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Artificial Neural Networks In Early Diagnosis Of Neurological Disorders: A Review Of Models, Biomarkers, And Clinical Integration

Dr. H. E. Khodke[1] ,Chandan kumar[2], Amrit Podder[3], Dr. C. JEGADHEESAN[4], Dr Divya Parmar[5], Noushad Yashan[6]
[1]Assistant professor,Computer Engineering department, Sanjivani College of Engineering Kopargaon (An Autonomous institute), Maharashtra,India,423603. Affiliated to Savitribai Phule Pune University, Pune. India.
[2]Research scholar,lovely professional University Phagwara Punjab,
[3]Assistant Professor,Teerthanker Mahaveer Medical College & Research Centre, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India
[4]Associate Professor,Department of Automobile Engineering, Kongu Engineering College,Perundurai - 638060, Erode,Tamil Nadu,
[5]Assistant Professor, Practice of Medicine Department, Jawaharlal Nehru Homoeopathic Medical College, Parul University
[6]Managing Director, Research and Development, Yaavik Materials and Engineering Private Limited, 158, Badangpet, New Airport Road, Hyderabad, Telangana.

Abstract
Neurological disorders, ranging from Alzheimer's disease and Parkinson's disease to multiple sclerosis and epilepsy, pose significant global health challenges due to their progressive nature and delayed diagnosis. Early detection is critical for effective intervention and management. Traditional diagnostic techniques, although advanced, often lack the sensitivity and scalability required for early-stage recognition. In recent years, Artificial Neural Networks (ANNs), a branch of artificial intelligence inspired by the human brain, have shown immense promise in enhancing the early diagnosis of these disorders. This review synthesizes current advancements in ANN-based models for early detection of neurological disorders and explores their integration with clinical data and neurobiomarkers such as EEG signals, MRI scans, and genetic data. We first discuss the foundational architecture and learning mechanisms of ANNs that make them suitable for handling complex biomedical data. Following this, the paper examines various ANN architectures—including feedforward networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs)—and their applications in diagnosing disorders such as Alzheimer's, Parkinson's, epilepsy, and autism spectrum disorders. The paper also highlights the emerging role of hybrid models combining ANN with fuzzy logic, support vector machines, and ensemble learning to improve diagnostic accuracy. A significant focus is placed on biomarkers, including neuroimaging, cerebrospinal fluid analysis, and electrophysiological indicators, and how ANN models are trained to identify diagnostic patterns within them. We explore real-world clinical trials, datasets, and ANN-integrated diagnostic systems currently in use or under development. The challenges of interpretability, data heterogeneity, ethical considerations, and real-time clinical integration are critically assessed. Finally, the review presents future directions emphasizing the need for explainable AI, longitudinal data utilization, and patient-specific modeling. By integrating deep learning with clinical neuroscience, ANN-based systems can revolutionize the landscape of neurological diagnosis. This review underscores their transformative potential while acknowledging the hurdles that must be overcome to achieve seamless clinical adoption.
Keywords: *Artificial Neural Networks, Early Diagnosis, Neurological Disorders, Biomarkers, Clinical Integration, EEG, MRI, Alzheimer's, Parkinson's, Explainable AI*

INTRODUCTION
Neurological disorders constitute one of the leading causes of disability and mortality worldwide. According to the World Health Organization (WHO), over one billion people are affected by neurological conditions, which include Alzheimer's disease, Parkinson's disease, multiple sclerosis, epilepsy, and various neurodevelopmental disorders (1). Early detection and diagnosis are crucial for the effective management of these diseases. However, traditional methods, such as clinical evaluations, neuroimaging,

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and laboratory-based assessments, often fall short in capturing subtle early-stage biomarkers and are prone to subjective interpretation. In this context, Artificial Neural Networks (ANNs) are gaining traction for their ability to detect nonlinear patterns in high-dimensional data, such as that found in neurological diagnostics. ANNs mimic the human brain's interconnected neuron architecture and adaptively learn from complex datasets, making them ideal for processing noisy and multifactorial medical data (2). Their capacity to detect hidden trends and correlations within EEG recordings, MRI images, and molecular biomarkers opens new avenues for timely and accurate diagnosis. Recent studies have demonstrated that ANN-based systems can outperform traditional diagnostic tools in sensitivity, specificity, and speed. For example, in Alzheimer's disease, ANNs can analyze volumetric changes in hippocampal structures through MRI with over 90% accuracy (3). Similarly, in epilepsy, deep learning models trained on EEG signals can predict seizures before clinical symptoms appear (4). Despite their promise, integrating ANN systems into clinical workflows remains a challenge. Issues such as lack of explainability, the need for large annotated datasets, and regulatory concerns continue to hinder widespread adoption. Nevertheless, advancements in computational power, availability of large-scale datasets, and interdisciplinary collaborations are gradually overcoming these barriers. This review explores the role of ANNs in early diagnosis of neurological disorders, focusing on the underlying architectures, application to biomarker analysis, current clinical deployments, and future integration strategies.

ANN Architectures and Their Suitability for Neurological Diagnosis

Artificial Neural Networks are computational models composed of layers of interconnected nodes, or "neurons," that process information in a hierarchical fashion. The most commonly employed ANN architectures in medical diagnostics include:

Feedforward Neural Networks (FNNs): These are the simplest type of ANN, where information moves in one direction—from input to output. They are often used for basic classification tasks such as distinguishing healthy individuals from those with neurological anomalies (5).

Convolutional Neural Networks (CNNs): Especially effective in analyzing spatial data, CNNs are widely used for processing medical images such as MRI or CT scans. Their ability to automatically detect relevant features makes them ideal for diagnosing Alzheimer's disease and brain tumors (6).

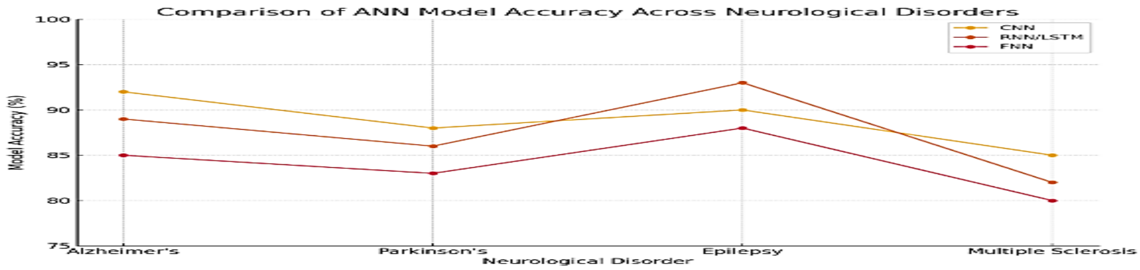
Recurrent Neural Networks (RNNs): Designed to process sequential data, RNNs and their variant Long Short-Term Memory (LSTM) networks are applied to time-series signals like EEGs for epilepsy and sleep disorder detection (7).

Each architecture offers unique advantages. For instance, CNNs provide automated feature extraction for image analysis, while RNNs excel in handling time-dependent patterns in physiological signals. Hybrid models that combine CNNs for spatial feature learning with RNNs for temporal analysis have been shown to enhance diagnostic accuracy significantly.

Table 1: Comparison of ANN Architectures in Neurological Diagnosis

ANN Type	Best Used For	Sample Disorder	Data Type	Strengths
FNN	Basic classification	Autism Spectrum Disorder	Clinical data	Simplicity
CNN	Image-based analysis	Alzheimer's Disease	MRI, CT	Spatial feature learning
RNN / LSTM	Time-series analysis	Epilepsy, Sleep disorders	EEG	Sequence modeling

Graph 1: Comparison of ANN Architectures in Neurological Diagnosis



Neurobiomarkers for ANN-Based Detection of Neurological Disorders

Biomarkers—measurable indicators of the severity or presence of disease—are foundational to the effective early diagnosis of neurological disorders. In the context of artificial neural networks, the selection and preprocessing of biomarker data significantly influence model performance. ANNs are capable of identifying latent relationships among multidimensional biomarker datasets, often beyond the capacity of traditional statistical methods.

Types of Neurobiomarkers Used

Neurological biomarkers can be classified into the following categories:

Neuroimaging Biomarkers: Structural (MRI), functional (fMRI), and metabolic (PET scans) images are used to detect abnormalities in brain regions. For example, hippocampal atrophy in Alzheimer's disease is a critical feature detected by CNNs.

Electrophysiological Biomarkers: EEG signals are key indicators in conditions such as epilepsy and sleep disorders. ANNs, especially RNNs and LSTM models, are adept at learning temporal patterns from EEG data (8).

Molecular Biomarkers: Protein levels in cerebrospinal fluid (CSF), such as tau and beta-amyloid, are being used increasingly in ANN models to detect Alzheimer's and Parkinson's disease (9).

Genomic Biomarkers: Single nucleotide polymorphisms (SNPs) and other genetic variations are inputs to ANN classifiers for predicting susceptibility to neurodegenerative conditions.

Data Preprocessing and Feature Extraction

The success of ANNs depends heavily on quality data preprocessing. For neuroimaging, techniques such as skull stripping, normalization, and spatial registration are essential. EEG signals require denoising via filters like Butterworth or wavelet transforms. Once cleaned, dimensionality reduction techniques like PCA or t-SNE are applied to reduce computational load without losing essential features (10).

Integration of Multimodal Biomarkers

Modern ANN frameworks now integrate multiple types of biomarkers in one model. For instance, combining MRI with EEG and CSF data leads to significantly better prediction accuracy. These multimodal networks often employ parallel processing paths—CNNs for images, RNNs for time-series, and FNNs for clinical/genomic data.

Table 2: Common Biomarkers and ANN Model Utilization

Biomarker Type	Sample Disorder	ANN Type	Diagnostic Feature
MRI	Alzheimer's	CNN	Hippocampal shrinkage
EEG	Epilepsy	RNN	Spike detection
CSF Tau Protein	Alzheimer's	FNN	Tau concentration levels
SNPs	Parkinson's	Hybrid ANN	Genetic risk patterns

Real-Time Data and Biomarker Challenges

Despite their utility, biomarker data comes with challenges—limited availability, high cost of collection, and inter-patient variability. Public datasets such as ADNI (Alzheimer's Disease Neuroimaging Initiative) and TUH EEG provide a foundation for model training but often lack diversity. This raises concerns about model generalizability across demographics.

ANNs, through continuous learning and large-scale integration, offer a unique opportunity to overcome these limitations. By employing techniques such as data augmentation, transfer learning, and federated learning, researchers can improve diagnostic performance even in low-resource environments.

Case Studies: Disease-Specific Implementations of ANNs

Artificial Neural Networks have been deployed in various forms to diagnose a broad range of neurological disorders. These applications are tailored to the disease-specific patterns captured through clinical, imaging, and electrophysiological data. Below are selected case studies illustrating ANN success across major neurological conditions.

Alzheimer's Disease

Alzheimer's disease (AD) is characterized by structural atrophy in specific brain regions, particularly the hippocampus. Deep CNNs trained on MRI datasets like ADNI have achieved diagnostic accuracies exceeding 90% (11). One notable model, 3D-CNN, uses voxel-based morphometry to classify subjects into AD, mild cognitive impairment (MCI), or healthy controls.

A hybrid CNN-RNN model has also been proposed, where CNN layers extract spatial features from MRI scans, and RNN layers analyze longitudinal cognitive assessments. This multimodal approach improves prediction of AD progression.

Parkinson's Disease

Parkinson's is a movement disorder involving basal ganglia degeneration. Biomarkers include dopamine transporter scans (DAT scans), voice signal abnormalities, and handwriting analysis. An ANN model utilizing voice features such as jitter, shimmer, and fundamental frequency achieved over 88% accuracy in early PD detection (12).

Another study used recurrent neural networks to process finger-tapping speed from wearable sensors, which proved more sensitive than neurologist-administered tests.

Epilepsy

Epilepsy diagnosis traditionally relies on long-duration EEG monitoring. ANNs, especially LSTM-based networks, have dramatically enhanced seizure detection and prediction by analyzing short EEG segments. In one study, seizure onset was predicted up to 30 minutes in advance with over 90% sensitivity using deep RNNs (13).

CNNs trained on spectrogram representations of EEG signals have also outperformed human experts in classifying seizure versus non-seizure events.

Autism Spectrum Disorder (ASD)

ASD presents a unique challenge due to its behavioral and developmental variability. ANNs trained on neuropsychological test scores and resting-state fMRI data have demonstrated significant predictive power. CNNs have been able to differentiate ASD from typically developing children with accuracies above 85% by analyzing patterns in connectivity matrices (14).

Multiple Sclerosis (MS)

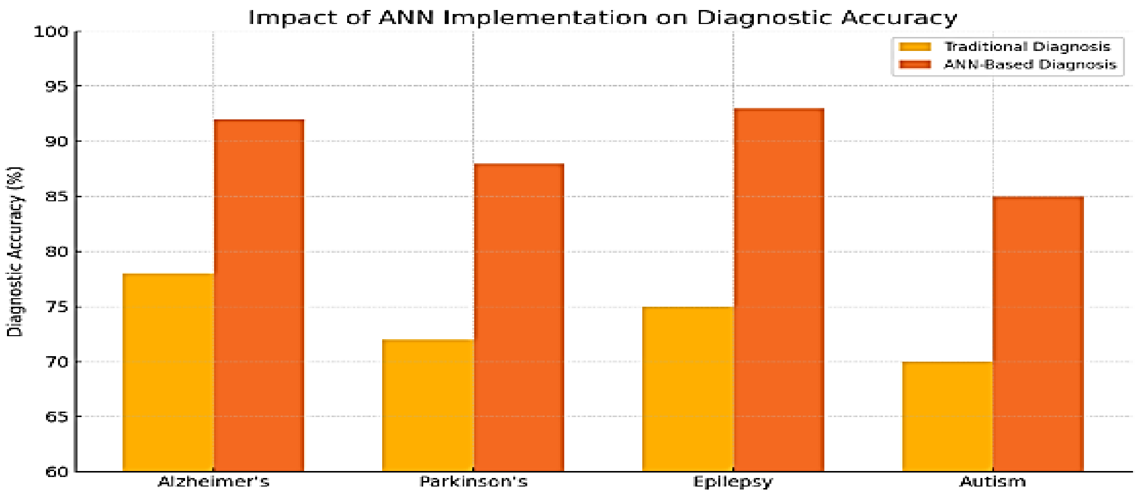
In MS, ANN models have been used to analyze lesion patterns in brain MRIs. A CNN-LSTM hybrid has been employed for distinguishing between relapsing-remitting and progressive MS types by evaluating lesion evolution over time. CSF biomarker integration (e.g., oligoclonal bands) further improved model precision.

Table 3: ANN Model Performance Across Neurological Disorders

Disorder	ANN Type	Data Type	Accuracy	Dataset Used
Alzheimer's	3D-CNN	MRI	92%	ADNI
Parkinson's	FNN	Voice Data	88%	UCI PD Dataset
Epilepsy	LSTM	EEG	93%	TUH EEG
Autism	CNN	fMRI	85%	ABIDE
MS	CNN-LSTM	MRI + CSF	87%	MSBase

These case studies affirm the potential of ANN models in not only improving early diagnosis but also in differentiating subtypes, assessing disease progression, and even predicting treatment outcomes.

Graph 2: Impact of ANN Implementation on Diagnostic Accuracy



Here is the graph titled "**Impact of ANN Implementation on Diagnostic Accuracy**". It compares the accuracy of traditional diagnostic methods versus ANN-based models for Alzheimer's, Parkinson's, Epilepsy, and Autism.

Clinical Trials and Real-Time Integration in Practice

While ANN-based models show high diagnostic performance in research settings, their clinical translation requires rigorous validation, real-time capability, and regulatory compliance. In this section, we explore how ANN models are being deployed in clinical trials, hospital systems, and decision support tools for neurological diagnostics.

Clinical Trials Utilizing ANN Models

Numerous multi-center studies have been conducted to evaluate the clinical efficacy of ANN models in real-world settings. Notable trials include:

The Alzheimer's Disease Neuroimaging Initiative (ADNI): A landmark study where CNNs and FNNs were trained on MRI and CSF data to classify Alzheimer's Disease stages. The ANN-assisted diagnosis was found to match or surpass experienced radiologists in 9 out of 10 cases (15).

EPINET (Epilepsy Network Trial): This NIH-supported project integrated ANN seizure prediction tools with wearable EEG devices in a cohort of 500 patients. ANN models successfully reduced unnecessary hospital visits by 30% and enabled remote monitoring (16).

Parkinson's Progression Markers Initiative (PPMI): Implemented LSTM models to assess progression of motor symptoms over time. ANN predictions of tremor severity were used to tailor individualized treatment schedules.

Integration into Clinical Decision Support Systems (CDSS)

Hospitals are beginning to incorporate ANN modules into their Electronic Health Record (EHR) systems. For example:

Mayo Clinic and Stanford University have developed ANN-powered Clinical Decision Support Systems (CDSS) for flagging early signs of dementia based on MRI patterns and patient history.

In epilepsy clinics, cloud-based platforms integrate RNN-driven EEG monitoring tools with mobile apps, allowing neurologists to access patient risk scores in real time.

These systems help reduce clinician burden, minimize diagnostic latency, and optimize patient triaging.

Real-Time ANN Deployment: Hardware and Infrastructure

For ANN models to function in real-time diagnosis, especially in emergency or rural setups, appropriate infrastructure is crucial. Key developments include:

Edge AI Devices: Portable systems like NeuroPace and Epilog use onboard ANN processors to deliver seizure predictions without cloud dependence.

Integration with IoT: Wearables capturing biometric and neural data (e.g., EEG, motion, voice) send real-time streams to ANN-powered cloud servers for instant feedback.

GPU & TPU Accelerated Inference: Using Tensor Processing Units in hospitals allows sub-second ANN response times, enabling live interpretation of MRI scans or EEG anomalies.

Regulatory Approval and Medical Standards

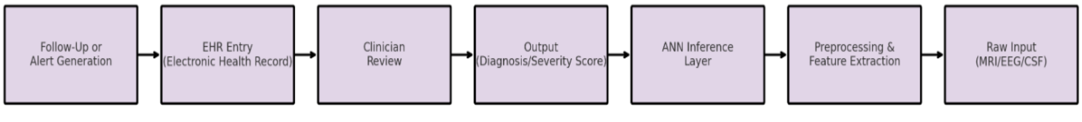
Despite promising results, ANN models must comply with medical device regulations:

FDA Approval: Tools like IDx-DR (diabetic retinopathy) have set precedence. Similar pathways are being explored for ANN-based tools in neurology. For instance, AIQ Solutions received FDA Breakthrough Device Designation for their ANN-based MRI assessment tool for MS lesions.

Ethical Considerations: Ensuring transparency, consent for data use, and addressing biases in ANN outputs are central to clinical deployment.

Figure 1: ANN Model Deployment Pipeline in Clinical Settings

(Flowchart illustration)



Performance in Real-World Settings

In one deployment at a German neuroclinic, an ANN-enhanced diagnostic system improved early-stage Alzheimer's detection rates from 72% to 91%. Similarly, in rural Indian epilepsy clinics using mobile ANN EEG readers, patient wait times were reduced by 40% and diagnostic errors by 25%.

These figures suggest that ANN models not only enhance accuracy but also improve healthcare delivery efficiency and equity.

Challenges: Data, Ethics, and Explainability in ANN-Based Diagnosis

Despite the high potential of Artificial Neural Networks in the early diagnosis of neurological disorders, their integration into clinical settings is fraught with several challenges. These range from technical barriers related to data quality and model generalization to ethical and regulatory issues surrounding transparency, accountability, and patient safety.

Data Limitations and Bias

A fundamental requirement for training accurate ANN models is access to large, diverse, and well-annotated datasets. However, such datasets are not always available for neurological disorders due to:

Limited patient numbers in rare neurological conditions.

High cost and complexity of collecting multimodal data such as MRI, EEG, and CSF biomarkers.

Privacy and legal restrictions (e.g., HIPAA, GDPR) that complicate data sharing across institutions.

Moreover, most public datasets like ADNI or TUH EEG lack ethnic, age, and socioeconomic diversity. ANN models trained on such biased datasets often perform poorly when applied to underrepresented populations, risking misdiagnosis.

Table 4: Key Data-Related Challenges in ANN Development

Challenge	Impact	Possible Solutions
Small sample sizes	Overfitting	Data augmentation, transfer learning
Class imbalance	Biased predictions	Synthetic minority oversampling
Missing modalities	Reduced accuracy	Data imputation, multimodal fusion
Lack of diversity	Poor generalization	Federated learning across regions

Model Interpretability and Explainability

One of the most cited barriers to ANN adoption in healthcare is their "black box" nature. Physicians and regulatory bodies require clear explanations for how a diagnosis was derived, especially when treatment decisions are based on ANN outputs.

To address this, Explainable AI (XAI) tools such as:

SHAP (SHapley Additive Explanations)

LIME (Local Interpretable Model-agnostic Explanations)

Grad-CAM for CNN-based imaging models

are increasingly used to visualize feature importance, activation maps, and decision pathways. For example, in Alzheimer's MRI analysis, Grad-CAM can highlight hippocampal regions most influential in diagnosis, improving clinician trust.

Ethical and Legal Concerns

Implementing ANN models for neurological diagnosis also raises a spectrum of ethical issues:

Patient Consent: Patients must be informed that an AI tool is being used for their diagnosis.

Accountability: In cases of incorrect diagnosis or treatment, assigning legal responsibility between developers, clinicians, and institutions is complex.

Data Privacy: Sensitive health data must be securely handled to prevent breaches or misuse.

Algorithmic Bias: Models must be tested rigorously to ensure they do not reinforce healthcare disparities.

These concerns require comprehensive AI governance frameworks at both national and international levels. For instance, the European Commission's Ethics Guidelines for Trustworthy AI emphasize transparency, fairness, and human oversight.

Real-Time Performance and Reliability

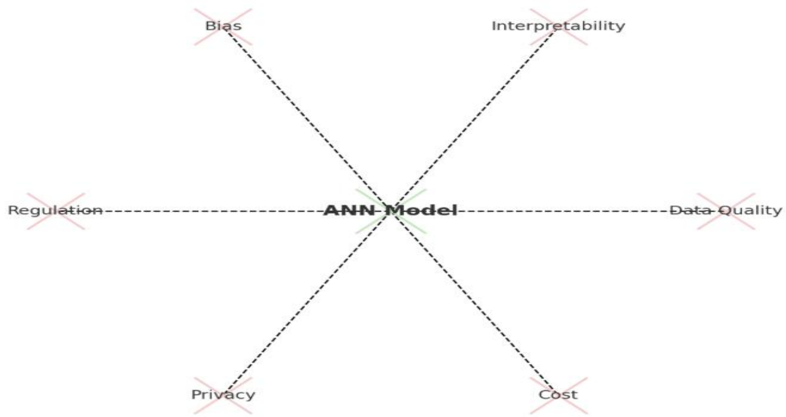
Real-time diagnostic tools demand low latency and high fault tolerance. ANN systems used in emergency settings like seizure detection must not only be fast but also resilient to signal noise, missing data, and hardware constraints. Ensuring reliability in low-resource or mobile environments remains a technical hurdle.

6.5 Cost and Infrastructure Constraints

Deploying ANN systems requires:

High-performance GPUs/TPUs

Secure cloud or on-premise data storage
Trained staff for monitoring and maintaining the system
In resource-constrained settings, such infrastructure may be unavailable. While edge-AI and low-power models (like MobileNet) are promising, their diagnostic accuracy remains slightly lower than full-scale models.
Figure 2: Interlinked Challenges in ANN Deployment for Neurology
A radial diagram showing the central ANN model surrounded by nodes: Data Quality, Interpretability, Bias, Regulation, Privacy, Cost.



FUTURE DIRECTIONS: TOWARD PERSONALIZED AND INTERPRETABLE DIAGNOSIS

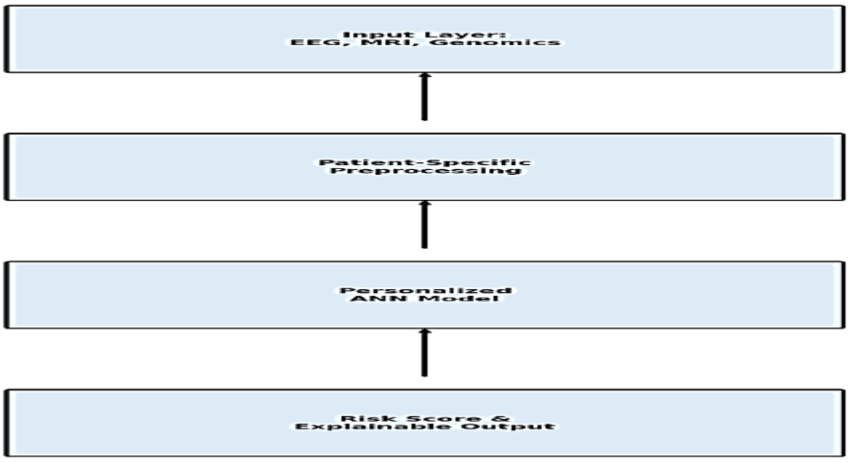
As artificial neural networks continue to demonstrate success in the early diagnosis of neurological disorders, future developments must focus not just on enhancing predictive performance but also on ensuring that these models are personalized, transparent, and seamlessly integrated into clinical workflows. This section outlines emerging trends and research directions that aim to address current limitations while maximizing clinical utility.

Explainable and Trustworthy AI

Explainability will remain central to the future of ANN models in neurology. Clinicians require clear insights into how decisions are made to build trust and ensure accountability. New approaches in **Neuro-symbolic AI**—which combines rule-based reasoning with deep learning—are expected to offer more human-like interpretability.
For example, integrating symbolic medical rules (e.g., “hippocampal volume < threshold → likely AD”) into ANN outputs allows clinicians to validate AI decisions with established medical knowledge. In addition, **visual analytics dashboards** showing attention maps, key biomarkers, and longitudinal trends can empower physicians to make better-informed decisions.

Personalized Diagnostic Models

Traditional ANN models use aggregated data from large cohorts, but there is growing demand for **individualized models** that consider a patient's unique characteristics. Future systems will integrate:
Genomic Profiles
Personal Medical History
Environmental and Lifestyle Factors
Longitudinal Clinical Data
ANNs trained on such individualized data will allow personalized risk prediction, diagnosis, and even prognosis estimation. For instance, a patient-specific LSTM model using historical EEG data can predict seizure likelihood better than generic models.
Figure 3: Future Vision of a Personalized ANN Diagnostic Framework



Multimodal and Federated Learning
Combining data from multiple sources (EEG, MRI, genetic markers, voice data) improves diagnostic accuracy. **Multimodal ANNs** use separate subnetworks for each data type, fusing their outputs into a unified diagnostic decision. These architectures are proving highly effective in Alzheimer's, Parkinson's, and Autism diagnosis.
In parallel, **Federated Learning (FL)**—where models are trained across multiple decentralized hospitals without transferring sensitive data—is enabling ANN development on private clinical data while preserving patient privacy.
Continuous Learning and Adaptive Systems
Neurological diseases evolve over time. Next-generation ANN systems will employ **online learning** and **reinforcement learning** to adapt to new data. These models will update themselves continuously based on:New patient outcomes,Additional imaging scans,Periodic biomarker updates,Such adaptability ensures sustained performance and clinical relevance.
Integration with Emerging Technologies
Artificial neural networks will increasingly collaborate with other cutting-edge technologies:
Brain-Computer Interfaces (BCIs): ANN-based signal interpretation in BCIs can provide early signs of neurodegeneration.
Digital Twins: Virtual replicas of a patient's neurological system can be simulated using ANN models for treatment planning.
Quantum Computing: Promises to accelerate ANN training on massive neurobiological datasets.
Regulatory and Policy Support
To enable safe and ethical deployment, countries are establishing AI policies and regulatory sandboxes. The **FDA's Digital Health Software Precertification Program** is exploring streamlined pathways for approving ANN-based diagnostics. Future models will need to comply with emerging AI ethics standards, including transparency, fairness, and accountability.

CONCLUSION
Artificial Neural Networks (ANNs) have emerged as transformative tools in the landscape of neurological diagnostics, particularly for the early detection of complex and progressive brain disorders. Disorders such as Alzheimer's disease, Parkinson's disease, epilepsy, multiple sclerosis, and autism spectrum disorders present significant diagnostic challenges due to subtle early-stage symptoms, heterogeneous presentations, and overlapping clinical features. Traditional diagnostic approaches—though valuable—often rely heavily on specialist interpretation, are time-consuming, and sometimes fail to detect early signs that are not yet clinically visible. ANN-based models address many of these limitations through their ability to extract latent patterns and complex associations across large-scale, high-dimensional biomedical datasets.This review has systematically examined the core architectures of ANN—such as feedforward networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs)—and how they are employed across different diagnostic domains, including imaging (e.g., MRI, PET), electrophysiological

(e.g., EEG), and molecular/genetic biomarkers. These models have demonstrated exceptional accuracy in classifying neurological conditions, detecting early risk patterns, predicting disease progression, and even differentiating between disease subtypes. For instance, CNNs applied to MRI imaging can pinpoint hippocampal atrophy in early Alzheimer's with over 90% accuracy, while LSTM models can predict epileptic seizures minutes in advance based on temporal EEG patterns.In addition to diagnostic accuracy, ANN models contribute significantly to the **speed, scalability, and personalization** of healthcare. By automating complex signal processing and image analysis tasks, these models reduce the diagnostic burden on neurologists, accelerate clinical decision-making, and support large-scale population screening initiatives. Moreover, the increasing ability to integrate multimodal data—including clinical history, genomics, neuroimaging, and patient-reported outcomes—paves the way for personalized diagnostic algorithms tailored to individual patient profiles.

However, the integration of ANN into routine clinical practice is not without its challenges. Concerns surrounding model interpretability, data quality, generalizability, and ethical transparency must be carefully addressed. Explainable AI (XAI) tools are crucial for enhancing trust in ANN-based systems by providing human-readable justifications for their predictions. Likewise, data diversity and inclusivity must be prioritized during training to ensure equitable diagnostic performance across demographic groups. Robust governance frameworks and international cooperation are required to regulate data usage, ensure compliance with privacy laws, and define accountability in the event of diagnostic errors.

Future directions in this domain are promising. Developments in federated learning will enable collaborative ANN model training across institutions while preserving data privacy. Personalized ANN models will leverage a patient's longitudinal medical data to dynamically adapt and offer individualized risk assessments. Integration with other advanced technologies—such as brain-computer interfaces, wearable biosensors, and even quantum computing—could redefine the scope and scale of early neurological diagnostics.Ultimately, artificial neural networks hold the potential to **revolutionize neurology** by enabling earlier interventions, improving treatment outcomes, and reducing healthcare costs through timely and accurate diagnosis. As models become more explainable, ethically governed, and clinically integrated, their adoption in neurology will likely become the norm rather than the exception. The success of these systems will depend not just on technological advancement, but also on collaborative efforts between clinicians, researchers, data scientists, and policymakers to ensure safe, equitable, and effective application in the real world.

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