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Research article

PD-DETECTOR: A sustainable and computationally intelligent mobile application model for Parkinson's disease severity assessment

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ABSTRACT

This paper introduces a mobile cloud-based predictive model for assisting Parkinson's disease (PD) patients. PD, a chronic neurodegenerative disorder, impairs motor functions and daily tasks due to the degeneration of dopamine-producing neurons in the brain. The model utilizes smartphones to aid patients in collecting voice samples, which are then sent to a cloud service for storage and processing. A hybrid deep learning model, trained using the UCI Parkinson's Telemonitoring Voice dataset, analyzes this data to estimate the severity of PD symptoms. The model's performance is noteworthy, with accuracy, sensitivity, and specificity metrics of 96.2 %, 94.15 %, and 96.15 %, respectively. Additionally, it boasts a rapid response time of just 13 s. Results are delivered to users via smartphone alert notifications, coupled with a knowledge base feature that educates them about PD. This system provides reliable home-based assessment and monitoring of PD and enables prompt medical intervention, significantly enhancing the quality of life for patients with Parkinson's disease.

1. Introduction

Parkinson's Disease (PD) is mainly caused by the gradual decay of dopamine secreting neurons which results in motor abilities degeneration and abnormal brain activities [1]. Studies suggest that people mainly at a higher age are more vulnerable to PD, as only about 4 % of people below 50 are diagnosed with PD. There are various symptoms of PD like slowed movement, rigid muscles, change in speech, writing variation, etc. as shown in Fig. 1. Though this disease's root factor is unknown, researchers have predicted that specific mutation genes and toxic chemical exposure are causes of this disease [2]. This disease severely affects the quality of life of a person by affecting regular motor and non-motor activities. It also hinders their social interaction by affecting their speeches. As PD treatment is expensive, the financial condition of the patient worsens as well. The most common motor activity that gets affected is the quality of speech and, at times, difficulty in speaking. These activities do not affect all persons at the same stage but worsen over time like voices getting softer, whispery, or hoarse with time. The voice generally becomes a kind of monotone and lacks the general ups and

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downs, which causes difficulty in understanding for the listeners.

The changes in the voice of the patient are identified by analyzing the patient's voice data. The voice becomes stuttered and gets more affected as the disease gets severe. There are different scales developed for assessing the stage of PD [3]. Among them, the Unified Parkinson's Disease Rating Scale (UPDRS) is the most widely used scale [4]. The UPDRS is evaluated by different metrics like assessment of behavior, mood, and assessment of daily activities like speaking, swallowing, cutting food, drawing, handwriting, and medical monitoring-based motor assessment. Through speech variations of patients, it is possible to analyze the progress of this disease by applying modern technology-based frameworks involving predictive analytics, cloud computing, and mobile healthcare.

1.1. Related works

Inspired by recent information technologies, proper observation of PD-related health metrics along with appropriate assessment model development can be done to regulate its severity level. A lot of research has been done for the detection of PD but not much has contributed to the severity analysis. All these works have mainly used machine learning as a tool. In a survey by Das et al. [5] on the application of diagnosing the disease by different classification techniques, neural networks performed as a better classifier than decision tree and regression. Genain et al. [6] used a Bagged decision tree to predict the severity of the disease from the voice signals of the patients and found an improvement of 2 % accuracy. Maleket et al. [7] used a dataset containing 40 features and selected 9 most suitable features based on Local Learning Based Feature Selection (LLBFS) to classify Parkinson's into four major labels namely Healthy, early, Intermediate, and advanced based on UPDRS score. The use of dynamic machine learning algorithms to identify the severity of tremors and Dyskinesia was studied in Ref. [8]. Cole et al. [8] used wearable sensors to extract the required data. To further improve the data collection, Angeles et al. [9] have developed a sensor system to record kinetic data from the arm that can assess symptom severity changes during Deep Brain Stimulation Therapy. Nilashiet al. [10] developed a new hybrid intelligent system by combining a fuzzy inference system and support vector machine (SVM) based regression to predict PD progression. Chen et al. [11] have proposed a new diagnostic system for the detection of Parkinson's Disease using principal component analysis (PCA) for the extraction of features and Fuzzy k-nearest neighbors (KNN) for the classification. Polat [12] proposed a model using Fuzzy C means (FCM) clustering and KNN for the detection of Parkinson's Disease. Åström and Koker [13] used a Parallel feed-forward Neural network to detect Parkinson's Disease and then the predicted output was compared against a rule-based system to make the final decision. Li et al. [14] suggested using a fuzzy-based nonlinear method where PCA is used to extract the features and SVM helps in the prediction of the PD. Hariharan et al. [15] have suggested an intelligent system using clustering feature reduction and classification methods for the diagnosis of PD. Indira R. et al. [16] proposed a machine learning algorithm that helps in the automatic detection of PD through the voice samples or speech of the person. Here the model used fuzzy C means clustering and pattern recognition-based approach to differentiate between a healthy and a PD affection person and achieved an accuracy of 68.04 %, 75.34 % sensitivity, and 45.83 % specificity. Tsanas et al. [17] have used feature selection, random forest, and support vector machines to detect PD and achieved a classification accuracy of 99 % using only 10 dysphonia features. Shahbakhi et al. [18] also suggested that PD can be predicted using a Genetic Algorithm (GA) and SVM. Das et al. [19] made a comparative analysis between Neural networks, Data Mining Neural analysis, Regression analysis, and Decision Trees and achieved an accuracy of 92.9 %, 84.3 %, 88.6 %, and 84.3 % respectively on Parkinson's data. The detection of Parkinson's Disease was based on statistical software suite (SAS) software. Ene M. et al. [20] proposed a probabilistic neural network (PNN) to distinguish between a healthy and a Parkinson Disease disease-affected person. Three types of PNN are used in the classification process namely: incremental search (IS) Monte Carlo search (MCS) and Hybrid Search (HS). The accuracies are found between 79 % and 81 % for the undiagnosed patients. Wu S et al. [21] have proposed various

Fig. 1. Common Symptoms of Parkinson's disease.

techniques like regression, decision tree, and neural network analysis to analyze the dataset of Parkinson's Disease and calculate the probability of error. The error probability by Logistic regression, classification, and neural network was 5.15 %, 8.47 %, and 23.73 % respectively. Yadav, G. et al. [22] proposed two classifiers like statistical classifiers and a support vector machine to distinguish between a healthy and Parkinson affected person. Support Vector Machine provides a classification accuracy of 76 %, sensitivity of 97 %, and specificity of 13 %. All these comparative studies are evaluated using University of California at Irvine (UCI) telemonitoring-based voice dataset. Fourteen main features of the voice signal were extracted, based on F0 (fundamental frequency or pitch), jitter, shimmer, and noise-to-harmonics ratio. The performance of different classification algorithms on Parkinson's data is provided in Tables 1–3.

Apart from the discussed existing works, some of more latest technological advancements in the context of Parkinson's disease assessment are also observed. In Ref. [24], T. Exley et al. performed a two-stage feasibility analysis on Parkinson's disease. An out-of-the-box quiet standing feature was evaluated to estimate the UPDRS-III score that relates to the severity level of motor risks. Secondly, using this additional feature for the detection of motor symptoms. R. Kaur et al. [25] discussed the impact of a vision-driven prototype to predict Parkinson's disease (PD) gait dysfunction and multiple sclerosis (MS). Here a data-oriented model was presented to categorize walking style in multiple sclerosis patients as well as patients with Parkinson's disease, which may be found across various walking subjects. In another work, M. Ullrich et al. [26] compared various data aggregation methods and predictive models for the estimation of fall risks utilizing gait metrics defined from regular recordings or unlabeled gait validations. Random forest achieved the optimum balanced accuracy of 74 %. Similarly S. Mazilu et al. Another research [27] studied skin-conductance and electrocardiography on 11 persons who had freezing of Gait issues and observed visible variation in the data readings before the gait freezing in comparison to usual walking. Later an anomaly-enabled method was designed to predict freezing of gait from vital skin-conductance attributes. A prediction accuracy of 71.3 % among 184 gait freezing data having a mean of 4.2 s before the freeze round was noted. A four-step automated Parkinson's disease assessment model driven by mixed emotional facial expressions was proposed by W. Huang et al. in Ref. [28]. At first, facial scans comprising six main expressions are synthesized through an adversarial learning approach. Then an efficient screening technique is designed to analyze synthesized image quality thereby selecting the superior quality scans. It is followed by training the raw face scans of PD patients, good quality images, and the normal facial scans from publicly available datasets applying a deep attribute extraction method with a face expression classifier. At last, this system-trained model was used to retrieve different expression features to differentiate a PD patient from a normal person. Table 4 summarizes the pros and limitations of the relevant works conducted in the PD analysis.

As discussed, various existing literature are available in context to PD risks assessment but still some visible limitations are there. Most of the existing models were trained with a very small dataset and the accuracy of prediction is reasonable. Even if a few models generated good accuracy, their interfacing with the user is complex. There exists no model that provides a more personalized diagnosis of PD symptoms in patients. also the models lack alert notification functionality to close contacts of the elderly patients in emergency scenarios. Moreover, most of the models lack real time validation in clinical settings. Our proposed model aims to overcome these limitations by introducing a novel and effective smart phone operated PD detection tool which is more reliable, robust and easy to use for users. It is tested with different datasets which make sit more generalizable and scalable. Here not only the patients will be notified but also alert will reach their close contacts if any discrepancy arises. The proposed model also provides high security with proper clinical validation.

1.2. Motivation and contributions

As the people affected with Parkinson's Disease have symptoms like vocal and speech impairments it is possible to track the progression of this disease by analyzing the voice signals. A predictive approach comprising phases like pre-processing, feature retrieval, and classification for Parkinson's Disease analysis can be employed. However, the effectiveness of the classifier depends on the feature extraction method used. Also, another vital issue faced in predicting PD risks through voice signals is the selection of a suitable classification model that can operate with semi-structured voice data. Traditional classification methods like Decision Tree (DT), Support Vector Machine (SVM), and Naive Bayes (NB) give reasonable outcomes but with compromised efficiency. However, deep learning techniques have been seen to perform significantly better in handling less structured data like audio and voice instances.

Table 1
Accuracy analysis of existing relevant works on Parkinson's dataset [23].

Machine learning	Data description	Accuracy
fuzzy C- means	Speech signal dataset	68.04 %
SVM	Age and voice recording	76 %
SVM	Speech signal dataset	85.29 %
Nested SVM	Speech dataset	93.5 %
Neural network (NN) classifier	Speech signal dataset	92.9 %
PNN	Voice recording dataset	92.9 %
Bayesian Naive Classifier (BNC)	Video recordings	74.31 %
Linear discriminant analysis (LDA)	Gait patterns	95 %
Decision Tree	Recorded speech signals	95 %
Random Forest	Voice dataset	90.26 %
Multi-Layer Perceptron (MLP)	Audio Input	93.22 %
Fuzzy entropy	Voice recording	84.52 %
KNN	Speech dataset	93.3 %

Table 2
Sensitivity analysis of existing relevant works on Parkinson's dataset [23].

Machine learning	Data description	Sensitivity
fuzzy C- means	Speech signal dataset	75.34 %
SVM	Age and voice recording	34 %
SVM	Speech signal dataset	70.12 %
ANN	PD dataset	87.5 %
Nested SVM	Speech dataset	90.53 %
SVM	Magnetic resonance imaging (MRI)	90 %
GA-SVM classifier	microarray dataset	92 %

Table 3
Specificity analysis of existing relevant works on Parkinson's dataset [23].

Machine learning	Data description	Specificity
fuzzy C- means	Speech signal dataset	45.83 %
Nested SVM	Speech dataset	93.83 %
SVM	Speech signal dataset	92.8 %
SVM	Magnetic resonance imaging (MRI)	85 %
GA-SVM classifier	Microarray dataset	95 %

Table 4
Previous works details in context to PD assessment

Previous works	Advantages	Limitations
Das et al. [5]	Comparison of different classifiers was cohesively done and the evaluated performance was satisfactory.	The model was restricted to few classifiers only and it was tested on only one dataset.
Genain et al. [6]	The model was tested upon two different data samples with multiple classifiers to compute the PD severity level and it resulted in an increase in accuracy rate.	The model suffered from overfitting as less less records were considered for evaluation and it lacked any clinical validation.
Cole et al. [8]	The smart model intended to track the severity degree of PD symptoms by using machine learning algorithms and sensors. The error rate was quite less.	The developed model was not so generalizable and scalable. Also clinical validation of the model was lacking.
Nilashiet al. [10]	The model used data preprocessing along with an integration of clustering and classification. Remote motioning of patients was feasible.	A predetermined PD dataset was used and a fixed data records for training a cluster was used. Also the computational delay was quite high.
Polat [12]	The model is an offline deployed approach which uses a clustering method to map a linearly non separable data to a separable set thereby enhancing class label performance. It uses two different datasets.	The model is not so robust and reliable for personalized PD diagnosis. Also there is no provision to send notification to close contacts.
Indira R. et al. [16]	The model is an automated PD detection method using speech or voice data and applying cluster analysis with pattern recognition on the dataset.	The accuracy of prediction can be improved while the model's scalability and reliability can be enhanced by using more advanced mobile healthcare technology.
Chakraborty et al. [19]	The model is capable to capture and learn inter-dependencies among sequential data samples. Also it can deal with complicated patterns in continuous data of PD risks.	The model suffers from overfitting mainly when dealing with restricted datasets.
Ene M. et al. [20]	Objective of the study was to validate the efficiency of probabilistic model in PD detection and it involved varying features based attributes.	The model lacks generalization of data samples and is also not secure and easy to use.
Yadav, G. et al. [22]	The main purpose is to develop an effective machine learning model using speech dataset for symptoms determination of PD disease.	The model is not clinically validated and security of the model is unknown.

These deep neural networks use multiple input layers integrated to build feature selection and classification models. Also, with the constant growth of smart sensors, cloud resources, and ubiquitous computing online access from smartphones has accelerated the emergence of telemedicine approaches to track critical symptoms and physiological signals. Embedded sensory units with powerful processors in advanced smartphones make them efficient and cost-effective. With this evolution in mobile technology and deep learning techniques, it is technically feasible to extend monitoring of PD risks from usual medical centers oriented analysis to the remote home-enabled ambiance and determine its severity level in patients.

The main contributions of the research work include the following.

1. We present a novel deep learning-based mobile cloud-driven telemonitoring healthcare model 'PD-DETECTOR' to assess the severity level of Parkinson's disorder at an early phase.

2. The model supports an interactive telemonitoring detection system designed to remotely monitor the patients' PD risk level by analyzing the voice data collected through smartphones. Moreover, early-stage PD risk level is notified to patients and corresponding caretakers with recommendations.
3. A cooperative amalgam of min-max normalization and correlation coefficient feature selection-based dataset optimization is used. While min-max normalization standardized the voice samples, correlation coefficient feature selection eliminated less relevant features.
4. The model was evaluated in a resource-constrained setting and it generated reliable outcomes. While the computed accuracy, sensitivity, and specificity metrics were 96.2 %, 94.15 %, and 96.15 respectively, the overall computational delay recorded in smartphones was only 13 s thereby delivering optimum performance.

The rest of the paper is organized as follows. Section II discusses the problem formulation and system model. Section III presents the proposed PD-Detector model for Parkinson's disease assessment. Implementation analysis and outcomes are further highlighted in Section IV. The work is concluded in Section V.

2. Problem formulation and system model

This section presents the formulation of the problem, the PD dataset used in the study, and the system model of the proposed Parkinson's disease assessment framework.

2.1. Problem formulation

The main issue of the existing works is the lack of a robust and reliable easy to use framework for PD disease assessment. Patients have to rely on regular physical visits to healthcare centers for treatment. But recently technology has made significant advancements in the healthcare sector. Telehealth service is the latest innovation to capitalize upon. The purpose of this work is to develop and provide a more personalized and accurate model to facilitate reliable usage of the model by Parkinson's patients for accurate outcomes based on voice data received from patients. Motivated by the existing problem, we develop a novel mobile-based deep learning model for Parkinson's disease assessment using voice data of patients. The voice data samples are trained with a DNN model. Later using a patient's voice, the severity level of Parkinson's disease is detected and the outcome is communicated through the smartphone. If the risk is high then the report is also sent to the patient's close people and medical experts if recommended by the patient through cloud storage. Apart from this, information and the latest news related to Parkinson's disease are continuously broadcast to patients regularly.

2.2. Dataset used

The developed DNN-based predictive model takes the Parkinson's disease dataset as input. The dataset is publicly available at the University of California at Irvine (UCI) repository [29]. The data consists of a wide variety of voice modulations of 31 individuals

Table 5
Features and UPDRS scores of the Parkinson's telemonitoring dataset

Feature Label	Description
MDVP:Fo(Hz)	Mean vocal fundamental frequency
MDVP:Fhi(Hz)	Highest vocal fundamental frequency
MDVP:Flo(Hz)	Lowest vocal fundamental frequency
MDVP:Jitter (%)	Measures of variation in fundamental frequency
MDVP:Jitter (Abs)	
MDVP:Jitter:RAP	
MDVP:Jitter:PPQ	
Jitter:DDP	
MDVP:Shimmer	Several measures of variation in amplitude
MDVP:Shimmer (dB)	
Shimmer:APQ3	
Shimmer:APQ5	
Shimmer:APQ11	
Shimmer:DDA	
NHR	Measures of ratio of noise to tonal components in the voice
HNR	
RPDE	Nonlinear dynamical complexity measure
D2	
DFA	Signal fractal scaling exponent
PPE	Nonlinear measures of fundamental frequency variation
Spread1	
Spread2	
Status	Health status of person (low) - Parkinson's, (high) - healthy

among which 23 are affected with Parkinson's diseases denoted in Table 5. Every column denotes a specific voice variation while every row represents one of the 195 tone samples among those individuals. The purpose of the dataset is to distinguish between people affected with Parkinson's disease from the healthy ones.

2.3. System model

This section discusses the proposed mobile-driven intelligent detection model for Parkinson's risk in patients. In this research, authors developed and evaluated a mobile cloud-based predictive healthcare framework for Parkinson's disease home-based monitoring and assessment. The model assesses users' performance by capturing voice sample data using the smartphone, identifying key symptoms, and estimating symptom severity based on the captured data. Relying upon the detected outcome, alert notification and disease risk awareness information are communicated not only to the user but also to the user's close people and the selected predefined medical experts if the severity level is high. In this model, the system architecture consists of the deep neural network (DNN) based predictive approach, and the smartphone functionality is integrated into the model. The proposed DNN-based predictive methodology for predicting Parkinson's disease severity is outlined in Fig. 2. The proposed framework is used in a node with Intel Core i5-5200U CPU @2.20 GHz and 8 GB RAM. The Python library, TensorFlow implements the Deep Neural Network.

At first voice instances of patients affected with PD are gathered for processing. This dataset which consists of recordings from 42 patients is collected from an open source UCI repository and it is in ASCII.csv form. The reliability of these voice samples is determined by applying Wiener filtering method which is a low pass filter and it reduces the mean square error between the desired filtered voice sample and the voice sample with noise. Further the filtered voice samples are subjected to a noise cancellation approach which uses a noiseless background sample and the target voice sample. It then compares the two samples where the irrelevant background noise is detected and removed through suitable adjustment of the filter parameters that are suited to variation in the noisy settings.

The aggregated noise free data is initially normalized and thus organized into columns and tables thereby resembling a relational database to decrease the redundancy and enhance integrity of data to make it more consistent. Min-max normalization is used to normalize it within the 0–1 domain range as depicted in equation (1).

$$Norm(d) = \frac{d - min(d)}{max(d) - min(d)} \tag{1}$$

Where d denotes the value of the attribute while min(d) and max(d) represent the minimum and maximum values of that attribute respectively.

The normalized dataset is subjected to feature selection using the correlation coefficient method. It primarily determines the features which exhibit a high association with the class label. Let us assume that every feature constitutes a value set {p1, p2, … …, p_k}

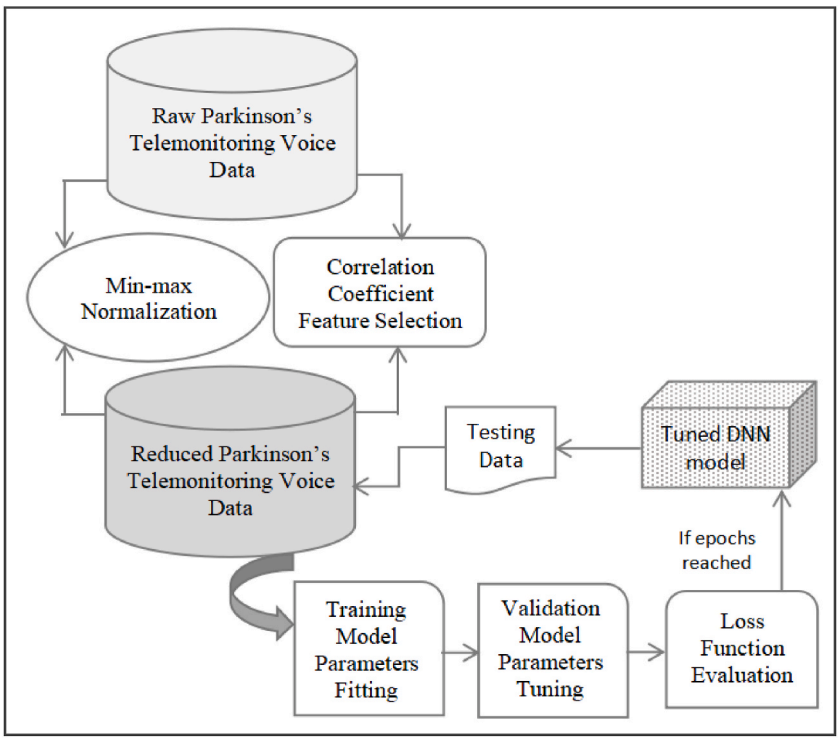

Fig. 2. Process flow of the hybrid DNN model.

for instances 1 through k at vector P while the respective labels may be denoted as {q1, q2, … …,q_k} saved at vector Q. Thus here the correlation coefficient ($Coef_{PQ}$) for every feature may be determined as shown in equation (2).

$$Coef_{PQ} = \frac{\sum_{i=1}^{k}(p_i - p')(q_i - q')}{\sqrt{\sum_{i=1}^{k}(p_i - p')^2}\sqrt{\sum_{i=1}^{k}(q_i - q')^2}} \tag{2}$$

Equation (2) generates a value in the range [−1,+1] where +1 gives the highest correlation, 0 gives zero correlation and −1 gives the minimum correlation with the class label. Student's t-distribution statistics is used to compute p-values for mapping of correlations. Features with p-values less than 0.05 in the correlation coefficient vector are chosen.

After the feature selection process, training of the model happens with Deep neural networks (DNNs). It uncovers complex patterns in the voice PD data samples using a back-propagation procedure by applying the error function, which is the net difference between actual output and predefined output value expected to update the internal weight values. During the training phase, the labeled voice data is the input to the model and it possesses two parts. While the first part contains information regarding all attributes of the PD data domain, the second part possesses information regarding association to a specific target. Post training phase, the loss function is determined and it computes the error between the model's outcome and the predefined target expected. DNN has many adjustable weights with labeled samples used for training, and these weights are adjusted to enhance the model's efficiency. The gradient vector is calculated for better adjustment of the weight vector. Adam is the optimization method used to update the network weights in the training phase. This method utilizes first and second gradients for computing individual dynamic learning rates for various network weight values.

Another method called regularization is applied to decrease the generalization error to enhance the performance of the model using testing voice data by penalizing the weight vectors of nodes. This technique restricts the model's functionality by adding a metric penalty with the loss function. The L2 metric penalty called weight decay is widely used for this purpose. This L2 regularization retrieves the weight near to origin by adding a term $\phi(\theta) = \frac{\|w\|^2}{2}$ with the loss function. This term concerning L2 is denoted in equation (3).

$$Cost\ function = loss + \frac{\beta}{2m} * \sum \|w\|^2 \tag{3}$$

Where β represents a regularization parameter whose value is to be optimized for optimal performance.

In this work, we employ a deep learning model that consists of five hidden layers where the first three layers contain 64 neurons, and the last two layers contain 32 neurons as depicted in Fig. 3. To normalize the input data at each layer batch-normalization is used. Batch normalization also helps to coordinate the updation of weights in each layer by diminishing the internal covariance shift problem that takes place due to back-propagation. The details of the deep learning model are illustrated in Fig. 3. Due to the presence of multiple hidden layers, deep learning models are prone to overfitting. In overfitting, the training error decreases but the test error does not decrease. To avoid overfitting the deep learning model, we have added dropout layers with every hidden layer. The role of a dropout layer is to randomly ignore or drop the output of some neurons in that layer. This helps to regularize the data and thereby, mitigating the problem of overfitting. It has been observed that without the dropout layers, the accuracy of the same deep learning model drops by 3–4%.

In the case of Total-UPDRS, the range of score lies in between [5.0377, 54.992] while for Motor-UPDRS, the range is specified in the domain [5.0377,39.511]. Here the training and testing samples are created by partitioning the normalized data in the ratio of 80:20. Also, the training and testing set is built separately for both Total-UPDRS and Motor-UPDRS scores, thereby retaining these values as output in their respective directory. 'High' and 'Low' represent the output class labels. The predefined domain values for the metric are highlighted in Table 6.

Thus the model develops an input pipeline and iterates over the input voice samples providing random shuffling over the samples to

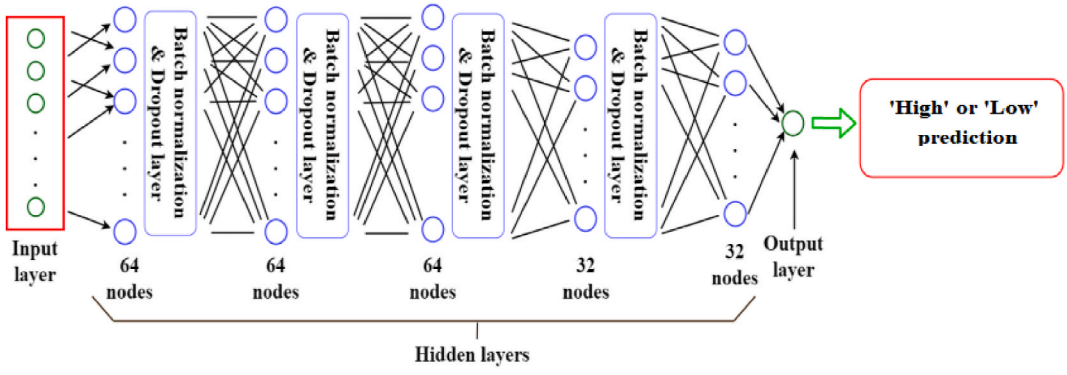

Fig. 3. Proposed DNN model.

Table 6
Severity Class range

Severity Level	Total-UPDRS	Motor-UPDRS
High	Above 25	0–25
Low	Above 20	0–20

create randomness. The DNN model after being successfully trained performs evaluation as well as prediction of new voice samples into its corresponding risk label. The parameter tuning values are represented in Table 7.

The evaluation of the developed DNN-based prediction model is performed using statistical error rates like mean absolute error (MAE) and root mean square error (RMSE). From these values, the coefficient of determination (R^2) is computed. The corresponding evaluation metrics are represented by equation (4) to equation (6).

$$MAE = \frac{1}{k}\sum_{i=1}^{k}\left|q_i'' - q_i\right| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{k}\left(q''_i - q_i\right)^2}{k}} \tag{5}$$

$$R^2 = 1 - \frac{\sum\left(q_i - q''_i\right)^2}{\sum\left(q_i - q'_i\right)^2} \tag{6}$$

where q_i, q'_i, and q'_i are respectively the actual value, predicted value by the method, average of [q_1, q_2, …, q_k], and n denotes the entire number of samples.

3. Proposed PD-Detector model for Parkinson's disease assessment

This section highlights the proposed smartphone-based PD-Detector model. The developed model presents a mobile application of a deep neural network-driven predictive model for Parkinson's disease risk assessment. Embedding a predictive learning model onto a smart phone application needs robust mapping to a mobile enabled template. In this study, TensorFlow Lite which is a version of TensorFlow framework is used to execute the DNN model on the mobile app. It facilitates several modules and interfaces required to compile and execute any machine learning model on smart phone. Training the DNN based predictive model in a smart phone application is an uphill task since it needs extensive computational resources which these smart phones are unable to facilitate. Also, the predictive analytics based libraries rarely have in-built APIs to access the framework embedded on mobile device storage. Thus, a client server model is deployed here such that the DNN model is trained and located at cloud server end. The mobile application 'PD-Detector' is the client here and its requests which are the input to the model are accepted by server. The outcome is predicted by the model and is communicated to the mobile app as its response. The mobile end acts as an interface to accept input parameters and to display outcome. The processing tasks are performed by the cloud server. The mobile app communicates with server through XML template.

Here, the mobile device is connected to the cloud server using mobile cloud technology which operates by redirecting between data on smart phone and that on the cloud. It permits an user to execute the 'PD-Detector' app on his smart phone by sending requests on smart phone to cloud over world wide web. The smart phone should have compatibility with the cloud to be accessible and the cloud's mobile application is to be installed on the user's phone. By opening the app and uploading relevant details to user's private cloud interface, the cloud interface can be enabled to access for remote processing.

The designed intelligent DNN-based predictive model for Parkinson's disorder detection among elderly citizens integrates into a reliable and secured mobile healthcare prototype, as illustrated in Fig. 4.

The user is well equipped with a working smartphone is a minimum prerequisite. The model exclusively takes into account the voice samples of users as the dataset. The voice sample of the elderly user can be captured on his smartphone at the desired time. The

Table 7
Setting and tuning of parameters

Parameters	Values
Optimizer	Adam
Learning Rate	0.002
Activation function	ReLu
Loss function	Mean Absolute Error (MAE)
Dense hidden layers with neurons in each layer	6 with 64, 64, 64, 32, 32, and 1
Regularization method with value at each layer	Dropout layer
Batch size	10
Epochs	200

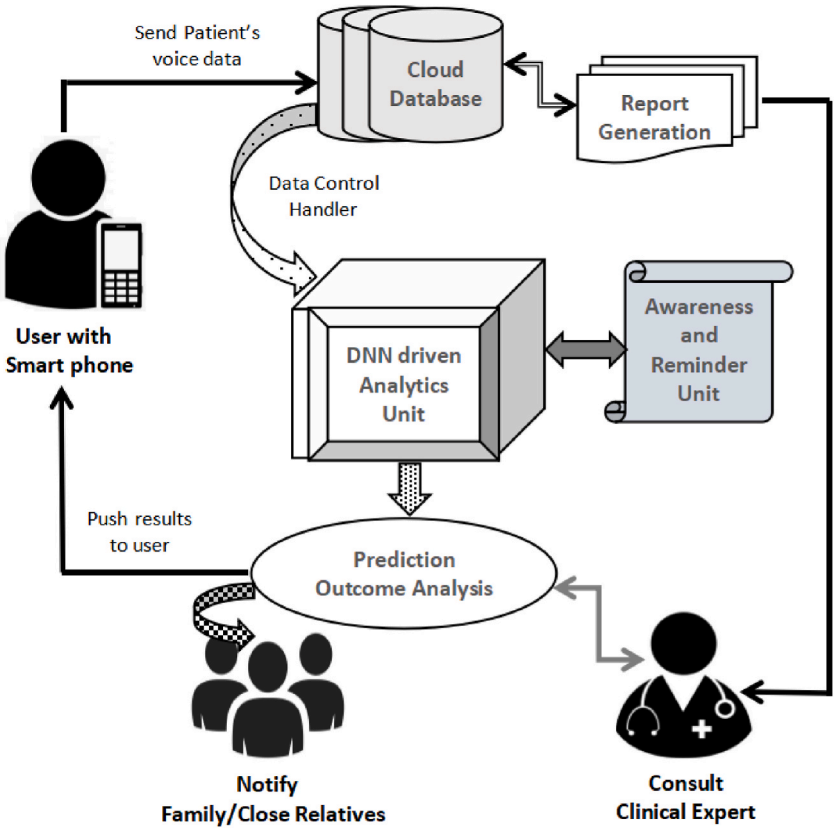

Fig. 4. Proposed m-healthcare model for intelligent Parkinson's disease assessment.

newly recorded test voice data is transmitted to the centralized cloud data repository for storage and processing. The model constitutes a cloud database that stores numerous voice data instances with the labeled severity level, which together act as the training dataset. The DNN-driven analytics unit is trained to utilize this dataset. Also, the data records of a specific user are made available in the cloud over a predefined period of 3 years which can be later used for analysis as well as generation of his health report concerning Parkinson's symptoms. The test voice sample is carried by the data control handler to the DNN-driven data analytics unit. The handler is an application program routine that forms a user-defined interface between the cloud database and the analytics unit. The voice data is validated in the analytics unit which determines whether the user is affected with Parkinson's risks or not. The predicted outcome is communicated to the user and he gets an alert message on his smartphone. Thus the cloud application is responsible for processing the received voice sample through a pipeline thereby estimating the severity level of PD risk and this result is communicated to the user's smartphone. Also if the predicted risk level is severe then his family members or his close people as well as consulting doctors are instantly notified. Whenever any testing of a new voice sample takes place, the 'Awareness and Reminder Unit' is auto-activated. This unit provides various information related to PD risks and the concerned user is notified about every aspect of Parkinson's disease like symptoms, causes, precautions, recent PD-related news and events, dos & and don'ts along with clinical remedies available. This helps in alerting the elderly user regarding the disease risks so that accordingly his health diet and lifestyle can be taken care of at the right time. Apart from this, all information and analytical outcomes are stored in the cloud repository that may be used to track disease test history. If any serious ambiguity or deviation from the normal pattern is detected in the generated report then a text alert notification will reach the chosen medical expert of the user. The privacy of user's data is ensured at the mobile app phase as well as at the data communication level. The user is required to log in to the mobile app on his smartphone to carry out the risk detection test and scan test history. Application level information is available only on the concerned user's mobile space and this data is dropped from the local device once it is sent to the cloud. The mobile app is not configured to retain and show any user-related identity details.

The important functionalities provided by the developed m-healthcare predictive model for Parkinson's risk detection are discussed here. The mobile app is made up of different operational interfaces. 'User Log-In' as shown in Fig. 5(a) is the first interface where registered users need to log in to the app using their ID and password. Then only they can evaluate themselves using PD tests. First-time users must register once to utilize its service.

After the user has successfully logged on to the app, he is directed to the 'Test and Upload' interface which provides different vital features as depicted in Fig. 5(b). Users can take note of their last visit-related information. Also, he can view all the previous test details and its outcome. Also, a separate link is provided to generate the previous reports if needed. At the bottom, a new voice sample can be uploaded using the upload button link. Upon successful uploading, a message "Upload Success" will appear on his smartphone, as

Figure 5(a)

Figure 5(b)

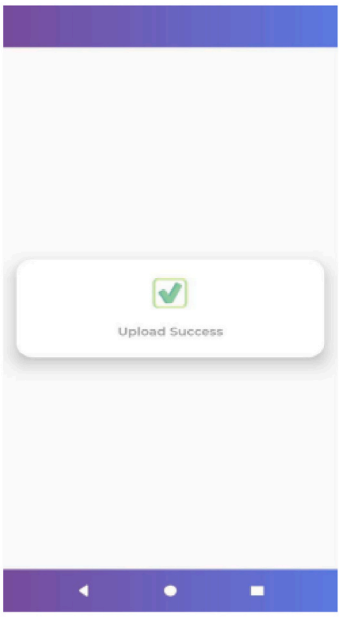

Figure 5(c)

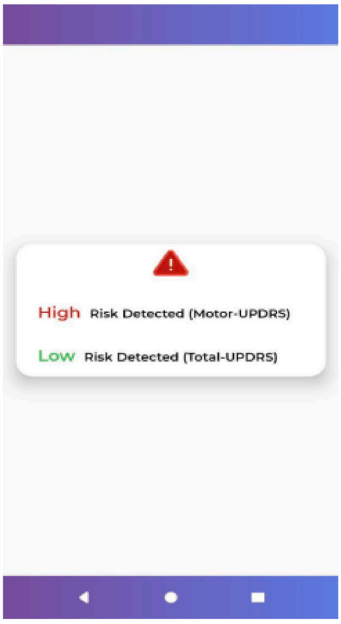

Figure 5(d)

Figure 5(e)

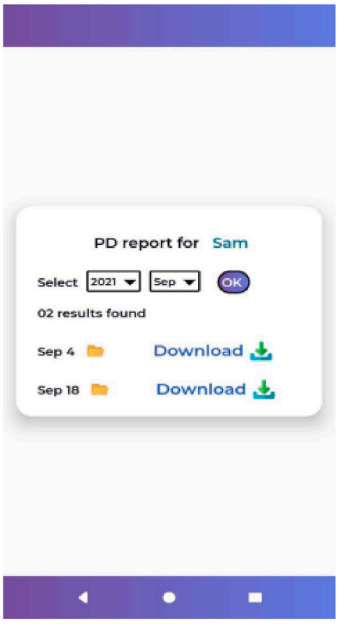

Figure 5(f)

Fig. 5. (a)Fig. 5(b) Fig. 5(c) Fig. 5(d)Fig. 5(e) Fig. 5(f).

shown in Fig. 5(c). Then in a quick time, the result will be generated as an alert box notification, as illustrated in Fig. 5(d). The DNN-driven analytics unit is responsible for processing and evaluating the prediction outcome. This will notify the user regarding the level of severity of PD risk detected for both Motor-UPDRS and Total-UPDRS. This is followed by a short message service (SMS). If the severity level is "High" then phone notification alert will be delivered to both family members and consulting medical experts. But if the detected risk is "Low" then only family members get the SMS alert. Also, whenever the predicted result is generated simultaneously, the 'Awareness and Reminder Unit' interface is enabled which is presented in Fig. 5(e). This unit is a kind of informative module that makes the user aware of various symptoms, therapies available, and the latest innovations and news related to PD worldwide. The last interface shown in Fig. 5(f) called 'Report Generator' acts as a health report retrieval unit. Here the user can select the desired year and month to download the corresponding PD risk reports for further analysis.

The sound quality from smart phone may get affected by some hardware and software elements like the phone speaker, the amplifier and the equalizers and tuning of audio output. The proposed model has taken addition steps to address the concern. A simple rule recommended during voice recording using a smart phone is to place the phone's speaker around 8–12 inches distance from mouth at a downward angle of 45° in airplane mode. The recording is supposed to be taken in a closed environment away from any external vibrations. Further, the noisereduce algorithm of python library is used to restrict noise from the voice recordings of user. It computes the signal's spectrogram and forecast a noise limit of every frequency corresponding to that signal. This limit value determines a mask that restricts noise less than the frequency changing limit. Also, the sampling frequency of the recorded voice samples are adjusted to 48000 samples per second and then through PyAudioAnalysis library, the voice data can be analyzed where audio quality can be enhanced by equalization and compression functionalities.

4. Experimental analysis

In the developed m-healthcare model for Parkinson's risk detection, the DNN model is trained using the telemonitoring voice data samples. Then it is ready to predict a new test voice data which can be visualized in the smartphone of the user. Eventually, the predictive model analyzes the prediction performance of the disease risks by predicting Motor and total UPDRS scores. The performance of the proposed DNN model is validated by experimenting multiple times to give optimal outcomes.

The impact of changing batch size is demonstrated in Table 8 and it is noted that with batch size 10, the model showed the highest efficiency in both the Motor and Total-UPDRS. For batch size 16, the R^2 value for Motor and Total-UPDRS is 0.9721 and 0.9632, respectively. The r-squared (R^2) metric for Motor and Total-UPDRS is quite good when the batch size is 16 or 20 but the best result is recorded with batch size 10. Also, any subsequent increase in batch size does not improve the model's performance.

Table 9 highlights the impact of altering the dense layers count as well as the dense layers neurons keeping the batch size 10. As per the observation, with an increase in neurons in dense layers 2 from (1, 20) to (160, 1), R^2 also increases. Also when the dense layers rise to 3 with a neuron configuration variation of (64, 32, 1) to (320, 160, 1), the R^2 metric for Motor-UPDRS increases from 0.9547 to 0.9762. At the same time, for Total-UPDRS, it decreases from 0.9652 to 0.9456. But when dense layers are incremented to 4 and neuron count is also increased in the configuration (128, 64, 32, 1), the R2 value performs best with 0.9741 and 0.9722 respectively for the Motor and Total-UPDRS. Further, with dense layers 5, evaluation of (80, 40, 20, 10, 1) configuration proved to be better as compared to other 4 dense layers structures. This verifies that this configuration is optimal.

The classification accuracy of different computational techniques as outlined in Table 1 was validated and the result is highlighted in Fig. 6. A relatively low accuracy was tested with the fuzzy C-Means model, while the developed DNN model showed the highest accuracy rate of 96.2 % on the voice dataset. Other models that generated good accuracy outcomes include multilayer perceptron (MLP) with 95 %, linear discriminant analysis (LDA) with 95 %, Nested SVM (93.5 %), and KNN (93.3 %).

The sensitivity analysis was undertaken with some comparative methods, as discussed in Table 2. The outcome of the comparison is shown in Fig. 7. An optimum sensitivity score of 94.15 % was recorded with the DNN model, which is much better than other models taken into consideration. Classification with the SVM model also provided a relatively high value while fuzzy C-Means got the least sensitivity value.

Similarly, a comparative analysis of different existing computational models concerning specificity metrics was undertaken. The methods for comparison are outlined in Table 3. The outcome of the comparison is shown in Fig. 8. While an optimum specificity score of 96.1 % was noted with the DNN model, the lowest value of 45.83 % was recorded with fuzzy C-Means.

Figs. 9 and 10 shows the model's convergence for the Motor and Total-UPDRS. It is observed from the result that in the training phase of Motor-UPDRS, the model converges around 350 epochs. Also, the smooth convergence of the loss in the validation phase with the training phase indicates that the model has been tuned properly. In the case of Total-UPDRS, the model converges around 200 epochs, as shown in Fig. 10.

The execution time latency analysis was carried out considering different comparative models. Latency analysis provided a fair idea of the response time of the model's performance. It was observed that the response period of the DNN model was only 27 s as compared to other computational methods. Among other methods used, classification models involving SVM were found to be quite slow in detecting Parkinson's risks. The overall outcome is shown in Fig. 11.

The model is tested against different PD datasets to determine its generalization and diverse utilization of its efficiency. Five distinct

Table 8
Effect of varying batch size on Error rates

Batch size	Measure	MAE	RMSE	R^2
4	Motor-UPDRS	0.032	0.0543	0.9594
	Total-UPDRS	0.046	0.0603	0.9429
8	Motor-UPDRS	0.0284	0.0394	0.9623
	Total-UPDRS	0.0305	0.0431	0.9491
10	Motor-UPDRS	0.0248	0.0362	0.9884
	Total-UPDRS	0.0291	0.0407	0.9845
16	Motor-UPDRS	0.0279	0.0412	0.9721
	Total-UPDRS	0.0316	0.0466	0.9632
20	Motor-UPDRS	0.0265	0.0415	0.9744
	Total-UPDRS	0.0307	0.0464	0.9635

Table 9
R^2 performance for a varying number of neurons in dense layers with a batch size of 10

Number of Dense Layers	Number of neurons in dense layers	Measure	R^2
2	20, 1	Motor-UPDRS	0.9098
		Total-UPDRS	0.9311
	80, 1	Motor-UPDRS	0.9392
		Total-UPDRS	0.9488
	160, 1	Motor-UPDRS	0.9433
		Total-UPDRS	0.9567
3	64, 32, 1	Motor-UPDRS	0.9547
		Total-UPDRS	0.9652
	160, 80, 1	Motor-UPDRS	0.9648
		Total-UPDRS	0.9568
	320, 160, 1	Motor-UPDRS	0.9762
		Total-UPDRS	0.9456
4	32, 16, 8, 1	Motor-UPDRS	0.9417
		Total-UPDRS	0.9546
	64, 32, 16, 1	Motor-UPDRS	0.9694
		Total-UPDRS	0.9685
	128, 64, 32, 1	Motor-UPDRS	0.9741
		Total-UPDRS	0.9722
5	40, 20, 10, 6, 1	Motor-UPDRS	0.9698
		Total-UPDRS	0.9675
	80, 40, 20, 10, 1	Motor-UPDRS	0.9751
		Total-UPDRS	0.9712
	120, 60, 30, 16, 1	Motor-UPDRS	0.9705
		Total-UPDRS	0.9697

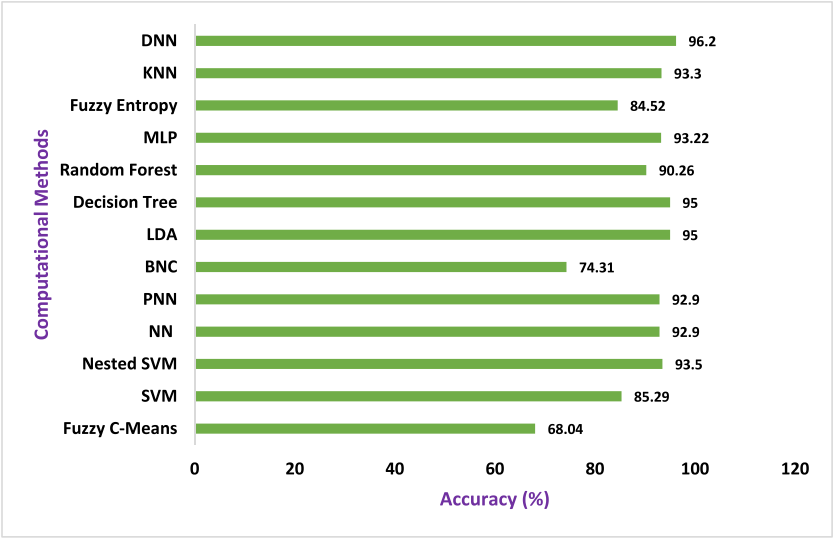

Fig. 6. Accuracy analysis of the DNN-based classification model with other existing models.

datasets used in previous papers are applied here and its outcome is summarized in Table 10. As observed form the analysis, the model performed extremely well with almost all datasets delivering an optimum result. 96.2 %, 94.15 %, 96.15 % and 95.2 % are the computed mean accuracy, precision, recall and f-score respectively.

The model is further evaluated in clinical settings with consultation with medical experts to determine its utility. A free medical awareness camp for Parkinson disease assessment was set up for 10 continuous days to make people alert of the disease and free check up of PD patients was held. In the camp, our model was also introduced to patients and got validated too. Many patients especially elderly citizens voluntarily came forward in the process to get a check up. Around 12 medical experts conducted the diagnosis of the patients. A comparison study was made between patients correctly diagnosed by medical experts and that by the PD-DETECTOR model. It was observed that the outcome of diagnosis was almost identical with both procedures. 79 patients were correctly detected with PD risks by experts while the model accurately detected 71 patients as PD patients. In fact in few days like day 5 and 7, the model outperformed experts in correctly detecting the disease. The overall results is outlined in Fig. 12.

In another analysis a shown in Table 11, an opinion of the available 12 medical experts were taken into consideration regarding the model's usage after the completion of the medical camp. Based upon the experience they had with the model's applicability, 7 metrics

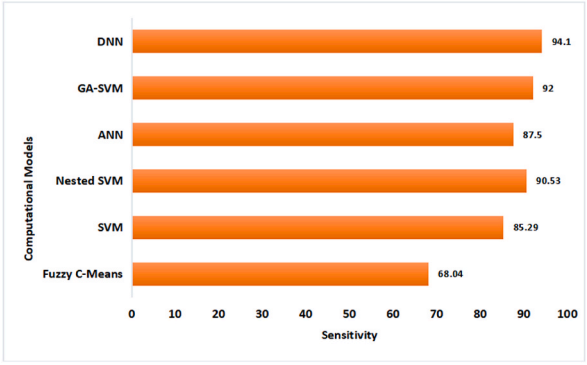

Fig. 7. Sensitivity analysis of the DNN-based classification model with other existing models.

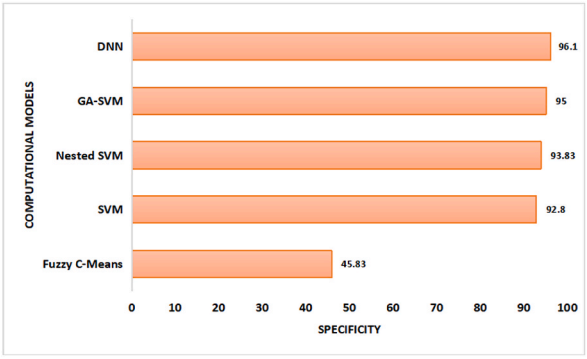

Fig. 8. Specificity analysis of the DNN-based classification model with other existing models.

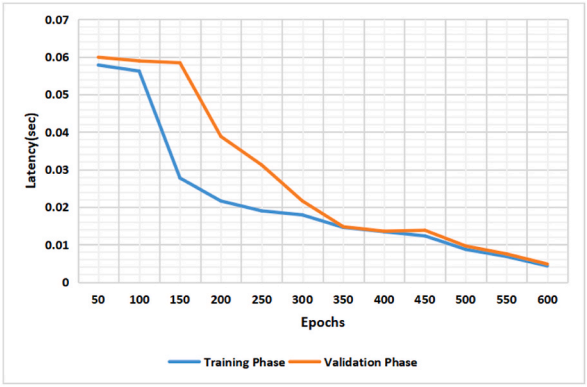

Fig. 9. Convergence analysis of DNN model for the Motor-UPDRS data.

like reliability, preciseness and others were there for evaluation with three class labels (high, moderate and low). The results were promising. The mean metrics score obtained for high, moderate and low were 6.5, 3.5 and 1.8 respectively. Metrics like reliability and navigation achieved the maximum score of 8 while a very less experts gave 'low' scores to the metrics under evaluation.

Thus the benefits of the model from the clinical usability perspective is immense. The model can be an useful tool for early detection of PD symptoms in patients. It can enable personalized remote diagnosis during emergencies without visiting clinical centers regularly. Also it can have a good check on the misdiagnosis rate of the disease. Hence, overall the model can assist the medical experts in their treatment providing a more fast, reliable and cost effective diagnosis.

5. Conclusion

Parkinson's disease (PD) is a global health issue for elderly citizens on a huge scale. Different computationally intelligent models

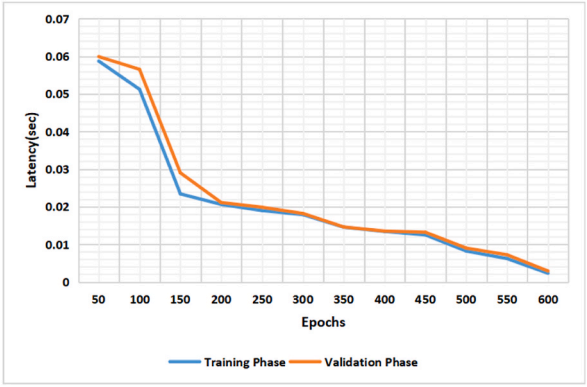

Fig. 10. Convergence analysis of the DNN model for the Total-UPDRS data.

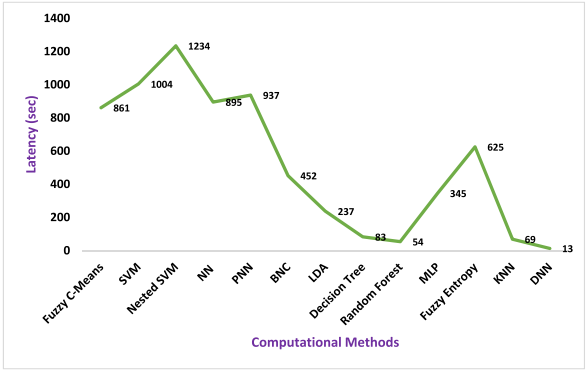

Fig. 11. Response time latency analysis of the DNN model with others.

Table 10
PD-DETECTOR performance analysis with different PD datasets

	Accuracy	Precision	Recall	F-Score
Frid et al. [30]	95.7 %	94.1 %	95.2 %	94.6 %
Rasheed et al. [31]	95.9 %	94.6 %	95.3 %	94.9 %
Gunduz et al. [32]	94.4 %	92.9 %	93.7 %	93.2 %
Karabayir et al. [33]	96.8 %	95.5 %	96.2 %	95.9 %
Zhang et al. [34]	96.1 %	94.7 %	95.6 %	95.2 %
PD-DETECTOR	96.2 %	94.15 %	96.15 %	95.5 %
Mean	95.85 %	94.32 %	95.35 %	94.88 %

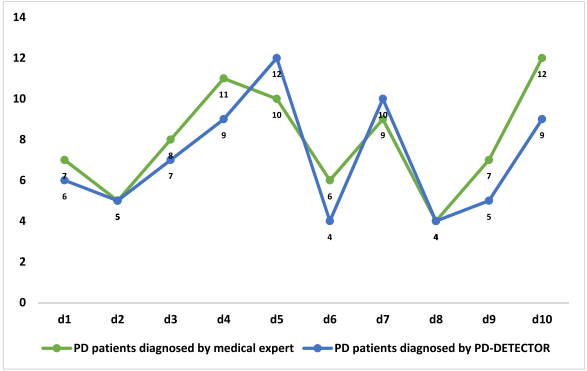

Fig. 12. Comparison of accurate diagnosis of PD patients by experts and PD-DETECTOR.

Table 11
Experts score level analysis on model's utility

	High	Moderate	Low
Reliability	7	4	1
Preciseness	6	4	2
Robustness	6	3	3
Operational speed	6	3	3
Navigation	8	3	1
Security	7	4	1
Contentment	6	4	2

can be applied for the effective distinction between normal and Parkinson-affected patients. With advances in mobile ubiquitous technologies, smartphone-based frameworks can also be designed for the effective determination of Parkinson's health risks. The research work undertaken in this study deploys a m-healthcare-driven predictive model for assessing Parkinson's disease risks in elderly citizens. In this research work, the authors presented a DNN-driven predictive model to detect the degree of severity of PD. The developed DNN approach generated an optimum accuracy of 96.2 % as compared to other existing techniques. Similarly, the sensitivity and specificity scores of 94.15 % and 96.15 respectively were generated after implementing the model. The overall convergence of the proposed model was also quite smooth in the context of epoch count. When the model was integrated into a smartphone, the response time of the model upon testing a new voice sample was also determined to be just 13 s. Also, it was determined that the classification for motor UPDRS score was better when compared with the classification for total UPDRS score. Thus, it may be inferred that this is a better parameter for assessing the level of severity. Therefore, the proposed DNN-based predictive method using m-healthcare can be robust and scalable and very reliable and precise in predicting the UPDRS score for Parkinson's risk assessment.

Data availability statement

The Parkinsons dataset used in this study is publicly available from the UCI Machine Learning Repository (https://archive.ics.uci.edu/dataset/174/parkinsons). The dataset can be accessed and downloaded without restrictions for research and educational purposes. It contains biomedical voice measurements from 31 people, 23 with Parkinson's disease, collected by Max Little of the University of Oxford in collaboration with the National Centre for Voice and Speech, Denver, Colorado.

CRediT authorship contribution statement

Sushruta Mishra: Writing – original draft, Methodology, Conceptualization. **Lambodar Jena:** Writing – original draft, Investigation, Conceptualization. **Nilamadhab Mishra:** Writing – review & editing, Writing – original draft, Supervision, Investigation. **Hsien-Tsung Chang:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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