[1] J. R. Duffy, *Motor Speech Disorders: Substrates, Differential Diagnosis, and Management*. Amsterdam, The Netherlands: Elsevier, 2005.

[2] J. W. Langston, ``Parkinson's disease: Current and future challenges,'' *NeuroToxicology*, vol. 23, pp. 443\_450, Oct. 2002.

[3] B. E. Sakar *et al.*, ``Collection and analysis of a Parkinson speech dataset with multiple types of sound recordings,'' *IEEE J. Biomed. Health Inform.*, vol. 17, no. 4, pp. 828\_834, Jul. 2013.

[4] N. Singh, V. Pillay, and Y. E. Choonara, ``Advances in the treatment of Parkinson's disease,'' *Prog. Neurobiol.*, vol. 81, pp. 29\_44, Jan. 2007.

[5] *Parkinson's Disease: National Clinical Guideline for Diagnosis and Man- agement in Primary and Secondary Care*, Nat. Collaborating CentreChronic Conditions, London, U.K., 2006.

[6] B. Harel, M. Cannizzaro, and P. J. Snyder, ``Variability in fundamental frequency during speech in prodromal and incipient Parkinson's disease: A longitudinal case study,'' *Brain Cogn.*, vol. 56, no. 1, pp. 24\_29, Jun. 2004.

[7] A. Tsanas, M. A. Little, P. E. McSharry, J. Spielman, and L. O. Ramig, ``Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease,'' *IEEE Trans. Biomed. Eng.*, vol. 59, no. 5, pp. 1264\_1271, May 2012.

[8] M. A. Little, P. E. McSharry, E. J. Hunter, J. Spielman, and L. O. Ramig, ``Suitability of dysphonia measurements for telemonitoring of Parkinson's disease,'' *IEEE Trans. Biomed. Eng.*, vol. 56, no. 4, pp. 1015\_1022, Apr. 2009.

[9] A. Tsanas, M. A. Little, P. E. McSharry, and L. O. Ramig, ``Nonlinear speech analysis algorithms mapped to a standard metric achieve clinically useful quantification of average Parkinson's disease symptom severity,'' *J. Roy. Soc. Interfaces*, vol. 8, pp. 842\_855, Jun. 2011.

[10] A. Tsanas, M. A. Little, P. E. McSharry, and L. O. Ramig, ``Accurate telemonitoring of Parkinson's disease progression by non-invasive speech tests,'' *IEEE Trans. Biomed. Eng.*, vol. 57, no. 4, pp. 884\_893, Apr. 2010.

[11] M. Gök, ``An ensemble of *k*-nearest neighbours algorithm for detection of Parkinson's disease,'' *Int. J. Syst. Sci.*, vol. 46, pp. 1108\_1112, Apr. 2015.

[12] A. Bayestehtashk, M. Asgari, I. Shafran, and J. McNames, ``Fully automated assessment of the severity of Parkinson's disease from speech,'' *Comput. Speech Lang.*, vol. 29, no. 1, pp. 172\_185, Jan. 2016.

[13] K. Taha, J. Westin, and M. Dougherty, ``Classification of speech intelligibility in Parkinson's disease,'' *Biocybern. Biomed. Eng.*, vol. 34, pp. 35\_45, Jul. 2015.

[14] J. Howell, ``When technology is too hot, too cold or just right,'' *Emerg. Learn. Des. J.*, vol. 5, no. 1, pp. 9\_18, May 2017.

[15] C.-W. Hsu and C.-J. Lin, ``A comparison of methods for multiclass support vector machines,'' *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415\_425, Mar. 2002.

[16] . Cantürk and F. Karabiber, ``A machine learning system for the diagnosis of Parkinson's disease from speech signals and its application to multiple speech signal types,'' *Arabian J. Sci. Eng.*, vol. 41, pp. 5049\_5059, Dec. 2016.

[17] X. Wen, L. Shao, W. Fang, and Y. Xue, ``Ef\_cient feature selection and classification for vehicle detection,'' *IEEE Trans. Circuits Syst. Video* *Technol.*, vol. 25, no. 3, pp. 508\_517, Mar. 2015.

[18] S.-S. Hong,W. Lee, and M.-M. Han, ``The feature selection method based on genetic algorithm for ef\_cient of text clustering and text classification,'' *Int. J. Adv. Soft Comput. Appl.*, vol. 7, pp. 2074\_8523, Mar. 2015.

[19] M. Zhu, C. Xu, and Y.-F. B. Wu, ``Positive unlabeled learning to discover relevant documents using topic models for feature selection,'' in *Proc.* *Int. Conf. Data Mining Streeing Committee World Congr. Comput. Sci.,* *Comput. Eng. Appl. Comput.*, 2014, pp. 1\_7.

[20] H. Daassi-Gnaba, Y. Oussar, M. Merlan, T. Ditchi, E. Géron, and S. Holé, ``Wood moisture content prediction using feature selection techniques and a kernel method,'' *Neurocomputing*, vol. 237, pp. 79\_91, May 2017.

[21] Z. Cai, J. Gu, and H.-L. Chen, ``A new hybrid intelligent framework for predicting Parkinson's disease,'' *IEEE Access*, vol. 5, pp. 17188\_17200, Sep. 2017.

22] L. Naranjo, C. J. Pérez, J. Martín, and Y. Campos-Roca, ``A two-stage variable selection and classification approach for Parkinson's disease detection by using voice recording replications,'' *Comput. Methods Programs* *Biomed.*, vol. 142, pp. 147\_156, Feb. 2017.

[23] M. A. Little, P. E. McSharry, S. J. Roberts, D. A. E. Costello, and I. M. Moroz, ``Exploiting nonlinear recurrence and fractal scaling properties for voice disorder detection,'' *Biomed. Eng. Online*, vol. 6, no. 23, pp. 1\_19, Jun. 2007.

[24] J. G. .vec, P. S. Popolo, and I. R. Titze, ``Measurement of vocal doses in speech: Experimental procedure and signal processing,'' *Logopedics* *Phoniatrics Vocology*, vol. 28, no. 4, pp. 181\_192, 2003.

[25] M. M. Hoehn and M. D. Yahr, ``Parkinsonism: Onset, progression, and mortality,'' *Neurology*, vol. 50, no. 2, p. 318, 1998.

[26] S. B. Kotsiantis, D. Kanellopoulos, and P. E. Pintelas, ``Data preprocessing for supervised leaning,'' *Int. J. Comput. Sci.*, vol. 1, no. 2, pp. 111\_117, 2006.

[27] V. Vapnik, *The Nature of Statistical Learning Theory*. Springer Science & Business Media, Jun. 2013.

[28] C. Cortes and V. Vapnik, ``Support-vector networks,'' *Mach. Learn.*, vol. 20, no. 3, pp. 273\_297, 1995.

[29] P. S. Bradley and O. L. Mangasarian, ``Feature selection via concave minimization and support vector machines,'' in *Proc. 15th Int. Conf. (ICML)*, 1998, pp. 82\_90.

[30] M. Moon and K. Nakai, ``Stable feature selection based on the ensemble L1-norm support vector machine for biomarker discovery,'' *BMC* *Genomics*, vol. 17, p. 1026, Dec. 2016.

[31] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines*. Cambridge, U.K.: Cambridge Univ. Press, 2000, p. 23.

[32] C.-C. Chang and C.-J. Lin, ``LIBSVM: A library for support vector machines,'' *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 3, pp. 27:1\_27:27, 2011.

[33] H.-L. Chen, B. Yang, J. Liu, and D.-Y. Liu, ``A support vector machine classifier with rough set-based feature selection for breast cancer diagnosis,'' *Expert Syst. Appl.*, vol. 38, pp. 9014\_9022, Jul. 2011.

[34] J. Mourao-Miranda, A. L. W. Bokde, C. Born, H. Hampel, and M. Stetter, ``Classifying brain states and determining the discriminating activation patterns: Support vector machine on functional MRI data,'' *NeuroImage*, vol. 28, pp. 980\_995, Nov. 2005.

[35] V. D. A. Sánchez, ``Advanced support vector machines and kernel methods,'' *Neurocomputing*, vol. 55, pp. 5\_20, Sep. 2003.

[36] A. H. Al-Fatlawi, M. H. Jabardi, and S. H. Ling, ``Ef\_cient diagnosis system for Parkinson's disease using deep belief network,'' in *Proc. IEEE* *Congr. Evol. Comput.*, Jul. 2016, pp. 1324\_1330.

[37] A. U. Haq, J. P. Li, M. H. Memon, S. Nazir, and R. Sun, ``A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms,'' *Mobile Inf. Syst.*, vol. 2018, Dec. 2018, Art. no. 3860146.

[38] A. U. Haq *et al.*, ``Comparative analysis of the classification performance of machine learning classifiers and deep neural network classifier for prediction of parkinson disease,'' in *Proc. IEEE Int. Comput. Conf.Wavelet* *Active Media Technol. Inf. Process.*, Dec. 2018, pp. 101\_106.

[39] A. Ul Haq, J. P. Li, M. H. Memon, M. H. Memon, J. Khan, and S. M. Marium, ``Heart disease diagnosis through machine learning predictive model using sequential backward selection feature algorithm,'' in *Proc.* *IEEE 5th Int. Conf. Converg. Technol. (I2CT)*, 2019, pp. 1\_5.

[40] M. Durairaj and N. Ramasamy, ``A comparison of the perceptive approaches for preprocessing the data set for predicting fertility success rate,'' *Int. J. Control Theory Appl.*, vol. 9, no. 27, pp. 255\_260, 2016.

[41] M. F. Akay, ``Support vector machines combined with feature selection for breast cancer diagnosis,'' *Expert Syst. Appl.*, vol. 36, no. 2, pp. 3240\_3247, 2009.

Tsanas *et al.* [7] used a dataset consisting of 263 speech samples from 43 people and 76.7 % of dataset were PD, the leftover dataset was healthy. They utilized an updated version of the dataset that was utilized in [8]. Little *et al.*

[8] present an assessment of measures for the identity of PD subjects from healthy by detecting dysphonia. They diagnosed 23 PD and 8 healthy people and their dataset recorded vowels and used a Support Vector Machine (SVM) for classification and achieved classification accuracy 91.4 %.

In [9] 132 extracted features from speech signals applied dysphonia methods. The database only contained vowels and some features extraction algorithms such as Least Absolute Shrinkage

Selection Operator (LASSO), Minimal Redundancy Maximal Relevance (MRMR), Relief and Local Learning Based Feature Selection (LLBFS), were used and 10 features selected from 132 were selected by FS algorithms. These 10 features were used as input parameters for classification with two machine learning algorithms (Random Forests and SVM).

In another study Tsana *et al.* [10] process speech signals of PD to compute a relationship between severity of the PD and disorder of speech.

In [11] Gök studied the dataset used in [8]. They applied an ensemble of k-nearest neighbor (k-NN) algorithms to increase the accuracy. Features selection was deployed to find suitable features for prediction of PD.

Bayestehtashk *et al.* [12] proposed a diagnosis of the severity of PD using speech signals. They designed a system that used analysis of regression for prediction of the severity of PD through sustained phonations.

In [13] Taha used a machine learning algorithm SVM for classification of speech signals in PD and utilized the N-fold Cross validation technique. The data set for the experiment contained 240 running voice samples recorded from 60 PD and 20 healthy people. Those samples of speech were clinically rated via unified Parkinson's, score scale motor exam of speech (UPDRS-S).

Sakar *et al.* [3] collected multiple voice recording from 40 people in which 20 PD and 20 healthy. The voice samples 26 inclusive of everyday sentences, numbers, words and contained vowels had been gathered for each concern and 26 features had been extracted from voice signals by Praat Acoustic Analysis Software [14]. They carried out Leave-One-Subject-Out (LOSO) and s-LOO validation methods to compute the performance of K-NN and Lib- SVM classifiers [15]. They compared the classifier performance using performance measuring metrics like accuracy, sensitivity, specificity and Matthews's correlation coefficient (MCC).

Cantürk and Karabibe [16] proposed approach was designed on a machine learning based system and use speech signals. Four FS algorithms (LASSO, relief, LLBS, and MRMR) were applied to filter out the most appropriate features from the dataset. Moreover; classifiers such as Ada boost, SVM, k-NN, multi-layer perceptron (MLP), and Naïve Bayes (NB) were applied for classification PD and healthy subjects. Moreover, two validation techniques i.e. k-Fold, and LOSO were utilized for correct classification of PD. The proposed system performances were measured by performance measuring metrics such as accuracy of classification, sensitivity and specificity, and MCC. The computation complexity of algorithm also computed and the system was evaluated on a PD dataset which contained multiple types of voice signals.

Wen *et al.* [17] proposed an efficient feature selection and classification system for vehicle detection. They used Haar-like feature section technique and RBF-SVM for vehicle detection. The proposed method achieved better performance.

Hong *et al.* [18] proposed a feature selection method to improve the effectiveness of the text mining analysis. A new genetic algorithm was designed for text mining to increase the search performance. Furthermore, FSGA improved the clustering and speed performance.

Zhu *et al.* [19] propose a framework of using PU learning for SbME using latent topics identified by a topic model for feature dimension reduction. The LDA method has a significantly smaller dimension than the term based method it is more practical in a SbME setting, where computational efficiency is crucial in providing real time update of search results per the user's query documents.

Daassi-Gnaba *et al.* [20] proposed a system for Wood Moisture Content Prediction Using Feature Selection Techniques and a Kernel Method. The proposed system obtained high performance.

Cai *et al.* [21] proposed framework for prediction of PD. They used SVM classifier and relief feature selection algorithm with bacterial foraging optimization (BFO) and achieved best classification performance.

Naranjo *et al.* [22] proposed a classification system. They used two-stage features and classification approach (TSFSA) for Parkinson's disease diagnosis by applied sound recording replication and achieved the best performance.

In another study Bi *et al.* [46] proposed a methodology for conducting importance-performance analysis through online review by the combination of LDA, IOVO-SVM and ENNM. The

proposed method obtained effective analysis results with low cost and with small time.

Liu *et al.* [47] proposed a framework for multi-class sentiment classification. They used different feature selection/machine learning algorithms and achieved good results compared to other existing studies.

In [48] Liu *et al.* proposed a method for multi-class sentiment classification based on an improved one-vs.-one (OVO) strategy and the support vector machine (SVM) algorithm. The experimental results demonstrated that proposed method achieved high performance as compared to existing studies.

The main contribution of this study is to propose a machine-learning based system to successfully diagnose people with PD and improve the patient's life. Machine learning predictive model SVM was used for PD and healthy people classification. The L1-Norm SVM was used for

appropriate features selection that improves the classification performance of the classier. We adopted the L1-Norm SVM for appropriate feature selection in this study because the classification performance of L1-Norm SVM FS based method is good as compare to other methods of classification for PD and healthy people. These methods where used other feature selection algorithms such as LASSO, MRMR, LLBFS [9], Relief with BFO [21] and two-stage feature selection method [18]. Furthermore, all these studies used these FS algorithms for the same dataset [8], [23]. The K Fold cross-validation was used in to select the best hyper parameters for best model evaluation. Performance evaluation metrics such as classification accuracy, sensitivity, and specificity were utilized to check the proposed system performance.

The proposed system has been tested on PD data-set multiple types of sound signals.

Following are the key contributions of the proposed research study:

I. The performance of classifier checked on selected features subsets which are selected by L1-Norm SVM algorithm along with Kfolds cross-validation technique.

II. The performance also checked on full features set and compared with performance on selected features sets.

III. The system has been tested on PD dataset and achieved very high classification performance.

IV. We suggest that the proposed system can be effectively diagnosis PD and easily incorporated in the healthcare system.