

Hybrid ML Model for Early Detection of Neurological Disorders Using IoT-Based Health Monitoring Systems

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ABSTRACT

The increasing adoption of telemonitoring, wearable sensing, and Internet of Things (IoT) technologies has created new opportunities for the continuous monitoring and computational prediction of neurological disorders (NDs). In this study, a hybrid machine-learning framework is proposed, which integrates Adaptive Neuro-Fuzzy Inference System (ANFIS), Grey Wolf Optimization (GWO), and Particle Swarm Optimization (PSO) in an IoT- and fog-based health-monitoring architecture. A chaotic tent-mapping strategy is employed to initialize the optimization population and improve the diversity of candidate solutions. The proposed PSO-GWO method is used to optimize the parameters of the ANFIS model. The framework consists of data acquisition, preprocessing, feature extraction, classification, and alert-generation stages, with fog computing considered for processing health information closer to the data source. Five datasets from the UCI Machine Learning Repository are used for the experimental evaluation and the proposed approach is compared with GWO, PSO, Differential Evolution (DE), Genetic Algorithm (GA), Ant Colony Optimization (ACO) and conventional ANFIS. The experiments are conducted with a 70:30 training-testing split and multiple trials to assess model performance with error and classification metrics. The proposed method has been tested on the Parkinson's disease dataset and has been reported to have an accuracy of 92.5% under the reported experimental conditions. The results show that the hybrid optimization approach can enhance the classification performance of the ANFIS, but the proposed framework needs to be further tested with larger clinically representative datasets and real-time data from IoT/wearable devices before clinical use.

KEYWORDS: Neurological Disorders, Machine Learning, Internet of Things, Healthcare

Received on 22.06.2026, Revised on 17.08.2026, Accepted on 28.09.2026

How to cite this article: Ricardo A. (2026). Hybrid ML Model for Early Detection of Neurological Disorders Using IoT-Based Health Monitoring Systems. *Bio-Science Research Bulletin*, 42(2), 28-40.

INTRODUCTION

Approximately one billion individuals live with a kind of disability (Saran et al., 2020). This

represents around 15% of the global population. The prevalence of disability is rising, attributed in part to the aging population and the escalation of chronic health conditions

(Khandelwal & Gupta, 2023). Lower-income nations experience this phenomenon more frequently than higher-income nations. Impoverished individuals have fewer means to get therapy.

Fifty percent of individuals with disabilities are unable to afford essential medical treatment, in contrast to one-third of non-disabled individuals who face the same financial barrier (Levine & Karner, 2023). Individuals with disabilities are over twice as likely to encounter substandard healthcare professional practices, as much as four times more likely to report incorrect treatment, and almost three times as likely to be refused health services.

Children with impairments or diseases are less likely to attend school and get a sufficient education (Paseka & Schwab, 2020). The likelihood of employment for individuals with disabilities is diminished. Global employment figures indicate that the employment rate for individuals with impairments is 54% for men and 22% for women. Still, for individuals without disabilities, it is 63% for men and 29% for women. Those with impairments are more susceptible to poverty. Their living circumstances are further exacerbated by the supplementary expenses associated with their specific needs, including specialized medical care, assistive devices, and support personnel. Individuals with disabilities often experience more poverty compared to their non-disabled counterparts with the same salaries.

Neurological Disorders (ND) are conditions that affect the central and peripheral nervous systems, specifically the brain, nerves throughout the human body, and the spinal cord (Ayub & Mallamaci, 2023). Millions globally endure ND. Annually, over 6 million individuals succumb to strokes, more than 50 million globally have epilepsy, and 7.7 million instances of ND, the predominant cause of dementia, are identified each year. The precise etiologies of ND are diverse, including genetic conditions, congenital disabilities, infections, behavioral or environmental health issues, cerebral traumas, spinal cord harm, and nerve injuries. Recent computational and mathematical approaches have demonstrated

the usefulness of machine-learning methods for modelling complex physiological processes, including neuronal excitability and disease progression, thereby supporting biomedical diagnosis and decision-making (Surekha et al., 2024).

ND includes a diverse array of illnesses, including epilepsy, cognitive difficulties, autism spectrum disorders, attention-deficit hyperactivity disorder, brain cancer, and stroke, among others (Kumar et al., 2023). Neurological disorders encompass a diverse range of conditions affecting the nervous system. These disorders may arise from genetic, congenital, infectious, traumatic, degenerative, vascular, or other causes. Various ND arise from tumors, degenerative conditions, trauma, infection, or anatomical anomalies. Neurological disorders may result from various factors, including genetic conditions, tumors, degenerative processes, trauma, infections, vascular abnormalities, and other disturbances of the nervous system. The need for technical solutions to assist those impacted by these illnesses is apparent.

Minor Correction – IoT Paragraph

The Internet of Things (IoT) has become an important technological development, enabling the development of intelligent and innovative applications and services in various fields (Shafique et al., 2020). Numerous IoT devices and software applications focus on developing eHealth solutions, thereby enhancing healthcare services. The primary objective of IoT is to improve the quality of life through pervasive connectivity among devices and systems. In this context, emerging technologies have the potential to transform healthcare through the implementation of the Internet of Health Things (IoHT), enabling applications such as remote patient monitoring, in-home treatment, and edge- and cloud-based computing for eHealth (Krishnamoorthy et al., 2023). Given the advantages that the overarching healthcare system will gain from using pervasive connections and technology, significant emphasis has been placed on identifying specialized intelligent solutions to detect, identify, and treat both common and complex

medical conditions. Recent machine-learning research in biomedical applications has further demonstrated the potential of automated computational models for disease detection and classification, particularly when clinical or imaging datasets require systematic feature extraction and pattern recognition (Rajeswari et al., 2024).

Alzheimer's (AD) and Parkinson's diseases (PD) are two of the most recognized ND. In 2019, over 7 million individuals globally were impacted by AD and PD illnesses, as reported by the World Health Organization (WHO) (Ji et al., 2024). Thus, significant emphasis is placed on identifying an innovative and effective approach for the early diagnosis of associated ND. The medical literature suggests a significant correlation between the onset of various brain disorders and their outward symptoms. Due to the considerable relevance of early symptom diagnosis, several research approaches have been presented to monitor health status. The current advancements include various methodologies to address the issue; some established solutions utilize stationary medical apparatus, while others rely on wearable IoT technologies. To enhance the likelihood of identifying ND at its initial stages, it is crucial to implement real-time and continuous monitoring of observable symptoms. This is only feasible via the use of lightweight, patient-friendly, wearable technologies.

RELATED WORKS

Rasool and Bhat (2025) presented a study that provided a substantial Machine Learning (ML) framework pertinent to brain tumor analysis, illustrating the extensive range of ML applications (Rasool & Bhat, 2025). This research examined the segmentation, categorization, prediction, and assessment of brain cancers using ML techniques. The key characteristics of this emerging field were discussed, and a detailed classification of the research environment was established based on the most recent research. Das and Goswami (2024) examined the essential principles of ML-based Brain Tumor Classification (BTC), including pre-processing, feature extraction, and classification, as well as its achievements and shortcomings (Das & Goswami, 2024). This review outlines the

benchmarking databases used to evaluate BTC. Critical issues, including the scarcity of public data and the lack of end-to-end ML methodologies, have been identified, along with extensive recommendations for future research in the BTC domain. Nailly et al. (2024) examined several works focused on automatic epilepsy detection and seizure detection using ML techniques and neuroimaging methods (Nailly et al., 2024). Various methodologies for the autonomous diagnosis of epileptic seizures using Electroencephalogram (EEG) and Magnetic Resonance Imaging (MRI) techniques are delineated. The substantial difficulties of combining ML with EEG and MRI technologies for the precise detection of automated epileptic episodes were examined. The most promising ML models were presented, along with potential future advancements. Raad et al. provided a detailed analysis of several ML architectures and preprocessing procedures for identifying anomalies in MRI data, specifically reviewing previous works on anomaly detection via MRI scans and categorization using neural network approaches for ND (Raad et al., 2023). The study presented a detailed analysis of the available datasets, including their sources and detailed information on the participants (e.g., patients, age, gender, and MRI scan modes).

Saeed et al. (2022) proposed an ML system for automated facial expression recognition (Saeed et al., 2022). This study represents the preliminary phase in the development of a non-invasive computational method for diagnosing ND, with the primary aim of enhancing service quality. The proposed framework combines part-based and holistic data to achieve efficient expression recognition. A novel framework using ML methods was proposed by Swaminathan and Vairavasundaram, (2024). The approach employs transfer learning and deep feature fusion for the recognition. It utilized raw embryonic brain images to construct three distinct Deep Convolutional Neural Networks (DCNNs). Gautam and Sharma (2020) conducted a comprehensive analysis of several ML methods for diagnosing severe neurological and ND. This research found that EEG- and MRI-derived data enhance the diagnosis of epilepsy, stroke, PD, and AD.

Data collection is the first step in the process, where clinical data such as medical records and neuroimaging data are gathered. Then, the data is preprocessed, such as data cleaning and normalization, to prepare the data for analysis. Then feature extraction is done to find the important patterns in the data. The extracted features are then fed into the classification stage with hybrid ML models to predict the occurrence of ND. The classification results can be used to aid diagnosis and monitoring of

diseases like AD and PD. The model's predictions can also be implemented on portable and wearable devices for monitoring purposes. The accuracy and effectiveness of the model are evaluated using performance metrics.

Suggested Disease Detection System Utilizing ML

Figure 2 illustrates the process for predicting and managing ND using hybrid ML algorithms.

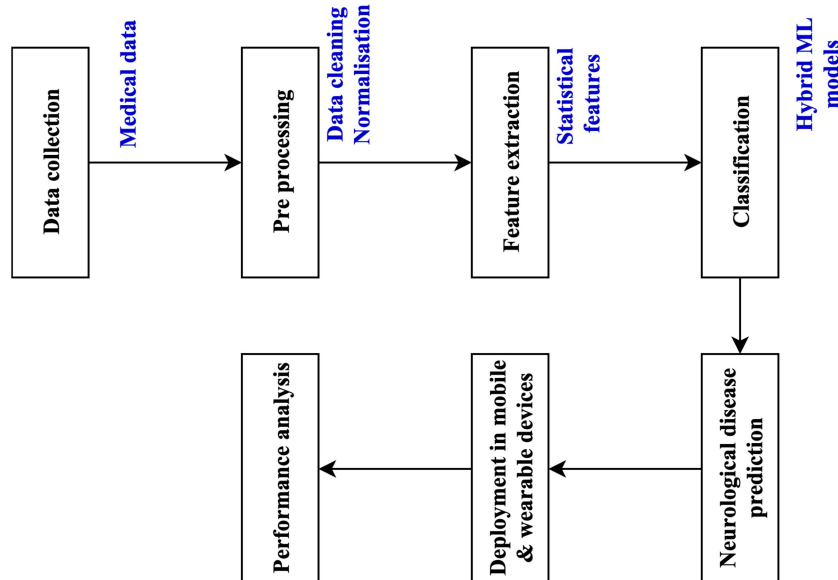


Figure 2: Hybrid ML model for ND prediction

The process begins with the collection of information, during which clinical data, including medical records and neuroimaging, are compiled. Subsequently, preprocessing is conducted, such as data cleaning and normalization, to prepare the data for evaluation. Feature Extraction ensues, entailing the computation of Statistical Features that facilitate the identification of significant patterns within the data. The collected characteristics are then input into a categorization phase using hybrid ML models to forecast the occurrence of ND. The categorization findings are used to predict ND, aid in diagnosis, and forecast the evolution of conditions such as AD or PD. The model's predictions can also be implemented on portable and wearable gadgets for monitoring purposes. Performance Metrics assess the model's correctness and efficacy, guaranteeing dependable forecasts.

Data Acquisition

Preprocessing for ND forecasting involves preparing gathered medical information for evaluation by rectifying errors, such as missing values, noise, and discrepancies. The first phase involves data cleansing, which entails addressing incomplete or incorrect data using methods such as imputation or eliminating problematic items. Subsequently, normalization or standardization is used to ensure that numerical information, such as arterial pressure or imaging pixel values, is on a uniform scale, facilitating processing by ML models. Categorical data (e.g., gender, healthcare history) is transformed into numerical forms, and extraneous characteristics are eliminated to minimize noise. Neuroimaging data undergoes procedures such as picture scaling and filtering to guarantee excellent quality and suitability for training models. Adequate preprocessing ensures that the information is sanitized,

uniform, and prepared for feature extraction and model construction.

Data Preprocessing

Preprocessing for ND prediction involves preparing gathered medical information for evaluation by rectifying errors, such as missing values, noise, and discrepancies. The first phase involves data cleansing, which includes addressing incomplete or incorrect data using methods such as imputation or eliminating problematic items. Subsequently, normalization or standardization is used to ensure that numerical information, such as arterial pressure or imaging pixel intensities, is on a uniform scale, facilitating processing by ML algorithms. Categorical data (e.g., gender, medical condition) is transformed into numerical forms, and extraneous characteristics are eliminated to minimize noise. Neuroimaging data undergoes procedures such as image scaling and filtering to ensure excellent quality and suitability for model training. Adequate preprocessing ensures that information is refined, standardized, and prepared for feature extraction and model building.

Feature Extraction

Feature extraction is the process of transforming raw data into meaningful and informative features that can be used by ML algorithms. In medical applications, feature extraction may include statistical analysis, signal processing, or image analysis to extract relevant features from clinical, sensor, or imaging data. CNNs can be used in medical imaging to learn spatial features from MRI or Computed Tomography (CT) scans. Likewise, time-series sensor data can be used to extract features like the mean, variance, and trend. For time-series analysis, the mean and standard deviation of signals can be computed to assess the variability or stability of a person's health over time. The formula for calculating the mean (μ) of a time-series dataset x_t (where t denotes time) is:

$$\mu = \frac{1}{m} \sum_{i=0}^{m-1} x_i \quad (1)$$

Hybrid ML model

Grey Wolf Optimization (GWO) techniques provide superior convergence characteristics when applied to various standard test functions. In several practical applications, GWO is straightforward to use and execute, requiring just a limited number of parameters. In the GWO method, the position update process considers just the first, second, and third solutions, disregarding the optimal location of each wolf throughout its search. The Particle Swarm Optimization (PSO) method is used to facilitate the process of position update. The particle's present location in the PSO method is revised based on the optimal location data for that specific particle and the best positioning details within the group. The hybrid integrates the exploitative capabilities of the PSO with the exploratory possibilities of the GWO. This study develops a hybrid framework that incorporates the GWO and PSO methods for optimal feature selection.

Theoretical analysis

The position update step has been amended to consider four options: the three optimum solutions derived from GWO and the best-experienced answer for each particle based on PSO. The revised position enhancement is given below:

$$P_x(t+1) = k_1 v_1 (b_1 P_1(t)) + b_2 P_2(t) + b_3 P_3(t) + k_2 v_2 (P_{ibest} - P_x(t)) \quad (2)$$

wherein v_1 and v_2 are randomly selected within the range $[0, 1]$, and k_1 , k_2 represent the social and cognitive learning elements, respectively. P_1 , P_2 , and P_3 are the optimum solutions identified by equations 3(a) to 3(c). The set Xibest provides the optimal location for every gray wolf from the start of the search. The factors b_1 , b_2 , and b_3 represent the inertia weights and are calculated as follows:

$$b_1 = \frac{|p_1|}{|p_1 + p_2 + p_3|} \quad (3a)$$

$$b_2 = \frac{|p_2|}{|p_1 + p_2 + p_3|} \quad (3b)$$

$$b_3 = \frac{|p_3|}{|p_1 + p_2 + p_3|} \quad (3c)$$

Non-linear control parameters were employed, which were more effective than linear optimization of the approach, and are described as follows:

$$o_1(t) = o_{init} - (o_{init} - o_{end}) \left(\frac{t}{T_{max}} \right)^2 \quad (4)$$

where o_{init} and o_{end} represent the first and final values of an inside period [2:0]. The current iteration is t , and the total number of cycles is T_{max} .

Adaptation of ANFIS with the PSO-GWO

This research uses PSO-GWO to adjust both the consequent and antecedent parameters of the

ANFIS framework. The ANFIS training methods use the conventional hybrid optimization, which integrates the Least Squares Estimation (LSE) and Gradient Descent (GD) methodologies. This traditional hybrid approach used LSE to adjust the variables of the then-part in the forward transmission. In the backward movement, GD was used to modify membership function parameters as a method of back-propagation.

The tendency to converge at local minima is a notable critique of gradient descent, which is circumvented by using metaheuristic algorithms, such as the suggested hybrid ML method. The hybrid ML method combines exploration and exploitation capabilities, enabling flexible optimization of ANFIS parameters.

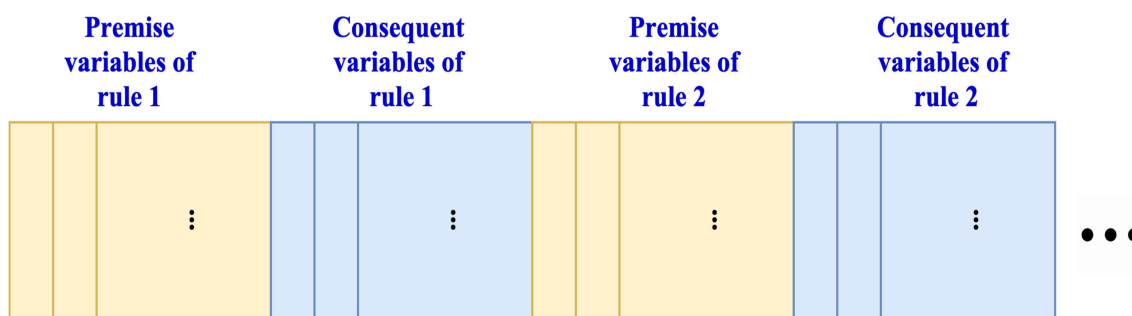


Figure 3: PSO-GWO position solution

In the hybrid ML method, the position of each particle represents a comprehensive set of variables for the ANFIS mechanism. These positions include two configurations for variables—initially, the variables of a membership function. The subsequent segment of the solution is allocated for the variables of the sequential component of the fuzzy rule, as shown in Figure 3. The required computational effort for adaptation makes the total number of changeable variables in an ANFIS system a

critical factor in its creation. The categories of membership must be carefully chosen. The Gaussian member type value, which requires just two parameters—width and center—is superior to other forms of member functions.

The suggested comprehensive cycle using the ANFIS framework is illustrated in Figure 4. The data are partitioned into training and testing sets at the commencement of the model. Both training and testing information are picked randomly.

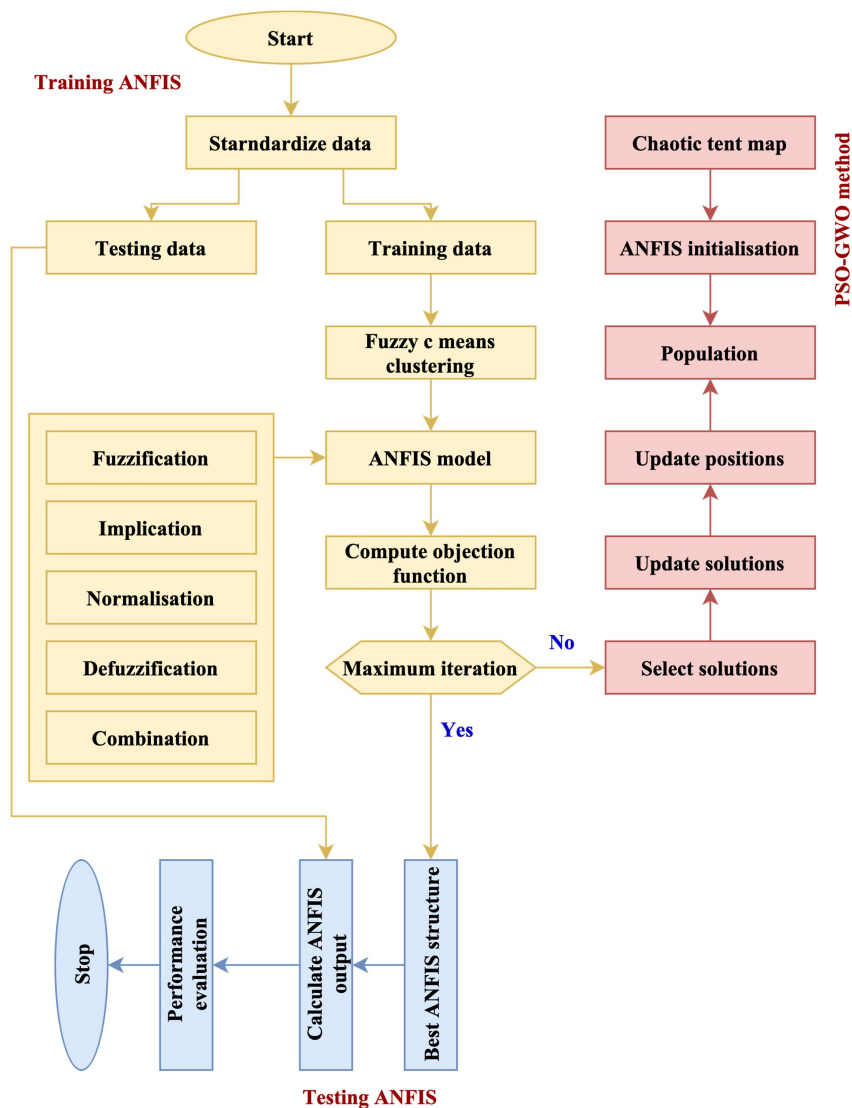


Figure 4: Workflow of the hybrid ML for ND detection

Numerous unconventional starting procedures exist, including ones focused on distributed Sampling (DS), chaotic maps, and others. Chaotic number arrays have recently been used in several applications as an alternative to random collections of integers. The fundamental attributes of chaotic movement include unpredictability, consistency, and ergodicity, which are crucial in addressing function optimization problems. The workflow of the suggested model is shown in Figure 4.

These attributes enabled the algorithms to avoid the local optima issue, hence maintaining the requisite variety of the population and augmenting global search capabilities. Various types of chaotic maps exist, including logistic

mapping and tent mapping. The search characteristics of different chaotic maps vary.

Although logistic mapping is prevalent in research, it results in an inhomogeneous range of values due to its elevated value rates within the intervals $[0, 0.1]$ and $[0.9, 1]$. The tent mapping is among the most basic chaotic structures that have been examined lately. Experiments demonstrate that the tent map provides a more uniform traversal than the logistic map in terms of traversal homogeneity. It enhances the algorithm's speed by producing a more uniform starting value within the range of $[0, 1]$. The convergence characteristic of the suggested method relies on the randomized

number sequence utilized to execute the procedure with varying variables.

The chaotic tent mapping was used to initialize the initial population of the proposed model. The tent mapping is expressed mathematically as follows:

$$p_{n+1} = \begin{cases} \mu p_n & 0 \leq p_n \leq 0.5 \\ \mu(1 - p_n) & \text{else} \end{cases} \quad (5)$$

Where μ is approximated to $1+R$, with R randomly chosen within the interval $[0,1]$. Any p_0 point inside the interval is generated with p_n in $[0,1]$ as delineated above, after the method's modification. The fitness, defined as the Mean Squared Error (MSE) between the goal value and the actual result, is expressed as:

$$MSE = \frac{\sum_{j=0}^{n-1} (q_0 - q_n^t)^2}{n} \quad (6)$$

q_n^t represents the goal output, q_0 signifies the average result, and m indicates the size of the database.

Prediction of ND

ND utilizing a hybrid ML method for forecasting entails analyzing multiple data sources to determine the probability of onset or progression of ND, including AD, PD, and various sclerosis. These prediction models utilize medical data, including health history, neuroimaging (e.g., MRI, CT scans), genetic information, and sensor data (e.g., EEG, wearable devices), by deriving significant characteristics from various data sources and training ML algorithms to discern patterns suggestive of early-stage ND. The objective is to provide early diagnosis, tailored therapy, and proactive management of illnesses, hence improving patient results by detecting dangers before the onset of severe symptoms. These models are continually enhanced through data gathering and feedback, ensuring increased accuracy and responsiveness to individual patient situations.

Implementation in mobile and wearable gadgets

Deployment in mobile and wearable devices involves integrating IoT and ML models into portable technologies to facilitate the

surveillance and prognosis of ND. By integrating forecasting algorithms into mobile applications or wearable devices such as smartwatches, EEG headphones, or fitness monitors, healthcare practitioners continually monitor individuals and gain immediate knowledge of their ND. These devices collect sensor data, including heart rate, movement, and brainwave activity, which is then analyzed by the implemented model to identify early indicators of ND, such as seizures, tremors, or cognitive deterioration. The primary advantage of implementing ML algorithms in mobile and wearable technology is the provision of continuous, individualized care, facilitating early detection, prompt alarms, and data-informed decision-making, regardless of the clinical environment. This method enhances patient involvement and convenience, facilitating more precise and consistent surveillance of health.

RESULTS

This study includes two trials to evaluate the effectiveness of the proposed hybrid ML method. The first experiment assessed the accuracy and efficacy of the proposed method in minimizing errors, using five datasets sourced from the repository.

Experimental Environment and Parameters

In this section, five datasets from the UCI database are used to test the effectiveness of the proposed system (Sun et al., 2020). The proposed system was compared with the Differential Evolution (DE), Ant Colony Optimization (ACO), GWO, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and the standard ANFIS framework in this experiment. Each dataset was divided into 70% for training and 30% for testing in all trials. All experiments were performed on the Windows operating system, using an Intel CPU with 16 GB of RAM at 1.80 GHz. All implementations are in MATLAB. All the optimization methods are set as follows: population size (n) = 30, maximum iterations = 100, lower limit = -10, upper bound = 10. The same settings were used for all optimization methods for comparison. Parameters are identified based on their effectiveness in previous studies.

Experiment Results

The present study employed four metrics to evaluate the proposed approach: Root Mean Square Error (RMSE), accuracy, Standard Deviation (SD), and Mean Square Error (MSE). The experiments were conducted 15 times, and the resulting measures were averaged and presented in Figs. 5-8. The proposed system showed better performance than the compared methods across the five datasets. In the breast cancer database, the suggested model

demonstrated superior performance during the training phase; however, the proposed system showed better performance than the compared methods during the assessment stage. The statistics presented in Figure 8 indicates that the suggested system outperformed all methods across all databases used. The study demonstrates the efficacy of the proposal and is expected to enhance the optimization of ANFIS's variables.

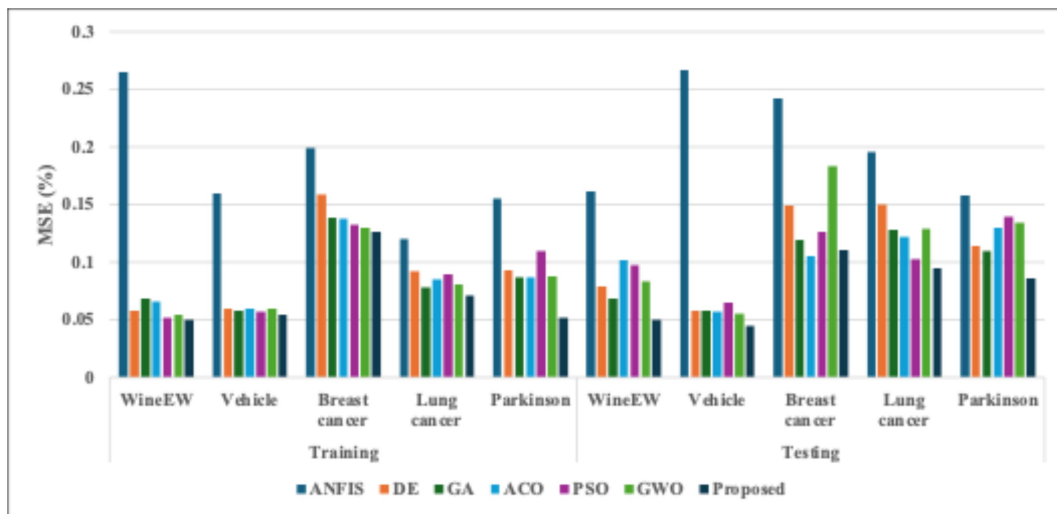


Figure 5: MSE analysis

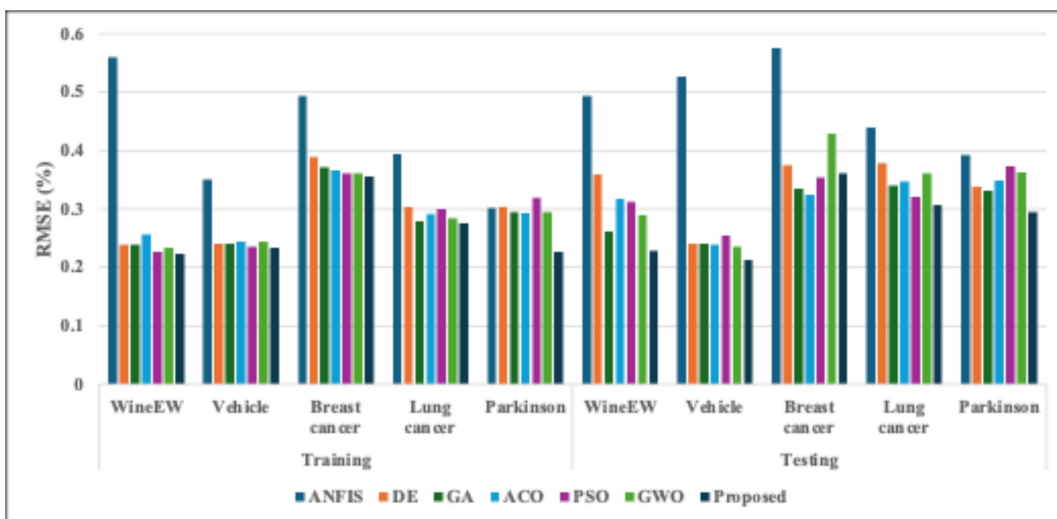


Figure 6: RMSE analysis

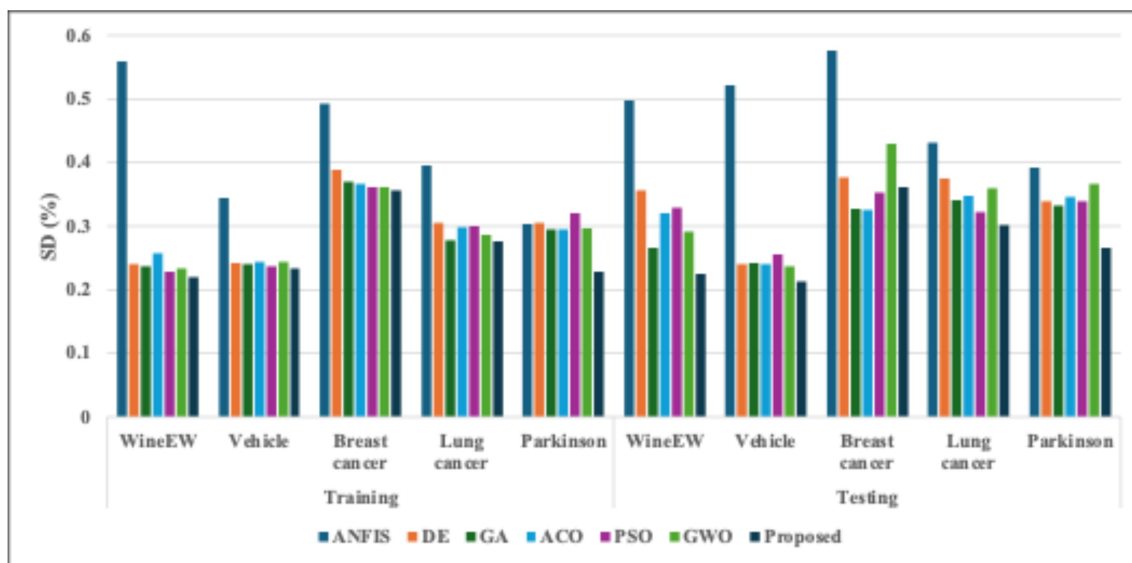


Figure 7: SD analysis

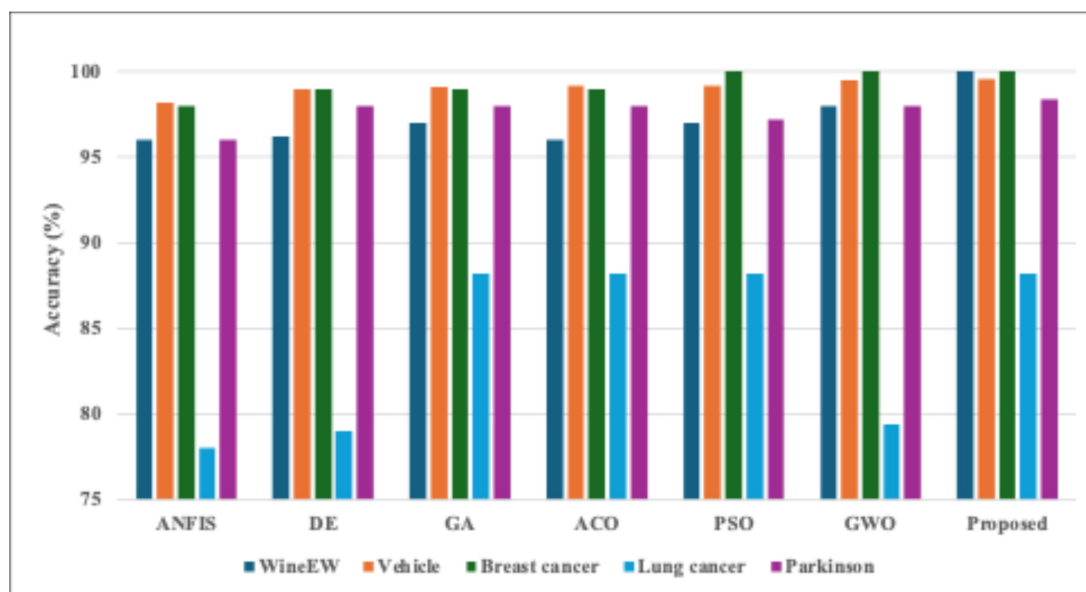


Figure 8: Accuracy analysis

The suggested model for ND demonstrated superior performance in accuracy assessment compared to all other variations, as seen in Figure 8.

CONCLUSION

This research introduces an innovative approach to collecting clinically relevant information to assess Parkinson's disease using learning techniques to build reliable decision support systems. This work proposes a system model for predicting ND in fog-cloud environments based on sets of voice data. The fog infrastructure facilitates real-time data processing and

evaluation, therefore surmounting the limits of cloud computing. The proposed system combines the exploration and exploitation capabilities of GWO and PSO in a complementary way. To enhance the diversity of the population and to prevent premature convergence, chaotic tent mapping is used for initialization. The proposed model was tested with several datasets and performance measures. The recommended approach shows better performance than existing approaches, with an accuracy of 92.5% for the Parkinson's disease prediction task. In the future, the proposed model will be extended to incorporate

a larger number of data sets for additional ML methods that can be used to train fog learning. Modern metaheuristic approaches like dragonfly optimization, whale optimization, and chimpanzee optimization strategies can also be used for hybridization.

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