Tuijin Jishu/Journal of Propulsion Technology
ISSN:1001-4055
Vol. 44 No.3 (2023)

A Study on Parkinson's Disease Parameters Using Data Mining with Machine Learning Approaches

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Abstract

Parkinson's disease is a long-term condition that demands continuous attention and care. While it can substantially affect an individual's quality of life, with appropriate treatment and support, people diagnosed with Parkinson's can enjoy meaningful lives for numerous years. Research into Parkinson's disease remains active, with ongoing progress in comprehending the condition and discovering innovative treatment options. Data mining, also known as Knowledge Discovery in Database (KDD), is a highly valuable technique employed by entrepreneurs, researchers, and individuals for extracting valuable insights from extensive data collections. The knowledge discovery process encompasses several key steps, including data cleaning, data integration, data selection, data transformation, data mining, pattern evaluation, and knowledge presentation.This paper considers Parkinson’s disease Data Set.The machine learning approaches which is used to analysis and predict the dataset usinglinear regression, multilayer perceptron, SMOreg, random forest, random tree, and REP tree**.** Numerical illustrations are provided to prove the proposed results with test statistics or accuracy parameters.

Keywords: *Machine learning, parkinsons disease, decision tree, correlation coefficient, and test statistics.*

1. Introduction and Literature Review

Parkinson's disease, a global affliction impacting millions, stands as a neurodegenerative condition. The promise of machine learning and data mining techniques lies in their capacity to offer substantial advancements in Parkinson's disease research by facilitating early diagnosis, tracking disease progression, and enhancing treatment optimization.

Machine learning (ML) is a branch of artificial intelligence (AI) specifically concerned with developing systems capable of learning and enhancing their performance through the information they ingest. Artificial intelligence encompasses a wide range of technologies and systems designed to mimic human intelligence.Data mining involves the exploration and analysis of extensive sets of unprocessed data to uncover patterns and extract valuable insights. Businesses utilize data mining software to gain deeper insights into their customer base, enabling the development of more potent marketing strategies, heightened sales, and reduced operational costs.

A machine learning-based approach for diagnosing Parkinson's disease, which involves a two-step process: feature selection and classification. We considered Feature Importance and Recursive Feature Elimination methods for feature selection and employed Classification and Regression Trees, Artificial Neural Networks, and Support Vector Machines for patient classification. Notably, Support Vector Machines with Recursive Feature Elimination outperformed other methods, achieving an accuracy of 93.84% while utilizing the fewest voice features [1].

Early prediction of Parkinson's disease is crucial, and this study extends prior work by incorporating non-motor features such as RBD and olfactory loss, along with important biomarkers. Novel machine learning models, including Multilayer Perceptron, BayesNet, Random Forest, and Boosted Logistic Regression, were developed to automate diagnostics. Impressively, Boosted Logistic Regression demonstrated the best performance, with an

accuracy of 97.159% and an area under the ROC curve of 98.9%. These models show promise for early Parkinson's disease prediction [2].

A novel deep-learning technique is introduced for the early detection of Parkinson's disease based on premotor features. The study utilizes various indicators, including Rapid Eye Movement and olfactory loss, Cerebrospinal fluid data, and dopaminergic imaging markers. Compared to twelve other machine learning and ensemble learning methods, the deep learning model consistently achieved the highest accuracy, averaging 96.45%. Additionally, the study provides insights into the feature importance in the PD detection process using the Boosting method [3].

The use of voice signal processing to detect Parkinson's disease, a prevalent neurological disorder. It evaluates eighteen feature extraction techniques and four machine learning methods using data from sustained phonation and speech tasks. The study differentiates between phonation (vowel /a/ voicing task) and speech (pronunciation of a short Lithuanian sentence). Data was recorded using two microphone channels, acoustic cardioid (AC) and a smartphone (SP). Various performance metrics, including Equal Error Rate (EER), Area Under Curve (AUC), Accuracy, Specificity, and Sensitivity, were used for classification analysis. The study demonstrates that the phonation task was more efficient than speech tasks for disease detection, with the AC channel achieving an accuracy of 94.55%, AUC of 0.87, and EER of 19.01%. Meanwhile, the SP channel achieved an accuracy of 92.94%, AUC of 0.92, and EER of 14.15% [4].

Author literature review summarizes the diverse data modalities and machine learning methods employed in diagnosing and differentiating Parkinson's disease (PD). A total of 209 studies published until February 14, 2020, were analyzed, focusing on their research goals, data sources, data types, machine learning methodologies, and outcomes. These studies collectively highlight the potential of machine learning methods and novel biomarkers to enhance clinical decision-making and contribute to systematic and informed PD diagnosis [5].

Data mining is avaluable tool for the practice of examining large pre-existing databases to generate previously unknown helpful information; in this paper, the input for the weather data set denotes specific days as a row, attributes denote weather conditions on the given day, and the class indicates whether the conditions are conducive to playing golf. Attributes include Outlook, Temperature, Humidity, Windy, and Boolean Play Golf class variables. All the data are considered for training purpose, and it is used in the seven-classification algorithm likes J48, Random Tree (RT), Decision Stump (DS), Logistic Model Tree (LMT), Hoeffding Tree (HT), Reduce Error Pruning (REP) and Random Forest (RF) are used to measure the accuracy. Out of seven classification algorithms, the Random tree algorithm outperforms other algorithms by yielding an accuracy of 85.714% [6].

Author introduce a methodology for predicting the severity of Parkinson's disease using deep neural networks. We applied this methodology to UCI's Parkinson's Telemonitoring Voice Data Set, and our neural network implementation was built with the 'TensorFlow' deep learning library in Python. Our approach achieved superior accuracy compared to prior research efforts [7].

Author suggest critically assesses and compares the performance of existing deep learning-based methods for the detection of neurological disorders, with a specific focus on Alzheimer's disease, Parkinson's disease, and schizophrenia. The analysis encompasses MRI data obtained through various modalities, including functional and structural MRI. It is evident from the comparative analysis that the Convolutional Neural Network surpasses other methods in the detection of neurological disorders. Additionally, the article outlines current research challenges and suggests potential directions for future studies [8].

A wearable inertial device, known as SensHand V1, to collect motion data from the upper limbs while individuals performed six tasks selected by the MDS-UPDRS III. Three groups, comprising 30 healthy subjects, 30 individuals with idiopathic hyposmia, and 30 Parkinson's disease patients, were included in the research. We computed forty-eight parameters per side through spatiotemporal and frequency data analysis and identified a significant feature array for distinguishing between the different groups in two-group and three-group classification scenarios. We conducted multiple analyses, comparing the performance of three supervised learning algorithms—Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes—across three distinct datasets. The results were exceptional for the classification of healthy individuals versus patients (F-Measure of 0.95 for RF and 0.97 for SVM) and good when including subjects with hyposmia as a separate group (0.79 accuracy, 0.80 precision with RF) within a three-group classification. Overall, RF classifiers proved to be the most effective approach for this application. In conclusion, the system holds promise for supporting an

objective diagnosis of Parkinson's disease. Furthermore, by combining motion analysis with a validated olfactory screening test, it is possible to define a two-step, non-invasive, cost-effective procedure for assessing individuals at risk of developing Parkinson's disease. This approach can assist clinicians in identifying subtle changes in motor performance characteristic of the onset of Parkinson's disease [9].

Data mining is discovering hiding information that efficiently utilizes the prediction by stochastic sensing concept. This paper proposes an efficient assessment of groundwater level, rainfall, population, food grains, and enterprises dataset by adopting stochastic modeling and data mining approaches. Firstly, the novel data assimilation analysis is proposed to predict the groundwater level effectively. Experimental results are done, and the various expected groundwater level estimations indicate the sternness of the approach [10] and [11].

The input for the chronic disease data denotes a specific location as a row; attributes denote topics, questions, data values, low confidence limit, and high confidence limit. All the data are considered for training and testing using five classification algorithms. In this paper, the authorspresent the various analysis and accuracy of five different decision tree algorithms; the M5P decision tree approach is the best algorithm to build the model compared with other decision tree approaches [12].

2. Backgrounds and Methodologies

A data mining decision tree is a widely used machine learning technique for classification and regression tasks. It visually depicts a sequence of decisions and their possible outcomes in a tree-like structure. Each internal node represents a decision based on a specific feature, and each branch corresponds to the potential result of that decision. The tree's leaf nodes represent the final decision or the predicted outcome. The "CART" (Classification and Regression Trees) algorithm is the most used algorithm for building decision trees [13].

2.1 Linear Regression

Linear regression is a statistical technique employed to comprehend and forecast the connection between two variables by discovering the optimal straight line that most effectively aligns with the data points. It aids in ascertaining how alterations in one variable correspond to changes in another, proving valuable for predictions and trend recognition.

The core idea of linear regression is to find the best-fitting straight line (also called the "regression line") through a scatterplot of data points. This line represents a linear equation of the form:

$$y = m_x + b \quad \ldots (1)$$

Where:

- y is the dependent variable (the one you want to predict or explain).
- x is the independent variable (the one you're using to make predictions or explanations).
- m is the slope of the line, representing how much
- y changes for a unit change in x.

b is the y-intercept, indicating the value of y when x is 0.

2.2 Multilayer Perception

A Multilayer Perceptron (MLP) is an artificial neural network consisting of multiple layers of interconnected nodes or neurons. It's a fundamental architecture in deep learning and is used for various tasks, including classification, regression, and more complex tasks like image recognition and natural language processing. The architecture of an MLP typically includes three types of layers:

i. **Input Layer:** This layer consists of neurons receiving input data. Each neuron corresponds to a feature in the input data, and the values of these neurons pass through the network.
ii. **Hidden Layers:** These layers come after the input layer and precede the output layer. They are called "hidden" because their activations are not directly observed in the final output.
iii. **Output Layer:** This layer produces the network's final output. The number of neurons in the output layer depends on the problem type.

2.3 SMO

SMO stands for "Sequential Minimal Optimization," an algorithm used for training support vector machines (SVMs), machine learning models commonly used for classification and regression tasks. The SMO algorithm is particularly well-suited for solving the quadratic programming optimization problem that arises during the training of SVMs.

Step 1. **Initialization**
Step 2. **Selection of Two Lagrange Multipliers**
Step 3. **Optimize the Pair of Lagrange Multipliers**
Step 4. **Update the Model**
Step 5. **Convergence Checking**
Step 6. **Repeat**

2.4 Random Forest

Random Forest is a popular machine learning ensemble method for classification and regression tasks. It is an extension of decision trees and is known for its high accuracy, robustness, and ability to handle complex datasets. Random Forest is widely used in various domains, including data science, machine learning, and pattern recognition. The main idea behind Random Forest is to create an ensemble (a collection) of decision trees and combine their predictions to make more accurate and stable predictions. The steps involved in building a Random Forest are as follows:

Step 1. Data Bootstrapping
Step 2. Random Feature Subset Selection
Step 3. Decision Tree Construction
Step 4. Ensemble of Decision Trees
Step 5. Out-of-Bag (OOB) Evaluation
Step 6. Hyperparameter Tuning (optional)

2.5 Random Tree

In machine learning, a Random Tree is a specific type of decision tree variant that introduces randomness during construction. Random Trees are similar to traditional decision trees but differ in how they select the splitting features and thresholds at each node.The primary goal of introducing randomness is to create a more diverse set of decision trees, which can help reduce overfitting and improve the model's generalization performance. Random Trees are commonly used as building blocks in ensemble methods like Random Forests.The critical characteristics of Random Trees are as followsRandom Feature Subset, Random Threshold Selection, No Pruning and Ensemble Methods. Steps involved in Random Tree.

Step 1. Data Bootstrapping:
Step 2. Random Subset Selection for Features:
Step 3. Decision Tree Construction:
Step 4. Voting (Classification) or Averaging (Regression):

2.6 REP Tree

REP (Repeated Incremental Pruning to Produce Error Reduction) Tree is a machine learning algorithm for classification and regression tasks. A decision tree-based algorithm constructs a decision tree using incremental pruning and error-reduction techniques.The key steps involved in building a REP Tree are Recursive Binary Splitting, Pruning, Repeated Pruning and Error Reduction. Below are the steps involved in building a REP Tree.

Step 1. Recursive Binary Splitting
Step 2. Pruning
Step 3. Repeated Pruning and Error Reduction
Step 4. Model Evaluation

2.7 Accuracy Metrics

The predictive model's error rate can be evaluated by applying several accuracy metrics in machine learning and statistics. The basic concept of accuracy evaluation in regression analysis is comparing the original target with the predicted one and using metrics like R-squared, MAE, MSE, and RMSE to explain the errors and predictive ability of the model [14]. The R-squared, MSE, MAE, and RMSE are metrics used to evaluate the prediction error rates and model performance in analysis and predictions [15] and [16].

R-squared (Coefficient of determination) represents the coefficient of how well the values fit compared to the original values. The values from 0 to 1 are interpreted as percentages. The higher the value is, the better the model is.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad \dots (2)$$

MAE (Mean absolute error) represents the difference between the original and predicted values extracted by averaging the absolute difference over the data set.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \quad \dots (3)$$

RMSE (Root Mean Squared Error) is the error rate by the square root of MSE.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \quad \dots (4)$$

Relative Absolute Error (RAE) is a metric used in statistics and data analysis to measure the accuracy of a forecasting or predictive model's predictions. It is particularly useful when dealing with numerical data, such as in regression analysis or time series forecasting.

$$RAE = \frac{\sum|y_i - \hat{y}_i|}{\sum|y_i - \bar{y}|} \quad \dots (5)$$

Root Relative Squared Error (RRSE) is another metric used in statistics and data analysis to evaluate the accuracy of predictive models, especially in the context of regression analysis or time series forecasting.

$$RRSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}} \quad \dots (6)$$

Equation 3 to 7 are used to find the model accuracy, which is used to find the model performance and error. Where Y_i represents the individual observed (actual) values, $\hat{Y}_i$ represents the corresponding individual predicted values, $\bar{Y}$ represents the mean (average) of the observed values and Σ represents the summation symbol, indicating that you should sum the absolute differences for all data points.

3. Numerical Illustrations

The corresponding dataset was collected from the open souse Kaggle data repository. The parkinson'sdataset include24 parameters whichhavedifferent categories of data like name, mdvp: fo(hz), mdvp:fhi(hz), mdvp:flo(hz), mdvp:jitter(%), mdvp:jitter(abs), mdvp:rap, mdvp: ppq, jitter:ddp, mdvp:shimmer, mdvp:shimmer(db), shimmer:apq3, shimmer:apq5, mdvp:apq, shimmer:dda, nhr, hnr, status, rpde, dfa, spread1, spread2, d2, ppe[17]. Adetailed description of the parameters is mentioned in the following Table 1.This dataset is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). Each column in the table is a particular voice measure, and each row corresponds to one of 195 voice recordings from these individuals ("name" column). The main aim of the data is to discriminate healthy people from those with PD, according to the "status" column which is set to 0 for healthy and 1 for PD. The attribute information as mentioned bellow.

i. name - ASCII subject name and recording number

ii. MDVP:Fo(Hz) - Average vocal fundamental frequency

iii. MDVP:Fhi(Hz) - Maximum vocal fundamental frequency

iv. MDVP:Flo(Hz) - Minimum vocal fundamental frequency

v. MDVP:Jitter(%) , MDVP:Jitter(Abs) , MDVP:RAP , MDVP:PPQ , Jitter:DDP - Several measures of variation in fundamental frequency

vi. MDVP:Shimmer , MDVP:Shimmer(dB) , Shimmer:APQ3 , Shimmer:APQ5 , MDVP:APQ , Shimmer:DDA - Several measures of variation in amplitude

vii. NHR , HNR - Two measures of ratio of noise to tonal components in the voice

viii. status - Health status of the subject (one) - Parkinson's, (zero) - healthy

ix. RPDE , D2 - Two nonlinear dynamical complexity measures

x. DFA - Signal fractal scaling exponent

xi. spread1 , spread2 , PPE - Three nonlinear measures of fundamental frequency variation

Table 1 (a). parkinson'ssampledataset

Name	MDVP: Fo (Hz)	MDVP: Fhi (Hz)	MDVP: Flo (Hz)	MDVP: Jitter (%)	MDVP: Jitter (Abs)	MDVP: RAP	MDVP: PPQ	Jitter: DDP	MDVP: Shimmer	MDVP: Shimmer (dB)	Shimmer: APQ3
phon_R01_S01_1	119.992	157.302	74.997	0.00784	0.00007	0.0037	0.00554	0.01109	0.04374	0.426	0.02182
phon_R01_S01_2	122.4	148.65	113.819	0.00968	0.00008	0.00465	0.00696	0.01394	0.06134	0.626	0.03134
phon_R01_S01_3	116.682	131.111	111.555	0.0105	0.00009	0.00544	0.00781	0.01633	0.05233	0.482	0.02757
phon_R01_S01_4	116.676	137.871	111.366	0.00997	0.00009	0.00502	0.00698	0.01505	0.05492	0.517	0.02924

Table 1 (b). parkinson's sample dataset

Shimmer: APQ5	MDVP: APQ	Shimmer: DDA	NHR	HNR	status	RPDE	DFA	spread1	spread2	D2	PPE
0.0313	0.02971	0.06545	0.02211	21.033	1	0.414783	0.815285	-4.81303	0.266482	2.301442	0.284654
0.04518	0.04368	0.09403	0.01929	19.085	1	0.458359	0.819521	-4.07519	0.33559	2.486855	0.368674
0.03858	0.035	0.0827	0.013	20.6	1	0.4298	0.8252	-4.4431	0.3111	2.3422	0.3326

	9		09	51		95	88	8	73	59	34
0.04005	0.03772	0.08771	0.01353	20.644	1	0.434969	0.819235	-4.1175	0.334147	2.405554	0.368975

Table 2: Machine Learning Models with Correlation coefficient

ML Approaches	Correlation Coefficient
Linear Regression	0.9759
Multilayer Perceptron	0.9660
SMOreg	0.9747
Random Forest	0.9498
Random Tree	0.8427
REP Tree	0.9425

Table 3: Machine Learning Models with Mean Absolute Error and Root Mean Squared Error

ML Approaches	MAE	RRSE
Linear Regression	0.0131	0.0196
Multilayer Perceptron	0.0169	0.0239
SMOreg	0.0113	0.0205
Random Forest	0.0199	0.0288
Random Tree	0.0340	0.0513
REP Tree	0.0188	0.0301

Table 4: Machine Learning Models with Relative Absolute Error (%) and Root Relative Squared Error (%)

ML Approaches	RAE (%)	RRSE (%)
Linear Regression	18.2633	21.7496
Multilayer Perceptron	23.6182	26.4511
SMOreg	15.7465	22.7300
Random Forest	27.8914	31.9337
Random Tree	47.5213	56.8922
REP Tree	26.2354	33.4249

Table5: Machine Learning Models with Time Taken to Build Model (Seconds)

ML Approaches	Time taken (seconds)

Linear Regression	0.1800
Multilayer Perceptron	0.8000
SMOreg	0.1700
Random Forest	0.6000
Random Tree	0.0100
REP Tree	0.0400

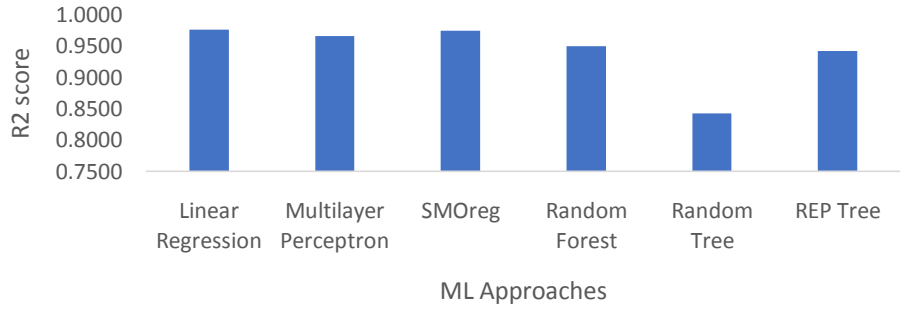

Fig. 1. R2 Score for Machine Learning Approaches

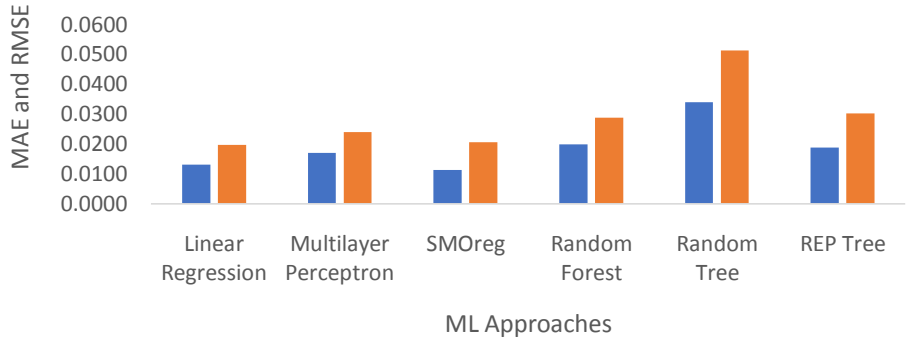

Fig. 2. Machine Learning Models with MAE and RMSE

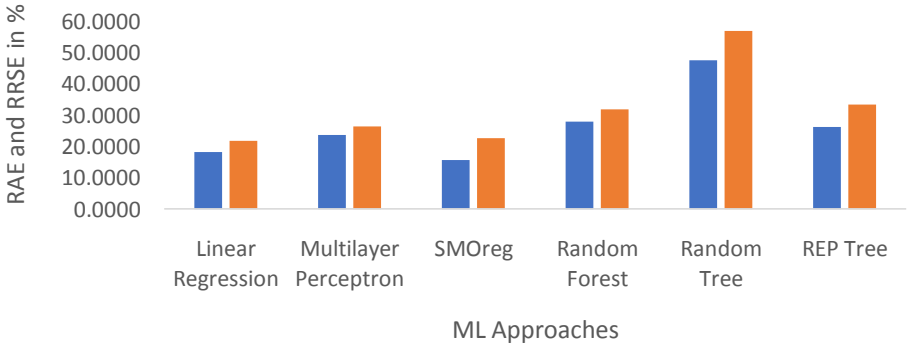

Fig. 3. Machine Learning Models with RAE (%) and RRSE (%)

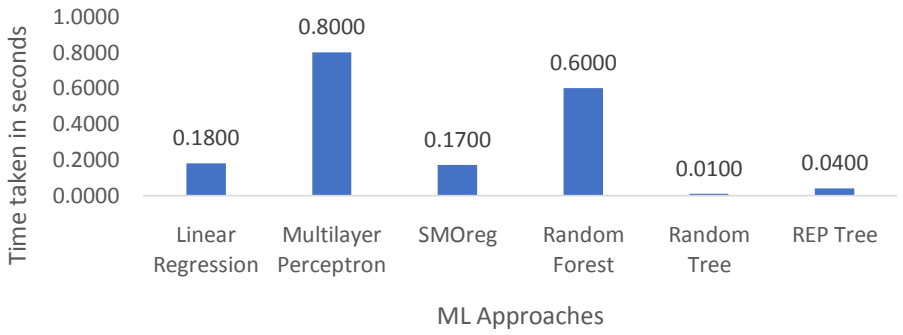

Fig. 4. Machine Learning Models and its Time Taken to Build the Model (Seconds)

4. Result and Discussion

Table 1 explains include 24 parameters which have different categories of data like name, mdvp: fo(hz), mdvp:fhi(hz), mdvp:flo(hz), mdvp:jitter(%), mdvp:jitter(abs), mdvp:rap, mdvp: ppq, jitter:ddp, mdvp:shimmer, mdvp:shimmer(db), shimmer:apq3, shimmer:apq5, mdvp:apq, shimmer:dda, nhr, hnr, status, rpde, dfa, spread1, spread2, d2, ppe. Based on the dataset, it is evident that five different machine learning decision tree approaches are used to find the hidden patterns and which is the best or influencing parameter to decide future predictions. Related results and numerical illustrations are shown between Table 1 to Table 5 and Figure 1 to Figure 4.

They are based on Equation 2, Table 2, and Figure 1, which is used to find the R2 score or correlation coefficient by comparing 44 parameters. Numerical illustrations suggest that there may be a significant difference from one parameter to another. In this case, using five different decision tree approaches among these results, random forest, random tree, REP tree, and M5P, return a robust, strong positive correlation of nearly 0.9 when using different soil properties. Decision stump machine learning approaches also produce positive correlations of 0.8642.

Further data analysis revealed a gradual improvement in test scores over time. The MAE is used to find model errors using Equations 3. Five machine-learning algorithms will be used in this case. The random forest, random tree, and REP tree return a minimum error for using MAE test statistics. Decision stump and M5P approaches produce the maximum error. The RMSE (root mean square error) measures the difference between predicted and actual values using Equation 4. In this case, the random forest, random tree, and REP tree return a minimum error for using MAE test statistics. Decision stump and M5P approaches produce the maximum error. The related numerical illustration is shown in Table 3 and Figure 2.

Relative Absolute Error (RAE) measures accuracy using equation 5 to compare the difference between predicted and actual values in percentage. In this research, taking into consideration five ML classification algorithms, except decision stump remaining four algorithms return a minimum error. Similar error approaches are reflected in RRSE. Similar numerical illustrations are shown in Table 4 and Figure 3.

Time taken is one of the significant tasks in machine-learning approaches. Based on Table 5 and Figure 4, random tree take minimum time to build the model. Subsequently, the Decision stump, REP tree, and random forest take the time to make the models. Finally, M5P takes the maximum time to build the model. Similar approaches are reflected in the mentioned visualization.

5. Conclusion and Further Research

It is essential to consider the limitations of this study. The sample size of each group was relatively small, which could impact the generalizability of the results. Additionally, other variables could influence the Parkinson's performance. The findings presented in this study contribute to our understanding that all the parameters return robust positive correlations. In this research, the maximum of the machine learning approaches returns a minimum error with less processing time. Finally, all the parameters consider for fining the Parkinson's. In this research, very useful to the medical department, medical researchers and affected persons for improve the health conditions and behaviors. Future studies can build upon these, finding the suitable variable for future prediction with increased accuracy using different deep learning approaches.

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