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Monitoring Parkinson's Disease in Smart Cities

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ABSTRACT Parkinson's Disease (PD) is one of the most severe neurological diseases prevalent in the world. A neurodegenerative disease, it impairs the body's balance, damages motor skills, and leads to disorder in speech production. These problems also affect decision-making processes and the expression of emotions. In this paper, we propose a PD monitoring framework for use in smart cities. Using this framework, city residents will have their health constantly monitored and get feedback on their PD situation. Early PD symptoms can, therefore, be detected and the proper medication provided. In this framework, we use speech signals from clients captured from various sensors and transmitted to the cloud for processing. In the cloud, decisions are made using a support vector machine-based classifier. Decisions, along with the signal features, are sent to registered doctors, who then prescribe certain medications to the client. Several experiments were performed, with the results demonstrating that the proposed framework can achieve 97.2% accuracy in detecting PD.

INDEX TERMS Smart cities, health monitoring, Parkinson's disease, cloud computing.

I. INTRODUCTION

Neurodegenerative diseases, such as Parkinson's, Alzheimer's, and Huntington's, are caused by the degradation of the general functions of neurons. In general, neurodegenerative diseases cannot be fully cured, but they can be controlled with medical or surgical treatment. Control is more successful if a disease is diagnosed at its early stage. In this paper, we propose a cloud-based framework to monitor Parkinson's disease (PD).

PD was named in 1817 after the British scientist James Parkinson [1]. It is the second-most-common neurodegenerative disease today, after Alzheimer's, with 1% of people older than 65 years having PD [2]. One of the main causes of PD is deficiency of dopamine in neurons. If the dopamine-producing neurons are damaged or die, PD occurs. Some major motor symptoms of PD are tremors of hands, legs, arms, or jaws, rigidity of limbs, slowness of organ movements, and weakened balance. Non-motor symptoms of PD include dementia, depression, digestive problems, sensitivity to temperature, and leg discomfort [3]. Though PD cannot be fully cured, its severity can be controlled by both invasive and non-invasive methods. Among the non-invasive methods, medicines can be used to suppress nerve impulses and improve the sense of control. The invasive methods include surgeries, such as Pallidotomy and deep brain stimulation [4]. Speech therapy can also be used to improve the patient's control over the jaw [5].

Before treatment, PD must be detected. A simple, yet useful and non-invasive method to detect PD is to check for a voice disorder, because almost 90s% of PD patients suffer from the impairment or disorder of the vocal folds. According to the literature, certain features of a voice signal can differentiate a potential PD patient from a healthy person. Little *et al.* introduced a feature, pitch period entropy, to distinguish a PD patient from a healthy subject based on their voices [6], obtaining 91.4% accuracy. A method using Big Data analytics was proposed in [7]. A method comprising an artificial neural network (ANN) and a support vector machine (SVM) was used to detect PD in [8], obtaining accuracy of 90%.

Four classifiers—neural networks, data mining, regression, and a decision tree—were investigated in [9], obtaining accuracy of 92.9%, 84%, 88.6%, and 84.3%, respectively. The data mining tool, WEKA, was used for PD detection in [10]. The Levenberg-Marquardt algorithm and scaled conjugate gradient–based MLP were analyzed to detect PD from voice signals in [11], with these two algorithms achieving 92.9% and 78.2% accuracies, respectively.

Recently, the use of cloud computing has become popular in healthcare frameworks, as cloud computing enables a framework to use large amounts of computational resources on demand. Cloud computing is characterized by on-demand self-service, secured access, resource pooling, a wide range of accessibility, and rapid elasticity [12]. A healthcare framework for patients' monitoring using a cyber-physical

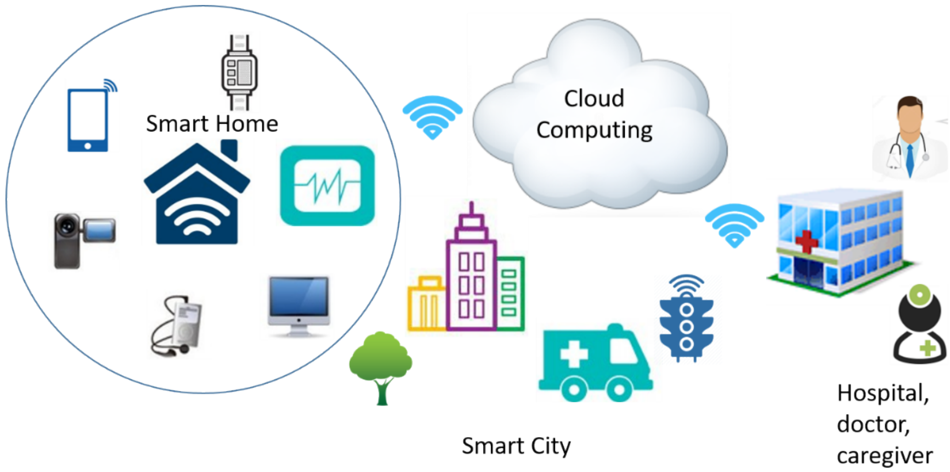

FIGURE 1. The proposed framework of the cloud-based PD detection.

system was proposed in [13], with multisensory data used to improve their lifestyles. A software defined a cloud-based telemedicine system was proposed in [14]. In this system, different sensors measured blood pressure, monitored an electrocardiogram, and measured heart rate; these data were sent to the cloud for proper automatic diagnosis, with the patient then notified of the outcome.

Hossain developed a patient state monitoring system using cloud computing [15]. This system used both speech and facial expression as inputs, obtaining better than 90% accuracy. An automatic speech-recognition system for a health-monitoring framework was proposed by Muhammad [16], using an interlaced derivative pattern on the spectrograms of client voice signals. A large-scale, portable health-monitoring system using the cloud was developed in [17], with a significant number of rural people in Bangladesh treated using this system. A cloud gaming framework was realized in [18] to support obese people by detecting users' emotions using a cloud server, with the gaming visualization changed accordingly.

In this paper, we propose a healthcare monitoring system for PD patients using cloud computing. The system takes a voice signal as input, processes the signal on the cloud server to detect whether the signal is from a PD patient or from a healthy subject, sends the results to registered doctors for a proper prescription, and notifies the client about the results and prescription. Experimental results suggest that the proposed system works quickly and reliably.

The remaining of the paper is structured as follows. Section II describes the proposed PD detection system. Section III gives the experimental setup and discusses its results. Section IV draws some conclusions.

II. MATERIAL AND METHOD

A. PROPOSED SYSTEM FOR PD DETECTION

The proposed PD detection system is outlined in Fig. 1. The framework comprises several components: a smart home equipped with sensors, the smart city, the cloud, the doctors, and the clients. The client resides in a smart home, which has many sensors, but we are interested in those that can capture voice signals, including smart phones, voice recorders, and portable computers or tablets. First, the client registered with the service provider through a web application. Second, after successfully registering, the client records a voice signal and uploads the signal for processing in the cloud. After processing, the results are sent to a doctor, who prescribes medication to the client via the cloud. The smart city controls vehicles and traffic to provide the client with the service as smoothly and early as possible.

In general, the cloud integrates both hardware and software. The software is mainly on the client side, while the hardware is mainly on the service-provider side. The cloud provides some basic services: infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). IaaS includes computing resources, storage, communication networks, virtual machines, and servers. The PaaS comprises the design, modeling, development, testing, databases, and web servers. SaaS includes the user interface, virtual desktop, and email and office applications. The client interacts with the SaaS via a web browser or mobile app. Fig. 2 shows the general structure of the cloud.

The cloud has several components, which are described below.

(i) Cloud manager: Registers and authenticates users, manages user and doctor profiles, handles communication between the client and the system management, and manages context.

(ii) Resource allocation: allocates virtual machines between sessions and distributes work to the servers.

(iii) Metering: Monitors the performance of the virtual machines.

(iv) Media content server: Stores all client, doctor, and voice signal information.

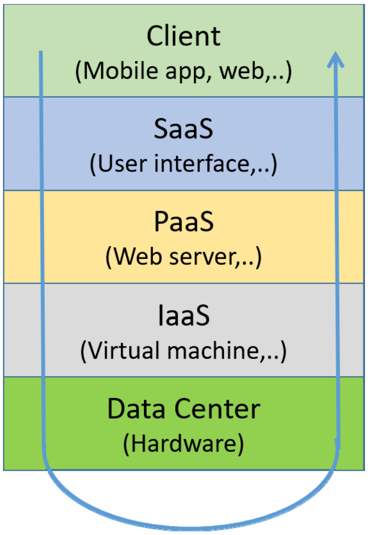

FIGURE 2. The structure of the cloud services.

(v) Sensing server: Detects voice signals received from clients.

(vi) Transcoding server: Transcodes voice signals for sending to the streaming server.

(vii) Streaming server: Manages to receive the voice signal in real-time.

(viii) Feature extraction and classification: Actually processes the voice signal in terms of feature extraction and classification.

Fig. 3 shows a block diagram of the proposed PD detection system. The client uploads a voice signal to the cloud. The cloud manager authenticates the client and receives the signal. The manager then sends the signal to the feature extraction and classification server, which extracts and selects some features from the signal, which is then classified as PD or healthy based on the selected features. Once the signal is classified, the cloud manager establishes a connection with an available registered doctor, sending the result and the voice sample to the doctor. The doctor then sends a prescription back to the cloud, and the cloud manager notifies the client with the decision and the prescription. Based on the prescription, the client obtains treatment.

The task flow of the system is depicted in Fig. 4. The tasks are listed below.

1. Request service (from client to the web).
2. Registration / authentication (to the cloud manager). First-time clients are registered, while already registered clients are authenticated.
3. Request granted (by the cloud manager).
4. Upload voice (the client uploads a voice signal to the web).
5. Send voice sample to the cloud.
6. Distribute the task among servers (by the cloud manager).
7. Send result to the cloud manager (by the servers).
8. Send sample, patient information, and result (by the cloud manager to the registered doctor).
9. Notify the registered doctor.
10. Send decision and prescription (by the doctor to the web).
11. Send decision and prescription to the cloud manager.
12. Send prescription to the patient (by the cloud manager).
13. Receive prescription (by the patient).

B. DATA

1) DATABASE 1 (DB1)

For the experiments in this study, we used data from the UCI machine learning repository [19], which was established by Max Little of the University of Oxford. The voice samples were recorded at the National Center for Voice and Speech in Denver, Colorado, USA. There were 31 male and 31 female participants, with an average age of 65.8 years (standard deviation 9.8 years). Twenty-three of the participants had been diagnosed with PD, while the remaining 39 were healthy subjects. The database comprises 195 persistent vowel phonations, of which 147 were uttered by the PD subjects. On average, each subject uttered six phonations. The lengths of the phonations vary between one and 36 seconds. [6].

a: Features

There are 22 linear and nonlinear features extracted from the voice signal. These features are fundamental frequency: F0 (Hz), highest frequency: Fhi (Hz), lowest frequency: Flo (Hz), percentage jitter: Jitter (%), absolute jitter: Jitter (Abs), relative average perturbation: RAP, pitch perturbation quotient: PPQ, average absolute difference of successive period derivatives: Jitter-DDP, Shimmer, shimmer in decibel: Shimmer (dB), three-point average amplitude perturbation quotient: Shimmer-APQ3, five-point average amplitude perturbation quotient: Shimmer-APQ5, average amplitude perturbation quotient-APQ, average absolute difference of successive amplitude derivatives: Shimmer-DDP, noise to harmonic ratio: NHR, harmonic to noise ratio: HNR, recurrence period density entropy: RPDE, detrended fluctuation analysis: DFA, pitch period entropy: PPE, correlation dimension: D2, and two nonlinear measures of pitch variations: Spread1 and Spread 2. Most of the features are extracted using the multidimensional voice program (MDVP) software [20].

2) DATABASE 2 (DB2)

We used another database for the PD. In this second database, the voice signals were recorded at the Department of Neurology in Cerrahpasa, Faculty of Medicine in Istanbul University [21]. 28 patients having the PD recorded their sustained vowel /a/ and /o/ three times each. Therefore, there were 168 recordings in the database; it can be mentioned that the database provided wave signals only for the test data, and the test data contained these 168 recordings. It is proven that the sustained vowels are good for the voice disorder detection [22]. The average age of the patients was 64.86 years with a standard deviation of 8.97. The recording was sampled at 96 kHz. As for the voice signals of the healthy subjects, we used the Saarbrucken Voice Disorder (SVD)

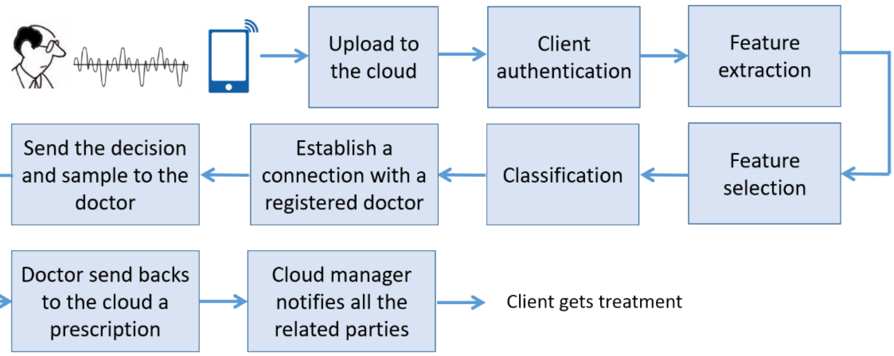

FIGURE 3. The proposed PD detection system.

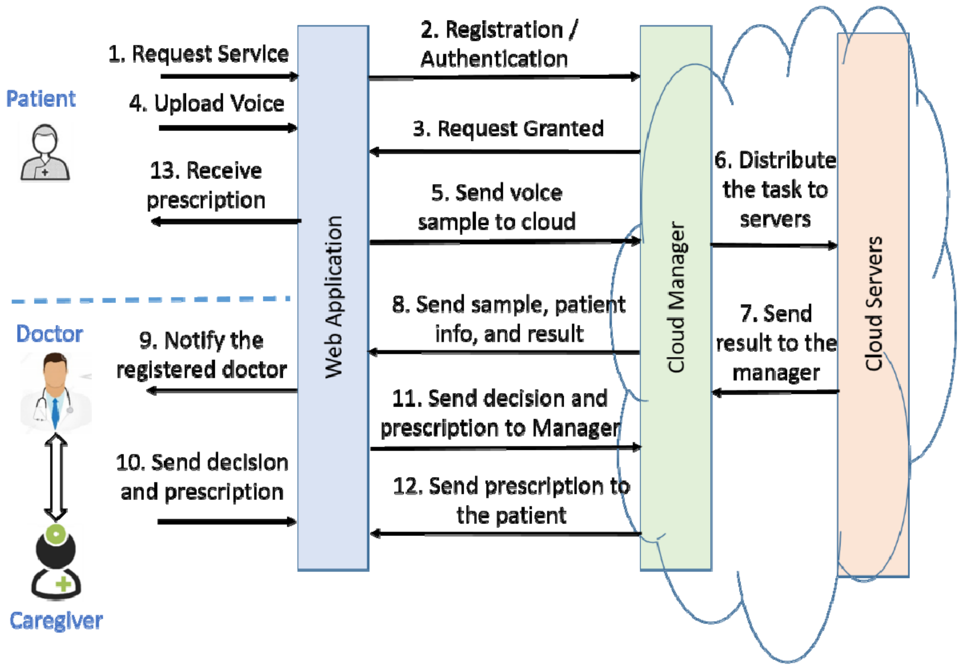

FIGURE 4. Task flow of the proposed framework.

database [23]. We chose samples of sustained /a/ and /o/ uttered by 100 healthy subjects at a normal pitch. Therefore, there were 200 recordings of the healthy subjects.

a: Features

The MDVP software was used to extract 20 features from the voice signals. The features are listed in Table 1. These features are the different measures of the fundamental frequency, pitch, and amplitude perturbation. Some of these features are also listed in the features of the first database. We chose these features because they are proven to be good in a voice disorder detection task [24], [25].

3) CLASSIFICATION

Several machine learning algorithms were investigated in this study. These algorithms are a support vector machine (SVM), an extreme learning machine (ELM), a Gaussian mixture model (GMM), and a random forest tree (RFT). These algorithms are very powerful and proven to work in many pattern recognition applications. The ELM is fast and works well with less amount of data. The SVM is a powerful binary classifier. The description of these algorithms can be found in many kinds of literature including [26]–[28].

III. EXPERIMENTAL SETUP AND DETECTION RESULTS

Each database (database 1: DB1 and database 2: DB2) was divided randomly equally into four parts. During the training, three parts were used, while the fourth part was used in the testing. This was repeated until all the four parts were tested. This technique was done to reduce the biases of the system towards any specific data.

First, we present the results using the SVM. There are several kernels in the SVM; however, we investigated only

TABLE 1. List of 20 MDVP features extracted from the voice signal.

Parameters	Parameters
Average Fundamental Frequency (F_o)	Absolute Jitter (Jita)
Average Pitch Period (T_o)	Jitter Percentages (Jitt)
Highest Fundamental Frequency (Fhi)	Pitch Perturbation Quotient (PPQ)
Lowest Fundamental Frequency (Fl_o)	Relative Average Perturbation (RAP)
Standard Deviation of F_o (STD)	Smoothed Pitch Perception Quotient (sPPQ)
Phonatory Fo-Range (PFR)	Fundamental Frequency Variation (vFo)
Length of Analyzed Sample (Tsam)	Shimmer in dB (ShdB)
Total Pitch Periods (PER)	Shimmer Percent (Shim)
Number of Segments Computed (SEG)	Amplitude Perturbation Quotient (APQ)
Peak-Amplitude Variation (vAm)	Smoothed Amp. Perturbation Quotient (sAPQ)

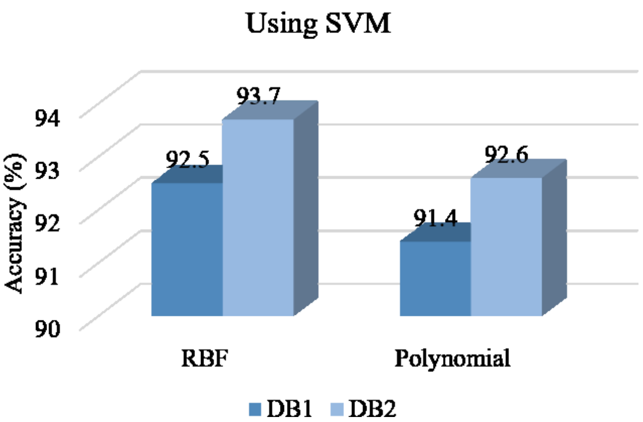

FIGURE 5. The PD detection accuracy using the SVM.

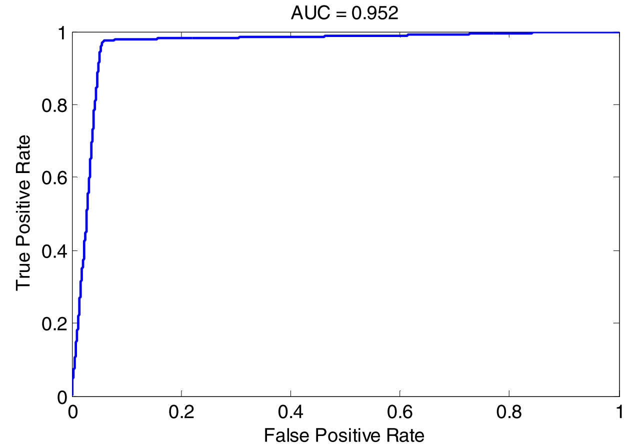

FIGURE 6. The ROC curve of the system using the SVM with the RBF kernel.

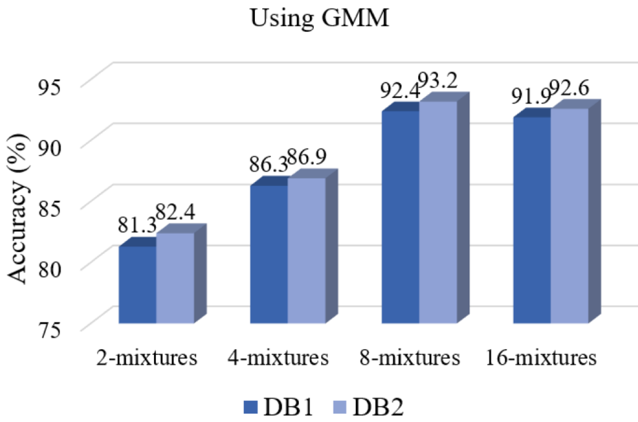

FIGURE 7. The PD detection accuracy using the GMM.

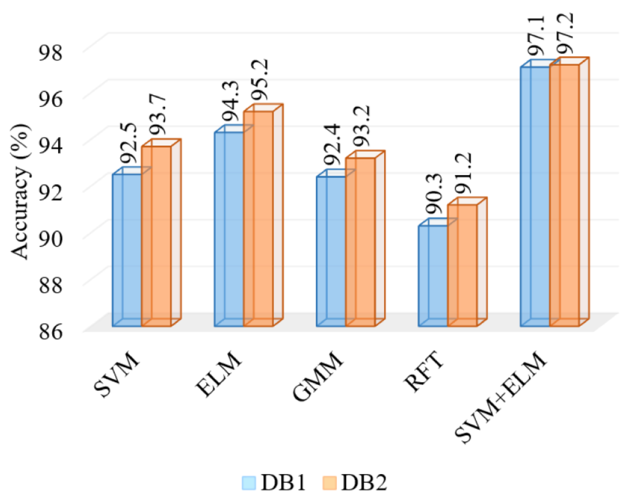

FIGURE 8. The PD detection accuracy using different machine learning algorithms.

the radial basis function (RBF) and the polynomial kernels, because these two performed reasonably better than other kernels in the literature. Fig.6 shows the PD detection accuracy using the two kernels with the databases DB1 and DB2. The figure demonstrate that the RBF kernel performed better than the polynomial kernel in both the databases. In the subsequent experiments, we used the RBF kernel of the SVM. Fig. 6 show the receiver operating characteristics (ROC) curve of the system using the SVM. The area under the curve (AUC) was 0.952.

Next, we present the results using the GMM. We chose different numbers of the Gaussian mixtures. Fig. 7 displays the accuracy of the system at various mixtures. In the experiments, we realized that the 8-mixtures produced the highest accuracy in both the databases. 2-mixtures and 4-mixtures had relatively lower accuracies.

For the RFT and the ELM, we chose the default values of the corresponding algorithms.

It is widely known that combining classifiers can accomplish great accuracy in various applications. In our proposed system, we selected the SVM and the ELM (because they achieved better performance than the other two). The scores of these two classifiers were normalized, and a final score was obtained by the Bayesian sum rule [18].

Fig. 8 shows the detection accuracies of the system using different machine learning algorithms. The last two right bars

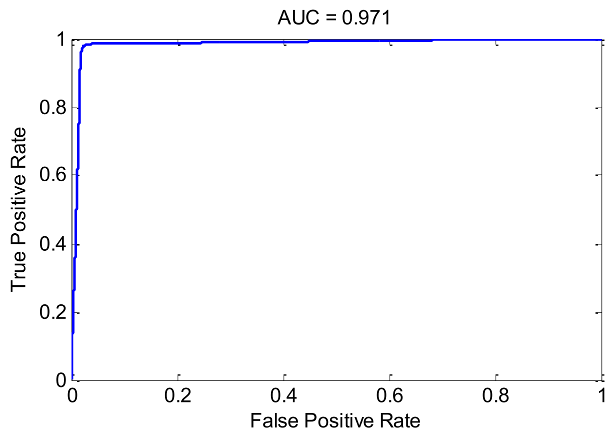

FIGURE 9. The ROC curve of the system using SVM+ELM.

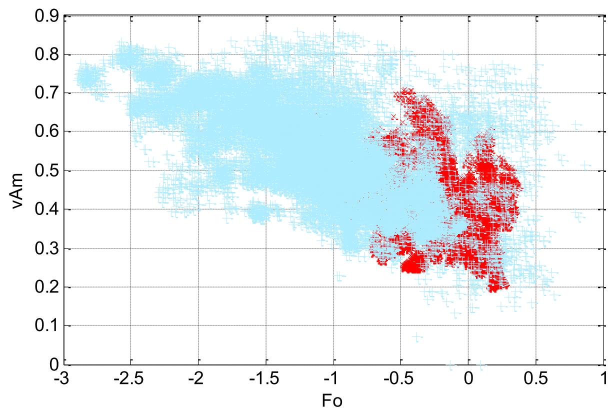

FIGURE 10. Distribution of Fo and vAm features for healthy and patient samples. Healthy and patient samples are marked by magenta and red colors, respectively.

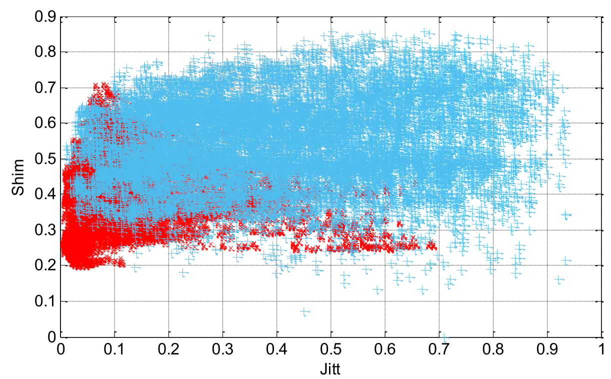

FIGURE 11. Distribution of Jitt and Shim features for healthy and patient samples. Healthy and patient samples are marked by blue and red colors, respectively.

represent the accuracies using the SVM and the ELM combined (SVM+ELM). The highest accuracies of 97.1% and 97.2% were obtained using the SVM+ELM with DB1 and DB2, respectively. The ROC curve of the system using the SVM+ELM with DB2 is shown in Fig. 9. The AUC, in this case, was 0.971. Using the ELM only, the accuracy was 95.2% with DB2.

Fig. 10 and Fig. 11 show the distribution of features of healthy and PD samples. Specifically, Fig. 10 illustrates the distribution of Fo and vAm features, while Fig.11 shows that of Jitt and Shim features. From these two figures, we see that only two features at a time are not good enough to distinguish healthy and PD samples.

TABLE 2. Accuracy comparison between the systems.

Systems	Accuracy (%)
[29]	91.8
[6]	91.4
[30]	92.8
Proposed	97.1

Table 2 gives an accuracy comparison between different related systems. All the systems mentioned in the table used the same database (DB1). The systems mainly differed in the classification part. The accuracies of the references systems were obtained from the corresponding papers. From the table, we observe that the proposed system outperformed all other systems by a momentous number. From this observation, we can say that combining classifiers is a good option to improve the accuracy.

IV. CONCLUSIONS

A PD monitoring system over the cloud was proposed. A complete framework for this system was also given. Two different databases were used for the experiments. Four different machine learning algorithms (classifiers) were investigated. In the experiments, the ELM and the SVM produced the best results, followed by the GMM and the RFT. The best PD detection accuracy was obtained by combining the two classifiers: ELM and SVM. The proposed system achieved more than 97% accuracy with both the databases. This accuracy is momentously higher than that of other related systems.

In a future work, we will explore the performance of the whole framework in a real-life scenario.

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