANNs, and every one addressed the mean worth of calculations for shine. Likewise, contrasted with investigations of amount kind, our investigation discovered that specific examination was more successful at recognizing promotion (0.96 versus 0.87). By utilizing ANN and unfair examination, our outcomes have likewise been accounted for as the responsiveness and explicitness of promotion determination. Explicitness characterizes the probability of a legitimate promotion rejection, while responsiveness characterizes the probability of an appropriate advertisement conclusion.

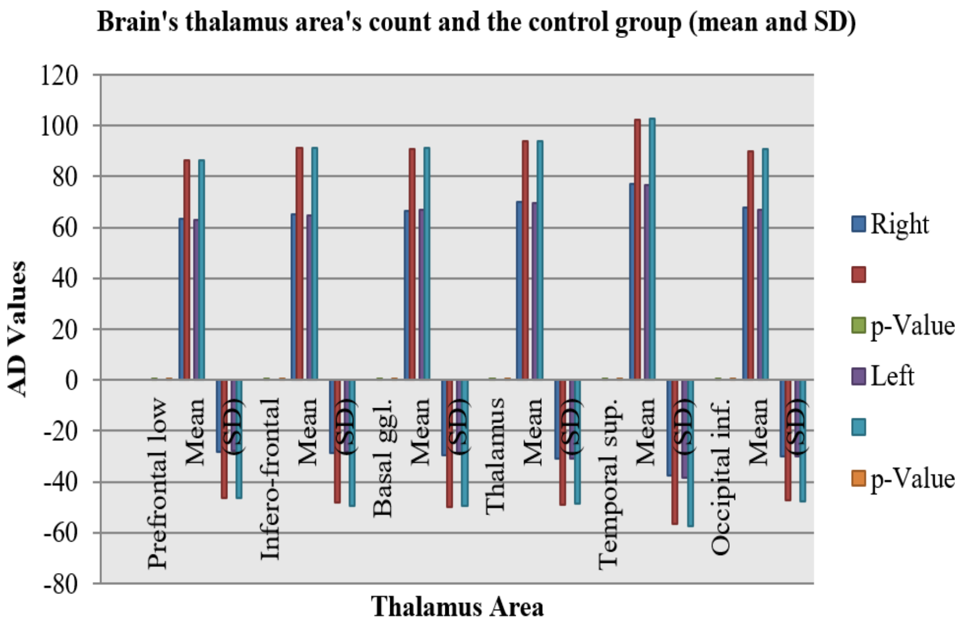


Figure 8. Brains thalamus area and control group count

5. Conclusion

The study analyzes every one of the different techniques that artificial neural networks can be applied to in the area of nervous system science for clinical analysis. Following element extraction, a neural organization is utilized to group the pictures of the brain. The exact decision of component extraction methods immensely affects how precisely and accurately the order is finished. The recommended strategy diminishes treatment costs and raises personal satisfaction by predicting strokes early. Artificial neural networks permitted us to accomplish a shocking 98 percent precision on a specific dataset, which is an unimaginable outcome as far as science and inventiveness and will assist us with saving additional lives from malignant growth and give essential guide prior. The determination of Alzheimer's disease can be supported by artificial neural networks and conventional factual methods (discriminant investigation). Our review's discoveries recommend that artificial neural networks can recognize promotion patients and sound controls. Artificial neural networks can be a useful device for clinical practice, as shown by our review re-enactments.

6. Future scope

It ought to be additionally explored by social occasion an on-going dataset of different people and afterward examining it as per the model by playing out all vital pre-handling. This point plays had a critical impact in the exploration and clinical progression that is as of now occurring all over the planet. The accompanying stage is trying different things with data sets on different group models, which can be utilized to get higher precision and help with bringing down the intricacy of the division in a lot more limited measure of time than the techniques presently used in brain jumble research. Future directions in case of heart-related diseases detection using ANN, DNN, AI, and ML techniques:

1) **Early detection of heart disease:** Further exploration can be done to develop ANN-based systems that utilize wearable devices and real-time monitoring to detect early signs of heart disease, such as abnormal heart rhythms or fluctuations in blood pressure. Recent studies have shown the effectiveness of AI algorithms in analyzing continuous physiological data and providing timely alerts, allowing for early intervention and prevention of adverse cardiac events.
2) **Decision support systems:** AI and ML techniques, combined with ANN and DNN models, can be employed to develop decision support systems for clinicians in the diagnosis and treatment of heart-related diseases. Comparative analyses have demonstrated the potential of these systems in assisting

healthcare professionals by providing accurate risk assessments, suggesting optimal treatment plans, and predicting patient outcomes based on clinical data.

Conflict of interest

The authors declare no conflict of interest.

Abbreviations

ANN	Artificial Neural Networks
SPECT	Single Positron Emission Computed Tomography
ASD	Autism Spectrum Disorder
ADHD	Attention Deficit Hyperactivity Disorder
RNN	Recurrent Neural Networks
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory
GAN	Generative Adversarial Networks
DNN	Deep Neural Network
MRI	Magnetic Resonance Imaging
SVM	Support Vector Machines
DNN	Deep Neural Networks
GPU	Graphics Processing Units
CAD	Computer-Aided Detection System
EEG	Electroencephalogram
MNN	Modular Neural Networks
DSM	Diagnostic and Statistical Manual of Mental Disorders
TIBCO	The Information Bus Company
ROC	Receiver Operating Characteristic
NOVA	Analysis of Variance
QOS	Quality of Services
AUC	Area under Curve
AI	Artificial Intelligence
ML	Machine Learning

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