A Review on AI-Based Risk Stratification and Explainable Models for Wearable Neurological Health Monitoring Systems

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Abstract: Epilepsy, Parkinson's Disease, Alzheimer's Disease, and stroke are major contributors to disability or handicap on a global basis both clinically and economically; furthermore, while wearable sensor technology with artificial intelligence (AI) has the potential to monitor continuously and live outside the clinic, the use of black-box deep learning models continues to struggle due to the concerns of lack of transparency, lack of accountability, and inadequate regulatory compliance. This paper becomes a systematic review of AI-based risk stratification and explainable AI (XAI) models such as SHAP, LIME, Grad-CAM, attention-based visualizations, and layer-wise relevance propagation across the four neurological disease areas of epilepsy, Parkinson's, Alzheimer's/dementia, and stroke, categorizing the types of sensors and models used and the associated measured metrics of performance. Although wearable, AI-based devices are typically very accurate (e.g., ≥ 95% accuracy for detecting seizures), they are still faced with challenges in real-life implementation, such as regulatory compliance, energy efficiency, standardization of XAI evaluation systems, and generalizability to new data; future efforts will focus on multimodal sensor fusion, foundational models, and human-centered explainability within the clinical workflow.

Keywords: Explainable Artificial Intelligence (XAI); Wearable Sensors; Neurological Health Monitoring; Risk Stratification; SHAP; Epilepsy; Parkinson's Disease.

1. Introduction

Brain disorders have become the single largest group of diseases causing disability and early deaths worldwide. More than a billion people suffer from these disorders, which account for about 16.8% of all disability-adjusted life years. Brain health has been identified by the WHO Intersectoral Global Action Plan on Epilepsy and Other Neurological Disorders (2022-2031) as a key global public health issue which needs the development of novel, highly efficient, and sustainable methods of disease surveillance [1,5].

Conventionally, neurological evaluations comprise occasional, clinic-based tests like electroencephalography (EEG), magnetic resonance imaging (MRI), and standardized clinical scales. Such measures can hardly reveal the changing and variable characteristics of brain disorders such as epilepsy, Parkinson's disease (PD), and Alzheimer's disease (AD). Besides being expensive, these diagnostic procedures are time-consuming and not easily reaching patients especially in developing countries, thereby resulting in major gaps in diagnosis and monitoring [2,4]. Technologies in wearable sensors range from EEG headbands, inertial measurement units (IMUs), photoplethysmography (PPG) patches, electrodermal activity (EDA) wristbands, to multimodal smartwatches. With the integration of machine learning (ML) and deep learning (DL) technologies, these devices have the capability to remotely and in real time identify seizures, tremors, gait abnormalities, and cognitive impairments [5-7].

To close the trust gap created by black-box AI models, Explainable Artificial Intelligence (XAI) has gained recognition as a vital field of research. Methods like SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), Gradient-weighted Class Activation Mapping (Grad-CAM), and attention mechanisms offer interpretable glimpses of model behavior, supporting physicians in trust, auditing, and validation of AI-supported decisions [1,3]. This review contributes to the growing literature by: (a) a structured approach to reveal the AI architectures and XAI techniques employed in wearable neurological monitoring devices targeting major neurological disorders; (b) an evaluation of the documented effectiveness of different solutions highlighting areas of inconsistency in the methodologies used.

2. Wearable Sensor Modalities for Neurological Monitoring

To precisely and non-stop capturing neurological signals in ambulatory settings, a broad set of sensor modalities is necessary. Table 1 lists all the modalities and their strengths, weaknesses, and the needs for AI processing.

Table 1. Summary of Wearable Sensor Modalities for Neurological Monitoring

Sensor Type	Signal Captured	Target Disorders	Key Advantages	Limitations
EEG (scalp/in-ear)	Brain electrical activity	Epilepsy, Sleep, Cognitive decline	Gold standard, high temporal resolution	Motion artifacts, comfort, high power, limited channels in wearables
IMU (Accelerometer + Gyroscope)	Kinematics, Gait, Tremor	Parkinson's, Fall risk, Stroke rehab	Low-cost, long battery life	Activity confounding, no direct neural signal
PPG (Wrist/Finger)	Heart rate, SpO2, HRV	Epilepsy (autonomic), Sleep apnea	Convenient, continuous HR monitoring	Motion artifacts, indirect measure of neural state
EDA / GSR	Sympathetic arousal, Skin conductance	Epilepsy, Stress, Anxiety	Autonomic biomarker of ictal events	High inter-subject variability, sweat artifacts
fNIRS	Cerebral hemodynamics	Cognitive load, Dementia, Rehabilitation	Portable hemodynamic imaging	High cost, hair interference, limited depth
Multimodal Fusion	Combined physiological streams	Epilepsy, PD, Comprehensive monitoring	Improved robustness; complementary information	Synchronization complexity, increased power, data fusion challenges

3. Explainable AI Methods for Neurological Monitoring

XAI-based wearable neurological monitoring is a clinical necessity, as regulatory structures for AI/ML-based Software as a Medical Device (SaMD) increasingly require explanation transparency etc. is the leading method assigning each feature a Shapley value representing its marginal contribution to a prediction, making it the most widely used XAI approach for seizure detection, Parkinson’s evaluation and personalized monitoring [11,12,17].LIME complements this by building local linear approximations around individual predictions, enabling patient-specific explanations in IoMT-based epilepsy systems [15,18]. Grad-CAM and its variants (Grad-CAM++, Score-CAM) generate visual saliency maps that highlight which regions of an EEG spectrogram or time-frequency input most influence a CNN's output [1,17]. and finally, attention mechanisms in transformer and RNN architectures provide intrinsic temporal saliency visualization, while Layer-wise Relevance Propagation (LRP) backpropagates relevance scores layer by layer to pinpoint the exact input features particularly in raw EEG signals that drive each model decision [13,17].

4. Application Domains: Comparative Analysis

The comparative performance in table 3, emphasizes the consistent trends formed within Ai-powered wearable neurological monitoring for epilepsy, Parkinson's, stroke and multimodal anomaly detection. Comparing epilepsy-driven seizure detection, the highest reported performances are the Shawly & Alsheikhy NAM-CNN + SHAP hybrid setup which gained 99.3% accuracy + 99.5% F1-score on the CHB-MIT EEG dataset [11], the Random Forest with LIME & SHAP integration from Nour et al which scored a 99.89% accuracy (equal to a 0.11 error rate) + 100% recall on IoMT-based EEG [15], and Halimeh et al. deep learning model with Empatica E4 wristband which gained variable sensitivity due to signal quality issues-not algorithmic failures, with SHAP discovering auto-generated clonic motor + autonomic features to be the best discriminating indicators [12]. With Parkinson's disease, Bhatt et al's multimodal CNN-Transformer setup using IMU, voice + vision sensors gained 94.2% accuracy + 92.1% sensitivity, which was more than 5% better than uni-modal approaches on early stage diagnosis [19], contrasting with Wu et al. more objective ML-powered assessment which outperformed traditional clinician scoring with MDS-UPDRS (~93%) accuracy [17], Most Worth noting, di Biase et al's systematic review of 51, predominately disorder studies, showed a high accuracy range of 7899.7% with a much more clinically relevant AUC of 0.944 with subject-independent validation revealing the substantial optimism bias of subject-dependent validation [16]. In predicting fall risk for stroke patients (a disorder category), the MTS meta-analysis revealed that wearable inertial sensors with time-delay neural networks can achieve >85% prediction accuracy (a 27% improvement over the usual clinical practice [10]) while the Edge-AI federated learning system utilizing PoA blockchain hit 91.9% accuracy and 90.8% F1-score with a 8.7% latency overhead from homomorphic encryption in multimodal IoMT sensor data [18], indicating that an all categories benchmark standard of performance is conceivable, but clinical practice readiness still depends on subject-individual generalizability, actual signal fidelity, and computing resources.

Table 3. Comparative Performance of AI Models in Wearable Neurological Monitoring (Key Studies, 2022–2026)

Study / Year	Disorder / Task	AI Model / XAI	Sensor	Acc. / AUC	F1 / Sens.	Key Finding
Shawly & Alsheikhy, 2025 [11]	Epilepsy / Seizure Detection	NAM-CNN + SHAP	EEG (CHB-MIT)	99.3%	F1: 99.5%	SHAP explanations enable frequency-band clinical validation
Halimeh et al., 2023 [12]	Epilepsy / Seizure Logging	Deep Learning + SHAP/UMAP	Empatica E4 (EDA, ACC, HR)	—	Sens: variable	SHAP identified clonic motor & autonomic features
Nour et al., 2024 [15]	Epilepsy / Seizure Classification	RF + LIME + SHAP	EEG (IoMT)	99.89%	Recall: 100%	RF significantly outperforms SVM (97.26%) and k-NN (72.69%)
Bhatt et al., 2025 [19]	Parkinson's / Early Detection	Multimodal DL (CNN+Transformer)	IMU + Voice + Vision	94.2%	Sens: 92.1%	Multimodal fusion outperforms unimodal by >5% in early-stage PD
Wu et al., 2024 [17]	Parkinson's / ON-OFF Status	Interpretable ML + XAI	WSD (multi-sensor)	~93%	Higher than MDS-UPDRS	Wearable ML shows superiority over clinician scoring

di Biase et al., 2024 [16]	Parkinson's / Motor Symptoms	CNN/LSTM/SVM (51 studies)	IMU, Force sensors	78–99.7%	AUC: 0.944	Subject-independent validation yields more conservative performance
MTS Meta-analysis, 2025 [10]	Stroke / Fall Risk	TDNN + Autoregressive Models	Wearable Inertial	>85%	27% improvement	MTS+wearable approach achieves 27% improvement over traditional methods
Edge-AI FL, 2025 [18]	Multimodal / Anomaly Detection	CNN-LSTM + FL + PoA Blockchain	Multi-sensor IoMT	91.9%	F1: 90.8%	8.7% latency overhead from homomorphic encryption

5. Discussion

The review unveils a discipline that has technically achieved an extraordinary feat over the past five years but its clinical counterpart relies on very few trials so far.AI-driven wearable neurological monitoring devices have showcased their ability to detect seizures, motor symptoms, and expose cognitive biomarkers regularly and accurately. Employing XAI techniques, most of all SHAP and Grad-CAM, has enabled researchers to convert deep learning results into clinically understandable outputs. So, the major barrier of gaining physician's trust and acquiring regulatory approval has been tackled [1,3,6].

The comparative critique uncovers that in in-depth retrospective subject-dependent evaluations, accuracy figures of 97-99% achieved by the models should be subject to careful consideration only. Surprisingly prospective subject-independent, multi-institutional validations reveal quite less performance. They also show that domain shift and model generalizability will remain challenging issues. The biggest area of neglect is human-centered XAI validation - verifying the extent to which clinicians actually use, comprehend and trust AI explanations in their practice of neurology [1,4]. Federated learning together with edge-AI systems are now advanced enough to be implemented in real-world settings where they...... are capable of delivering diagnostic accuracy of 91% and above, besides satisfying the conditions for privacy protection. Incorporation of blockchain for data tracing and use of homomorphic encryption for doing federated computation securely.

6. Conclusion

Artificial intelligence-based risk stratification supported with explainable models for wearable systems monitoring neurological health have proven to be among the scientifically most important advances in digital health. Data from various papers in this review demonstrate that: (1) AI-enabled wearable biosignal systems can perform with clinically relevant levels of accuracy regarding seizure detection, motor assessment of individuals with Parkinson’s disease, fall risk assessment, and monitoring of cognitive decline; (2) Explainable Artificial Intelligence (XAI) systems' use of techniques including SHAP, LIME, Grad-CAM, and Attention visualization will provide necessary transparency to provide clinical trust and meet regulatory requirements; (3) Federated learning strategies enabled by edge computing modalities enhance the ability to deploy these applications at scale while preserving the privacy of users data; and (4) Issues of generalizability, XAI assessment methods, regulatory framework, and clinical integration have not been fully resolved. To realize this desired level of development, it will require alignment of requisite elements across multiple areas including: validated tests that are tightly controlled against predefined criteria; datasets that are as representative as possible; coordinated efforts around the assessment of XAI performance; awareness of the regulatory frameworks applicable to adaptive AI applications; and the design of human-centric interfaces for clinicians and patients.

Acknowledgements

The authors gratefully acknowledge the financial support provided by the **Indian Council of Medical Research (ICMR)** under the project titled "Seizure-Sentry: Wearable Epilepsy Prediction Device for Enhanced Patient Safety through Timely Alerts and Personalized Seizure Management" (Project ID: **IIRPSG-2024-01-01197**).

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