Machine Learning Techniques for Parkinson's Disease Detection

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***Abstract*— A neurological disease is Parkinson's disease. It causes trembling in the hands, trouble walking, losing balance, and coordination. In the high-level stage, there is no access to medical care. Blood test reports, CT scan results, and X-ray reports are not accessible early enough. Early Parkinson's disease detection is crucial to implement effective treatment. The purpose of the proposed effort was to identify Parkinson's disease in early prediction using clinical imaging and machine learning technologies. Despite the fact that there are numerous methods for detecting Parkinson's disease, using MRI scan images still it is a big challenge. In this study, an Adaboost classifier is used with a hybrid PSO algorithm to propose a novel technique for detecting Parkinson's disease. Adaboost acted as the best classifier among other classifiers. Initially, MRI image best features are extracted and identified by the curvelet transform and principal component analysis. This Ad boost classifier receives optimal features as input. Finally, Adaboost classifieds the MRI images and gave excellent classification accuracy. To evaluate the proposed method three methods metrics namely accuracy, specificity, and sensitivity are used. Based on the results the proposed methods yield greater accuracy than the existing systems.**

Keywords— Parkinson disease, Support Vector Machine, Random forest, Convolutional neural network models.

I. INTRODUCTION

Parkinson's disease is a neuro developmental disorder that worsens over time. Parkinson's symptoms typically start out mildly and get worse over time. As a result of the disorder of many persons, walking and speaking may be quite difficult. Psychological changes in behavior include depression, memory issues, exhaustion, and sleep issues. Dejection and other nerve abnormalities, such as difficulties swallowing, eating, orally, urine issues or constipation, husk issues, and hibernation irregularities, may also be present. Each person's Parkinson's disease develops differently. On occasion, the onset of Parkinson's disease is attributed to normal ageing. The absence of pharmaceutical research to clearly treat the ailment and the challenge of making an appropriate diagnosis [1] are just a couple of the essential characteristics. Over 20 million people worldwide still experience PD. Parkinson's disease progression is 2.5 times more common in men than in women [2].

Motor signs and on-motor signs are two different kinds of Parkinson's disease symptoms. Most individuals are aware that traffic signs get attention since they are visible. Often referred to as cardinal symptoms [3], these symptoms include hardness, postural instability, and sluggish walking. It takes longer to diagnose and treat Parkinson's disease, and more testing visits to the hospital are required. Patients, particularly the elderly, feel uncomfortable as a result. It is crucial to create self-serve diagnosis and treatment models since they can be used for any computer-aided pharmaceutical services [4]. There were no neurological issues before the development of Alzheimer's disease. The second eye infection is primarily caused by Parkinson's disease [5]. Figure 1 depicts the progression of Parkinson's disease from a healthy to ill state as well as before and after symptoms. According to neuropathological research, Parkinson's sporadic circumstances first damage the dopamine system by activating serotonergic neurons. Even though those SNCA mutations are extremely rare, carriers are more likely than non-carriers to develop Parkinson's disease during the course of their lives. Toxic risk is one danger connected to Parkinson's disease. Parkinson's disease can primarily be divided into five stages.

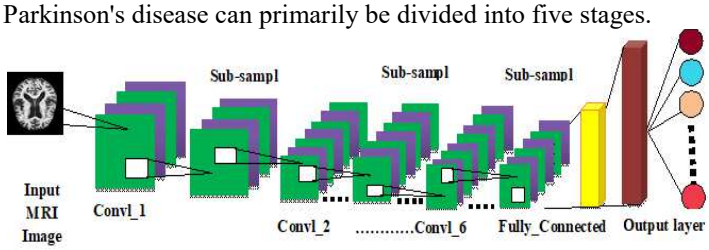

Fig. 1. Overall Architecture for Parkinson's disease Net model

II. RELATED WORKS

The review of earlier initiatives in the literature is now being introduced in this domain. Yadav et al[6] .'s accurate collection of the ideal points from the support vector machine had a 78 percent accuracy rate thanks to three separate data mining techniques: improvement of consecutive reductions, logistic regression, and Parkinson's disease prediction. In contrast to Convolutional Neural Networks, they performed comparison analyses, which demonstrated that ELM does not lack recurring mutations that would disclose neurons that are hidden. The ELM is a more reliable option than other forecasts because of its simple construction. A feature-selection system that Kumar Tiwari [7] has developed gives great consistency and requires little data to forecast Parkinson's illness (PD).

Additionally, they created Random Forest, which has an accuracy rate of 90.5 percent and outperforms other machine

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learning algorithms like Support Vector Machine and Random Forest. Modern machine learning methods are used in Jaskirat Kaur et al.'s[8] analysis of the utilization of speech sounds for Parkinson's disease prediction. The sample paper for the patient's voice is appropriate for the search. The model, with an accuracy rating of 82%, may be created using data from the UCI machine learning repository. The Markov models and algorithms used by the current authors improve neuronal regeneration efficiency and Parkinson's disease phase forecasting. The Parkinson stage forecasts, and application of the Deep Learning technique help the model, which mimics the vibrating section of the brain through the electrical release. The treatment is less invasive and more expensive, making it unsuitable for all demographics, and since there is no permanent solution, many diseases persist continuously [9]. Based on the Kaggle dataset, M. Shaban et al. [10] developed a hypothesis for Parkinson's disease. In order to prevent overload when photographs are condensed into picture augmentation based on image, a data collection of 102 wave spiral patterns was manually created. This data collection allows for rotation. Utilizing both 6 and 12 cycles of cross-validation, convolutional neural network models are trained utilizing the data from the prior model. Using a 12-fold cross-validation, a CNN model with 82 percent accuracy, 92 percent precision, and 84 percent sensitivity was created.

J. Goyal et al. evaluate a two-phase element's efficacy as a potential means of reducing database size and enhancing system performance. Two feature selection methods combine the SVMRFE and Genetic Algorithm (GA) feature selection methodologies. SVM may boost sensitivity from 52.08 percent to 70.83 percent and accuracy from 87.69 percent to 88.71 percent. They continue to make efforts to lessen the problem of inequality among classes without shrinking the sample size, i.e., by creating smaller samples or increasing repetition through oversampling technologies. Future research will also examine the effectiveness of selecting features for data sets with two or more categories to see if the accuracy impacts are excessively strong in huge databases. In order to continuously monitor the evolution of the diagnostic structure, a variety of precise collection approaches are used [11].

A. Salimi-Badr et al method.'s for diagnosing patients in healthy individuals creates transient patterns. By measuring 16 sensors that were pointed at each subject's shoes, the Vertical Ground Reaction Force (vGRF), which was responsible for the transient cycle circumstances, was eliminated using data. In order to decrease the number of sensors while increasing the amount of the data, a series of parallel sensors set up on various feet are linked together. Without the output characteristics showing the statistics of the numerous cycles, this analyses the temporal pattern of time series that have been received from several sensors. With an accuracy rate of 97.66 percent and a score of 97.78 percent, the suggested method can correctly identify between situations involving healthy individuals and those involving ill individuals. Future directions for this study suggest examining how well it might identify illnesses like Parkinson's disease [12].

The support vector machine, random forest, and particle swarm optimization algorithms are among the cutting-edge techniques included in P. Das [13] et al's collection that make use of the benefits of binary categories. The revisions to the proposed law have taken into account the well-known and widespread UCI illness. The accuracy rating for the Oxford shire Parkinson's obtained Data Set and are was 92.3 percent. In addition, 96 percent after verification at 8 times the expected rate and testing at 30%, respectively. As a result, the recommended integration strategy beats the current Predicting models for the PD method.

Company K and Polat Data processing and categorization are the two stages of the suggested hybrid machine learning approach. Datasets for Parkinson's disease may be binary datasets. 192 data are regarding the healthy, compared to 564 data on the sick. This approach is used by Synthetic Minority Over-Sampling Technique. The collection of data includes PD,753 attributes. In the Parkinson's dataset, the split was assessed as 87.037 percent for only random forests. The planned blended approach is accomplished to a degree of 94.89 percent. The hybrid model can also be used to address further global classification problems involving real medical devices [14].

To forecast Parkinson's disease, E. Celik et al. [15] study the different classification techniques and use a support vector machine, AdaBoost, random forest, logistic regression, and decision tree. 26 appearances from data sets with Parkinson's patients and non-patients were collected during the categorizing phase. Correlation maps can be used to disseminate the dataset's retail space. Information Gain and Principal Component Analysis are shown separately. The categorization results achieved with the data's initial presentation are unquestionably superior to those acquired with the gathering of various broadcast features. Machine learning algorithms are used to determine whether healthy individuals or those who have Parkinson's disease will be classified. For efficient professional help, it makes sense to apply the various AI-based classification techniques. The model's accuracy, impact, and dependability of diagnoses will all be improved with the help of machine learning techniques, which will also help with risk reduction.

The confusion matrices for the four models—KNN, Random Forest, SVM, and XGBoost—from the test dataset are shown in Figures 5 through Figure 8. The results from all four models are summarized in Table I. The overall performance of each model has been evaluated using all five metrics: reliability, responsively, recall, specificity, and F1 score. Each of the four models' accuracy demonstrates the validity of the Random Forest methodology for analyzing Parkinson's disease. Random Forest wins with the highest F1 score among the four models. It is found that only random forest and SVM share the highest recall, which reflects a model's capacity to identify parkinson's disorders.

There is no cure for Parkinson's disease unless it is discovered early, which destroys the CNS of the brain. Mortality and incontinence are effects of late diagnosis. Therefore, early detection is crucial. As well as for vocal biometrics speech

analysis, these models can be used to predict a number of disorders related to Alzheimer's disease. They employed Random Forest and SVM classification techniques in order to get an early diagnosis of the illness. The best algorithm for predicting the onset of diseases is Random Forest, which enables earlier treatment and potentially life-saving measures. Parkinson's disease prognosis has been achieved using a variety of machine learning techniques. In any case, the employment of techniques of deep learning prevented a thorough assessment of the PD predictions. An in-depth reading framework with default coders can be used in the future to speed up the presentation of data and extract the best ones, improving the activity. The pertinent UCI dataset is severely constrained and not especially difficult for this function. As a result, the default installer might not read properly.

III. The Proposed Methodology

A. AdaBoost Classifier

AdaBoost operates in T rounds, with each round involving the training of a weak learner. Following training, the algorithm increases sample weights, which is predicted to be misclassification; in response, the sample weight decreases, which is correctly identified. This results in a decrease in the likelihood that correctly identified samples will be used in the subsequent iteration and an increase in the likelihood that mistakenly categorized samples will be used [16].

Adaboost uses $S = (a_1 b_1) \dots \dots \dots (a_n, b_n)$ training samples of size N as information, where a_ia variable of attributes for the sector of space P is and b_i is each sample's identifier a_i in the label space of Q [17].

The weights are evenly initialized across the training set when the algorithm starts its initial iteration, and they are increased in each subsequent iteration for every case that was incorrectly identified. The hard samples in the data set would be particularly important to a weak learner in order to accomplish this.

AdaBoost is coupled with a weight vector on the training samples, which adjusts each sample's weight using a weight function after each iteration (6).

$$R_{s+1,i} = R_{s,i} A_s^{1-bi} \quad (1)$$

It computes and employs an error rateϵ_j of this classifier based on the weight of each sample in (7), in so that the probability distribution for training samples can be adjusted [22]:

$$\epsilon = \sum_{i-1} W_{s,i}^{bi} \quad (2)$$

During the training phase, each classifier is weighed based on its accuracy, which aids in the construction of a final strong classifier V (x). Thus, the program focuses on examples of patterns that are difficult to classify. This essay concentrates on problems with binary categorization Q = {-1 + 1} [23].
The algorithm's pseudo code is as follows :

Provide M examples $(a_1 b_1), \dots . (a_i b_i) \dots \dots, (a_m b_m)$ Where $b_i \in \{-1,1\}$
Initialize $R_{1,t} = {}^{1}/_{2d}, {}^{1}/_{2z} \text{for} b_i = 1$
Where d and z are the negative and positive element counts, respectively.
For s=1……..T do

(1) Train a classifier k_j for each feature j
(2) Analyze the error the least amount of error $\epsilon_t = \sum_{i=0} K, R_{s,i} b^i$
(3) Select the classifier V_s with the lowest error ϵ_t
Update weight $R_{s+1,i} = R_{s,i} A_s^{1-bi}$

Where $b_i = 0$ if$V_s(a_i) = z_i b_i = 1$
Where $A_s = \epsilon_s/(1 - \epsilon_s)$
End for
Classifier with high output

$$V(x) = \begin{cases} 1 & \text{ifsign } (\sum_{i=0} \alpha, \beta_s^{1-b}{}_s v_s) \\ -1 & \text{otherwise} \end{cases}$$

With $\alpha_s = \log(1/\beta_s)$

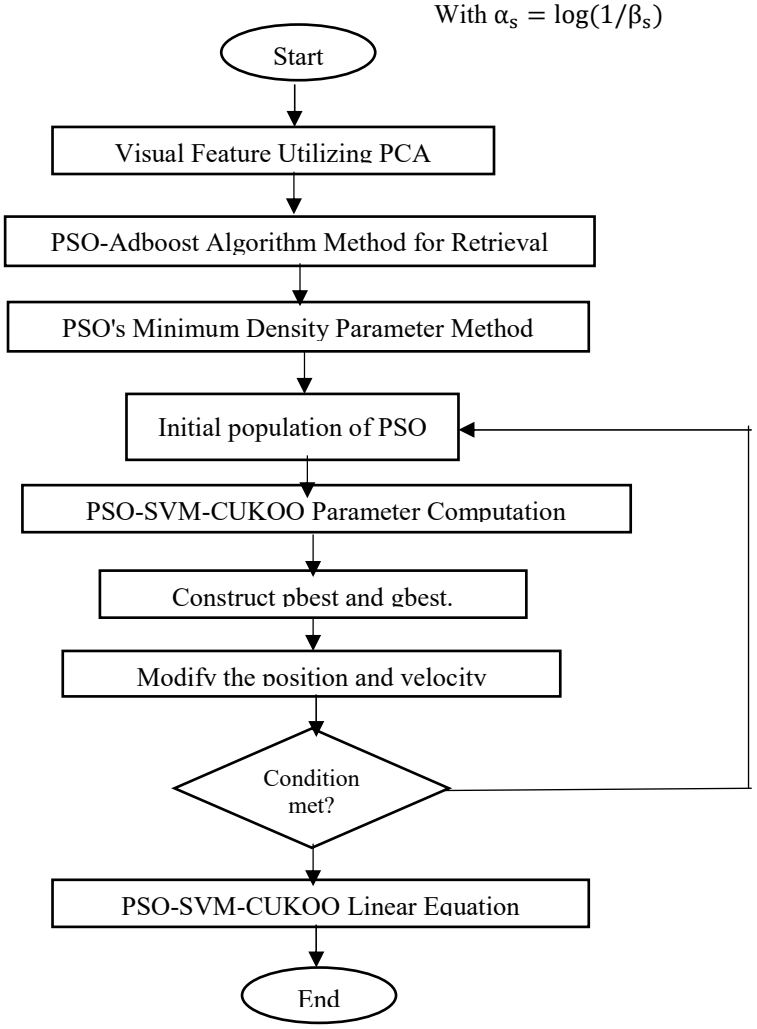

Fig. 2. Proposed Parkinson's Disease Detection

Working Principle of AdaBoost

AdaBoost is the most widely used boosting method. Weak classifiers are combined to create a powerful classifier in this example. A weak classifier is a simple classifier that fails to

correctly label the procedure set probably have the best classification function. When the AdaBoost algorithm iterates,, the classification error and an optimal weak classifier are calculated. The final strong classifier includes all of the selected weak classifiers and weights them equally. The AdaBoost framework uses EAs and heuristics to reduce the AdaBoost's training time. This reduces the need for such a comprehensive search.

In every round of AdaBoost, a sort of optimization problem, exhaustive search is carried out to choose the feature that can best decrease the classification error. Additionally, the AdaBoost makes no mention of how the decision threshold is determined, despite the fact that average means are frequently used in literature. These two issues are dealt with in this study by enabling the PSO to construct the weak classifier, which implies that finding its feature and figuring out the selection threshold are the results of an optimization process [21].

This illustration uses a weak classifier with features (type, R, T, L, J) as well as two centroids N− and N+. The means of the negative and positive paradigms in an ID characteristic can roughly be represented by these centroids. The first five parameters are all integers (type, R, T, J, L). The detection sub-window dimension limits their values, whereas the real numbers can be used for centroid parameters[24]. This method converts an unconstrained optimization issue into a restricted optimization model. The instance is the requirement for the second category for comparison purposes (two perpendicular squiggles) a + 2D ≤ Z and (with two horizontal rectangles) for the first type feature, the constraint is b + 2J ≤ M. The label of the examples that are displayed in Fig 1 are decided by the two centroids N+ and N-

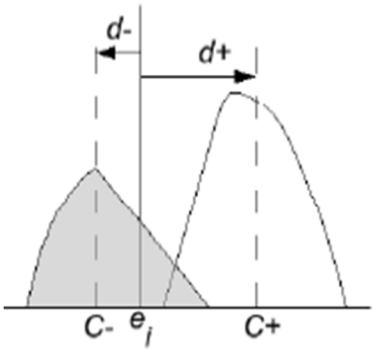

Fig. 3. PSO is used to find 1N- and N+ features, for example, feature ei is labeled with class N because t-< t+.

The distance $|N-e_i|$ between the centroids is determined for a specific example feature e_i. The example is labeled for the class that is closest to its centroid. It should be highlighted that relative proximity between the centroids rather than exact placements is more crucial for correct classification. The two points are regarded as optimal centroids if they can maximize the distance across class and minimize the distance within the class on the corresponding feature axis. The search is for two centroids (N− and N+) so that the class separation criteria in (3) can be maximized:

$$R(N_-, N_+) = \frac{|N_- - N_+|}{l/M \sum_{i=1}^{S} |N, N - g_i^-| + \frac{1}{l \sum_{i=1}^{S} |N_+ - g_e^+|}} \quad (3)$$

Here, m stands for the number of negatives and l for the number of positives. Instead of maximizing the distance-based criteria, the criteria are indirectly maximized using PSO to reduce inaccuracy. This is similar to the idea of reducing both the classification error and the class separation, as indicated by the Fisher discriminant formula. However, Equation (4) is restricted by a single characteristic. This approach to finding the centroids of examples should be more accurate than just averaging their replies, it is hoped[19].

With two centroids and feature parameters, the particles encoding shown in Figure 2 can classify instances as belonging to a positive or negative class. The seven parameters are to be optimized using the [18] fitness function. The fitness function lowers the weighted error rate, just like the original AdaBoost [20].

$$\epsilon = \sum_{i-1} W_{s,i}^{bi} \quad (4)$$

type	R	T	J	L	N-	N+

Fig. 4. Particle Encoding

The parameters of the weak classifier optimize integers whereas the basic PSO is used to optimize non-discrete problems. In this study, the feature parameters are also subject to limits that display the sub-window directions, and particles are penalized for breaking the restriction.

IV. Experimental Analysis

This section makes use of the PD-Ada boost, PD-PCA-Ada boost, PD-PSO-Ada boost, and PD-PCA-PSO-Ada boost. It is possible to maximize the number of classification trees (ranging from 25 to 300) as well as the depth of the trees (from 1 to 6). Table I is a summary of the findings. Figures 3 to 5 illustrate the accuracy of the categorization, the true positive and true negative rates for normal, MCI, and PD, respectively.

TABLE I. Results

	PD-Ada boost	**PD-ANN-Ada boost**	**PD-PCA-Ada boost**	**PD-PSO-Ada boost**	**PD-PCA-PSO-Ada boost**	**PD-PSO-SVM-CUKOO**
Accuracy	70	76	86	88	90	97
Normal True Positive	86	87	91	92	95	96
True Positive MCI	67	69	73	80	82	85
True Positive PD	57	60	58	67	75	78
True Negative Normal	78	79	81	84	88	90
True Negative MCI	88	89	93	95	96	98
True Negative PD	89	90	93	94	96	97

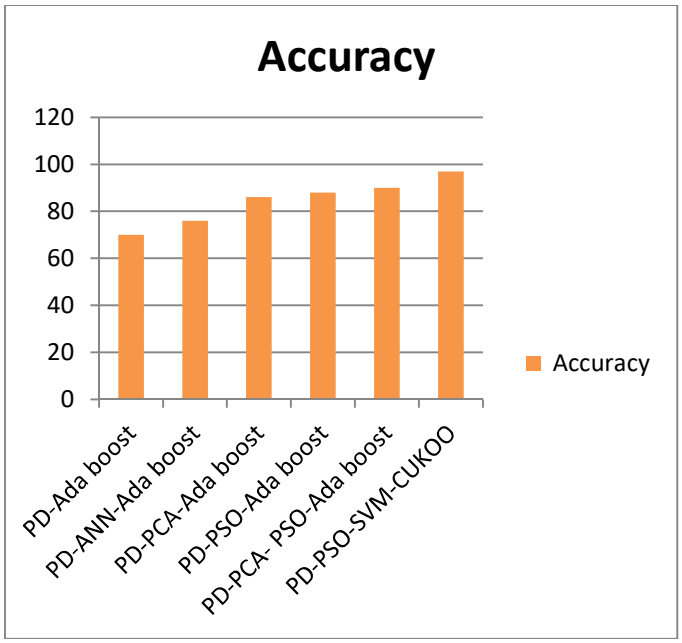

Fig. 5. PD-PSO-SVM-CUKOO Accuracy

From the figure 5, it is found that the PD_PCA-PSO-Adaboost has improved classification accuracy by 16.47% than PD-Ada boost, by 12.72% than PD-PCA-Adaboost and by 5.21% than PD-PSO-Ada boost and by 3.34% PD-PSO-SVM-CUKOO-Ada boost.

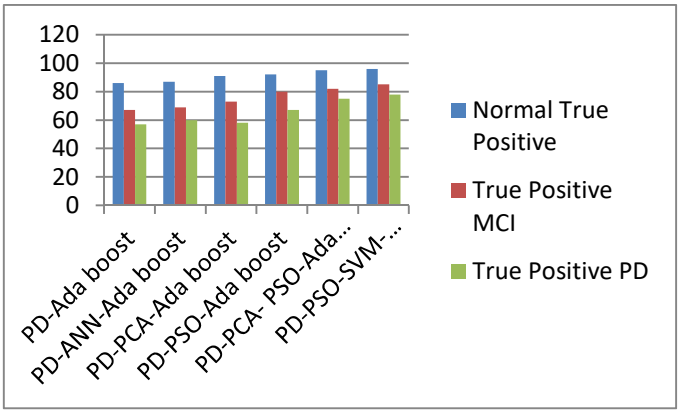

Fig. 6. True Positive Rate for PD-PSO-SVM-CUKOO-Ada boost

The average true positive rate for Adaboost is 9.75% for PD-PCA-PSO-Adaboost, compared to 6.73% for PD-PCA-Ada boost and 3.54% for PD-PSO-Ada boost and 3.21 for PD-PSO-SVM-CUKOO-Adaboost, as shown in figure 6.

Figure 7 shows that the PD-PCA-PSO-Adaboost has a higher average true negative rate for Adaboost than the Pd-PCA-Adaboost, the PD-PCA-Adaboost, and the PD-PSO-Adaboost and PD-PSO-SVM-CUKOO-Adaboost.

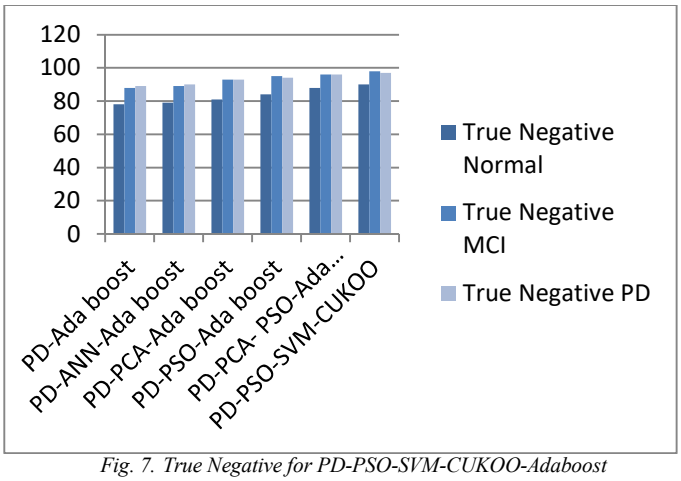

Fig. 7. True Negative for PD-PSO-SVM-CUKOO-Adaboost

TABLE II. CLASSIFICATION RESULTS

Classification	F-Measure	Sensitivity	Specificity	Accuracy
PD-Ada boost	82.8	75.9	84.5	70.02
PDANN-Ada boost	76.2	77.9	89.7	76.06
PD-PCA-Ada boost	90.77	84.1	91.28	86.03
PD-PSO-Ada boost	83.15	76.03	84.27	88.07
PD-PCA-PSO-Ada boost	85.4	78.4	86.5	90.2
PD-PSO-SVM-CUKOO	90.05	80.56	88.7	97.02

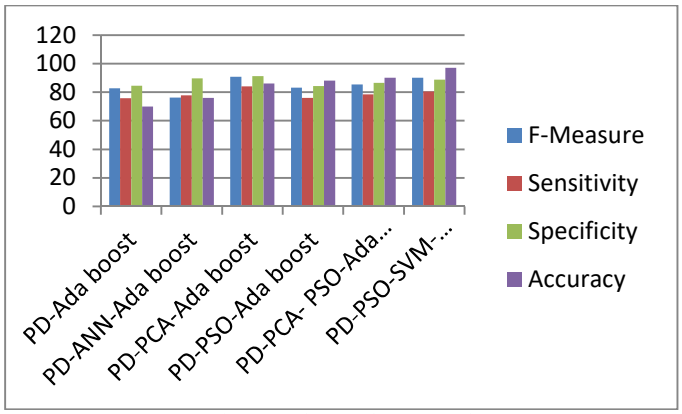

Fig. 8. Parkinson's disease detection achievement

Figure 8 shows that the PD-PCA-PSO- parkinson's disease detection achievement for Ada boost than the PD-PCA-Ada boost, the PD-PCA-Ada boost, and the PD-PSO-Ada boost and PD-PSO-SVM-CUKOO-Ada boost.

V. CONCLUSION

MRI data processing method allows for automatic detection of localized brain volume anomalies across the entire brain when comparing PD sets to control sets. The possibility of misinterpreting the significant difference is reduced when using an optimized technique. An AdaBoost

classifier with optimized PSO approach has been used in this study to diagnose PD in patients with magnetic resonance imaging (MRI). This paper shows an improvised AdaBoost technique that reduces the time it takes to build a weak classifier by utilizing the PSO algorithm. The in-depth search is replaced by PSO-based optimized search in the weak classifier, which is merely a decision stump. AdaBoost's time consumption is improved when PSO is applied on it, as evidenced by empirical results. On facing huge problem, evolutionary algorithms can both reduce search time and increase algorithmic performance at the same time. According to the results, the PD-PCA-PSO-Adaboost has greater classification accuracy than the PD-PCA-Adaboost by 16.47 percent, the PD-PCA-Adaboost by 12.72 percent, and the PD-PSO-SVM-CUKOO-Adaboost by 5.21 percent. The future work can be enhanced by using the hybrid optimization algorithms.

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