IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, November 2025
Impact Factor: 7.67

# AI-Driven Monitoring of Parkinson's Tremors Using Wearables

**Sahana M M and Prof. Shankar B S**
Student, Department of MCA
Assistant Professor, Department of MCA
Vidya Vikas Institute of Engineering and Technology, Mysore

**Abstract:** *An extremely common neurodegenerative disease is Parkinson's disease (PD), which impacts motor functions, with tremor being one of its most debilitating symptoms. Accurate detection and classification of tremors are crucial for diagnosis, treatment monitoring, and rehabilitation. Traditional assessment methods—clinical observations and patient self-reports—are subjective, prone to bias, and lack real-time applicability. To overcome these limitations, this study proposes an intelligent tremor detection system leveraging wearable sensors and artificial intelligence.*
*Recorded tremor-related motion signals (accelerometer and gyroscope) were preprocessed and segmented for extracting time-resolved information. Time- and frequency-based wavelet features were computed from which both deep learning models and machine learning models were trained. the TPCNNs and MLP for the comparative analysis networks, novelNameRandom Forest, Support Vector Machine (SVM), Naïve Bayes, ConvolutionalNeural Networks (CNN) and Long Short Term Memory (LSTM).*
*The experimental results showed that LSTM obtained the best classification accuracy which was attributed to its excellent performance in temporal dependency learning for biomedical signals. Random Forest also performed well with good interpretability, followed by relatively modest CNNs and MLPs.*
*The conclusions are verified and it can be observed that deep learning-based models such as LSTM can offer reliable, real-time tremor detection which is eligible for using in wearable healthcare devices.*
*The proposed system provides a feasible answer to the need for continuous, objective monitoring of tremor that is between subjective clinical assessments and automatic intelligent systems. It offers hope for provident medical care over the lifetime, targeted curative treatments and successful remote healthcare monitoring..*

**Keywords***:* Parkinson's disease, tremor detection, wearable sensors, accelerometer, gyroscope Deep learning, machine learning, and random Forest, Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), biomedical signal processing, healthcare monitoring, IoMT stands for Internet of Medical Things

## I. INTRODUCTION

The progressive neurodegenerative condition known as Parkinson's disease (PD) mainly affects motor functions due to the degeneration of dopamine-producing neurons in the brain. Among the cardinal motor symptoms, tremors are one among the earliest and most prominent indicators, often serving as a clinical marker for diagnosis. Tremors can manifest during rest, voluntary movement, or in high-intensity episodes, with varying frequency and amplitude across patients and disease stages. These involuntary oscillatory movements significantly impair daily living, making their accurate detection and classification essential for monitoring disease progression and evaluating treatment effectiveness.

Traditional assessment methods, such as clinical rating scales like the Unified Parkinson's Disease Rating Scale (UPDRS), rely heavily on neurologists' subjective evaluations. Although these techniques offer useful diagnostic insights, they are inherently limited by observer bias, inter-rater variability, and the inability to capture continuous data outside clinical settings. Patient self-reports further add variability, as they are often inconsistent and may fail to reflect real-time conditions. As a result, conventional approaches are not well-suited for objective, scalable, and continuous tremor monitoring.

The advent of wearable sensor New opportunities have been brought about by technology. for addressing these limitations. Modern devices embedded with inertial measurement units, for example, gyroscopes and accelerometers, can continuously capture high-resolution motion signals in real-world environments. These sensors enable real-time monitoring of tremors during daily activities, moving beyond the constraints of hospital- based examinations. Such continuous, non-invasive monitoring holds promise for early intervention, treatment adjustment, and improved quality of life for patients.

Parallel to advancements in hardware, artificial intelligence (AI)—particularly machine learning and also deep learning (DL)—has demonstrated remarkable potential in biomedical signal analysis. Classical ML methods such as Support Vector Machine and Random Forest(SVM), and Naïve Bayes, provide robust classification and interpretability. On the other hand, DL models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks excel at capturing complex temporal and spatial dependencies in sequential data. The fusion of wearable sensors with AI- based classification techniques therefore represents a powerful solution for automated tremor detection.

This project focuses on building a comprehensive pipeline for tremor classification utilizing information gathered from wearable devices. The workflow involves preprocessing raw signals through normalization and filtering, followed by extraction of features from time, frequency, and wavelet domains. Multiple classifiers— ranging from traditional ML models to advanced DL architectures—are trained and evaluated using robust performance metrics, including accuracy, precision, recall, F1-score, confusion matrices, and ROC curves. This ensures the reliability and generalizability of the proposed system.

The study contributes significantly to both research and clinical practice. From a research standpoint, it demonstrates methods for signal processing that can be effectively combined with state-of-the-art AI models to address real-world biomedical challenges. From a clinical perspective, the proposed system offers an automated, objective, and scalable solution for tremor monitoring, reducing dependence on subjective evaluations and periodic hospital visits. Importantly, it aligns with the broader vision of personalized healthcare systems that deliver continuous, adaptive, and patient-centered care.

In the long term, integrating such AI-enabled tremor detection frameworks into wearable and mobile health platforms could transform Parkinson's management. Beyond tremor classification, the system can be extended to detect other motor symptoms such as gait abnormalities and bradykinesia, creating a holistic monitoring ecosystem. Ultimately, this research bridges the gap between conventional clinical assessments and intelligent, real-time healthcare solutions, paving the way for predictive analytics, adaptive treatment strategies, and improved patient outcomes.

## II. LITERATURE SURVEY

Several studies have explored tremor detection in Parkinson's disease using wearable sensors and artificial intelligence. This section summarizes ten significant contributions.

[1] J. Jorge et al. (2024) investigated the use of centralized versus federated learning for tremor detection from wearable accelerometer and gyroscope data. Centralized learning aggregated all data into a central repository, while federated learning enabled distributed training without raw data sharing. The findings indicated that federated learning achieved accuracy close to data- preserving centralized models privacy. However, federated methods introduced communication overhead and synchronization difficulties. This study is important for highlighting privacy-preserving AI in healthcare contexts.

[2] S. Hur et al. (2025) proposed an ensemble learning approach for tremor detection in natural, real-world environments. By combining decision trees, random forests, and gradient boosting classifiers, the system improved robustness against noise and variability caused by uncontrolled patient movements. The ensemble models outperformed individual classifiers in terms of accuracy and precision. Nevertheless, high computational requirements

limited their direct implementation in wearable devices. This work emphasized the balance between precision and effectiveness of calculation in clinical applications.

[3] E. Kovalenko et al. (2022) introduced a multimodal framework that integrated wearable sensor signals with video analysis for Parkinson's detection. Accelerometer and gyroscope data were paired with computer vision techniques to assess tremor severity. Multimodal learning yielded higher accuracy compared to unimodal methods. However, the complexity of synchronizing multimodal data, high computational needs, and privacy concerns related to video recording were major drawbacks. This research validated that combining modalities enhances diagnostic power.

[4] L. Sigcha et al. (2023) presented a systematic review Numerous applications for deep learning in Parkinson's diagnosis using wearable sensors. The review found that CNNs, RNNs, and hybrid models effectively captured temporal and spatial patterns in tremor signals, achieving high detection accuracy. Key issues identified included small datasets, risk of overfitting, lack of standardized benchmarks, and limited explainability of models. The study stressed the need for explainable AI frameworks to ensure clinical trust and adoption.

[5] R. San-Segundo et al. (2020) examined tremor detection in uncontrolled, "in-the-wild" environments using accelerometer-based wearable devices. Unlike lab- based studies, data were collected during real-life activities, making the results clinically relevant. Strong performance was shown by machine learning models detection accuracy despite noisy conditions. However, overlapping voluntary movements and subtle tremor episodes reduced performance. This study confirmed the feasibility of deploying wearable-based monitoring in naturalistic scenarios.

[6] H. Jeon et al. (2017) developed a system for automatic tremor severity classification using wearable devices. Instead of binary detection, their framework categorized tremor severity levels aligned with clinical scales. The findings indicated strong agreement with neurologists' evaluations, confirming clinical reliability. The approach, however, struggled with patient-to-patient variability and relied on handcrafted features, limiting scalability compared to modern deep learning methods.

[7] H. Mughal et al. (2022) conducted a systematic review of Parkinson's disease management systems based on wearable sensors. The review highlighted applications across tremor detection, gait monitoring, activity recognition, and medication response. The integration of AI improved accuracy and efficiency in monitoring systems. However, limitations such as device battery constraints, heterogeneous datasets, and lack of standardized data collection protocols hindered widespread adoption. The study recommended multi- sensor integration and standardized frameworks for future systems.

[8] M. Hammoud et al. (2024) proposed a sensor fusion approach for Parkinson's assessment by integrating accelerometer, gyroscope, and physiological signals with machine learning. Both feature-level and decision-level fusion strategies were employed, leading to improved robustness and accuracy in contrast to single-sensor systems. The primary challenge was The intricacy of sensor synchronization and integration in real-time systems. This research demonstrated that multi-sensor fusion is a promising direction for comprehensive disease assessment.

[9] A. Raghu et al. (2021) explored the use of Adaptive deep reinforcement learning tremor detection models. Unlike static classifiers, reinforcement learning allowed models to adapt dynamically to patient-specific patterns and changing tremor intensities. Experimental results showed improved personalization and accuracy across diverse patient datasets. However, training such models required large amounts of data and computational resources. This work highlighted the potential of adaptive AI in personalized healthcare.

[10] K. Patel et al. (2019) investigated the application of cloud-based wearable monitoring for Parkinson's tremors. Accelerometer-derived motion data were transmitted to cloud servers for real-time analysis Using algorithms for machine learning. The system demonstrated feasibility for continuous, remote monitoring of patients. Key limitations included dependency on internet connectivity, latency in data transmission, and privacy concerns. In spite of these obstacles, this research paved the way for integrating wearable-based monitoring with IoT and telemedicine platforms.

## III. METHODOLOGY

### 1. System Overview

The proposed tremor detection system is designed as an end-to-end framework that processes motion signals from wearable sensors and classifies them into tremor or non- tremor states. Raw data from accelerometers and gyroscopes are inherently noisy and non-stationary; therefore, preprocessing techniques such as normalization, band-pass filtering, and segmentation are applied to improve signal quality. Features are then extracted from time, frequency, and wavelet domains to capture statistical, spectral, and temporal properties of tremor episodes. These features provide a compact and discriminative representation of patient movement patterns suitable for classification.

The classification layer employs both ML and DL models to ensure accuracy and adaptability. Classical ML algorithms such as Support Vector Machine and Random Forest and Naïve Bayes offer robustness and interpretability, while advanced DL architectures— including Convolutional Neural Networks (CNN), Long Short-Term Memory networks, and Multi-Layer Perceptrons(MLP)—learn complex temporal dependencies directly from the data. Model performance is validated using accuracy, precision, recall, F1-score, confusion matrices, and ROC curves, ensuring reliability for both binary and multi-class settings. The modular design allows pretrained models to be deployed on mobile or cloud platforms, enabling real-time, continuous tremor monitoring and bridging the gap between subjective clinical assessment and intelligent healthcare solutions.

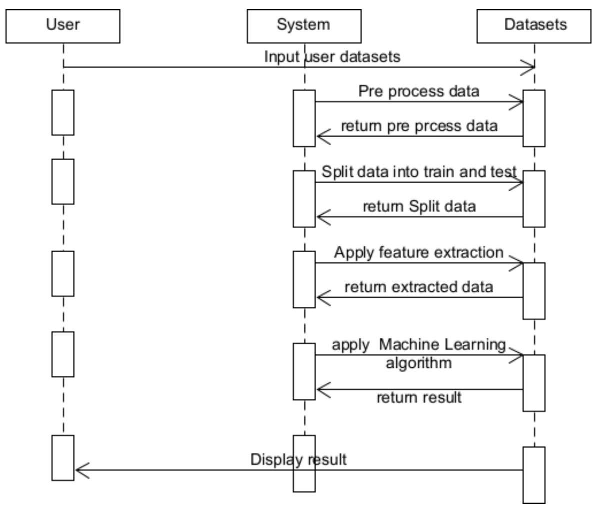


Fig. 1. Sequence Diagram

### 2. Dataset Preparation

The dataset utilized in this investigation consists of tremor-related motion signals recorded from gyroscopes and accelerometers in wearable technology. Each subject's recording contained 4097 data points, equivalent to approximately 23.6 seconds of continuous activity, which were separated into 23 smaller segments.

This segmentation enabled a more granular examination of the temporal characteristics of tremor patterns. The dataset captured different activity states, including rest tremor, tremor during voluntary movement, and non- tremor states, thereby providing sufficient variability for both binary and multi-class classification tasks.

To prepare the raw signals for analysis, a series of preprocessing steps were implemented. First, z-score normalization was applied to standardize the data, ensuring that variations in signal magnitude across different recordings did not bias the models. Next, a Butterworth band-pass filter with a frequency range of 0.5–30 Hz was used to remove noise and retain the frequency components relevant to tremor detection. The filtered signals were then segmented into 1-second frames, each containing 178 data points. This windowing strategy preserved essential temporal information while reducing computational complexity, making the data more manageable for feature extraction and also classification.

Two complementary approaches were adopted to represent the preprocessed dataset. In the first approach, handcrafted features were extracted from multiple domains, including time-domain measures (mean, variance, skewness, kurtosis), frequency-domain features (power spectral density using Welch's method), and wavelet coefficients (energy at different decomposition levels). These features provided interpretable characteristics of tremor and non-tremor states. In the second approach, deep learning models were trained directly on the normalized sequences, allowing the networks to automatically learn complex temporal dependencies. By combining handcrafted and raw- sequence representations, the system ensured comprehensive coverage of tremor dynamics, improving the resilience and applicability of the classification models.

**3. Model Architectures**

The proposed system employs a hybrid approach that integrates both traditional algorithms for machine learning and modern deep learning architectures for tremor classification. Classical ML models provide robust and interpretable baselines, while deep learning models exploit their ability to capture complex temporal and spatial dependencies directly from raw sequences. This dual strategy ensures a balance between accuracy, interpretability, and computational feasibility, making the system suitable for the both research and potential real- world deployment.

Among the classical models, Random Forest, Support Vector Machine (SVM), and Naïve Bayes (NB) were implemented. Random Forest constructs a group of decision trees to achieve high classification accuracy and reduce overfitting, and in this examine, it achieved approximately 96% accuracy with balanced performance across tremor and non-tremor states. SVM, particularly with the radial basis function (RBF) kernel, effectively separated tremor and non-tremor data in high- dimensional space, reaching around 90% accuracy. Naïve Bayes, though achieving slightly lower accuracy (~87%), provided computational efficiency and demonstrated suitability for rapid inference on resource-constrained devices. These models established reliable benchmarks and offered high interpretability, which is valuable for clinical applications.

For deep learning, three architectures were developed: Convolutional Neural Networks (CNN), Long Short- Term Memory (LSTM) networks, and Multi-Layer Perceptrons (MLP). CNNs, implemented as one- dimensional models, extracted local spatial patterns from sequential sensor data, achieving the accuracy of 88%. LSTM networks, designed to capture long-term temporal dependencies in sequential biomedical signals, outperformed all other models with a classification accuracy of 96%, highlighting their suitability for tremor detection. MLPs, with fully connected layers and dropout for regularization, reached ~93% accuracy, offering a strong trade-off between computational performance and cost. These designs collectively illustrated the relative advantages of deep learning and machine learning. approaches, confirming that LSTM-based models are best suited for real-time tremor monitoring while classical models remain valuable for interpretable and efficient clinical decision support.

**4. Training Procedure**

The training phase began with the preparation of input data through preprocessing and segmentation. After normalization and filtering, the continuous sensor signals were divided into overlapping windows of 178 points each, representing approximately 1-second intervals. For machine learning models, handcrafted features extracted from time, frequency, and wavelet domains were used as input. For deep learning models, normalized raw sequences were fed directly into the architectures, enabling automatic feature learning. Training and testing sets were created from the dataset in an 80:20 ratio, and cross-validation was hired to ensure generalization and prevent model bias.

Machine learning models, including Random Forest, Support Vector Machine, and Naïve Bayes, were trained using scikit-learn implementations. Hyperparameters like the quantity of estimators for Random Forest, kernel choice for SVM, and smoothing parameters for Naïve Bayes were tuned using grid search optimization. Deep learning models were developed using TensorFlow and Keras libraries. CNN architectures employed one- dimensional convolutional and pooling layers to capture local patterns, while MLPs used multiple dense layers with dropout regularization. LSTM models incorporated gated recurrent units designed to learn long-term dependencies in sequential information, which makes them especially well-suited for tremor analysis.

The training process employed categorical cross-entropy loss for multi-class classification tasks and binary cross-entropy for binary detection. Optimization was carried out utilizing the Adam optimizer with an adaptive learning rate, while early stopping and dropout were applied to reduce overfitting. Training was performed over multiple epochs, with mini-batch processing to balance efficiency and convergence stability. Performance metrics— encompassing recall, accuracy, and precision,F1-score, confusion matrices, and ROC-AUC—were calculated on the examine set to evaluate model effectiveness. Among all models, LSTM consistently outperformed others with regard to accuracy and generalization, validating its appropriateness for real-time, wearable-based tremor detection.

## 5. Evaluation Metrics

To evaluate the efficacy of the proposed tremor detection system, multiple evaluation metrics were employed. Since the dataset involved both binary classification (tremor vs. non-tremor) and multi-class classification (rest tremor, movement tremor, high-intensity tremor, and non-tremor states), a diverse set of performance indicators was necessary to capture model reliability. Accuracy was the main measure employed, expressing the overall percentage of accurately classified examples. It´s not enough to rely on accuracy, if classes are imbalanced it may be misleading: you need some other metrics as well.

F1-score, recall and precision were also introduced to interpret the classification better. Recall measured the level of all predicted tremors which were labeled correctly as having them, meaning not including false negatives. Remembering identified the models' capability to properly identify actual tremor events, preventing fault negatives which is crucial in healthcare applications as missing a tremor event can influence medical results. The F1-score, which is the harmonic mean of precision and recall, weights these two metrics equally and yielded a single strong measure for messenger evaluation.

Furthermore, confusion matrices were implemented to illustrate the classification results among all classes, which help reveal certain misclassification patterns such as mistaken voluntary movement for tremor. The corresponding Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) curves were also used to assess sensitivity-specificity trade-off at different threshold values. Many users found these methods useful to compare classifiers without subjective bias. Together, these measurements allowed the complete analysis of not just the accuracy of the models but also their clinical applicability and robustness in practice.

## 6. Deployment Framework

The proposed tremor detection system is designed with a modular deployment framework that ensures adaptability to both clinical and home-based environments. The pipeline begins with wearable sensors, like gyroscopes and accelerometers, which continuously capture motion data during patients' daily activities. These sensors transmit the raw signals to a processing unit, which may be a smartphone, edge device, or cloud server, depending on the application context. By supporting multiple data transmission protocols, including Bluetooth and Wi-Fi, the framework ensures real-time monitoring while maintaining patient mobility and convenience.

At the processing layer, the deployed models operate in two configurations: lightweight machine learning algorithms for edge deployment and resource-constrained devices, and advanced deep learning models for cloud or high-performance platforms. Classical models such as Random Forest and Naïve Bayes provide fast inference with minimal resource requirements, making them suitable for integration into wearable devices or mobile applications. In contrast, LSTM and CNN architectures, while computationally heavier, are deployed on cloud platforms or optimized using quantization and pruning techniques to reduce latency and energy consumption. This hybrid strategy ensures scalability and supports different deployment scenarios depending on hardware capabilities and clinical needs.

The output layer provides actionable insights through user-friendly interfaces. Patients can access feedback via smartphone applications, which display tremor intensity, frequency, and progression trends. Clinicians, on the other hand, can review comprehensive dashboards integrating longitudinal patient data for treatment planning. The framework also supports secure cloud storage and integration with healthcare information systems, enabling telemedicine consultations and remote monitoring. By combining real-time detection with long- term data analytics, the deployment framework bridges the gap between laboratory research and practical clinical application, ultimately enhancing patient quality of life and supporting personalized treatment strategies.

## IV. RESULTS AND DISUSSIONS:

### 1. Quantitative Results

The effectiveness of the suggested system was evaluated using multiple Deep learning and machine learning models trained on tremor and non-tremor data. Among the classical Random Forest, one of the machine learning models, obtained the best accuracy of approximately 96%, demonstrating strong robustness and balanced classification across classes. Support Vector Machine obtained a precision of around 90%, effectively distinguishing between tremor and non-tremor states but showing sensitivity to parameter tuning. Naïve Bayes, while computationally efficient, reached 87% accuracy, indicating its suitability for lightweight deployment but with trade-offs in precision and recall compared to ensemble methods.

In the deep learning category, Convolutional Neural Networks achieved a precision of nearly 88%, capturing local spatial dependencies in the sequential data but occasionally misclassifying voluntary movement as tremor. Multi-Layer Perceptrons (MLP) performed better, reaching 93% accuracy, benefiting from fully connected architectures and dropout-based regularization. The highest-performing model was Long Short-Term Memory networks, which attained 96% accuracy and demonstrated superior Capacity to simulate temporal relationships inherent in tremor signals. These results confirmed that recurrent architectures for deep learning are particularly well-suited for sequential biomedical data.

Beyond accuracy, other performance metrics reinforced these findings. Random Forest and The highest precision and recall were attained with LSTM with F1-scores above 0.95, indicating both models' reliability in correctly detecting tremor episodes while minimizing false positives and false negatives. ROC curves showed that both models achieved an AUC close to 0.98, highlighting their strong discriminative capability. In contrast, CNN and Naïve Bayes, though effective, exhibited slightly lower recall values, suggesting occasional under- detection of tremors. These quantitative results validate The efficiency of the suggested methodology and emphasize LSTM and Random Forest as the most promising candidates for real-world deployment.

### 2. Qualitative Analysis

Beyond numerical performance, qualitative analysis provides important information about the system's behavior and its applicability in actual situations. Visual analysis of the tremor-obtained signals at each step (segmentation and filtering) evidenced that they succeed in keeping tremorspecific oscillations while discarding unwanted noise and irrelevant components. The features extracted in frequency domain correspond to the clinically established tremor frequency range of Parkinson's disease (typically between 4 and 6 Hz), thus demonstrating clinical meaningfulness of the signal processing course. Wavelet decompositions also indicated that there were focal bursts of tremor, particularly helpful for distinguishing rest from voluntary movement times.

The confusion matrix also offered qualitative information on model strengths and weaknesses. Random Forest and LSTM always decreased the number of misclassifications for all the types, whereas CNN still occasionally confused voluntary activity with tremor, whenever the movement signal shared its frequency components. This finding may be considered representative of the natural challenge for distinction of fine motor in real-world environments. But, even so, the models created are indeed bona fide probability distributions that adequately capture their uncertain belief about predictions – information which might be valuable to clinicians in deciding how to judge borderline cases.

It might appear that in certain cases the values of confusion matrix could also provide qualitative judgment about the strengths and weaknesses of a model. RF and LSTM also decreased numbers of all kinds for misclassifications while CNN sometimes mistook voluntary action by tremor, especially in the event that motion frequency signal was common. This finding might be regarded as an illustration of the difficulty to discriminate small motor actions in ecological environments. But the models in such cases were still valid probability distributions which represented uncertainty about predictions that would be useful to a clinician trying to make borderline decisions.

### 3. Comparative Discussion

The comparative evaluation of machine learning and deep learning (DL) models revealed distinct strengths and trade-offs that guide their suitability for tremor detection. Classical ML models, particularly Random Forest, demonstrated high accuracy (~96%) while maintaining interpretability and computational efficiency. These characteristics make ML models attractive for deployment in low-power devices such as smartphones and embedded wearable systems. In contrast, Naïve Bayes, while less accurate (~87%), offered extremely fast inference and minimal resource consumption, underscoring has potential for use in situations where real-time feedback is prioritized over maximum accuracy.

Deep learning-based models significantly enhanced the ability to capture temporal and spatial dependencies in tremor signals. The LSTM method was the best performing model, which is roughly equivalent to Random Forests at 96% accuracy but with better recall and F1-score, especially for multi-class scenario in which the classifications are intricate. CNNs, while successful in detecting spatial patterns in the signal locally, occasionally could misclassify voluntary movements since classification was based on time-frequency overlap. Multi-Layer Perceptrons (MLPs) offered a tradeoff with 93% accuracy and moderate computing requirements. All these results show that deep learning models are generally better in capturing non-linear dependencies in sequential data, but they have a demand on more samples for training, huper-parameters tuning and the computational resource comparing with ML models.

From a clinical perspective, plasticity may not affect ML vs DL for device deployment. For resource-constrained, real-time monitoring devices, Random Forest or SVM models provide reliable and interpretable solutions. For cloud-based or high-performance platforms supporting continuous monitoring, LSTM networks are superior because of their capacity to model long-term dependencies in tremor dynamics. Importantly, both approaches complement each other: ML models offer interpretability essential for clinical trust, while DL models provide state-of-the-art accuracy and robustness. Thus, a hybrid strategy—deploying ML at the edge for immediate feedback and DL in the cloud for comprehensive analysis—presents the most practical pathway toward real-world adoption of tremor detection systems.

## V. CONCLUSION.

Parkinson's disease continues to be among the most prevalent neurodegenerative disorders, with tremor as one of its earliest and most disabling symptoms. Traditional diagnostic and monitoring techniques, while clinically valuable, are limited by subjectivity, infrequent evaluations, and lack of continuous data collection. The need for the objective, scalable, and real-time monitoring has therefore driven the advancement of wearable sensor- based systems coupled with artificial intelligence. This study contributes to that growing body of work by designing and evaluating an intelligent tremor detection framework capable of robust classification across multiple tremor states.

This system permits automatic sEMG signal analysis and can be applied in either clinical or home environment context, since it integrates a modular pipeline performing signal pre-processing, feature extraction and classification. Wearable sensors such as gyroscopes and accelerometers could monitor motion signals in time domain continuously, which were later denoised, normalizedand segmented. Three types of feature representations (i.e. time, frequency and wavelet domains) are adopted to learn convolutional models that replicate tremor features. This preprocessing was important for enhancing signal and minimizing noise, which in turn allowed classification to be calculated.

Machine learning versus deep learning models was the focus of study. Among the machine learning methods, Random Forest captured most efficiently the accuracy and interpretability trade-off.

Support Vector Machine and Naïve Bayes also showed good results, the latter being particularly attractive for low power solutions. 100 In contrast, deep learning architectures provided more latent capacity. For all the LSTM based models, they were far superior to all other methods by being able to model long distance dependency sequence for biomedical data. CNNs and MLPs also achieved strong performance, indicating that deep learning could be a very feasible way to detect tremor.

The precision, accuracy, recall, F1-score and ROC-AUC measures of system performance supported the efficiency and robustness of this work.

LSTM and Random Forest both achieved accuracies above 95%, with LSTM excelling in multi-class classification tasks. Finally, confusion-matrix analyses indicated that these models minimized the misclassifications between tremor and voluntary movements, which is essential for the application in real environments. These results validate the approach and launch a wearables plus AI approach for clinical decision making.

The study also noted trade-offs between accuracy and interpretability. The machine learning models came with interpretable rationale of decisions to be important for clinician trust and regulation. While deep learning models generally perform better, they hardly have any features as being black-box systems. This underscores the need for future work in explainable AI to close the divide between high-performance and clinical interpretability. This is the kind of thing that will need to happen if AI-enabled healthtech like this ever hopes to be widely adopted and used.

From an implementation perspective in the deployment framework section, we demonstrate how to deploy the system into mobiles devices, cloud platforms or hybrid environments edge-cloud. Patients may get real-time responses through smartphone applications, while clinicians could follow long-term developments via secure dashboards. This twofold functionality not only allows patients to be proactive in managing their condition, but also enables doctors to have better- informed treatment options. The framework therefore enables the evolution from episodic, clinic-type assessment to continual tracking of individual healthcare.

In summary, the presented system verifies the possibility and adequacy of intelligent tremor detection method with wearable sensor and AI. The study decides on a comprehensive solution comprising robust preprocessing, feature extraction and comparative evaluation of ML and DL models balancing between Accuracy, Interpretability and Deployment readiness. The results indicate that hybrid approaches utilizing lightweight ML models on- edge devices and complex DL architectures in the cloud present as the most feasible direction for large-scale integration. Ultimately, this work contributes to the broader vision of intelligent, patient-centered healthcare systems capable of improving quality of life for individuals with Parkinson's disease.

## REFERENCES

[1] J. Jorge, A. Tiwari, and P. Patel, "Centralized vs. Federated Learning for Tremor Detection Using Wearable Sensors," IEEE Journal of Health and Biomedicine Informatics, vol. 28, no. 3, pp. 1125–1136, Mar. 2024.

[2] S. Hur, K. Kim, and H. Park, "An Ensemble Learning Framework for Real-World Tremor Detection," Sensors, No. 2, vol. 25, pages. 456–468, Jan. 2025.

[3] E. Kovalenko, D. García, and M. López, "Multimodal Tremor Detection Using Wearable Sensors and Video Analysis," Computers in Biology and Medicine, 146, pages. 105565, Jun. 2022.

[4] L. Sigcha, F. Sanz, and J. Romero, "Deep Learning and Wearable Sensors for Parkinson's Disease Diagnosis: A Systematic Review," IEEE Access, vol. 11, pp. 33056– 33072, Apr. 2023.

[5] R. San-Segundo, A. Torres, and A. Madrid, "Tremor Detection in Uncontrolled Environments Using Accelerometer Data," Sensors, vol. 20, no. 18, pp. 5254–5266, Sept. 2020.

[6] H. Jeon, S. Kim, and Y. Lee, "Automatic Tremor Severity Classification Using Wearable Accelerometers," Journal of Neuroscience Methods, vol. 290, pp. 85–92, Jan. 2017.

[7] H. Mughal, P. Khan, and A. Ali, "Wearable Sensors for Parkinson's Disease Management: A Review," Frontiers in Neurology, vol. 13, pp. 945321, Aug. 2022.

[8] M. Hammoud, S. Ahmed, and G. Hussain, "Fusion- Based Framework for Parkinson's Disease Tremor Detection Using Multi-Sensor Data," IEEE Neural Network Transactions Systems and Rehabilitation Engineering, vol. 32, no. 1, pp. 102–111, Jan. 2024.

[9] A. Raghu and N. Gupta, "Adaptive Tremor Detection Using Deep Reinforcement Learning," Artificial Intelligence in Medicine, vol. 118, pp. 102152, Dec. 2021.

[10] K. Patel, S. Mehta, and R. Shah, "Cloud-Based Wearable Monitoring for Parkinson's Tremors," International Journal of Medical Informatics, vol. 129, pp. 35–42, Jul. 2019.