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Original Article

Optimal Stacked Autoencoder-Based Automated Parkinson's Disease Detection by Implementing Feature Selection Process

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Abstract - *Parkinson's Disease (PD) recognition generally depends on the valuation of clinical signs and medical observations, which includes the characterization of various motor symptoms. However, classical diagnostic techniques may undergo bias since they depend on activity assessment that can be irregularly delicate to human vision and thus tough to categorize, causing probable misclassification. Simultaneously, initial non-motor PD indications will be insignificant, and others will occur in many other circumstances. Hence, such indications were often unnoticed, making PD diagnosis at an initial stage challenging. For solving such complexities and for refining the assessment procedures and diagnosis of PD, Deep Learning (DL) approaches were applied for classifying PD and vigorous controls or patients who have clinical performances (for example, other Parkinsonian syndromes or movement disorders). This study develops an Automated PD Detection using Feature Selection with Optimal Stacked Autoencoder (APDD-FSOSAE) technique. The presented APDD-FSOSAE technique focuses on assessing PD using Feature Selection (FS) and DL approaches. To attain this, the presented APDD-FSOSAE model comprises the design of a chicken swarm optimization-based FS approach for the selection of optimum features. Next, the APDD-FSOSAE technique utilizes SAE for detecting and classifying PD. Finally, the hyperparameters of the SAE model can be optimally selected by the Bayesian Optimization (BO) model. The investigational output evaluation of the APDD-FSOSAE approach is examined on a benchmark PD dataset. The experimental outputs suggested that the APDD-FSOSAE approach results in improved PD detection results over other models.*

Keywords - *Data mining, Healthcare, Parkinson's disease, Deep learning, Feature selection.*

1. Introduction

PD affects people's movement, including speech changes, muscle stiffness, writing skills, and tremors [1]. It is important to diagnose PD at the primary phases so that an individual can lead a peaceful life in the long run. The severe levels of PD were extremely perilous because the victims get continuous stiffness, which may lead to the inability to walk or stand [2]. Previous research has concentrated on detecting PD efficiently by utilizing speech and voice exams and writing exams. Currently, data has been enhanced by several illustrations and many features that turn out the data louder [3]. The noisy data sets make the model diminish predictive accuracy, surge the complexity, raise the computation cost and train the data slower [4]. Thus, FS formulated a vital mission for ML beforehand training models. FS was a technique that focused on discovering a subset from a presented complete set of attributes; accordingly, subsets of features predict the targets with precise analogous to the efficiency of a novel set of attributes and by diminishing computational costs [5]. The FS technique can be classified into filter-oriented and wrapper-oriented methods.

Recently, machine learning has developed as an auspicious domain of research in PD diagnosis, both in industry and academia [6]. Due to its data-driven techniques, ML brought a pattern alteration in a manner related to information in PD biomarkers that were analyzed and extracted. Additionally, ML approaches offer relevant data that grants guidance associated with PD categorization and analysis to hasten decision-making [7]. Numerous ML approaches were enforced to sort out the PD recognition issue. Unlike the FS methods utilized in conventional ML-related techniques, one strong point of DL can be accurately hierarchical FS along the successive level of increasing abstraction in identifying paradigms. Some research works have explored PD recognition from speech depending on DL, like convolutional neural networks [8].

Many existing works attempted made their efforts to discover potential static features for PD speech classification; certain studies utilized continuous speech features while neglecting the interdependency in features sequences of DL methods [9], which are of surging interest with big data and may resolve certain limitations of ML methods by eradicating the necessity for FS, feature extraction tools [10]. These models can use dimensional data and may operate analogously to neurons in the human brain.

This study develops an Automated PD Detection using Feature Selection with Optimal Stacked Autoencoder (APDD-FSOSAE) technique. The presented APDD-FSOSAE model comprises the design of a chicken swarm optimization-based FS approach for selecting optimum features. Next, the APDD-FSOSAE technique utilizes SAE for detecting and classifying PD. Finally, the hyperparameters of the SAE model can be optimally selected by the Bayesian Optimization (BO) model. The investigational output evaluation of the APDD-FSOSAE approach is examined on a benchmark PD dataset.

2. Related Works

Bahaddad et al. [11] examine an Improved Sailfish Optimizer method with a DL (ISFO-DL) approach for PD classifier and analysis. Also, the Rat Swarm Optimizer (RSO) with BiGRU was utilized as a classification for defining the presence of PD. In [13], the vocal feature of an individual infected by PD is investigated with hi-fi calculation methods. Primarily, instances are pre-processing, while they comprise further lost values. Afterwards, the subset of the predictor candidate was recognized in the managed vocal factors utilizing the adaptive Grey Wolf Optimizer (GWO) technique, a metaheuristic global search optimizer system. Moreover, the hidden depiction of candidate factors is extracted with Sparse Auto-Encoders (SAE) to effectual discrimination betwixt the PD control and affected cases.

Dao et al. [14] introduce an ML-based system for categorizing healthy people in people with diseases employing GWO for FS, together with a Light Gradient Boosted Machine (LGBM) for optimizing the method efficiency. Lamba et al. [15] examine a speech signal-based fusion PD analysis method for its initial detection. For this purpose, the authors tested many groups of FS techniques and classifier techniques and planned the model with a better combination. For formulating several groups, three FS systems, like an extra tree, mutual information gain, and GA, and 3 classifications, like RF, NB, and KNN, are employed.

Gunduz et al. [16] exposed a PD classifier method dependent upon vocal extraction features in the voice recording of persons and presented a fusion dimensionality lessening scheme for extracting the vigorous factors. The presented system benefited from prominent features of VAE and filter-based FS methods [17]. For assessing the efficacy of the devised process, the multi-kernel SVM technique is trained with achieved deep feature representation. In [18, 19], 2 hybrid methods dependent upon SVM combined with PCA and SAE can be presented for detecting PD patients dependent upon its vocal feature.

A primary method extracts and reduces the major component of vocal factors dependent upon the described discrepancy of all the features utilizing PCA. For once, the second method utilized a new DNN of an SAE, comprising several Hidden Layers (HLs) with L1 regularized for compressing the vocal feature as to lower dimension latent space.

3. The Proposed Model

In this article, a novel APDD-FSOSAE approach for the recognition of PD using FS and DL approaches. The APDD-FSOSAE technique follows a three-stage process: CSO-FS technique, SAE-based PD classifying, and BO-based optimization of the hyperparameter. Fig. 1 illustrates the comprehensive workflow of the APDD-FSOSAE model.

3.1. Design of CSO-FS Approach

Primarily, the presented APDD-FSOSAE approach involves the design of CSO based FS approach. The CSO is initiated by the primary population (population of cuckoos), like other evolutionary methods [20]. This cuckoo has taken a few eggs that are located in another species' nest. Suppose any eggs that look similar to the host egg can be further possibly increased and turn into cuckoos. Another egg was observed with the hosts and passed away. The rate of maximum eggs describes the fitness of the place. Once another egg exists in the area, it could bring additional profits to that region.

Consequently, the condition that other eggs survived is a parameter to the cuckoos that augment. The cuckoos search for an optimal location to maximize the egg's life length. Next, they hatch and become mature cuckoos; the community and society might produce them. Each community is their habitat to live in. An optimal habitat for all the communities is the following target to cuckoo from another group. All the groups immigrate to a present optimal location. Every single group is a resident from the region toward an existing optimal location. An Egg-Laying Radius (ELR) was computed, which concerns the egg counts, every cuckoo location and the length in an existing optimal location.

Next, the cuckoo begins to lay eggs from the nest, assigning radii arbitrarily. Still, this process achieves the optimal position for placing eggs (a region with maximal profits). This optimal region has been placed in which the greatest quantity of cuckoos gathers together.

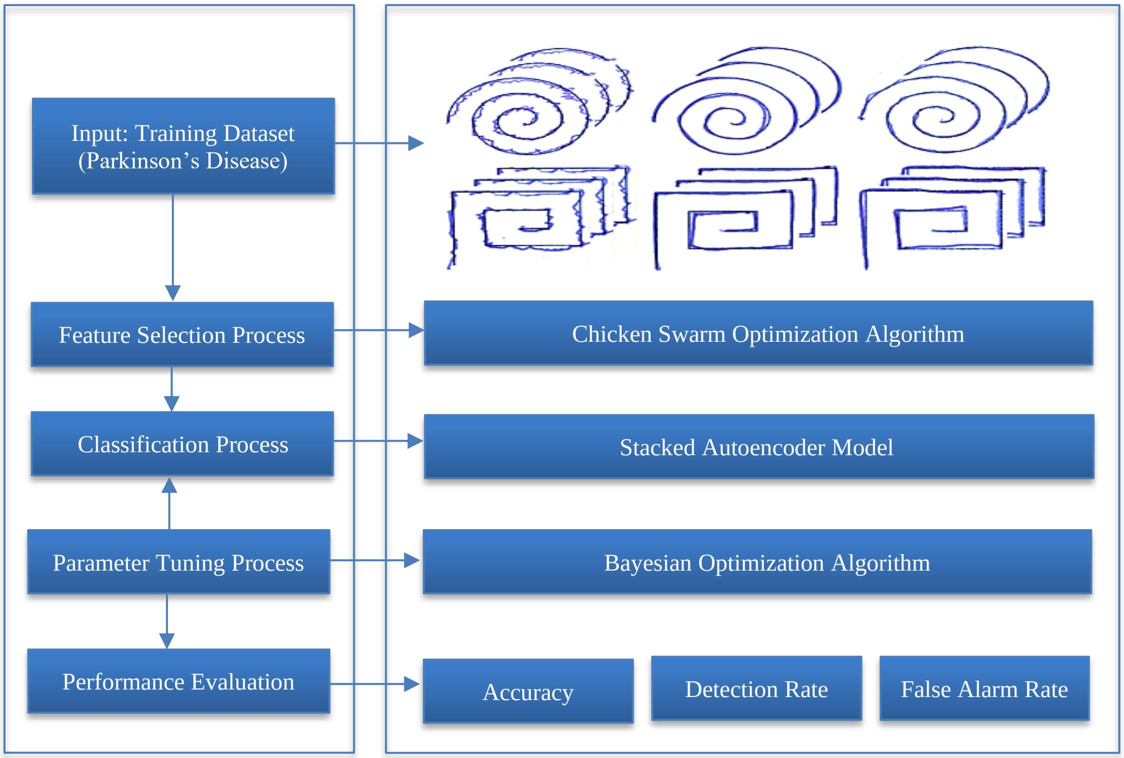

Fig. 1 Workflow of APDD-FSOSAE model

It is essential to generate a variable as an array that an optimized problem was resolved. In PSO and GA, this array was identified by "particles' positions" and "chromosome," but in CSO, these arrays are called "habitat".

In 1D Nvar optimized issues, habitat is a $1 \times Nvar$ array that portrays the existing location of cuckoo life as follows:

$$Habitat \ = [x_1, x_2 \dots x_{Nvar}] \tag{1}$$

The amount of suitability or profit rate to the existing habitat is acquired as profit function estimation.

$$Porofit \ = f_p(habitat) = f_p(x_1 x_2, \dots, x_{Nvar}) \tag{2}$$

The COA maximizes the profit function. The function of cost is enhanced by a negative sign that the issue was resolved by using CSO. For initial optimization, a habitat matrix-sized $N_{pop} \times N_{var}$ was generated. Next, the number of arbitrary eggs was recognized in every habitat matrix. Naturally, every cuckoo will be laying 5- 20 eggs. This number was used as the minimal and maximal constraints from the egg conditions of all cuckoos under dissimilar iterations. Every real cuckoo lays an egg from a certain range. Consequently, the highest range of egg placing is the ELR. In the optimized issue, with upper and lower boundaries of var_{hi} and var_{low}, every cuckoo takes ELR that corresponds to the existing amount of eggs, the overall egg amount, and the upper or lower boundaries of the variable of the issue, and it can be expressed as follows:

$$ELR = \alpha \times \frac{Number\ of\ current\ cuckoos\ eggs}{Total\ number\ of\ eggs} \times (var_{hi} - var_{low}) \tag{3}$$

In Eq. (3), α signifies the parameter that the highest ELR is fixed. Each cuckoo arbitrarily places an egg from the host bird's nest in ELR. Thus, in every procedure of laying the egg, p percent of eggs (generally 10%) whose profit function values were demolished.

The remaining chicks from the host nest were fed and maintained. Another stimulating factor on the cuckoo chick is that one egg is the opportunity that grows from every nest. Once the cuckoo chick hatches, they are discarded. The individual host chick is dying of hunger, and the cuckoo chick is alive. When the cuckoo chick develops and becomes mature, it survives from the neighbouring position. But if the egg place time is closer, it has found an optimal habitat in that the possibility of bringing its eggs is higher. Next, the making cuckoo group from numerous positions, the group with the optimal location, was selected as the destination group for other cuckoos to have immigrated. The number N_{max} was used for controlling the highest amount of cuckoos living from the position based on the detail that keeps the balance among the population of birds. This balance is due to determining inappropriate nests for eggs, competing for limited food, and being hunted by predators.

The CSO-FS approach's Fitness Function (FF) considered the classifier accuracy and the FS numbers. It maximized the accuracy of the classifier and reduced the FS set size. Then, the subsequent FF was implemented for assessing discrete solutions, which is represented in Eq. (4).

$$Fitness = \alpha * \ ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \qquad (4)$$

In which ErrorRate depicts the classifier ErrorRate through the FS. ErrorRate can be calculated as the percent of inappropriate classifiers to the number of categorizations made, represented as a value within [0-1]. $\#SF$ designates the FS number, and $\#All\_F$ was the overall features in the actual database. α can be implemented for regulating the critical quality of the classifier and subset length. In these researches, α is static to 0.9.

3.2. PD Categorization using the SAE Model

To detect and classify PD, the APDD-FSOSAE technique uses the SAE model. AE is a NN that matches output values with input values via a backpropagation [21].

Firstly, the input can be compressed into spatial representations and later exploited to reconstruct the outcome. The AE comprises decoded and encoded parts that can be further split into 3 layers, such as the HL h, the input and output layers x, y. The function of cost exploited in traditional AE is MSE, as given below.

$$J_{AEcost}(W) = J_{MSE}(W) = \frac{1}{m}\sum_{i=1}^{m}[\frac{1}{2}\|y_i - x_i\|^2] \qquad (5)$$

In Eq. (5), m denotes the sample counts, x_i indicates the input vector, y_i refers to the resultant vector, and W denotes each parameter set in the networking. To resolve duplication defects in the abstracted feature learned by the AE, the regular limit of $L1$ is augmented to attain an SAE.

SAE applies constraints for eliminating feature redundancy at the time of decoding and encoding. It raises the constraint on the response of all the HLs, such that most of the neurons were "inhibited", and a scarce "excited" can be replicated in the method through the inclusion of sparse constraint to the cost function. In the cost function of AE, add the subsequent sparse constraint:

$$J_{SAEcost}(W) = J_{MSE}(W) + Js_{Parse}(W) \qquad (6)$$

$$J_{Sparse}(W) = \beta\sum_{i=1}^{2} K\,L(\rho|\rho_j) \qquad (7)$$

$$KL(\rho|\rho_j) = \rho \log \frac{\rho}{\rho_j} + (1-\rho)\log \frac{1-\rho}{1-\rho_j} \qquad (8)$$

Now ρ_j indicates the average activation of the HL unit's neuron, ρ denotes the constraint level of the sparsity, β represents the sparsity penalty term's weight, and KL denotes the discrepancy that ensures the sparsity of the neuron in HLs. As demonstrated in Eq. (8), the closeness of ρ and ρ_j is directly proportional to the cost function subtleness.

3.3. Hyperparameter Tuning

Finally, the BO algorithm is exploited for the optimum tuning process. BO refers to a global optimizing technique for black-box functions [22].

In the presented method, tuning can be regarded as the black-box function's optimizing. Firstly, a sequence of first parameter combinations has been organized. In the study, RI and LHD are utilized for these purposes. The model was estimated for all the combinations to evaluate the efficiency.

A Gaussian Process (GP) was adapted to devise the relationships between model performance and parameter combination. This GP was boosted to discover the potential parameter combinations. The optimizing considers exploitation and exploration with the acquisition function that relies on the covariance. $\hat{\Sigma}_\Theta$and the expected model performance $\hat{\mu}_\Theta$ at parameter combination Θ.

In the proposed model, the upper confidence bounds, provided in Eq. (9), were exploited as a function of acquisition.

The κ parameter defines the quantity between exploration and exploitation. For a high value of κ, exploration can be preferable, while a low value favours exploitation. Fig. 2 depicts the steps comprised in the BO model.

$$UCB(\Theta) = \hat{\mu}_\Theta + \kappa \cdot \hat{\Sigma}_\Theta \qquad (9)$$

The ML algorithm's achievement was estimated by employing the novel parameter integration and included in the GP mechanism. This procedure was reiterated till the ending condition was satisfied.

Choosing FF will be a significant component of the BO model. Solution encoding is implemented to evaluate the candidate solution's goodness. The value of accuracy was the major case used to devise an FF.

$$Fitness \ = \ \max(P) \qquad (10)$$

$$P = \frac{TP}{TP + FP} \qquad (11)$$

From the above equations, TP and FP depict the true and false positive values.

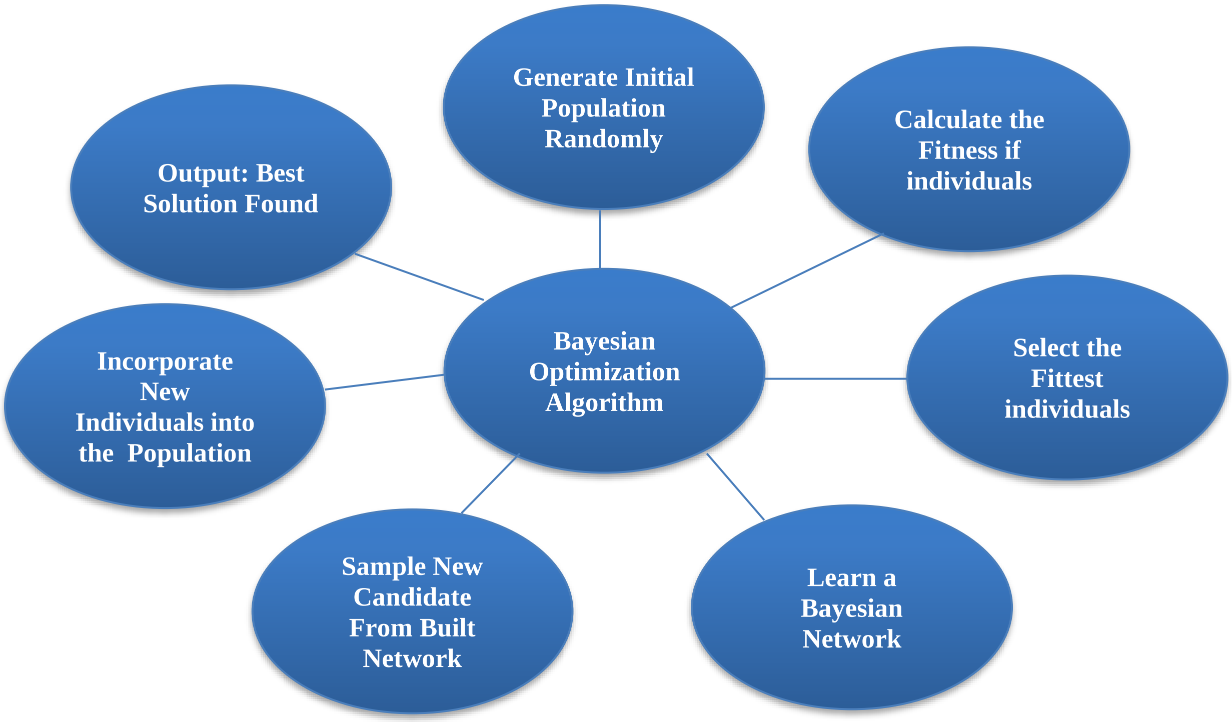

Fig. 2. Steps involved in the BO algorithm

Table 1. FS outcome of APDD-FSOSAE approach with existing methods under 4 datasets

Dataset	Overall Features	MGOA	MGWO	OCFA	IFSO-DL	APDD-FSOSAE
HPD-S	13	5	7	8	4	5
HPD-M	13	8	8	7	6	7
S-PD	23	11	12	13	10	7
V-PD	26	8	9	17	7	6

4. Results and Discussion

In this segment, the simulation values of the APDD-FSOSAE method take place using four databases: Speech PD (S-PD), HandPD Spiral (HPD-S), Voice PD (V-PD) and HandPD Meander (HPD-M). Table 1 and Fig. 3 represent the FS results of the APDD-FSOSAE approach on four datasets.

The outcomes implied that the APDD-FSOSAE model had selected the minimum factor numbers related to other models. It is noticed that the APDD-FSOSAE model has selected 5, 7, 7, and 6 features under S-PD, HPD-S, V-PD, and HPD-M respectively.

Table 2 represents the comprehensive PD classifying accomplishment of the APDD-FSOSAE method with current models on the HPD-S dataset. The outcomes indicated that the MGOA-KNN, MGOA-DT and MGWO-KNN models obtain lower classification performance. Then, the MGWO-DT, MGOA-RF, and MGWO-RF models result in moderately improved classifier results. Next to that, the IFSO-DL model has managed to report reasonable outcomes with $accu_y$ of 93.49%, DR of 98.29%, and FAR of 7.21%.

The TACC value and VACC value of the APDD-FSOSAE methodology under the HPD-S database are represented in Fig. 4. The figure depicts that the APDD-FSOSAE methodology has advanced achievement with enhanced TACC and VACC values. Visibly, the APDD-FSOSAE method has attained optimal TACC outputs.

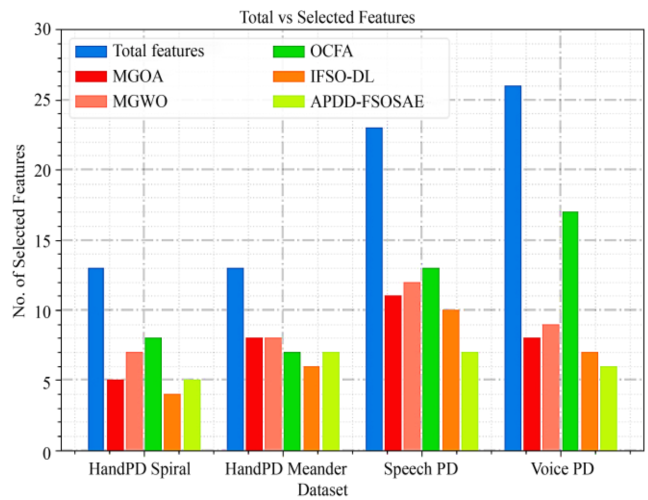

Fig. 3 FS outcome of APDD-FSOSAE approach under 4 datasets

Table 2. PD classifier outcome of APDD-FSOSAE approach with recent systems under HPD-S dataset

HPD-S Database			
Methods	**Accuracy**	**Detection Rate (Recall)**	**FAR**
MGOA-KNN	75.60	85.30	53.10
MGOA-RF	92.90	97.90	21.90
MGOA-DT	89.00	94.70	28.10
MGWO-KNN	73.40	81.90	50.00
MGWO-RF	92.40	94.00	11.90
MGWO-DT	92.40	94.00	11.90
IFSO-DL	93.30	98.20	8.00
APDD-FSOSAE	93.49	98.29	7.21

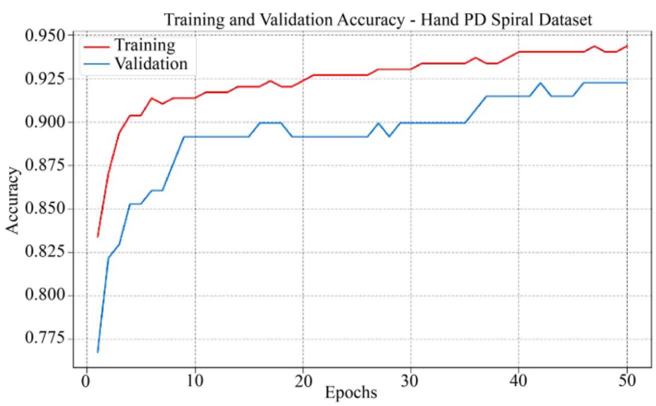

Fig. 4 TACC and VACC output of APDD-FSOSAE approach under HPD-S database

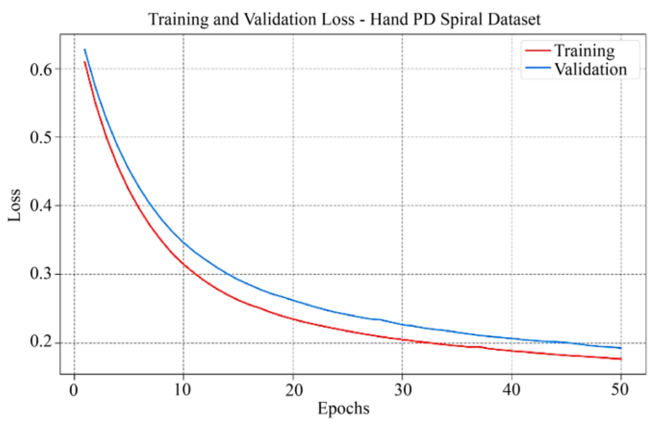

Fig. 5 TLS and VLS output of APDD-FSOSAE approach under HPD-S database

The TLS value and VLS value of the APDD-FSOSAE model under the HPD-S database are represented in Fig. 5. The figure designated that the APDD-FSOSAE model has depicted advanced achievement with lesser TLS and VLS values. Notably, the APDD-FSOSAE technique has mitigated VLS outputs.

Table 3. PD classifier outcome of APDD-FSOSAE approach with recent systems under HPD-M database

HPD-M Database			
Methods	**Accuracy**	**Detection Rate (Recall)**	**FAR**
MGOA-KNN	74.80	85.80	47.60
MGOA-RF	93.70	100.00	19.10
MGOA-DT	89.00	91.80	16.70
MGWO-KNN	72.80	85.80	60.00
MGWO-RF	93.00	99.10	22.20
MGWO-DT	88.00	92.00	22.20
IFSO-DL	94.00	100.00	13.50
APDD-FSOSAE	94.62	100.00	9.84

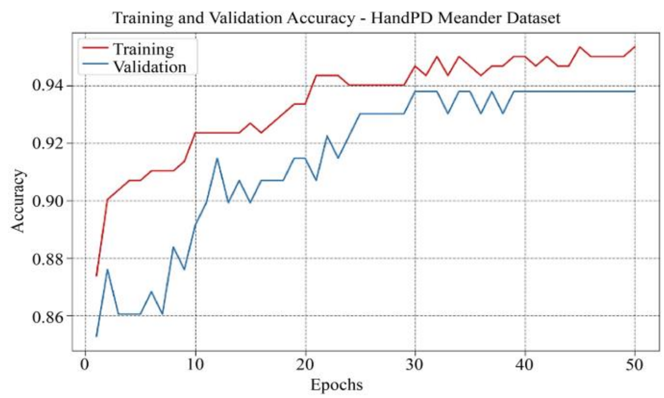

Fig. 6 TACC and VACC output of APDD-FSOSAE method under HPD-M database

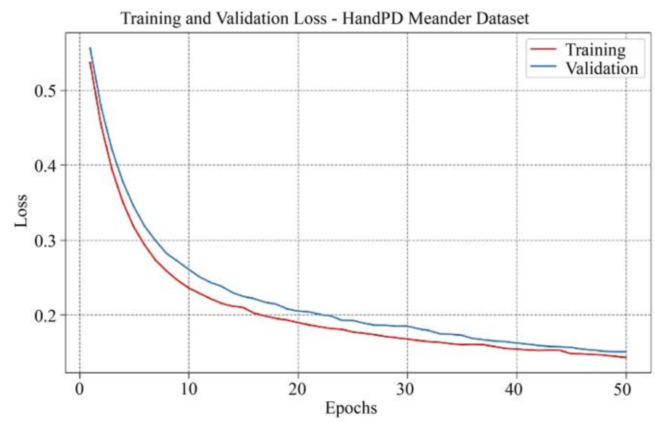

Fig. 7 TLS and VLS output of APDD-FSOSAE method under HPD-M database

Table 3 signifies an overall PD classification performance of the APDD-FSOSAE system with current models on the HPD-M database. The outcomes illustrate that the MGOA-KNN, MGOA-DT and MGWO-KNN approaches gain lower classification performance. Then, the

MGWO-DT, MGOA-RF, and MGWO-RF systems result in moderately improved classifier results. Afterwards, the IFSO-DL algorithm has managed to report reasonable outcomes with $accu_y$ of 94.62%, DR of 100%, and FAR of 9.84%.

The TACC value and VACC value of the APDD-FSOSAE approach under the HPD-M database are represented in Fig. 6. The figure indicates that the APDD-FSOSAE approach has increased accomplishment with enhanced TACC and VACC values. Notably, the APDD-FSOSAE algorithm has attained optimum TACC outputs.

The TLS value and VLS value of the APDD-FSOSAE algorithm under the HPD-M database are depicted in Fig. 7. The figure represents that the APDD-FSOSAE technique has depicted advanced accomplishment with the lesser TLS and VLS values. Visibly, the APDD-FSOSAE technique has mitigated VLS outputs.

Table 4 exhibits an overall PD classification performance of the APDD-FSOSAE technique with current methods on the S-PD database. The outcomes highlighted that the MGOA-KNN, MGOA-DT and MGWO-KNN methods gain lower classification performance. Then, the MGWO-DT, MGOA-RF, and MGWO-RF approaches result in moderately improved classifier results. Next to that, the IFSO-DL method has managed to report reasonable outcomes with $accu_y$ of 96.98%, DR of 100%, and FAR of 12.10%.

The TACC value and VACC value of the APDD-FSOSAE model under the S-PD database are stated in Fig. 8. The figure represents that the APDD-FSOSAE model has advanced accomplishment with advanced TACC and VACC values. It is clearly stated that the APDD-FSOSAE methodology has attained greater TACC outputs.

Table 4. PD classifier outcome of APDD-FSOSAE approach with recent systems under S-PD database

S-PD Database			
Methods	**Accuracy**	**Detection Rate (Recall)**	**FAR**
MGOA-KNN	89.70	96.70	30.00
MGOA-RF	94.90	100.00	22.20
MGOA-DT	84.60	90.00	30.00
MGWO-KNN	91.80	97.40	30.00
MGWO-RF	93.90	100.00	30.00
MGWO-DT	89.80	94.90	30.00
IFSO-DL	95.30	100.00	18.50
APDD-FSOSAE	96.98	100.00	12.10

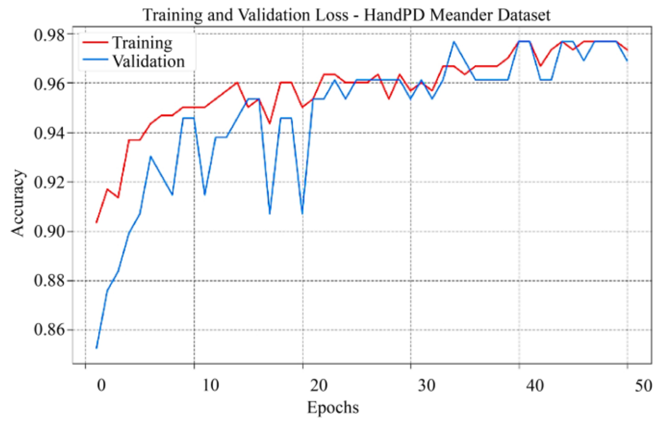

Fig. 8 TACC and VACC outcome of APDD-FSOSAE technique under S-PD database

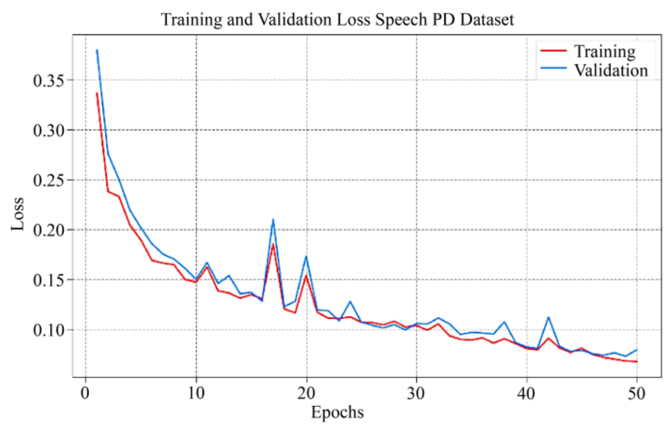

Fig. 9 TLS and VLS outcome of APDD-FSOSAE technique under S-PD database

The TLS value and VLS value of the APDD-FSOSAE model under the S-PD database are represented in Fig. 9. The figure displayed that the APDD-FSOSAE model has depicted advanced accomplishment with lesser TLS and VLS values. The APDD-FSOSAE approach has mitigated VLS outputs.

Table 5. PD classifier outcome of APDD-FSOSAE approach with recent systems under V-PD database

V-PD Database			
Methods	**Accuracy**	**Detection Rate (Recall)**	**FAR**
MGOA-KNN	91.80	83.50	0.90
MGOA-RF	100.00	100.00	0.00
MGOA-DT	100.00	100.00	0.00
MGWO-KNN	85.80	80.30	8.10
MGWO-RF	100.00	100.00	0.00
MGWO-DT	100.00	100.00	0.00
IFSO-DL	100.00	100.00	0.00
APDD-FSOSAE	100.00	100.00	0.00

Table 5 signifies a comprehensive PD classifying performance of the APDD-FSOSAE technique with current systems on the V-PD database. The outcomes display that the MGOA-KNN, MGOA-DT and MGWO-KNN methods gain lower classification performance. Then, the MGWO-DT, MGOA-RF, and MGWO-RF approaches result in moderately improved classifier results. Similarly, the IFSO-DL system has managed to report reasonable outcomes with $accu_y$ of 100%, DR of 100%, and FAR of 0%.

The TACC value and VACC value of the APDD-FSOSAE methodology under the V-PD database are stated in Fig. 10. The figure emphasized that the APDD-FSOSAE methodology has advanced accomplishment with advanced TACC and VACC values. The APDD-FSOSAE method has attained optimum TACC outputs.

The TLS value and VLS value of the APDD-FSOSAE model under the V-PD database are stated in Fig. 11. The figure displayed that the APDD-FSOSAE model has illustrated advanced accomplishment with lesser TLS and VLS values. The APDD-FSOSAE approach has given an outcome in mitigated VLS outputs.

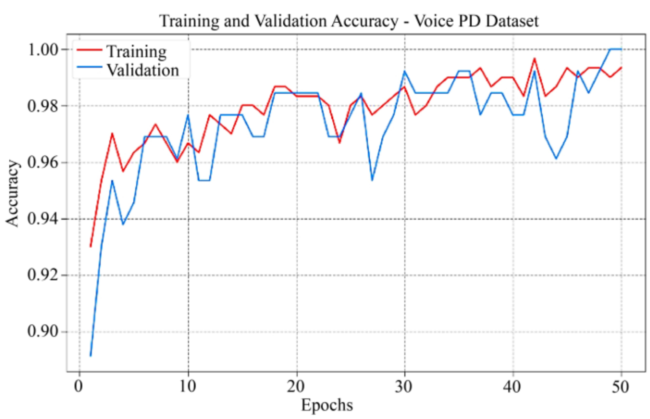

Fig. 10 TACC and VACC outcome of APDD-FSOSAE technique under V-PD database

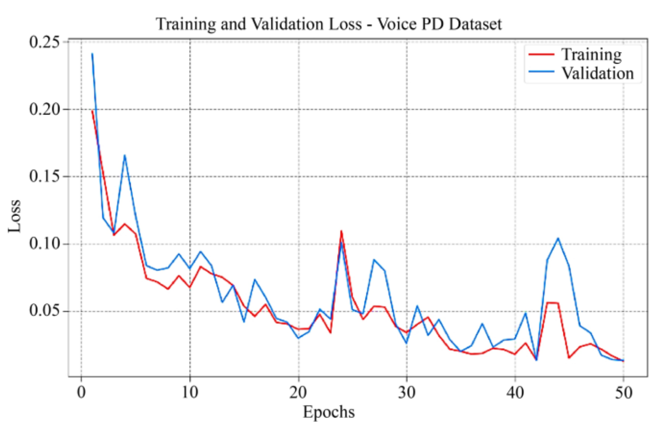

Fig. 11 TLS and VLS outcome of APDD-FSOSAE method under V-PD database

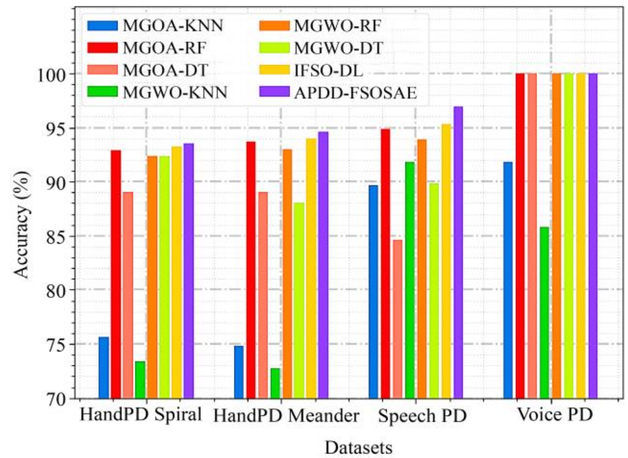

Fig. 12 $Accu_y$ analysis of the APDD-FSOSAE method with other existing systems on 4 databases

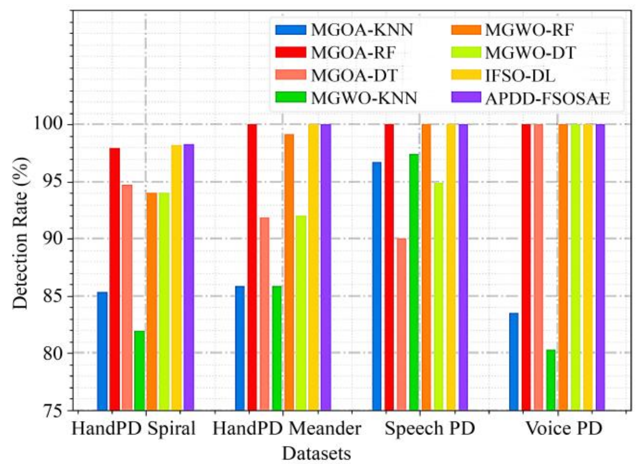

Fig. 13 DR analysis of APDD-FSOSAE approach with other existing systems on 4 databases

Fig. 12 demonstrates a comprehensive comparative evaluation of the APDD-FSOSAE model with current models on four databases in terms of $accu_y$ [11]. The experimental results specified that the APDD-FSOSAE method outperformed the other models with maximum $accu_y$ values under each database.

Fig. 13 portrays the overall relative research of the APDD-FSOSAE approach with current models on four databases in terms of DR. The results show that the APDD-FSOSAE approach outperformed the other methods with maximal DR values under each database.

Fig. 14 displays an overall comparative inspection of the APDD-FSOSAE method with recent approaches on four databases by means of FAR. The outputs indicated that the APDD-FSOSAE method outperformed the other models with maximal FAR values under each database. These outputs demonstrated that the APDD-FSOSAE method achieved enhanced accomplishment on the automated PD classification procedure.

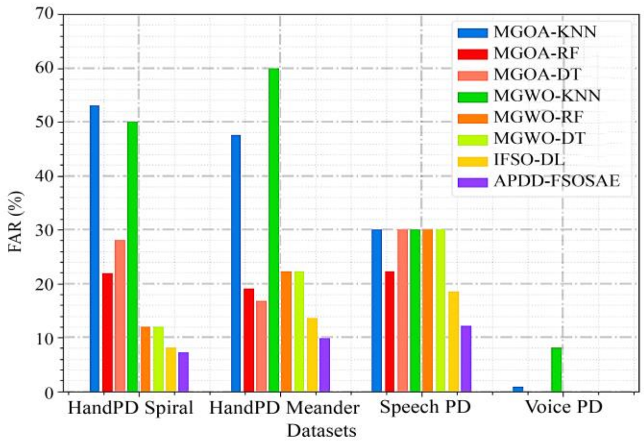

Fig. 14 FAR analysis of APDD-FSOSAE approach with other existing systems on 4 databases

5. Conclusion

In this article a novel APDD-FSOSAE methodology for detecting PD using FS and DL approaches. The presented APDD-FSOSAE technique involves the design of CSO based FS approach for the selection of optimum features. Next, the APDD-FSOSAE technique utilized SAE for detecting and classifying PD. Finally, the hyperparameters of the SAE technique can be optimally selected by the BO model. The investigational output evaluation of the APDD-FSOSAE model is investigated on a standard PD dataset. The experimental outputs suggested that the APDD-FSOSAE model results in improved PD detection results over other models. Thus, the APDD-FSOSAE approach appeared as an effectual tool for PD classifying. In the coming days, the accomplishment of the APDD-FSOSAE approach was enhanced by hybrid DL classifiers.

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