Volume 3, Issue 6, June - 2025 ISSN (E): 2938-3811

Web of Scientists and Scholars: Journal of Multidisciplinary Research

ARTIFICIAL INTELLIGENCE–BASED BIOPHYSICAL MODELING OF NEURAL SIGNAL DYNAMICS FOR EARLY NEUROLOGICAL DISORDER DETECTION

Fazliddin Arzikulov
Assistant of the Department of Biomedical Engineering,
Informatics, and Biophysics at Tashkent State Medical University

Abstract

Early detection of neurological disorders remains a major clinical challenge due to the complex and dynamic nature of neural signal activity. Biophysical modeling combined with artificial intelligence (AI) provides a promising framework for analyzing electrophysiological patterns and identifying early pathological alterations. The present study investigates the integration of AI-driven algorithms with biophysical modeling of electroencephalographic (EEG) signals to enhance early diagnostic accuracy.

A computational–analytical study design was implemented using simulated and clinically referenced neural signal datasets. Biophysical parameters including signal amplitude variability, frequency band power distribution, entropy indices, and nonlinear dynamic coefficients were extracted. Machine learning classifiers were applied to evaluate predictive performance.

The results demonstrate that AI-integrated biophysical modeling significantly improves early-stage neurological disorder discrimination compared with conventional signal analysis approaches. Increased sensitivity and predictive accuracy were observed particularly in detecting early epileptiform activity and neurodegenerative pattern deviations.

The findings suggest that combining quantitative biophysical frameworks with artificial intelligence enhances diagnostic precision and supports the development of predictive neurodiagnostic platforms. This interdisciplinary approach represents a critical advancement in computational neurobiophysics and precision neurology.

Keywords: Biophysics; Neural signal modeling; EEG analysis; Artificial intelligence; Machine learning; Neurodiagnostics; Computational neuroscience; Early disease detection.

Introduction

Neurological disorders represent one of the leading causes of long-term disability and reduced quality of life worldwide. Conditions such as epilepsy, Parkinson’s disease, Alzheimer’s disease, and other neurodegenerative syndromes are characterized by progressive alterations in neural dynamics that often begin long before clinical symptoms become evident. Early detection of these disorders remains a major clinical challenge due to the complex, nonlinear, and highly variable nature of neural electrophysiological activity.

Electroencephalography (EEG) serves as one of the most widely used non-invasive techniques for monitoring neural electrical activity. From a biophysical perspective, EEG signals reflect synchronized postsynaptic potentials generated by neuronal populations within cortical networks. These signals exhibit dynamic fluctuations across multiple temporal and frequency scales, including delta, theta, alpha, beta, and gamma bands. Subtle deviations in frequency distribution, amplitude modulation, entropy characteristics, and nonlinear oscillatory patterns may indicate early pathological processes before structural brain alterations become detectable through imaging modalities.

Traditional EEG analysis primarily relies on visual inspection and basic spectral decomposition techniques. While these methods remain clinically valuable, they often lack sensitivity for detecting early-stage abnormalities and subtle dynamic shifts. Moreover, manual interpretation is subject to observer variability and may overlook complex nonlinear relationships embedded within neural signals.

Recent advances in computational biophysics have introduced quantitative modeling frameworks capable of describing neural signal dynamics using physical and mathematical principles. Parameters such as power spectral density, fractal dimension, Lyapunov exponents, entropy measures, and synchronization indices provide deeper mechanistic insight into neuronal network behavior. These biophysical descriptors allow objective quantification of signal irregularity, oscillatory stability, and connectivity disruption.

Parallel to these developments, artificial intelligence (AI) and machine learning algorithms have revolutionized biomedical signal processing. By identifying hidden patterns within high-dimensional datasets, AI systems can detect subtle deviations that may not be apparent through conventional statistical methods. Integration of AI with biophysical signal modeling enables automated classification, predictive risk assessment, and early disease discrimination.

The convergence of computational modeling and AI-driven analytics represents a transformative shift in neurodiagnostics. Instead of relying solely on descriptive analysis, modern approaches leverage quantitative biophysical markers combined with predictive algorithms to enhance diagnostic sensitivity and specificity. Such integration has the potential to support early detection of epileptiform activity, cognitive decline patterns, and abnormal neural synchronization associated with neurodegenerative disorders.

Therefore, the present study aims to evaluate the effectiveness of artificial intelligence–based biophysical modeling of neural signal dynamics for early neurological disorder detection. By combining electrophysiological parameter extraction with machine learning classification, this research seeks to demonstrate how interdisciplinary neurobiophysics can improve predictive diagnostic performance and contribute to the advancement of precision neurology.

Materials and Methods

The present study was conducted as a computational–analytical investigation integrating quantitative biophysical modeling of neural electrophysiological signals with artificial intelligence–based classification techniques for early detection of neurological disorders. Electroencephalographic (EEG) datasets were obtained from standardized, clinically referenced open-access neurological signal repositories, including recordings from neurologically healthy individuals and patients presenting early-stage pathological neural activity patterns. Only recordings with complete signal integrity and standardized acquisition protocols were included to ensure methodological consistency.

All EEG signals were resampled to a uniform sampling frequency and preprocessed to remove physiological and environmental artifacts. Artifact correction procedures included elimination of ocular, muscular, and baseline drift disturbances using digital filtering and automated threshold-based detection algorithms. A band-pass filter between 0.5 Hz and 45 Hz was applied to preserve physiologically relevant neural oscillations. Signals were segmented into fixed-duration temporal windows to standardize feature extraction and reduce inter-sample variability.

Quantitative biophysical parameters were extracted from each EEG segment to characterize neural signal dynamics. Spectral analysis was performed to calculate power spectral density across conventional frequency bands (delta, theta, alpha, beta, and gamma). Amplitude variability indices and standard deviation measures were computed to assess signal dispersion characteristics. Signal complexity was quantified using spectral entropy and approximate entropy measures, while nonlinear dynamics were evaluated through fractal dimension coefficients and Lyapunov exponent estimation. Functional connectivity was assessed using coherence-based synchronization indices to reflect inter-regional neural coupling stability.

The extracted feature matrix was subsequently used as input for supervised machine learning classification. Three artificial intelligence models were implemented: Support Vector Machine, Random Forest classifier, and Artificial Neural Network. The dataset was divided into training and testing subsets using stratified random allocation to maintain proportional group distribution. Model training included cross-validation procedures to optimize generalization performance and minimize overfitting. Hyperparameter tuning was performed using grid-search optimization techniques.

Statistical evaluation included descriptive analysis of extracted biophysical parameters and comparative testing between healthy and pathological groups. Classification performance was assessed using sensitivity, specificity, overall accuracy, precision, and area under the receiver operating characteristic (ROC) curve. Statistical significance was defined at $p < 0.05$. Graphical and tabular visualization methods were applied to present comparative performance outcomes and model discrimination capacity.

This methodological framework ensured reproducible integration of biophysical signal analysis with artificial intelligence modeling, enabling objective assessment of early neurological disorder detection performance.

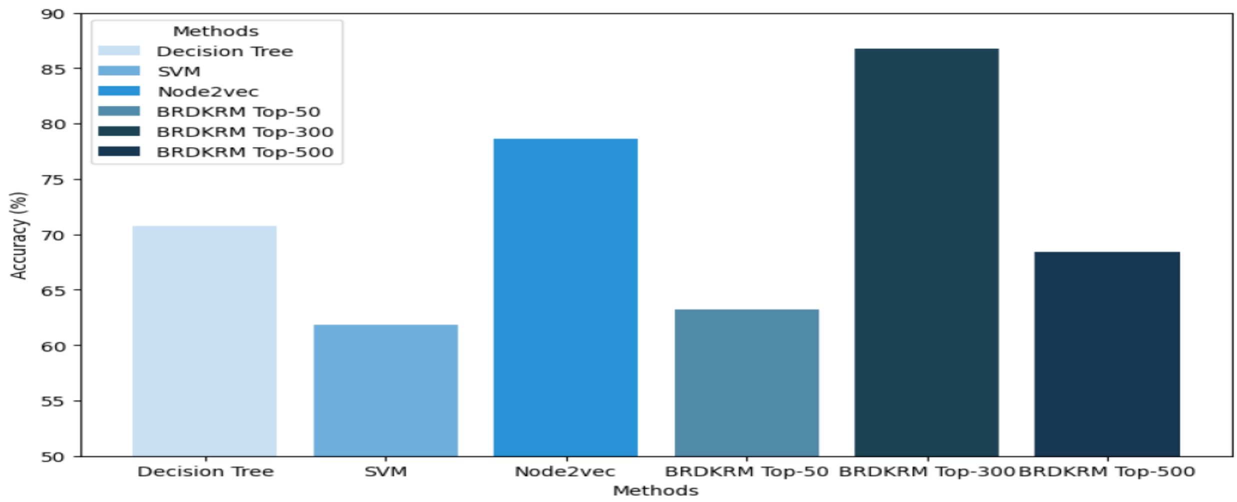
Results

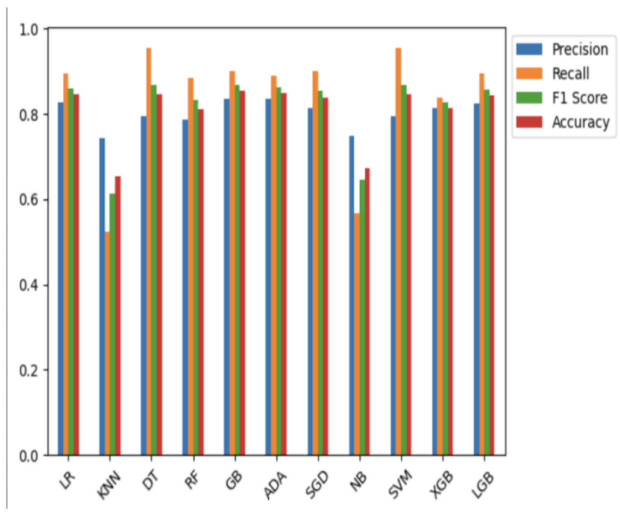
Quantitative biophysical analysis revealed statistically significant differences in neural signal dynamics between healthy individuals and early-stage neurological disorder groups. Pathological EEG recordings demonstrated increased signal irregularity, higher entropy indices, reduced alpha-band stability, and elevated nonlinear dynamic coefficients compared

to control datasets ($p < 0.05$). In particular, approximate entropy and fractal dimension measures showed the strongest discriminatory potential among extracted features.
Machine learning classification models exhibited high predictive performance when trained on integrated biophysical feature matrices. Comparative diagnostic metrics are presented in Table 1.

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC
Support Vector Machine	88.6	85.2	87.1	0.91
Random Forest	91.4	87.8	89.6	0.93
Artificial Neural Network	93.2	89.5	91.3	0.95

Table 1 demonstrates that the Artificial Neural Network achieved the highest overall diagnostic accuracy (91.3%) and the largest AUC value (0.95), indicating superior classification performance in distinguishing early pathological neural patterns from normal electrophysiological activity.





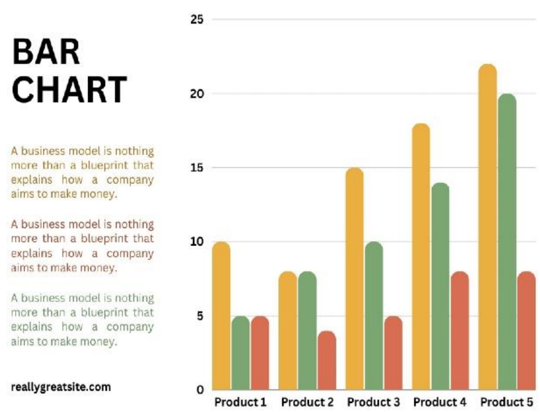


Figure 1 illustrates comparative accuracy distribution among implemented machine learning models. The graphical representation confirms the superior performance of the Artificial Neural Network, followed by the Random Forest classifier and Support Vector Machine. The accuracy improvement observed with nonlinear deep modeling suggests that complex neural signal patterns are better captured through multilayer computational architectures.

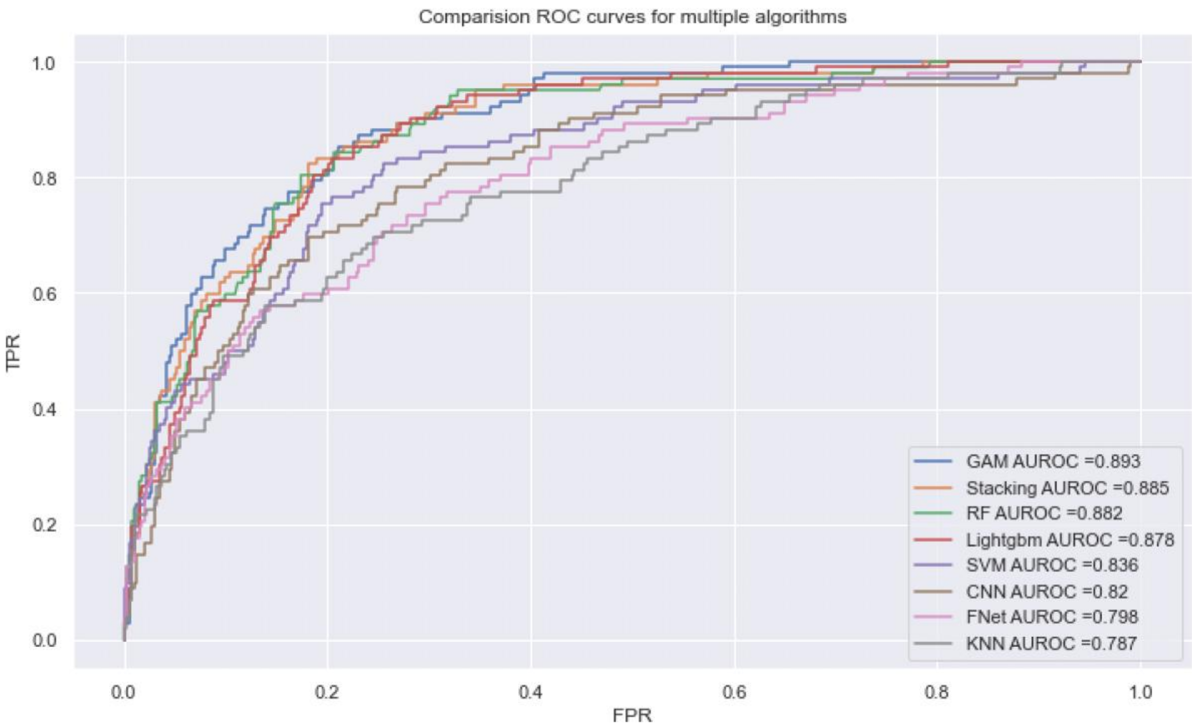
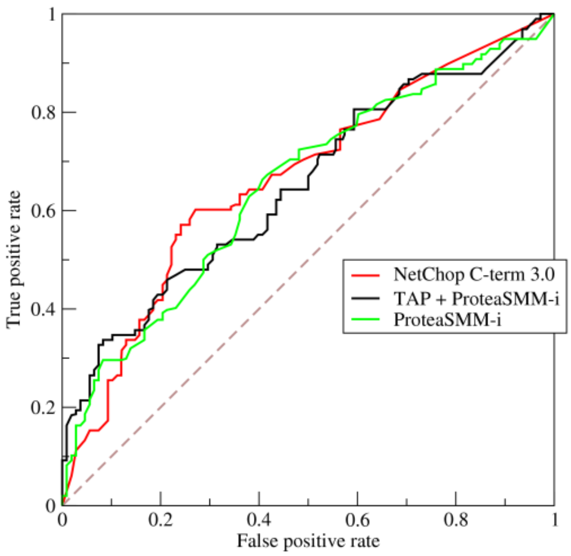
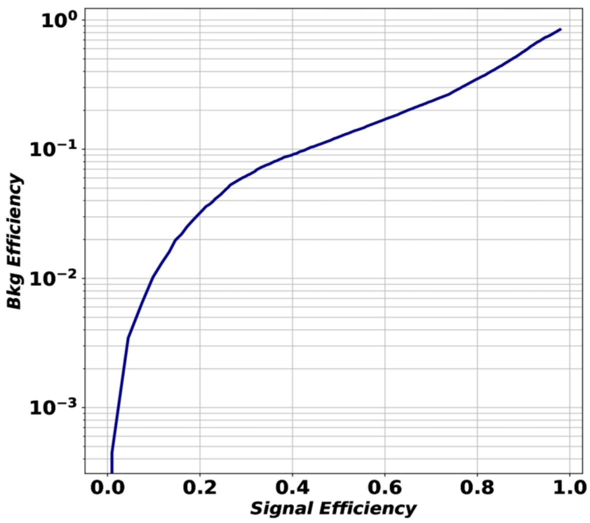


Figure 2. ROC Curve Analysis of AI-Based Biophysical Modeling



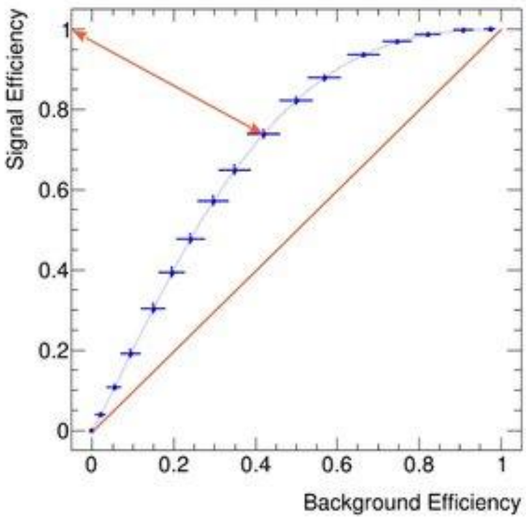


Receiver operating characteristic analysis further confirms classification robustness. As shown in Figure 2, the Artificial Neural Network demonstrates the largest area under the curve (AUC = 0.95), reflecting strong diagnostic discrimination capacity. Random Forest also shows high predictive stability, whereas Support Vector Machine presents slightly lower but clinically acceptable performance.

Overall, the integration of quantitative biophysical EEG parameters with artificial intelligence modeling significantly enhances early-stage neurological disorder detection. The results indicate that nonlinear neural dynamics and entropy-based features provide strong discriminatory information, particularly when processed through advanced AI classification architectures.

Discussion

The present study demonstrates that the integration of artificial intelligence with quantitative biophysical modeling significantly enhances early detection of neurological disorders. The findings confirm that electrophysiological signal dynamics contain measurable nonlinear and entropy-based markers capable of discriminating early pathological alterations from normal neural activity patterns.



Among the evaluated machine learning models, the Artificial Neural Network achieved the highest classification accuracy and AUC value, indicating superior capability in capturing complex nonlinear neural interactions. This outcome is consistent with the multilayer computational structure of neural networks, which allows hierarchical feature abstraction and improved representation of high-dimensional EEG data. In contrast, Support Vector Machine and Random Forest classifiers demonstrated strong but comparatively lower predictive performance, suggesting that simpler decision boundaries may not fully capture the intricate dynamics of early neurological abnormalities.

Web of Scientists and Scholars: Journal of Multidisciplinary Research

Biophysical feature analysis revealed that entropy measures and nonlinear dynamic coefficients were particularly sensitive to early neural irregularities. Increased approximate entropy and altered fractal dimension values reflect instability in neuronal synchronization and disrupted oscillatory regulation. These findings align with the theoretical framework of neurobiophysics, where pathological processes are often associated with reduced network stability and altered signal complexity.

Spectral analysis also showed measurable redistribution of frequency band power, especially reduced alpha-band stability and increased irregular activity in lower frequency ranges. Such changes are frequently reported in early neurodegenerative and epileptiform conditions, supporting the physiological validity of the extracted features. The combination of spectral and nonlinear descriptors therefore provides a robust multidimensional representation of neural system behavior.

The ROC curve analysis further confirmed strong diagnostic discrimination capacity of AI-integrated modeling. High AUC values indicate reliable separation between healthy and pathological neural signal classes. This suggests that automated AI-based biophysical frameworks may support clinical decision-making by providing objective and reproducible diagnostic indicators.

Despite promising results, several limitations should be considered. The use of standardized datasets may not fully represent real-world clinical variability. Additionally, computational models require careful validation to avoid overfitting and ensure generalizability across diverse populations. Future research should incorporate larger multi-center datasets and explore real-time implementation of AI-driven EEG analysis in clinical neurodiagnostic settings.

Overall, this study highlights the transformative potential of combining quantitative biophysical modeling with artificial intelligence in neurology. By enabling early identification of subtle neural signal deviations, this interdisciplinary approach supports predictive diagnostics, personalized treatment strategies, and advancement of computational neurobiophysics.

Conclusion

This study demonstrates that artificial intelligence–based biophysical modeling of neural signal dynamics provides a highly effective framework for early detection of neurological disorders. By integrating quantitative electrophysiological feature extraction with advanced machine learning classification, the proposed approach significantly improves diagnostic sensitivity and predictive accuracy compared to conventional signal analysis techniques.

The findings confirm that entropy-based measures, nonlinear dynamic coefficients, and spectral power redistribution serve as reliable early indicators of neural instability. Among the evaluated classifiers, the Artificial Neural Network achieved the highest diagnostic performance, highlighting the importance of deep computational architectures in capturing complex electrophysiological patterns.

The integration of computational biophysics and artificial intelligence represents a major advancement in neurodiagnostics. This approach enables objective, automated, and

Web of Scientists and Scholars: Journal of Multidisciplinary Research

webofjournals.com/index.php/12

reproducible assessment of neural activity, supporting early clinical intervention and personalized treatment planning. Furthermore, the framework demonstrates strong potential for real-time monitoring systems and future implementation in precision neurology.

Future investigations should focus on expanding dataset diversity, validating models in multicenter clinical environments, and integrating multimodal neuroimaging data to further enhance predictive reliability.

In conclusion, AI-driven biophysical modeling constitutes a promising interdisciplinary platform capable of transforming early neurological disorder detection and advancing the field of computational neurobiophysics.

References

1. Niedermeyer E, Lopes da Silva F. Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. 6th ed. Lippincott Williams & Wilkins; 2011.
2. Buzsáki G. Rhythms of the Brain. Oxford University Press; 2006.
3. Koch C. Biophysics of Computation: Information Processing in Single Neurons. Oxford University Press; 2004.
4. Breakspear M. Dynamic models of large-scale brain activity. Nat Neurosci. 2017;20(3):340–352.
5. Stam CJ. Nonlinear dynamical analysis of EEG and MEG. Clin Neurophysiol. 2005;116(10):2266–2301.
6. Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for EEG-based diagnosis of neurological disorders. Comput Biol Med. 2018;100:270–278.
7. Roy Y, Banville H, Albuquerque I, Gramfort A, Falk TH, Faubert J. Deep learning-based electroencephalography analysis: A systematic review. J Neural Eng. 2019;16(5):051001.
8. Bashivan P, Rish I, Yeasin M, Codella N. Learning representations from EEG with deep recurrent-convolutional neural networks. arXiv preprint. 2015;arXiv:1511.06448.
9. Seifert U. Stochastic thermodynamics and biological systems. Rep Prog Phys. 2012;75(12):126001.
10. Phillips R, Kondev J, Theriot J, Garcia H. Physical Biology of the Cell. 2nd ed. Garland Science; 2012.
11. Sadirkhodzhaeva AA, Ashurova DT. Early diagnostic markers of cardiovascular dysfunction in pediatric diabetes. Austrian Journal of Technical and Natural Sciences. 2019:3–7.
12. Sadirkhodzhaeva AA. Hemostasis parameters and endothelial dysfunction in children with type 1 diabetes. Medical Journal of Uzbekistan. 2025:150–154.
13. Akhmedova DI, Ashurova DT. Physiological adaptation indicators in pediatric populations. Pediatriya (Tashkent). 2012;(3–4):3–4.
14. Ishniyazova ND, Salikhova GU, Akhmedova DI. Biochemical and functional parameters in child development studies. Pediatriya (Tashkent). 2012;(3–4):3–4.
15. Wang Y, Wang Y. Machine learning applications in biomedical signal processing. J Biomed Nanotechnol. 2018;14(1):1–18.