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Implement ANFIS Classification with PSO Algorithm for MRI Images to Classify Parkinsons Images

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Abstract: Millions suffer from neurodegenerative Parkinson's disease (PD). Effective PD treatment requires early and precise diagnosis. MRI offers brain structural information. Machine learning has improved diagnostic accuracy in medical imaging in recent years. This paper presents a novel method to categorize Parkinson's disease MRI images utilizing the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) classification algorithm with optimization PSO feature Selection and image enhancement. Three main steps are proposed. First, MRI images are enhanced to increase quality and highlight significant features. Preprocessing includes noise removal, contrast improvement, and image sharpening. The next categorization phase uses improved photos. Second, this work presents illness diagnostic machine learning methods with optimization like PSO for feature extraction. Finally, ANFIS classifies MRI images as PD or non-PD. Parkinson's disease (PD) is a complex neurological ailment that needs early diagnosis and treatment. Machine learning can help diagnose PD by examining patient data attributes. This work provides an optimal hybrid model that classifies Parkinson's disease using numerous characteristics and multiclass diagnosis detection techniques. The hybrid model combines machine learning algorithms to boost classification accuracy. Clinical, demographic, and genetic data represent the disease. PD classification uses feature selection to find the most relevant and discriminative features. ANFIS fuzzy rules and parameters are designed for accurate classification. PD MRI scans are used to test the suggested method. Classification performance is measured by accuracy, sensitivity, specificity, and area under the curve. To prove its efficacy, the proposed classification method is compared to others. The findings show that ANFIS classification with image enhancement approaches can classify PD. The proposed MRI-based Parkinson's disease diagnostic method is accurate and sensitive. ANFIS's intelligent decision-making and MRI characteristics increase classification performance.

***Keywords*:** *Parkinson's disease, MRI images, Adaptive Neuro-Fuzzy Inference Systems, PSO.*

1. Introduction

Dopamine-producing nerve cells in the brain are the target of Parkinson's disease (PD), the second most prevalent [1] progressive neurological condition. Dopamine cells in the brain's Substantia Nigra, which normally serve as messengers to regulate movement, have begun to die. When the number of cells in the brain responsible for making dopamine drops significantly, it causes difficulties in regulating movement. The exact reason for this cell death is unknown. The breakdown of these cells has been linked by many researchers to both genetics and environmental factors. People aged 60 and up [2,] those in certain occupations, and those who have suffered severe head trauma are all at a higher risk of developing Parkinson's disease. Parkinson's disease symptoms don't appear all of a sudden. After Alzheimer's disease [3], the most frequent form of neurodegeneration is Parkinson's disease [4], often known as Shaking Palsy. After stroke, epilepsy, and migraine, it ranks as the fourth most expensive neurological disorder [5]. Dopamine-producing cells in the brain's Substantia Nigra die down, leading to the neurological illness known as Parkinson's disease. These cells ensure proper communication between the brain and the rest of the body. Walking, talking, writing, and even smiling are all under the strict control of these cells. Dopamine levels drop when these cells begin to die, causing disruptions in brain and body coordination. Patients struggle with even the most fundamental tasks of daily life.

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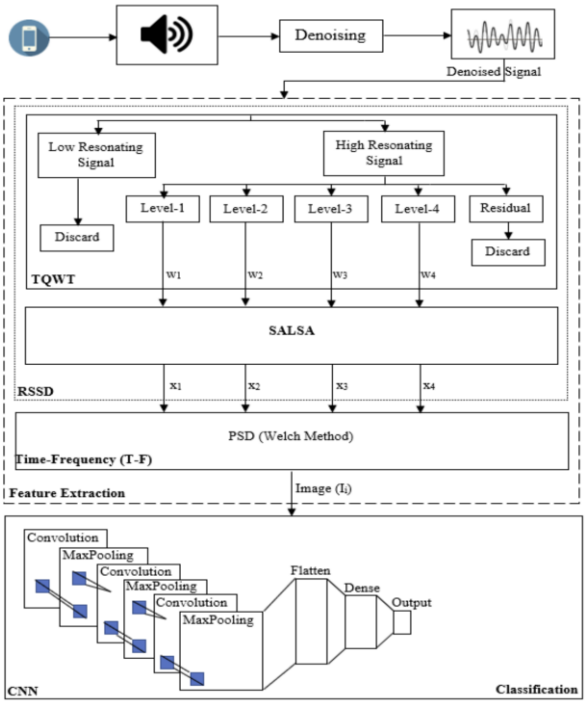


Fig 1: Overview of PD diagnosis system

PD is characterized by a wide range of symptoms. Patients may have a wide range of symptoms. This means that a patient's absence of some symptoms is not diagnostic [6]. To make a diagnosis of PD, one or more symptoms must be present. Symptoms may or may not be present at the outset, but as the condition worsens, they will change and become more noticeable. As the condition develops, new symptoms may emerge. There are two main types of symptoms, motor and non-motor. Parkinson's disease (PD) diagnosis systems are developed to aid doctors in making a correct diagnosis of PD using a wide range of available data and analysis methods [7]. Accurate and quick diagnoses are made possible by these systems' use of cutting-edge technology including machine learning, medical imaging, and clinical data analysis.

Voice transmissions contain both steady-state oscillations and brief, non-repetitive spikes. No amount of time-frequency analysis will ever be able to retrieve the information contained in these oscillations. These oscillations can be understood by a resonance-based non-linear analysis of the signal. Information from long-lasting oscillations makes up the high-resonating components, while non-oscillatory transients make up the low-resonating ones [8]. The signal is split into high- and low-resonance sub-components so that information can be extracted from both. Because most of the information in a voice signal is contained in its sustained oscillations, the signal's high-resonance components are preserved. Both low- and high-frequency components exist in the isolated high-resonating parts. So as to extract information based on time and frequency, a time-frequency analysis of the highly resonant component is necessary [9]. Therefore, we suggest a hybrid method that draws upon the best features of both resonant and time-frequency data. FIGURE 1 depicts the proposed structure. The first step is to get subjects to record their own voices speaking. After manually segmenting the audio to isolate its most crucial components from the background noise, a noise reduction approach is employed.

2. Background

Dopamine levels and other biochemical studies confirm a diagnosis of PD. Biochemical unit levels also indicate the severity of PD and the progression of the disease. PD markers, such as hydroxy-2-deoxyguanosine and 8-hydroxyguanosine, have been studied and used in analysis. These chemical levels and EEG activity can both be utilized to diagnose Parkinson's disease [10]. Few medical studies record EEG signals for a range of patient emotions (e.g., happiness, anxiety, sadness, anger, surprise, etc.). Rapid symptom progression can be identified using merely a trained PD detection system. The enhancement of medical technologies is aided by several studies that focus on biological neural architecture, neural functions, and neural modalities. There have been numerous methods developed throughout the years for detecting neurological disorders, much like those for detecting PD. The most advanced automatic diagnostics methods are required for disorders including Alzheimer's, Alcoholism, ADD/ADHD, and Epilepsy. Medical research tools require greater knowledge to analyze the spectrum of PD measures compared to standard pattern matching procedures [11]. More education and practice are required for the medical

data analysis tools (whether software or hardware). In the last few decades, many different kinds of decision-making systems have been incorporating artificial neural networks (ANN). When given data, ANN generates sophisticated analytical methodologies from which to draw conclusions. There are three primary tiers: input (for data collecting), processing (for analysis), and output (for sharing results). Researchers are more familiar with Machine Learning (ML) and Deep Learning (DL) methods. In the processing phase of medical data, these methods conform to a standard format [12]. Feeding in data, preprocessing the data, selecting features, extracting features, and classifying the data are the stages of ML and DL methods.

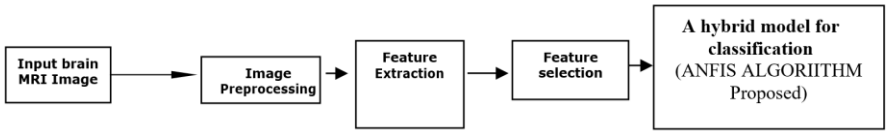


Fig 2: Block diagram of proposed methodology

Artificial intelligence algorithms have made important advances in the field of medical diagnosis. The goal of this work is to provide the necessary machine learning algorithm for Parkinson's disease classification, which will be useful to researchers and doctors [13]. In this study, we evaluate several Machine algorithms for picture classification and compare their accuracy to one another. Thus, this investigation's goal is to reflect the outcomes of various algorithms used to diagnose Parkinson's disease using machine learning models and to incorporate all important data regarding these models. This work develops a PSO-like method for feature extraction using machine learning techniques; this can be used in the diagnosis of disease. T1-weighted structural magnetic resonance imaging (sMRI) has been used in recent years for automatic discrimination between people with Parkinson's disease (PD) or its prodromal phase (i.e. mild cognitive impairment (MCI)) and healthy controls (HC). Several high-dimensional, accurate, and effective classification methods have been proposed [14]. Classification accuracy is limited since these techniques focus solely on using a single feature from sMRI images to differentiate between PD, MCI, and HC patients. In order to increase the classification accuracy of PD pictures, a cutting-edge multimodal approach is proposed here. This approach combines several features from various sMRI analysis methods.

3. Methodology

The ANFIS system's efficiency was ramped up with the help of the PSO algorithm. To begin, a completely random distribution function must be used to calculate the beginning values and velocity vectors for the particle vectors. It's important to remember that computers use the range 0-1 to represent random numbers [15]. First, we generate each Particle by multiplying the parameter by a random number. Selecting a sequence of parameters outside of the allowed range causes the model to crash. We converge on a finding. So, while the Particles' initial values are chosen at random, they must be chosen so that the parameters are within reasonable bounds. The gains from the initial parameters are introduced to the model independently.

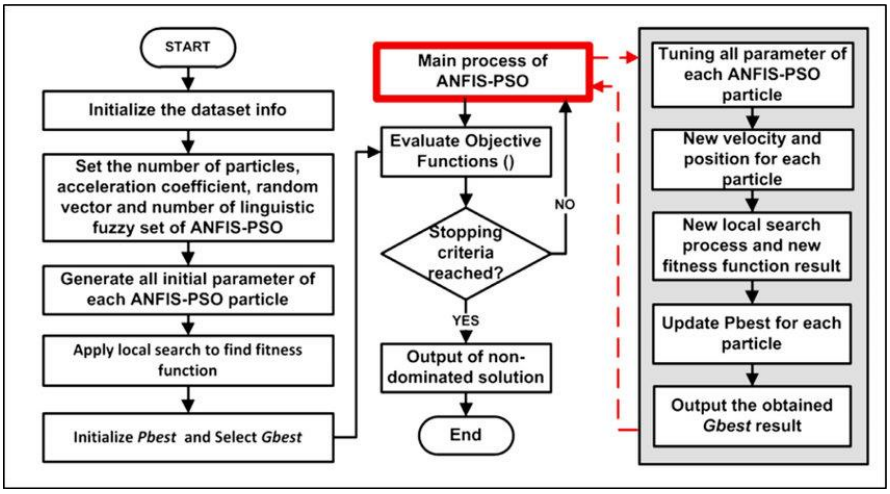


Fig 3: Flowchart for the proposed model

This setup is accomplished by coding in the values specified in one of the model's input files that contains the parameters. It should be emphasized that the n Particle count is verified at each time step. That's why it's important to run the ANFIS, n bar model at any given time epoch [16]. Inflationary time series simulations are introduced as output each time the model is run. The simulation inflation figures are compared to the constant inflation that has been observed. As a result, the n-bar model is implemented after the initial time step. One value for the goal function is calculated for each Particle in the first step [17]. First-round pbest values for all particles match their actual states. Finding the gbest, the best Particle encountered position in the swarm set, can be done by comparing the objective values of each Particle and selecting the largest quantity. Using the previous stage's particles' status and velocities as well as pbest and gbest values, the new stage speed is calculated in the second repetition using Eq. (1). Then, using Eq. (2), we can determine the most recent state of the Particle.

$$V_{id}^{n+1} = \left[WV_{id}^{n} + C_1 r_1^n (p_{id}^n - X_{id}^n) + C_2 r_2^n \left(p_{gd}^n - X_{id}^n\right)\right] \quad [1]$$

$$X_{id}^{n+1} = X_{id}^{n} + V_{id}^{n+1} \quad [2]$$

The PSO algorithm's particle orientation plays a crucial role in setting the pace and trajectory of particle motions throughout the optimization procedure. Particles' searches for the best possible orientation are often represented by a velocity vector. Although I cannot provide a direct explanation of the PSO algorithm as it is implemented in the ANSI code, I can provide a more general explanation of the concept of particle orientation inside the PSO algorithm. Particle swarm optimization (PSO) uses iterative updates to the position and speed of each particle in the swarm to find the best possible solution [18]. The search space is affected by the particle's orientation, which is specified by the velocity vector. Particle motion is described by a set of components known as the velocity vector. Particle's current velocity, cognitive component (personal best), and social component (best position of swarm) are all taken into account by the PSO algorithm while updating the velocity vector [19]. These parts help direct the particle to more fruitful parts of the search space. To see how the PSO algorithm's velocity vector can be updated in its simplest form, check out the ANSI code below:

Algorithm: Particle orientation in PSO algorithm

Start

for each particle in the swarm:

Update particle's velocity

for each dimension in the problem space:

Calculate cognitive component

cognitive_component = cognitive_weight * random() * (particle.best_position[dimension] - particle.position[dimension])

Calculate social component

social_component = social_weight * random() * (swarm.best_position[dimension] - particle.position[dimension])

Update particle's velocity

particle.velocity[dimension] = inertia_weight * particle.velocity[dimension] + cognitive_component + social_component

Limit the velocity within a certain range (optional)

particle.velocity = clamp(particle.velocity, min_velocity, max_velocity)

end

The particle's orientation is modified to efficiently probe the search space by altering the velocity vector based on the cognitive and social components. This procedure iterates until a stopping requirement is fulfilled, such as the number of iterations being exhausted or the quality of the solution being satisfied [20]. The preceding ANSI code snippet is a truncated version of the PSO algorithm's particle orientation notion. The precise method employed may change based on the nature of the problem at hand and the particular flavor of PSO employed. Predicting the existence or progression of Parkinson's Disease (PD) relies heavily on the design of the system used to do so. There are many parts and phases to this architecture, but training and developing trained models with varied parameters take center stage. The PD prediction system utilizes machine learning techniques on a large dataset to

generate accurate predictions for efficient diagnosis and therapy planning. Multiple critical processes are required during the training phase of the PD prediction system [21]. These processes include data collecting, preprocessing, feature extraction, model training, and the creation of learned models with varying parameters. Together, these processes improve the system's ability to recognize patterns and make accurate predictions about the course of PD. The first phase is data gathering, in which extensive information on patients is gathered using appropriate data sources such health records, surveys, genetic markers, or sensor devices. The following sections of the structure rely on this information as their basis.

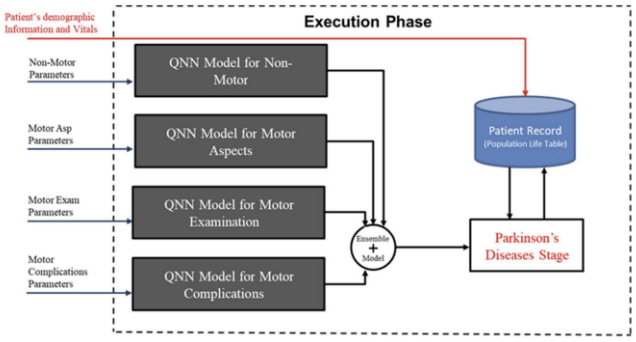


Fig 4: Architecture of Proposed methodology

The collected data must subsequently undergo preprocessing procedures to verify its quality and usefulness for analysis. Normalization or standardization may be applied to the entire dataset in order to create consistency and comparability by accounting for missing values, eliminating outliers, and reducing noise. If necessary, data can also be transformed using scaling or transformation methods. After the data has been cleaned and prepared, the next stage is feature extraction. Important PD-related patterns, traits, or biomarkers can be captured by these aspects. Depending on the nature of the data, many approaches may be used, including statistical evaluations, time-series analysis, frequency analysis, and image processing techniques. To improve the reliability of PD prediction models, it is necessary to identify useful and distinguishing information.

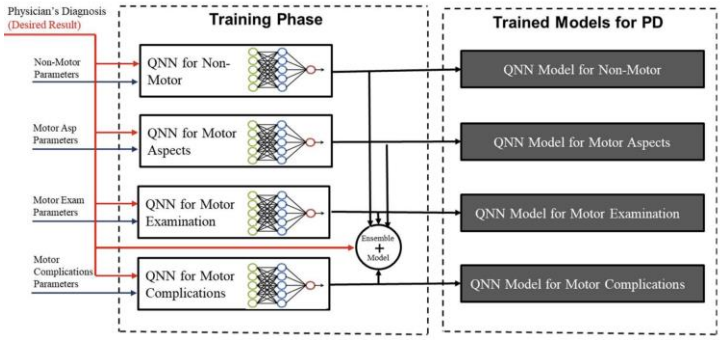


Fig 5: Execution phase

Using the retrieved features and the labeled data, machine learning algorithms are used to train the models during the model training phase. Depending on the characteristics of the data and the nature of the prediction task, many methods, such as Support Vector Machines (SVM), Random Forest, Neural Networks, and other relevant models, can be used. To improve the models' predictive abilities, training involves modifying various model parameters such as the learning rate, regularization, and architecture. During training, numerous models with various sets of parameters are created. These trained models record the associations discovered between the input characteristics and the PD forecast. Different trained models with different combinations of parameters and methods allow for deeper dives into the data and better predictions as a whole. The predictions of numerous trained models can be combined using ensemble techniques to improve prediction accuracy. By combining the results of multiple models into a single forecast, ensemble methods like majority voting and weighted voting can improve prediction quality and reliability.

4. Results

The datasets values are normalized in the range [0, 1] using a normalization technique to guarantee data consistency. Then, the system's efficacy is put to the test

via hold-out cross validation. As a result, we split the data sets into a training set and a test set. The testing set is not viewed during training but is used to evaluate the generalization performance of ANFIS after the network has been trained using the training set. These datasets are randomly split into a training set and a testing set, with the former containing 80 percent of the data and the latter 20 percent.

Table 1: PSO parameter Setup

PSO Parameter	**Value**
No. of Particles	100
No. of Linguistic Fuzzy Set	6
No. of Iterations	2000
Obj. Function 1(f1)	MSE
Obj. Function 1(f2)	Optimal Number of rules
Acceleration coefficient	c_1=0,5 c_2=1
Random vector r_1 and r_2	Random

Table 1 outlines the mandatory starting points for the ANFIS-PSO procedure. Each dataset is tested ten times in ANFIS-PSO's trials. The mean and standard deviation (mean value and standard deviation, respectively) are calculated and given for the mean squared error (MSE), the number of rules, and the amount of time spent.

Table 2: Performance Measures

Parameter	Expression
Mean square error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
RootMSE (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Coefficient of determination (R^2)	$R^2 = 1 - \sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)^2}{(y_i - \hat{y})^2}$
Standard deviation (SD)	SD = $\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Sensitivity	$\frac{TP}{TP + FN}$
Specificity	$\frac{TN}{TN + FP}$
Accuracy	$\frac{TP + TN}{TP + FN + TP + FN}$

The PSO-ANFIS approach proposed for medical diagnostics is evaluated. The input dataset is split 70% for training and 30% for testing. In addition, the suggested method is contrasted with a variety of existing approaches in the same general vein. Their usefulness as predictive models in diverse contexts led to their selection. Both the population size and the number of iterations play an important role in swarm algorithms. To demonstrate the

hybrid nature of the technique presented, we fixed the number of iterations but varied the population size.

Prediction findings for the Parkinson's dataset employing PSO-ANFIS as a classifier model with 100 iterations are shown in Table 2 in terms of prediction accuracy, sensitivity, and specificity. According to the statistics in the table, the PSO-ANFIS model with a population size of 10 achieved the highest accuracy (sensitivity of 98.4% and specificity of 94.97%). There are ups and downs in accuracy as the population size grows. Similarly, a population size of 10 allowed the PSO-ANFIS model to achieve 98.66% accuracy on the RIM-ONE dataset. The precision shifts as the population grows larger. Figure 6 displays PSO-ANFIS's overall performance on the Parkinson's disease dataset across different population sizes.

Table 3: Performance of the PSO_ANFIS Algorithm

Size	Accuracy	Specificity	Sensitivity
5	94.8	93.2	96.18
11	98.18	95.2	98.7
17	95.8	89.3	96.32
21	96.5	94.6	95.3

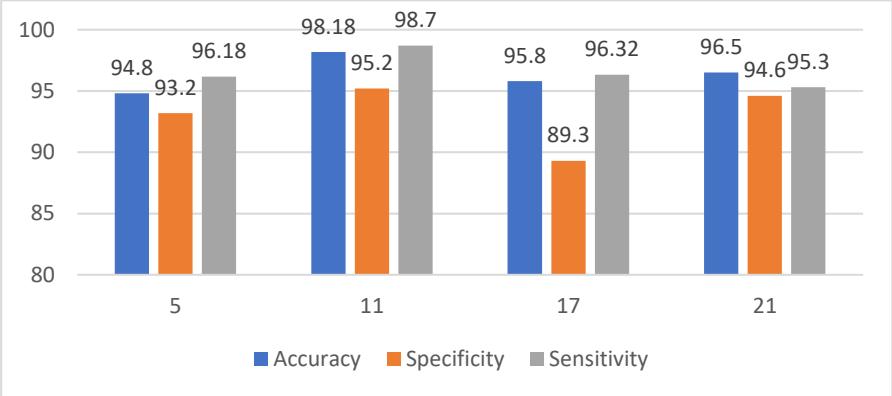


Fig 6: Plot for Performance of the PSO_ANFIS Algorithm

The average and standard deviation of PSO algorithms that use ANFIS learning are displayed in Table 4. According to the data in the table, Balloon has the lowest error rate during training, whereas Iris Flower has the lowest error rate during testing. This finding suggests that the error rate may be independent of the input parameters and sample sizes, and instead be attributable to differences in the dataset distributions. The significant error of its value is not so good compared to the balloon and iris data, for example, because the distribution of its classes is extremely imbalanced (there are 255 instances for class 1 and 81 instances for class 2). There is a significant discrepancy between the training and testing error rates, despite the fact that Balloon contains fewer occurrences than most and very normal distribution data. On the other hand, Iris data are normally distributed despite having greater variability than Haberman's data and more instances than balloon data. Both the training and test data indicate a small error value in the output. As a result of its higher variability and irregular distribution, thyroid data also achieved the worst results in both sets of data. The error rate value may therefore be inferred to be highly sensitive to the distribution of each class.

Table 4: PSO-ANFIS model performance for inflation

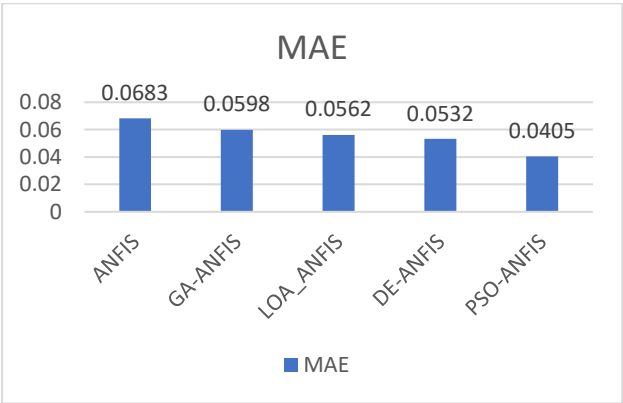
Parameter	Total Data	Train Data	Test Data
Mean square error (MSE)	0.0017	0.0001	0.0039
Mean Absolute Error (MAE)	0.0405	0.0134	0.0612

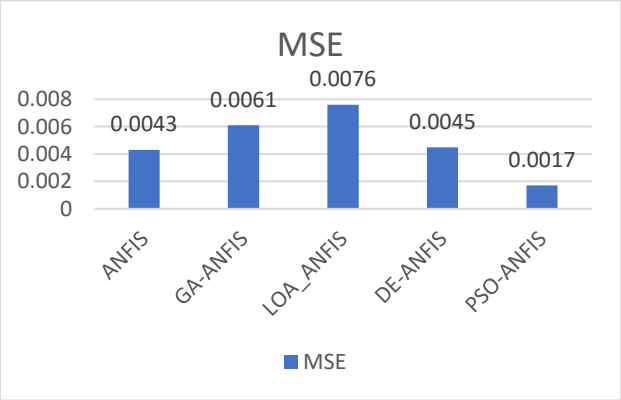
RootMSE (RMSE)	0.0213	0.0087	0.0398
Coefficient of determination (R^2)	0.9736	0.9845	0.9572
Standard deviation (SD)	0.0141	0.0132	0.0535

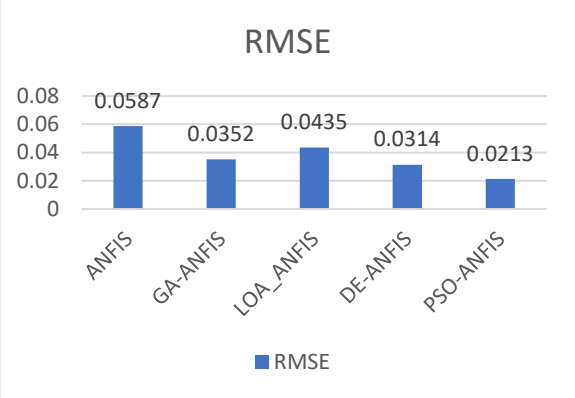
Tables 5 show the results of a statistical analysis comparing the proposed model to some industry standards. Figures 7 display the results of a statistical analysis comparing PSO-ANFIS to RIM-ONE on the Parkinson's disease dataset. The statistical metrics MSE, MAE, RSME, R2, and SD, along with the performance of the proposed model on many datasets, are displayed clearly.

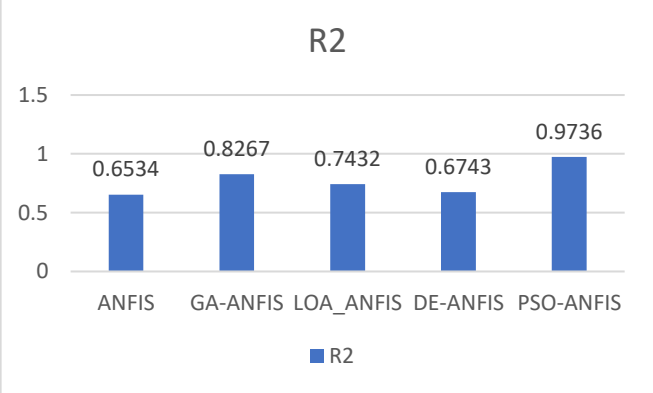
Table 5: Model based parameter Comparison

Model	MSE	MAE	RMSE	R^2	SD
ANFIS	0.0043	0.0683	0.0587	0.6534	0.0572
GA-ANFIS	0.0061	0.0598	0.0352	0.8267	0.0286
LOA_ANFIS	0.0076	0.0562	0.0435	0.7432	0.0435
DE-ANFIS	0.0045	0.0532	0.0314	0.6743	0.0345
PSO-ANFIS	0.0017	0.0405	0.0213	0.9736	0.0141









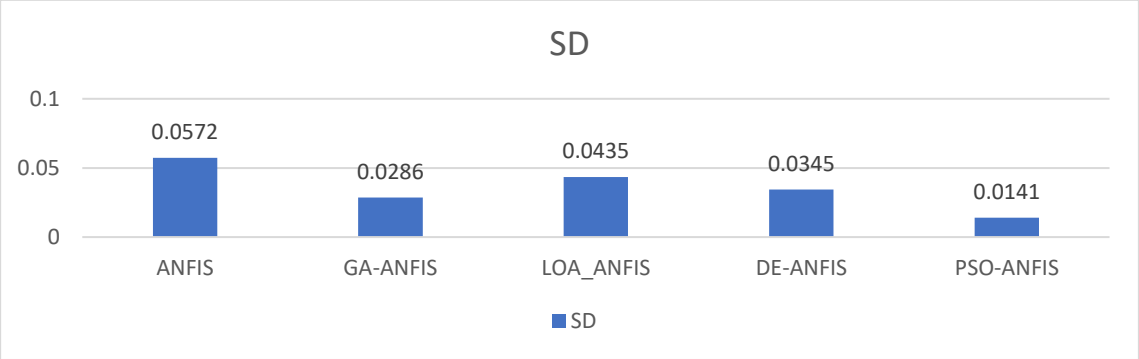


Fig 7: Plot for the Model based parameter comparison

5. Conclusion

In conclusion, a PD prediction system's architecture involves multiple steps, the most important of which are the training phase and the creation of learned models with varying parameters. Effective prediction of PD outcomes and useful insights for diagnosis and treatment planning are made possible by the system's incorporation of data gathering, preprocessing, feature extraction, model training, and ensemble approaches. The PD prediction system has the potential to enhance accuracy, early detection, and individualized therapy for people with Parkinson's Disease by combining machine learning algorithms and a rich dataset. Finding the best settings for each algorithm in the hybrid model requires hyper parameter tuning and cross-validation methods. This improves the model's ability to generalize to novel data and enhances its diagnostic precision. The efficacy of the hybrid model is evaluated with the use of a number of different measures. A sizable dataset including both PD patients and healthy controls is used to verify the accuracy of the proposed optimized hybrid model. The dataset is split into training and testing sets, with the latter used for validating the model's understanding of PD's foundational patterns. The model is then put through its paces on the testing set to see how well it does at accurately categorizing PD patients. The outcomes show that a very accurate and trustworthy multiclass PD diagnosis may be made using the optimized hybrid model. The model's improved classification performance and higher diagnostic accuracy are the result of its use of several characteristics and a number of different classification techniques. By integrating the supplementary data from multiple sources, the improved hybrid model sheds new light on the diagnostic process for PD. This study adds to the body of work utilizing machine learning approaches to construct a superior hybrid model for the diagnosis of multiclass PD. The proposed method has the potential to aid healthcare providers in correct patient classification, opening the door to early intervention and individualized treatment plans for people with PD. The model's resilience and reliability in actual clinical settings are further improved by the incorporation of different features and methods.

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