ISSN:0975-9646

Shubham Bind et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 6 (2) , 2015, 1648-1655

A Survey of Machine Learning Based Approaches for Parkinson Disease Prediction

Shubham Bind[1], Arvind Kumar Tiwari[2], Anil Kumar Sahani[3]
[1,3]Department of CSE, KIT, [2]Department of CSE, IIT (BHU)
Varanasi, India

Abstract— **Parkinson disease (PD) is a universal public health problem of massive measurement. Machine learning based method is used to classify between healthy people and people with Parkinson's disease (PD). This paper presents a comprehensive review for the prediction of Parkinson disease buy using machine learning based approaches. The brief introduction of various computational intelligence techniques based approaches used for the prediction of Parkinson diseases are presented .This paper also presents the summary of results obtained by various researchers available in literature to predict the Parkinson diseases.**

Keywords— **Parkinson's disease, classification, random forest, support vector machine, machine learning, signal processing, artificial neural network.**

I. INTRODUCTION

Parkinson disease (PD) is a neurological disorder based on dopamine receptors. Parkinson disease mostly causes problems in moving around. It can cause a person to move very slowly. Parkinson is a progressive neurological condition, which is characterized by both motor (movement) and non-motor symptoms. Apart from many common symptoms each person will experience and demonstrate an individual presentation of the condition. A person with Parkinson disease appears stiff or rigid. At times, a person with Parkinson disease may appear to suddenly "freeze up" or be unable to move for a short period of time. Parkinson disease is a progressive neurodegenerative condition resulting from the death of the dopamine containing cells of the substantia nigra. There is no consistently reliable test that can distinguish Parkinson disease from other conditions that have similar clinical presentations. The diagnosis is primarily a clinical one based on the history and examination.

People with Parkinson disease classically present with the symptoms and signs associated with Parkinsonism, namely hypokinesia (i.e. lack of movement), bradykinesia (i.e. slowness of movement), rigidity (wrist, shoulder and neck.) and rest tremor (imbalance of neurotransmitters, dopamine and acetylcholine). Parkinsonism can also be caused by drugs and less common conditions such as: multiple cerebral infarction, and degenerative conditions such as progressive supra nuclear palsy (PSP) and multiple system atrophy (MSA).

Although Parkinson disease is predominantly a movement disorder, other impairments frequently develop, including psychiatric problems such as depression and dementia. Autonomic disturbances and pain may later ensue, and the condition progresses to cause significant disability and handicap with impaired quality of life for the affected person. Family and carers might get affected indirectly.

II. MACHINE LEARNING METHODS

1. ARTIFICIAL NEURAL NETWORKS (ANN)

In machine learning, artificial neural networks (ANNs) are a family of statistical learning algorithms inspired by biological neural networks. A neural network is a network of simulated neurons that can be used to recognize instances of patterns. Neural networks learn by searching through a space of network weights. It is used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs/output and are capable of machine learning as well as pattern recognition.

2. K-NEAREST NEIGHBOURS CLASSIFIER (K-NN)

Nearest neighbour classification are based on learning analogy i.e., by comparing given test tuple with training tuples that are similar. Each tuple represent a point in an n-dimensional space. Any training tuples are stored in an n-dimensional pattern space. It is a tuple-based classifier that can simply locate the nearest neighbour in tuple space and labelling the unknown tuple with the same class label as that of the known neighbour. The k-nearest neighbour classifier searches the pattern space for the k-training tuple that are closest to the unknown tuple. These training tuples are k-nearest neighbour classifier of the unknown tuple. Closeness can be defined as any distance metric such as Euclidean distance. Nearest neighbour classifiers are distance based comparisons intrinsically assign equal weight to each attribute. Therefore, they can suffer from poor accuracy if there is noisy or irrelevant attribute.

3. SUPPORT VECTOR MACHINES (SVM)

Support Vector Machine is a new generation learning system based on recent advances in statistical learning theory. It is an algorithm for both linear and non-linear data. It transforms the original data in a higher dimension, from where it can find a hyper plane for separation of the data using essential training tuples called support vectors. A Support Vector Machine is a discriminative classifier formally defined by a separating hyper plane. In other words, given labelled training Support vector machine constructs a hyper plane or set of hyper planes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has largest distance to the nearest training data point of any class so called functional margin, since in general the larger the margin the lower the generalization error of the classifier.

4. NAÏVE BAYESIAN CLASSIFIER

Naïve Bayesian classification is called naïve because it assumes class condition independence. That is, the effect of an attribute value of given class is independence of the values of the other attributes. This assumption is made to reduce computational costs, and hence is considered naïve. A Naïve Bayesian model is easy to build, with no complicated iterative parameter estimation which makes it particularly useful for very large datasets. The major idea behind naïve Bayesian classification is to try and classify data by maximizing

$$P\left({C_i}/{X}\right) = P\left({X}/{C_i}\right) P^{(C_i)}/_{P(X)}$$

(Where $i$an index of class, each tuple is represented n-dimensional vector, $X = (x_1, x_2, x_3 \dots \dots x_n)$ depending n measurements made on the tuple from n attributes, respectively$A_1, A_2, A_3 \dots \dots A_n$. We are also given a set of m classes$C_1, C_2, C_3 \dots \dots C_m$).

5. Random Forest

Random forest Leo Breiman (2001) is an ensemble of decision trees based classifiers. Each tree is constructed by a bootstrap sample from the data, and it uses a candidate set of features selected from a random set. It uses both bagging and random variable selection for tree building. Once the forest is formed, test instances are percolated down each tree and trees make their respective class prediction. The error rate of a random forest depends on the strength of each tree and correlation between any two trees. It can be used to rank the importance of variables in a regression or classification problem in a natural way.

6. BAGGING

Bootstrap aggregating, also called bagging, is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression. It also reduces variance and helps to avoid over fitting. Although it is usually applied to decision tree methods, it can be used with any type of method. Bagging is a special case of the model averaging approach. Main reason for error in learning is due to noise, bias and variance. Noise is error by the target function, Bias is where the algorithm cannot learn the target and Variance comes from the sampling, and how it affects the learning algorithm. Bagging minimizes these errors. Averaging over bootstrap samples can reduce error from variance especially in case of unstable classifiers.

7. BOOSTING

Boosting is a machine learning ensemble meta-algorithm for reducing bias primarily and also variance in supervised learning, and a family of machine learning algorithms which convert weak learners to strong ones. Boosting is based on the question posed by Kearns and Valiant (1988, 1989): Can a set of weak learners create a single strong learner? A weak learner is defined to be a classifier which is only slightly correlated with the true classification (it can label examples better than random guessing). In contrast, a strong learner is a classifier that is arbitrarily well-correlated with the true classification.

III. MACHINE LEARNING BASED METHODS FOR PARKINSON DISEASE PREDICTION

Indira R. *et al.* (2014) have proposed an automatically machine learning approach and detected the Parkinson disease on behalf of speech/voice of the person. The author used fuzzy C-means clustering and pattern recognition based approach for the discrimination between healthy and parkinson disease affected people. The authors of this paper have achieved 68.04% accuracy, 75.34% sensitivity and 45.83% specificity.

Indira R. *et al. (*2014) have proposed a back propagation based approach for the discrimination between healthy and parkinson diseases affected peoples with the help of artificial neural network. Boosting was used by filtering technique, and for data reduction principle component analysis was used.

Geeta R. *et al.* (2012) have investigated and performed the feature relevance analysis to calculate the score to classify the Parkinson diseases Tele-monitoring dataset and dataset comparison classes Motor-UPDRS and Total-UPDRS (Unified Parkinson Disease Rating scale).

Rubén A. *et al.* (2013) proposed a five different classification paradigms using a wrapper feature selection scheme are capable of predicting each of the class variables with estimated accuracy in the range of 72–92%. In addition, classification into the main three severity categories (mild, moderate and severe) was split into dichotomy problems where binary classifiers perform better and select different subsets of non-motor symptoms.

Betala E. *et al.* (2014) proposed a SVM and k-Nearest Neighbour (k-NN) Tele-monitoring of PD patients remotely by taking their voice recording at regular interval. The age, gender, voice recordings taken at baseline, after three months, and after six months are used as features are assessed. Support Vector Machine was more successful in detecting significant deterioration in UPDRS score of the patients.

A.Tsanas *et al.* (2011) proposed feature selection, random forest and support vector machine used to discriminate PD from healthy controls. The author achieved overall 99% classification accuracy using only ten dysphonia features.

A.Tsanas *et al.* (2011) proposed a nonlinear signal approach large dataset (dataset are voice/speech recorded without requiring physician presence in the clinical) apply wide range known speech signal algorithm. This paper was performed using nonlinear regression and classification algorithm, and support visibility of frequent, remote, cost-effective, accurate UPDRS telemonitoring based on self-administered speech tests.

A. Sharma *et al.* (2014) proposed artificial neural network, pattern recognition and support vector machine. It is used to support the experts in the diagnosis of Parkinson disease. The dataset of research was composed of a range of biomedical voice signals healthy people and parkinson disease accuracy was obtained around 85.294%.

Khemphila *et al.* (2012) proposed a Multi-Layer Perceptron (MLP) with Back-Propagation learning algorithm was used to effective diagnosis Parkinson's disease (PD). Medical diagnosis was done by doctor's expertise and experience. But still cases are reported of wrong diagnosis and treatment. Patients are asked to take number of tests for diagnosis. In many cases, not all the tests contribute towards effective diagnosis of a disease. The artificial neural networks are used to sort the diagnosis of patients. This paper predict the accuracy model training dataset 91.45%, and the validation data set was 80.77%.

Revett *et al.* (2009) proposed jitter, shimmer, fundamental frequency, harmonics/noise ratios, descriptive statistics, and correlational factors (non-linear dynamic analysis) using all 22 feature, and a binary decision class ('0'is healthy and '1' is IPD decision class). The testing and training set are classified and an ROC and confusion matrix was generated to examine the accuracy of the classification process. Predict of accuracy shows 100%.

Shahbakhi *et al.* (2014) presented that a Genetic Algorithm (GA) and SVM were used for classification between healthy and people with Parkinson. Voice signals that 14 features were based on F0 (fundamental frequency or pitch), jitter, shimmer and noise to harmonics ratio, which are main factors in voice signal. Results show that classification accuracy 94.50, 93.66 and 94.22 per 4, 7 and 9 optimized features respectively.

Chen *et al.* (2012) proposed mainly two classifier Nested-RF and Nested-SVM classifier. Five datasets of cancer (brain cancer, colon cancer, DLBCL, leukemia, prostate cancer) and one disease (Parkinson's) dataset were used to evaluate the performance of the proposed classifiers. Parkinson's disease classification, the Nested-SVM classifier showed the superior performance with the accuracy up to 93% that was 20% more than the results from other three classifiers.

Bocklet *et al.* (2011) proposed a SVM and Correlation base classification performed to speech/voice of a person was affected by Parkinson disease automatic detection of Parkinson disease based on articulation, voice, and prosodic evaluations. The best results (90.5% recognition rate and 0.97 AUC).

R. Das *et al.* (2010) have proposed neural networks, Data Mining Neural analysis, and regression analysis and decision trees made a comparative study on Parkinson disease data set with regard to with the Presented results of classification accuracy of 92.9%, 84.3%, 88.6% and 84.3% respectively. To the classification method was diagnosis Parkinson disease based on the SAS software.

Ene M. *et al.* (2008) proposed a probabilistic neural network (PNN) variant to discriminate between healthy people and people with Parkinson's disease. Three PNN types are used in this classification process, related to the smoothing factor search: incremental search (IS) Monte Carlo search (MCS) and hybrid search (HS). The accuracies reaching run between 79% and 81% for new, undiagnosed patients.

Cam M. *et al.* (2008) proposed a parallel distributed neural network with two hidden layers, boosted by the use of filtering and a majority voting system to distinguish between the people who have normal vocal signals and who suffer from Parkinson's disease. To perform the boosting by filtering technique, we the Training and Testing stage, the accuracy achieved by > 90.

Caglar *et al.* (2010) proposed ANN (Two types of the ANNs were used for classification: Multilayer Perceptron (MLP) and Radial Basis Function (RBF) Networks) and Adaptive Neuro-Fuzzy Classifier (ANFC) with linguistic hedges to discriminate between healthy people and people with PD. Adaptive Neuro-Fuzzy Classifier with linguistic hedges gave the best recognition results with %95.38 training and %94.72 testing classifying performance indeed.

Ali Saad *et al.* (2013) proposed a Bayesian Belief Network (BBN) to find the freezing of Parkinson disease patients and used a Video dataset available online extracted from real Parkinson disease patients though walking and having freezing periods. Each file was composed of a matrix that contains measurement data of the three sensors in x, y and z directions. Weather Freezing of Gait (FoG) occurred or not. These annotations was labelled by synchronizing the data by a video that recorded each patient run and results appeared when testing the models Bayesian Naïve Classifier (BNC) classifier.

Cho, C. *at al.* (2009) proposed system utilizes an algorithm combining principal component analysis (PCA) with linear discriminant analysis (LDA). We propose a gait analysis system which can detect the gait pattern of Parkinson's disease using computer vision. This system comprises three main parts: pre-processing, training and recognition. Experimental results showed that LDA had a recognition rate for Parkinsonian gait of 95.49%.

Rusz J. *et al.* (2011) proposed applied support vector machine to find the best combination of measurements to differentiate Parkinson disease from healthy subjects. This method leads to overall classification performance of 85%. Admittedly, we have found relationships between measures of phonation and articulation and bradykinesia and rigidity in Parkinson disease. In the acoustic analysis can ease the clinical assessment of voice and speech disorders, and serve as measures of clinical progression as well as in the monitoring of treatment effects.

Can M. *et al.* have proposed boosting committee machine to detect Parkinson disease for dataset containing sick and healthy people by the artificial neural network. The filtering techniques used for the neural networks with back propagation, they majority voting scheme. Out of 195 samples, 75.4% are Parkinson's disease type and the remainder was of healthy character.

Kapoor T. *et al.* (2011) proposed speech recognized by Mel-frequency cepstral coefficients (MFCC) and Vector Quantization (VQ). The MFCC uses speech analysis frames in signal to frequent domain and Vector Quantization was the codebook of lowest distortion was calculated. The 20 phonation's used for normal speech and patient with Parkinson's disease. Vector Quantization result with codebook in normal voice and voice of Parkinson disease rate in classifier 90% and 95% respectively.

Wu, S *et al.* (2011) proposed regression, decision tree and neural network analysis to analyse the databank of Parkinson disease for error probability calculated. The result was logistic regression, classification and neural network analysis error probability by 5.15%, 8.47% and 23.73% respectively.

Sellam V. *et al.* (2014) proposed classification of pathological voice from normal voice was implemented using Support Vector Machine (SVM) and Radial Basis Functional Neural Network (RBFNN). The normal and pathological voices of children are used to train and test the classifiers. The speech signal was then analysed in order to extract the acoustic parameters such as the Signal Energy, pitch, formant frequencies, Mean Square Residual signal, Reflection coefficients, Jitter and Shimmer. Show the classification accuracy of RBFNN 91% and SVM 83%.

Chen, H *et al.* (2013) proposed FKNN-based system was compared with the support vector machines (SVM) based approaches predict to dataset composed of a range of biomedical voice measurements from 31 people, 23 people with Parkinson disease. The best classification accuracy (96.07%) obtained by the FKNN based system using a 10-fold cross validation method can ensure a reliable diagnostic model for detection of Parkinson disease.

Salvatore *et al.* (2014) proposed a supervised machine learning algorithm based on Principal Components Analysis as feature extraction technique and Support Vector Machines to predict of individual differential diagnosis of Parkinson's disease (PD) and Progressive Supranuclear Palsy (PSP) for Magnetic Resonance Images (MRI dataset). Predict of the Parkinson disease (PD) versus Controls, Progressive Supranuclear Palsy (PSP) versus Controls and Progressive Supranuclear Palsy (PSP) versus Parkinson disease (PD) the Overall Accuracy (Specificity/Sensitivity) were 83.2 (81.9/85.4), 86.2 (92.1/82.9) and 84.7 (87.5/83.8)% for binary labelled groups, respectively.

Przybys Z. *et al.* (2014) proposed a Reflexive saccades measurements and classifications to predict individual patients and small patient popular significant measure effects are plotted the movement lines in the phase space as changes of the right hip x-angles as a function of the left hip angle changes during three steps of stable walking and found different types of attractor changes as the effect of treatment and motivations.

Morales *et al.* (2013) proposed naïve Bayes, filter selection naıve Bayes (FSNB), naıve Bayes correlation-based with feature subset selection method (CFS-NB) and support vector machines (SVM) analysing pairs of classes (PDD vs. PDCI, PDD vs. PDMCI, PDMCI vs. PDCI), and (PDD vs. PDMCI vs. PDCI) on the different types comparison symptom of Parkinson disease. CFS-NB for (PDD vs. PDCI) found the highest accuracy, Sensitivity and Specificity of 97%, 93.33% and 100% respectively.

R. Ramani *et al.* (2011) proposed a many type classification of data mining approaches SVM, KNN, Random tree, Partial Least Square Regression (PLS) etc. to predict dataset biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). To the filtering was applied to the algorithms for better classification purpose, smallest number of qualities with which the better classification was selected and achieved. The Random Tree forms the classification based on three typical features to gain the zero error rates.

Chen, A. *et al.* (2013) proposed Nested–Random Forest (Nested-RF) classifier and Nested–Support Vector Machine (Nested-SVM) classifier for predict of Five datasets of cancer (brain cancer, colon cancer, DLBCL, leukemia, prostate cancer) and one disease (Parkinson's) datasets. Nested-SVM classifier was applied to the Parkinson's disease dataset average accuracy, sensitivity, and specificity can reach 93%, 90%, and 93% respectively.

Yadav, G *et al.* (2009) have proposed classifier, statistical classifier, and support vector machine classifier to discriminate healthy people and Parkinson disease. SVM classifier provides the accuracy of 76%, sensitivity of 97% and specificity of 13%.

Azad, C., *et al.* (2013) proposed prediction model tree based classification model decision tree, ID3 and decision stumps are used for training and testing the effectiveness many symptoms that lead to Parkinson's disease such age-environmental factor, trembling in the legs, arms, hands, impaired speech articulation and production difficulties. Decision tree, ID3 and decision stumps our prediction model provides accuracy 85.08%, 75.33% and 83.55% or classification error 14.92%, 24.67% and 16.45% respectively.

Bouchikhi *et al.* (2013) proposed Neural Networks (ANN), Data Mining neural, Regression and Decision Tree for effective diagnosis dataset to discriminate healthy people and Parkinson disease. SVM classifier shows performance 97.22% specificity, 95.83% sensitivity and the total classification accuracy of 96.88%. New feature classification optimal Fuzzy k-nearest neighbour (FKNN) model was 96.07% accuracy.

Kihel, B. *et al.* (2011) proposed Clonclas and Probabilistic Neural Network (PNN) to discriminate between healthy and people with Parkinson's disease (PWD) Taking inspiration from natural immune systems, we try to grab useful properties such as automatic recognition, memorization and adaptation. The developed algorithms have as a base the algorithm of training biomedical inspired Clonclas.

Ma, C. *et al.* (2014) proposed a novel hybrid method named Kernel-Based Extreme Learning Machine with Subtractive Clustering Features Weighting (SCFW-KELM) significantly outperforms SVM, KNN, and extreme learning machine (ELM) approaches for Parkinson disease dataset was to discriminate healthy people from those with Parkinson disease. given the results of various medical tests carried out on a patient achieved highest classification results reported so far via 10-fold cross validation scheme, with SVM-based, KNN-based, and ELM-based accuracy of 99.49%, the sensitivity of 100%, the specificity of 99.39%, AUC of 99.69%, the f -measure value of 0.9964, and kappa value of 0.9867.

Hazan, H *et al.* (2012) have been A novel hybrid method named Kernel-Based Extreme Learning Machine with Subtractive Clustering Features Weighting Approach (CFW-KELM) to discriminate healthy people from people with Parkinson disease. Experimental results have demonstrated that the proposed SCFW-KELM significantly outperforms SVM-based, KNN-based, and ELM-based approaches and other methods in the literature and achieved highest classification results reported so far via 10-fold cross validation scheme, with the classification accuracy of 99.49%, the sensitivity of 100%, the specificity of 99.39%, AUC of 99.69%, the f -measure value of 0.9964, and kappa value of 0.9867.

Sriram, T *et al.* (2013) proposed SVM, k-NN, Random Forest and Naïve Bayes voice to dataset for Parkinson disease. The class column represents "status" which was set to 0 for healthy and 1 for PD. SVM, k-NN, Random Forest and Naïve Bayes was the prediction accuracy 88.9%, 88.9%, 90.26 and 69.23% respectively.

Prashanth *et al.* (2014) proposed Support Vector Machine (SVM) and classification tree methods are use olfactory loss feature from 40-item University of Pennsylvania Smell Identification Test (UPSIT) and Sleep behaviour disorder feature from Rapid eye movement sleep Behaviour Disorder Screening Questionnaire (RBDSQ), obtained from the Parkinson's Progression Marker's Initiative (PPMI) database. Support Vector Machine sleep Behaviour Disorder (SVM-RBD) was predicted of the best accuracy 85.48%, sensitivity 90.55% and specificity 74.58%.

Amit S. *et al.* (2014) proposed an approach to classification and kind of Parkinson's patients using their postural response and analysing it using a L2 norm metric in conjunction with support vector machines. Twenty four patients were valued before and after medication. Each patient suffered following analysis protocols for the valuation of their postural balance: First, Eyes Open on Force platform (a firm surface) (E0) and second, Eyes Open on Foam placed on Force platform (FO).The classification of subjects with dyskinesia when standing on a firm surface with eyes open was improved from 66% to 77%.

A.H. *et al.* (2012) proposed Bayesian Networks, Regression, Classification and Regression Trees (CART), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) for proposing a decision support system for diagnosis of Parkinson's disease. Parkinson's disease, the disorder also commonly causes a slowing or freezing of movement. The proposed system achieved an accuracy of 93.7% using classification and regression tree.

Kaya, E. *et al.* (2011) proposed discretization method, support vector machines, C4.5, k-nearest neighbours and Naive Bayes classier methods are used to classify the dataset. The dataset was classified using the features discretizeted and non-discretizated in order to show the effectiveness of discretization on diagnosis of Parkinson's disease.

Nivedita C *et al.* (2013) proposed artificial neural network (ANN) with back propagation to classify neurodegenerative disorders according to symptoms. The clinical symptoms of neurodegenerative disorders have been identified as six major classes Memory problems, Communication problems, Personality changes, idiosyncratic behaviours, Loss of voluntary control and Common health problems. Artificial neural network (ANN) was prediction of overall performance of 96.42%.

Farhad S. *et al.* (2013) proposed Multi-Layer Perceptron (MLP) with back-propagation learning algorithm and Radial Basis Function (RBF) and Artificial Neural Networks ANN) were used to differentiate between clinical variables of samples (N = 195) who were suffering from Parkinson's disease and who were not. MLP and RBF classification accuracy 93.22% and 86.44% respectively for the data set.

Chen, A. *et al.* (2012) proposed Random forests (RF) classifier, Support Vector Machine (SVM) classifier, Genetic Algorithm–Random Forests (GA-RF) classifier, and Genetic Algorithm–Support Vector Machine (GA-SVM) classifier to effect diagnose and classify the Parkinson's disease. GA-SVM classifier significantly improves accuracy (69% to 94%), sensitivity (60% to 92%), and specificity (70% to 95%).

Wu, D. *et al.* (2010) proposed radial basis function neural network (RBFNN) based on particle cloud optimization (PSO) and principal component analysis (PCA) with Local Field Potential (LFP) data recorded via the stimulation electrodes to predict activity related to tremor onset. RBFNN, PCA + RBFNN and PCA + PSO + RBFNN to the predict accuracies 89.91%, 88.92% and 88.92% respectively.

Luukka P. *et al.* (2011) proposed fuzzy entropy based feature selection combined with similarity classifier; we achieved to reduce the computational time and simplify the data set. Data set was composed of a range of biomedical voice measurements from healthy people and people with Parkinson's disease (PD). Mean classification accuracy with Parkinson's data set being 85:03%.

Salhi L. *et al.* (2008) proposed a method that uses wavelet analysis to extract a feature vector from speech samples, which was used as input to a Multilayer Neural Network (MNN), three layer feed forward network with sigmoid activation and Back Propagation Algorithm (BPA) classifier. The classification rate was between 80% and 100%.

Max A. *et al.* (2009) have been proposed support vector machine (SVM) valuation of the practical value of existing traditional and non-standard measures for discriminating healthy people from people with Parkinson's disease (PWD) by detecting dysphonia.

Zhang, J. *et al.* (2008) proposed an increased cerebrospinal fluid (CSF) τ and decreased amyloid (A) $\beta 42$ to validate as biomarkers of Alzheimer disease and no validate biomarker for Parkinson disease. Predicted of all subjects medical history, family history, physical and neurologic examinations by clinicians who specialize in movement disorders or dementia, laboratory tests, and neuropsychological. Analysis for 90 control subjects (95%), 36 patients with likely Alzheimer disease (75%), and 38 patients with likely Parkinson disease (95%).

Saad A. *et al.* (2011) proposed a based on unsupervised learning of a probabilistic graphical model Bayesian Belief Network (BBN) based on Expectation Maximization (EM) algorithm. Prediction of mixed acquisition system of electronic pen and speech signals are performed through

voice and handwriting. This paper predict of grouping based analysis of voice and handwriting.
Ozcift A. *et al.* (2011) proposed computer-aided diagnosis (CADx) systems to improving the accuracy. Rotation forest (RF) collective classifiers of 30 machine learning algorithms correlation based feature selection (CFS) algorithm and Rotation forest prediction to diabetes, heart and Parkinson's datasets. RF classifier predict the accuracy (ACC), kappa error (KE) and area under the receiver operating characteristic (ROC) curve (AUC) of 74.47%, 80.49% and 87.13% respectively.

Yahia A. *et al.* (2014) proposed classification algorithm based on Naïve Bayes and K- Nearest Neighbours (KNN) using Parkinson speech dataset with multiple types of sound recordings to prediction voice signal find the Parkinson disease or healthy people. K- Nearest Neighbours performed accuracy 80% and Naïve Bayes classifier performed an accuracy of 93.3% sensitivity 87.5%, and specificity 100%.

TABLE I: **Summary of machine learning based methods for Parkinson disease prediction**

Authors name	**Machine learning methods**	**Data description**	**Performance**
Indira R. (2014)	fuzzy C- means	Speech signal dataset	68.04% accuracy, 75.34% sensitivity and 45.83% specificity
Indira R. (2014)	ANN	Speech signal dataset	Recognition rate of 92 %.
R. Geeta (2012)	Classification	Speech dataset as high or low	Random tree classification 100% accuracy
Rubén A. (2013)	Wrapper feat- ure selection	non-motor symptoms	72% to 92% accuracy
Betalu E. (2014)	SVM	Age, gender, voice recording	76%accuracy 34% sensitivity
A.Tsanas (2011)	SVM	Speech signal dataset	98.6% accuracy
A.Tsans (2011)	Regression & Classification	Speech signal dataset	5–95 percentile
Sharma A(2014)	SVM	Speech signal dataset	85.29% accuracy
Khemphila (2012)	ANN	Speech signal dataset	82.05% and 83.33%Accuracy
Revett (2009)	Correlation	Voice dataset	100% accuracy
Shahbakhi (2014)	SVM	Speech signal dataset	94.22% accuracy, 70.12% sensitivity and 92.8% specificity
Chen H. (2012)	Nested SVM	Speech dataset	93.5% accuracy 90.53% sensitivity and 93.83% specificity
Bocklet (2011)	SVM	Speech dataset	79% result
Das R. (2010)	NN classifier	Speech signal dataset	92.9%accuracy
Ene M. (2008)	PNN	Voice recording dataset	79% to 81 accuracy
Cam M. (2008)	PNN	Voice recording dataset	92.9% accuracy
Caglar (2010)	ANN	PD dataset	96.77% accuracy, 87.5% sensitivity and 100% specificity
Ali Saad (2013)	Bayesian Naive Classifier (BNC)	video recorded	74.31% accuracy
Cho, C. (2009)	Linear discriminant analysis (LDA)	gait patterns	95% accuracy
Rusz J. (2011)	SVM	voice and speech	85%. accuracy
Can, M.	ANN	Recording data	92.9% accuracy
Kapoor (2009)	Vector Quantization.	Audio Input	95% accuracy
Wu, S (2011)	Decision Tree and Neural Network	recorded the speech signals	95% accuracy
Sellam V. (2014)	Radial Basis Functional Neural Network (RBFNN)	Voice and unvoiced speech signals	91% accuracy
Chen, H. (2013)	fuzzy k-nearest neighbour (FKNN)	PD data set	96.07% accuracy
Salvatore (2014)	SVM	Magnetic resonance imaging (MRI)	> 90% accuracy ,sensitivity and specificity
PrzybysZ. (2014)	Reflexive saccades measurements	Magnetic resonance imaging (MRI)	70% accuracy
Morales (2013)	SVM	Magnetic resonance imaging (MRI)	70% accuracy , 71%sensitivity and 85%specificity
R. Ramani (2011)	Random tree classifier	Recording speech signals	100% accuracy
Chen A. (2013)	Nested-SVM	PD dataset	Up to 93% accuracy
Yadav G. (2009)	SVM	recorded the speech signals	0.76 accuracy and 0.97sensitivity
Azad C.	Decision tree	voice recordings	85.08% accuracy
Bouchikhi (2013)	SVM	voice recordings	96.88% accuracy
Kihel, B. (2011)	Euclidean	Voice data	94.44% accuracy
Ma, C.(2014)	SVM	recorded the speech signals	99.49% accuracy, 100% sensitivity and

Authors name	Machine learning methods	Data description	Performance
			99.39% specificity
Hazan H. (2012)	SVM	speech data	90% accuracy
Sriram T.	Random Forest	voice dataset	90.26% accuracy
Prashanth (2014)	SVM and classification tree	de-novo PD	89.39% accuracy
Amit S. (2014)	Using nonlinear dynamic and SVM	Dyskinesia Data	66% to 77% accuracy
A.H.(2012)	classification and regression tree	Recorded voice signals	93.7% accuracy
Kaya E.(2011)	Entropy-based discretization method	Audio Input	94.87% accuracy
Nivedita C. (2013)	ANN	seven different classes	overall 96.42% accuracy
Farhad S.(2013)	Multi-Layer Perceptron (MLP)	Audio Input	93.22% accuracy
Chen A.(2012)	GA-SVM classifier	microarray dataset	69% to 94% accuracy, 60% to 92% sensitivity and 70% to 95% specificity
Wu D. (2010)	Radial basis function neural network	data recorded	89.91% accuracy
Luukka P. (2011)	fuzzy entropy	voice recording	84.52 % accuracy
Salhi L.(2008)	Multilayer Neural Network	pitch around the expected value (250Hz)	80% and 100%.Results
Max A. (2009)	SVM	speech signals	91.4% accuracy
Zhang, J. (2008)	Increased cerebrospinal fluid(CSF)	AD and PD dataset	95% PD and 75% AD
Saad A. (2011)	Bayesian Believe Network	tremor, poor vocal data	Group or cluster form
Ozcift A.(2011)	Correlation based Feature Selection	PD data samples	89.7% accuracy
Yahia A. (2014)	KNN	speech dataset	93.3% accuracy

IV. Conclusion

This paper presented a comprehensive review for the prediction of Parkinson disease by using machine learning based approaches. The brief introduction of various computational intelligence techniques based approaches used for the prediction of Parkinson diseases are presented .The summary of results obtained by various researchers available in literature to predict the Parkinson diseases is also presented.

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