International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 01-09
OCLC – 1368736135
Crossref Google Scholar WorldCat MENDELEY
ISSN-2750-1396

Journal Website: http://sciencebring.com/index.php/ijasr

Research Article

Advanced Machine Learning and Deep Learning Architectures for Enhanced Early Diagnosis and Risk Stratification of Neurodegenerative Diseases in Precision Healthcare

Submission Date: April 08, 2026, **Accepted Date:** May 05, 2026,
Published Date: June 01, 2026

Kojo Frimpong
Department of Medicine, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Abstract

Neurodegenerative diseases (NDs) such as Alzheimer's disease, Parkinson's disease, and Huntington's disease represent a growing global health burden characterized by progressive neuronal loss and irreversible cognitive and motor decline. Early diagnosis and accurate risk stratification remain critical challenges due to the heterogeneous and multi-factorial nature of these disorders. Recent advancements in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) architectures, have demonstrated transformative potential in addressing these challenges through multimodal data integration, predictive modeling, and automated clinical decision support. This review critically synthesizes state-of-the-art ML and DL frameworks applied in precision healthcare for neurodegenerative disease detection and progression modeling. It explores the role of feature-based learning, imaging genomics, digital biomarkers, and biosensor-driven diagnostic systems in enhancing diagnostic accuracy. Furthermore, the study evaluates interpretability challenges, ethical considerations, and clinical integration barriers associated with AI deployment in healthcare systems. Evidence suggests that hybrid architectures combining convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models significantly improve early-stage detection performance and risk classification accuracy. However, limitations persist in dataset heterogeneity, model generalizability, and clinical validation. The findings emphasize the need for standardized AI frameworks and interdisciplinary collaboration to enable scalable precision diagnostics. Overall, this study highlights AI-driven architectures as a foundational pillar in next-generation neurodegenerative disease management systems.

Keywords

Machine Learning, Deep Learning, Neurodegenerative Diseases, Early Diagnosis, Risk Stratification, Precision Healthcare, Artificial Intelligence, Biomarkers, Predictive Modeling, Clinical Decision Support.

Introduction

Neurodegenerative diseases (NDs) constitute a class of progressive neurological disorders characterized by the gradual degeneration of neurons, leading to cognitive, behavioral, and motor dysfunction. These diseases, including Alzheimer's disease, Parkinson's disease, and Huntington's disease, pose significant clinical and socio-economic challenges worldwide due to aging populations and increasing prevalence rates. Early detection remains a crucial determinant in slowing disease progression and improving patient outcomes.

Traditional diagnostic approaches rely heavily on clinical observation, neuroimaging, and biochemical assays, which often fail to detect subtle preclinical changes. As a result, diagnosis frequently occurs at advanced stages when therapeutic interventions are less effective. In this context, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a powerful paradigm for enabling data-driven precision healthcare solutions.

ML and DL models can process large-scale heterogeneous datasets, including imaging, genomic, clinical, and digital biomarker data, to identify hidden patterns associated with early disease onset. According to recent studies, AI-assisted diagnostic systems significantly improve classification accuracy and predictive capabilities in complex neurological conditions (Alabi, 2025; Alam et al., 2024). Furthermore, AI-driven frameworks support risk stratification by integrating longitudinal patient data and identifying disease trajectories.

The foundational understanding of neurodegenerative disease classification and mechanisms is essential for developing robust AI models. As emphasized by Chand and Subramanian (2025), neurodegenerative disorders exhibit multi-factorial etiologies involving genetic, environmental, and molecular factors, making computational modeling indispensable for effective diagnosis and therapeutic planning. This multi-dimensional complexity necessitates the use of advanced computational architectures capable of handling non-linear relationships in biomedical data.

The primary objectives of this study are: (1) to analyze advanced ML and DL architectures used in neurodegenerative disease diagnosis, (2) to evaluate their role in early detection and risk stratification, (3) to identify existing challenges in clinical integration, and (4) to propose future directions for AI-driven precision healthcare systems.

International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 01-09
OCLC – 1368736135
ISSN-2750-1396

The significance of this research lies in its potential to bridge the gap between computational intelligence and clinical neurology, enabling scalable and interpretable diagnostic frameworks for real-world healthcare applications.

Literature Review

Recent advancements in AI-based healthcare systems have significantly transformed neurodegenerative disease research. Machine learning and deep learning approaches have been widely adopted for predictive diagnostics, medical imaging analysis, and biomarker identification.

Alam et al. highlight that ML applications in healthcare include disease prediction, classification, and personalized treatment planning, demonstrating strong adaptability across clinical datasets. Similarly, Sarker (2021) provides a foundational overview of ML algorithms such as supervised learning, unsupervised clustering, and reinforcement learning, emphasizing their real-world medical applications.

In neurodegenerative research, deep learning architectures such as convolutional neural networks (CNNs) have been extensively used for brain imaging analysis. Chudzik et al. (2024) demonstrate that digital biomarkers combined with ML models can detect early-stage neurodegeneration with high accuracy, particularly in Parkinson's and Alzheimer's disease. Cen et al. (2024) further extend this approach by integrating imaging genomics with interpretable AI frameworks, enabling better understanding of disease-related genetic expression patterns.

A critical advancement in the field is the integration of biosensor technologies for cerebrospinal fluid (CSF) analysis. Hatami-Fard and Anastasova-Ivanova (2024) highlight how biosensor-driven diagnostics can complement AI systems by providing real-time biochemical data, improving early detection accuracy.

From a clinical decision-making perspective, Khalifa et al. (2024) emphasize the role of AI in supporting multi-domain clinical decision systems, improving diagnostic consistency and reducing human error. Gabrani et al. (2024) further illustrate AI's transformative impact on healthcare systems, particularly in disease diagnosis and patient management.

Neurodegenerative disease-specific literature also provides essential context. Gupta and Sharma (2025) describe the biological mechanisms underlying neurodegeneration, including synaptic dysfunction and protein aggregation. Chand and Subramanian (2025) further classify these disorders into structured pathological categories, highlighting the importance of multi-factorial modeling approaches for computational diagnosis. This classification is particularly important for ML model design, as it informs feature selection and label structuring in supervised learning frameworks.

International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 01-09
OCLC – 1368736135

Additionally, Kunwar and Singh (2025) discuss neuroinflammation mechanisms in Huntington's disease, emphasizing the role of metals and environmental toxins, which can be incorporated into predictive modeling features.

Despite these advancements, Marques et al. (2024) highlight ethical challenges associated with AI decision-making in medicine, including transparency, accountability, and bias in algorithmic systems. These challenges remain critical barriers to clinical adoption.

Overall, literature suggests a strong convergence between AI technologies and neurodegenerative disease research; however, gaps remain in model interpretability, dataset standardization, and clinical validation.

Methodology

This study adopts a structured qualitative synthesis approach based on secondary data analysis of peer-reviewed literature, focusing on ML and DL applications in neurodegenerative disease diagnosis. The methodology integrates conceptual modeling, comparative analysis, and framework development.

3.1 Data Collection Strategy

Relevant studies were selected based on their contributions to AI-driven neurodegenerative research, particularly those focusing on ML/DL architectures, clinical decision systems, and biomarker integration. Studies spanning 2021–2025 were prioritized to ensure technological relevance.

3.2 Analytical Framework

The analysis is structured around three core dimensions:

1. Algorithmic Architecture Analysis – Evaluation of ML/DL models such as CNNs, RNNs, and hybrid transformer-based systems for imaging and clinical data processing.

2. Feature Integration Mechanisms – Assessment of multimodal data fusion, including imaging, genetic, and biosensor inputs.

3. Clinical Applicability and Risk Stratification Models – Examination of predictive accuracy, sensitivity, and real-world deployment feasibility.

According to Chand and Subramanian (2025), neurodegenerative disease classification requires a multi-factorial analytical approach due to overlapping symptomatology and heterogeneous disease progression patterns. This principle forms the conceptual foundation of the methodological framework used in this study.

3.3 Model Categorization

AI architectures are categorized into:

- Supervised learning models for disease classification
- Unsupervised learning models for clustering disease subtypes
- Deep learning models for imaging and sequential data analysis

- Hybrid models integrating multimodal datasets

3.4 Evaluation Metrics

Performance evaluation is based on diagnostic accuracy, sensitivity, specificity, computational efficiency, and interpretability. Special emphasis is placed on model generalization across heterogeneous datasets.

3.5 Ethical and Clinical Considerations

Ethical implications such as bias mitigation, data privacy, and clinical accountability are considered essential components of AI deployment frameworks (Marques et al., 2024).

Results

Further analytical synthesis of the reviewed studies reveals deeper performance stratifications and architectural advantages of advanced AI systems in neurodegenerative disease diagnostics, particularly when evaluated across multimodal and longitudinal datasets.

A key finding is that hybrid deep learning architectures—combining convolutional neural networks (CNNs) with recurrent neural networks (RNNs) and attention-based transformer modules—consistently outperform standalone models in both diagnostic accuracy and temporal disease progression tracking. CNN layers excel in extracting spatial features from neuroimaging data such as MRI and PET scans, while RNN and transformer layers enhance temporal dependency modeling in longitudinal clinical records. This synergy significantly improves early-stage detection sensitivity, particularly in pre-symptomatic Alzheimer's and Parkinson's disease cohorts.

Another major outcome is the increasing effectiveness of digital biomarker integration systems. Studies indicate that wearable sensor data, speech pattern analysis, and motor activity tracking contribute substantial predictive value when fused with clinical imaging datasets. Chudzik et al. (2024) demonstrate that ML models trained on combined digital biomarkers achieve higher early detection rates compared to traditional clinical assessments alone, particularly in identifying subtle motor impairments in Parkinsonian disorders.

In addition, imaging genomics frameworks show strong potential in enhancing disease classification granularity. Cen et al. (2024) highlight that integrating genetic expression profiles with neuroimaging data enables AI systems to identify latent disease subtypes that are not clinically distinguishable in early stages. This significantly improves risk stratification, allowing classification into low-risk, moderate-risk, and high-risk progression categories.

From a computational efficiency perspective, transformer-based architectures demonstrate superior scalability when processing large-scale heterogeneous datasets. However, their performance is highly dependent on dataset quality and training volume, indicating that smaller clinical datasets may limit their effectiveness. In contrast, traditional ML models

International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 01-09
OCLC – 1368736135

such as random forests and support vector machines maintain stable performance under limited data conditions but lack deep feature abstraction capability.

A critical observation across multiple studies is the improvement in clinical decision support systems (CDSS) powered by AI. These systems reduce diagnostic variability among clinicians by providing standardized risk scores and probabilistic disease predictions. Khalifa et al. (2024) report that AI-integrated CDSS frameworks improve diagnostic consistency across neurological departments, particularly in early dementia screening.

Another important finding is the role of biosensor-enhanced diagnostic ecosystems, where cerebrospinal fluid (CSF) biosensors and biochemical markers are integrated with AI models. Hatami-Fard and Anastasova-Ivanova (2024) demonstrate that biosensor-based AI systems significantly improve early detection of rare neurodegenerative conditions by identifying molecular-level changes before clinical symptom onset.

Despite these advancements, model interpretability remains a persistent limitation. Deep learning models often function as black-box systems, making it difficult for clinicians to understand decision pathways. This reduces trust and slows clinical adoption. Explainable AI (XAI) frameworks are emerging as a partial solution, enabling visualization of feature importance and decision logic, although their application remains limited in large-scale clinical environments.

Risk stratification analysis further indicates that AI systems are capable of predicting disease progression trajectories with moderate to high accuracy when trained on longitudinal datasets. However, variability in patient demographics, comorbidities, and imaging protocols introduces generalization challenges.

Importantly, Chand and Subramanian (2025) emphasize that neurodegenerative disorders are inherently multi-factorial, involving genetic, environmental, and biochemical interactions. This reinforces the necessity of multi-layered AI architectures capable of integrating heterogeneous data streams for reliable prediction. Their framework supports the observed superiority of hybrid and multimodal AI systems in current research.

Finally, ethical and regulatory considerations continue to influence deployment feasibility. Bias in training datasets, lack of standardization, and privacy concerns limit real-world implementation despite strong experimental results. These constraints highlight the gap between algorithmic performance and clinical readiness.

DISCUSSION

The findings of this study underscore the transformative potential of ML and DL architectures in neurodegenerative disease diagnostics. The integration of multimodal data sources enables comprehensive disease modeling, improving both early detection and risk stratification accuracy.

From a theoretical perspective, deep learning models provide a robust framework for capturing non-linear relationships in biomedical data. However, their black-box nature raises concerns regarding interpretability and clinical trust. This limitation is particularly critical in high-stakes medical decision-making environments.

The study also highlights significant trade-offs between model complexity and clinical usability. While advanced architectures such as transformers offer superior performance, they require substantial computational resources and large annotated datasets.

Ethical concerns remain a major barrier to widespread adoption. Issues related to bias, transparency, and accountability must be addressed to ensure equitable healthcare deployment (Marques et al., 2024).

Chand and Subramanian (2025) emphasize that neurodegenerative diseases require multi-factorial diagnostic frameworks, reinforcing the need for hybrid AI models that integrate biological, clinical, and environmental factors. This aligns with the observed superiority of multimodal learning systems.

Despite advancements, limitations include dataset heterogeneity, lack of standardization, and insufficient clinical validation in real-world environments. Future research must focus on explainable AI models and federated learning approaches to enhance data privacy and model generalization.

Conclusion

This study provides a comprehensive analysis of advanced machine learning and deep learning architectures for early diagnosis and risk stratification of neurodegenerative diseases. The findings confirm that AI-driven systems significantly enhance diagnostic accuracy and enable personalized healthcare interventions.

The integration of multimodal data sources, including imaging, genomic, and biosensor inputs, represents a major advancement in precision healthcare. However, challenges related to interpretability, ethical governance, and clinical validation remain unresolved.

Future research should focus on developing explainable AI frameworks, improving dataset standardization, and enhancing real-world clinical integration. Chand and Subramanian (2025) highlight the importance of multi-factorial classification systems, which should guide future AI model development for neurodegenerative diseases.

Overall, AI-based diagnostic systems represent a promising frontier in neurodegenerative disease management, with the potential to transform early detection and personalized treatment strategies in clinical neuroscience.

References

1. Alabi, M., AI-Assisted Medical Diagnosis Using Deep Learning and Computer Vision. 2025.

International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 01-09
OCLC – 1368736135

2. Alam, T., et al., Machine Learning in Healthcare: Key Applications and Insights from Recent Studies.
3. Chand, J. and G. Subramanian, Neurodegenerative Disorders: Types, Classification, and Basic Concepts, in Multi-Factorial Approach as a Therapeutic Strategy for the Management of Alzheimer's Disease. 2025, Springer. p. 31-40.
4. Cen, X., et al., Towards interpretable imaging genomics analysis: methodological developments and applications. Information Fusion, 2024. 102: p. 102032.
5. Chudzik, A., A. Śledzianowski, and A.W. Przybyszewski, Machine learning and digital biomarkers can detect early stages of neurodegenerative diseases. Sensors, 2024. 24(5): p. 1572.
6. De Giorgi, R., et al., 12-month neurological and psychiatric outcomes of semaglutide use for type 2 diabetes: a propensity-score matched cohort study.EClinicalMedicine, 2024. 74.
7. Gabrani, G., et al., Revolutionizing healthcare: impact of artificial intelligence in disease diagnosis, treatment, and patient care, in Handbook on Augmenting Telehealth Services. 2024, CRC Press. p. 17-31.
8. Gadhave, D.G., et al., Neurodegenerative disorders: Mechanisms of degeneration and therapeutic approaches with their clinical relevance. Ageing research reviews, 2024: p. 102357.
9. Gupta, A. and B. Sharma, Neurodegenerative Diseases (ND): An Introduction, in Synaptic Plasticity in Neurodegenerative Disorders. 2025, CRC Press. p. 3-20.
10. Hatami-Fard, G. and S. Anastasova-Ivanova, Advancements in Cerebrospinal Fluid Biosensors: Bridging the Gap from Early Diagnosis to the Detection of Rare Diseases. Sensors, 2024. 24(11): p. 3294.
11. Khalifa, M., M. Albadawy, and U. Iqbal, Advancing clinical decision support: The role of artificial intelligence across six domains. Computer Methods and Programs in Biomedicine Update, 2024. 5: p. 100142.
12. Kunwar, O.K. and S. Singh, Neuroinflammation and neurodegeneration in Huntington's disease: Genetic hallmarks, role of metals and organophosphates.Neurogenetics, 2025. 26(1): p. 1-15.
13. Mauro, D., et al., The role of early treatment in the management of axial spondyloarthritis: challenges and opportunities. Rheumatology and Therapy, 2024. 11(1): p. 19-34.
14. Marques, M., A. Almeida, and H. Pereira, The medicine revolution through artificial intelligence: ethical challenges of machine learning algorithms in decision-making. Cureus, 2024. 16(9).
15. Ogwu, M.C. and S.C. Izah, Artificial Intelligence and Machine Learning in Tropical Disease Management, in Technological Innovations for Managing Tropical Diseases. 2025, Springer. p. 155-182.
16. Proskauer Pena, S.L., Cellular Mechanisms of Segregation and Consolidation of Memory in a Rat Model of Alzheimer's Disease. 2025.
17. Rashid, M. and M. Sharma, AI-Assisted Diagnosis and Treatment Planning—A Discussion of How AI Can Assist Healthcare Professionals in Making More Accurate

International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 01-09
OCLC – 1368736135

Diagnoses and Treatment Plans for Diseases. AI in Disease Detection: Advancements and Applications, 2025: p. 313-336.

18. Rawat, A.S., J. Rajendran, and S.S. Sikarwar, Introduction to AI in Disease Detection—An Overview of the Use of AI in Detecting Diseases, Including the Benefits and Limitations of the Technology. AI in Disease Detection: Advancements and Applications, 2025: p. 1-26.
19. Sarker, I.H., Machine learning: Algorithms, real-world applications and research directions. SN computer science, 2021. 2(3): p. 160.
20. Shah, H.H., Early Disease Detection Through Data Analytics: Turning Healthcare Intelligence. International Journal of Multidisciplinary Sciences and Arts. 2(4): p. 252-269.
21. Singh, L., et al., Ethical and Regulatory Compliance Challenges of Generative AI in Human Resources. Generative Artificial Intelligence in Finance: Large Language Models, Interfaces, and Industry Use Cases to Transform Accounting and Finance Processes, 2025: p. 199-214.
22. Singh, P., et al., General Introduction to Different Neurodegenerative Diseases, in Neurodegenerative Diseases. 2025, CRC Press. p. 1-19.
23. Valarmathi, P., et al., Enhancing parkinson disease detection through feature based deep learning with autoencoders and neural networks. Scientific Reports, 2025. 15(1): p. 8624.