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Parkinson Data Analysis and Prediction System Using Multi-Variant Stacked Auto Encoder

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ABSTRACT Parkinson Disease (PD) is a kind of neural disorder that affects a range of people. This disease has continuously growing stages to halt entire neural activities of any people. There are many techniques proposed to detect and predict PD using medical symptoms and measurements. The medical measurements provided by different experiments must be effectively handled to produce concrete results on the detection of PD. This saves many people from PD at earlier stage itself. Recent technologies focus on Machine Learning (ML) and Deep Learning (DL) techniques for effective PD data analysis for making efficient prediction system. They are concentrating to build complex artificial neural systems using effective learning functions. However, the existing systems are lacking to attain multi-attribute and multi-variant data analysis to predict PD. To attain multi-variant Parkinson symptom analysis, the artificial neural systems must be equipped with more characteristics. In this regard, the Proposed system is developed using Multi-Variant Stacked Auto Encoder (MVSAE). The MVSAE based PD Prediction System (MSAEPD) helps to analyze more PD symptoms than existing systems. This article provides four different variants of SAE construction procedures to predict PD symptoms. The MSAEPD is implemented and compared with existing works such as MANN, GAE and UMLBD. This comparison shows the MSAEPD system gives 5% to 10% better results than existing works.

INDEX TERMS Parkinson disease, detection, machine learning, accuracy and auto encoder.

I. INTRODUCTION

Parkinson's Disease creates neural system disorder for various people. The disease affects the people at different age groups around the world. Medical research works collaborate with computational intelligence techniques for predicting Parkinson symptoms. PD has numerous types based on the human abnormalities. Mostly it disturbs the nature of neural activities and the body movements. Researches evolved in recent years use Machine Learning (ML) and Deep Learning (DL) approaches for finding early stages of PD [1], [2]. The research works used different types of medical observations such as voice levels, handwriting variations, body movements, brain signal variations and protein aggregations. These kinds of observations are measured using various medical apparatuses. The devices like acoustic sensors, ultrasonic sensors, motion sensors, wearable sensors and Electro Encephalo Graph (EEG) are mainly used for gathering Parkinson measurements. ML and DL techniques found from various research works are encouraged to evaluate these medical data [3]. The newly developed PD detection techniques are always requiring more accuracy in detection [4]. The requirement is achieved by using effective ML and DL approaches, which are adaptable to the data features. Many works have been identified for detecting Parkinson symptoms from various datasets. Each existing work is implemented using specific learning and detection techniques. However, these techniques are mainly using limited set of Parkinson features and less effective ML techniques [5]. A few researches are using ML and DL based Parkinson detection with real-time sensor datasets. But they are limited to certain observation ranges. This is a kind of research problem which is to be resolved.

To resolve these issues, the Proposed system uses Stacked Auto Encoder (SAE) variants on huge Parkinson dataset. SAE is the technique of Artificial Neural Network (ANN), that

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is used to effectively code the input data features based on relevant learning rates. SAE allocates the data features in a stacked format and expertise the decision making system in data prediction. Also, SAE helps to reduce the data features according to the dimensions. The data reduction eliminates noise rates and missing data.

The Proposed MSAEPD System is implemented with various types of Auto Encodes (AEs) such as Classless SAE, Clustered SAE, Multi-level Balanced SAE and Multi-Variant SAE techniques. The Classless SAE, Clustered SAE are used for making trained data features under unsupervised and supervised categories respectively. Multi-level Balanced SAE and Multi-Variant SAE are used for feature classification based on trained Parkinson data.

Multi-Variant is the term used to indicate the multiple PD features (Voice, motor and non-motor). These are varying for each iteration for each patient. Multi-Variant SAE is constructed with multiple parallel AEs to handle these PD features.

Comparing to AEs, SAEs are working efficiently. SAEs are the DNNs constructed using line of complex parallel AEs. In this implementation, AEs maintain limited set of hidden layers under one AE network. In contrast, SAEs are maintain highly efficient cooperative AEs. The Proposed System contributes for the deep analysis over numerous Parkinson data items. In addition, the Proposed MSAEPD helps for finding the abnormal variants in each attribute of multi-level data features. AEs are mainly used against dimensionality reduction problems. In this work, the motive of using SAE is to create multiple AE stacks to reduce data dimensionality. In addition it is used for building efficient PD recommendation system.

The article is organized from related work analysis section (section2). From the survey section, research problems and solutions are identified. Section 3 describes the Proposed System with many SAE techniques. There are two SAE approaches are used for feature identification and training processes. Among these, once SAE is implemented for feature class formation. Another SAE is developed for classless training set creation. Then Multi-Level Balanced SAE and Multi-Variant SAE are incorporated for Parkinson feature classification. Finally, section 4 illustrates the implementation section that gives the overall performance evaluation scenario and the result discussions. Section 5 concludes the article with future ideas.

II. RELATED WORK

Researches have been conducted on PD detection strategies using medical and computational biology techniques. Sadek *et al* [1] designed and applied Artificial Neural Network (ANN) and Back Propagation (BP) techniques for predicting PD symptoms. ANN and BP techniques were used for identifying continuous patient movements. The work used ANN based pattern matching techniques. The patterns of various patient movements were registered and trained for optimal disease evaluation. The work delivered acceptable PD analysis results on homogeneous medical features. At the same time, this work got limitations in multi-variant feature analysis.

Gao *et al.* [2] proposed a specific prediction and classification technique for Parkinson data analysis. This work was implemented with the help of data preprocessing techniques, cross fold validations, and ML approaches. The neuro data features and the tremor data features were analyzed to predict the symptoms. The methods used in this work provided valuable results but lacked in PD detection and sensitivity rate. Many research works were inherited with different perspectives for predicting PD.

In this manner, Mostafa *et al.* [3] found the solution using multi-agent data analysis system. The multi-agent system was designed for evaluating vocal disorders. Patient's vocal records were identified as major features for disease detection. The vocal variations were analyzed with the help of Reinforcement Learning (RL), Decision Tree (DT), Naïve Bayes classification and Random Forest (RF) techniques. This work collected the medical data from Tel Aviv Sourasky Medical Center. However, the work was lagging with real-time issues.

Biswajt *et al.* [4] proposed the system to detect D symptoms using speech attributes. In this work, SVM and Naïve Byes techniques were discussed using voice data features. The novel work constructed ML based voice analysis models for finding the PD symptoms. The work attempted to project more accurate results. However, this work lacked with the limited dataset features.

Rastegari *et al* [5] developed information gain analysis model for detecting PD features from the given dataset. This technique used various ML and information gain approached in combined manner. This strategy worked well in PD findings. But they produced insignificant results compared to DL based PD analysis models.

Seppi *et al.* [6] analyzed and conducted Parkinson treatment analysis for various non-motor symptoms. This work suggested that the treatment analysis helps to improve and update the future next level treatments. In this regard, the work collected the evidences of various treatments and produced valuable suggestions.

Many systems created medical review reports on PD and treatments. But these systems were not equipped with own specific techniques. Espay *et al.* [7] proposed new techniques for evaluating Synuclein protein disorders and aggregation rate for the detection of Parkinson and Alzheimer symptoms. Particularly, the protein aggregation techniques used for sporadic Parkinson and Alzheimer. At that time, the system did not take DL and ML assistance to train the protein features. Finding different types of PD and predicting the symptoms were really complex tasks. Bot *et al.* [8] used mobile datasets and mobile based data collections for PD analysis. In this work, the techniques were trained to produce less overhead data features on the detection of Parkinson. The techniques were effectively operated but limited with scalability issues. Bouwmans *et al.* [9] undergone with Idiopathic PD (IPD) symptoms for diversified feature classification. In this work,

TABLE 1. Literatures reviewed and key points indications.

APPROACH	YEAR	OBJECTIVE	PROS	CONS
RamziSadek et al. [1]	2019	The work proposed PD prediction using Artificial Neural ANNand BP.	This was used to recognize the patient's movements and shaking using ANN.	Gives good results than simple pattern matching techniques
Gao et al. [2]	2018	The system was designed for Prediction and classification of clinical Parkinson dataset.(Tel Aviv Sourasky Medical Center)	The work was developed to collect and observe neuro data using ML techniques.	Tremor based recognition gives real impact in research work
Mostafa et al. [3]	2019	It was a Multi-Agent system with ML techniques. The techniques were used for finding voice disorders.	It was intended to develop multiple voice feature and data valuation models using various ML techniques	Several voice disorders are counted for evaluation togive optimal outcomes
Biswajt et al. [4]	2019	The system used patient's Speech variations to detect PD	The techniques used Multiple voice feature for effective detection	More data features are used to get better results
Rastegari et al. [5]	2019	The proposed ML and similarity approaches were used for patient's data analysis	The technique was used to implement information gain based Parkinson data analysis	Multiple ML techniques are used to deliver more variety of results
Seppi et al. [6]	2019	The work analyzed the treatments given for various Parkinson patients based on non-motor symptoms	It was a medical review system based on the treatments given to patient	Review system helped for better treatment
Espay et al. [7]	2019	This proposed systemextracted specific Synuclein protein features for detecting sporadic Parkinson and Alzheimer symptoms	The techniques concentrated on the creation of Protein feature evaluation.	This odd work perceptiveness provided another view for Parkinson detection
Bot et al. [8]	2016	The system had mobile data collection for PD. The dataset was used for lightweight Parkinson detection.	The techniques used in this approach were mainly collaborated with hand held data items.	A simple and less computed data features helped for fast Parkinson detection.
Bouwmans et al. [9]	2013	This study work was conducted on identifying ultrasound features of Parkinson patients.	Idiopathic Parkinson symptoms were detected and analyzed for improving detection accuracy	Numerous data were collected from 196 patients for effective Parkinson study process.
Choi et al. [10]	2017	The work evaluated dopamine transporter image features using Deep Neural Networks (DNN) to detect PD..	Dopamine transporter images were taken for feature extraction. Then the samples were given in to DNN and CNN.	The DL based DNN and CNN combination gave effective accuracy rate.
Abdulhay et al. [11]	2018	The ML based work investigated gait and tremor features gathered from many patients. It was developed using peak detection and kinetic feature analysis techniques.	The ML techniques were utilized to observe the frequency variations of tremor and gait.	The tremor and gait oriented cutoff frequency evaluation system was effective in easy handling of the system
Frid et al.[12]	2014	This system proposed natural voice and speech variations. It helped to detect idiopathic PD.	The techniques were identified to determine the abnormal variations in certain vocal observations.	Natural speech processing techniques helped to get valuable Parkinsonobservations
Pereira et al. [13]	2016	DL techniques were used for extracting writing disorders of individual. Multiple sensors were fixed in pen for checking the abnormalities.	Writing disorders were sequentially noted and determined using numerous sensors.	DL and sensor readings were manipulated for real-time detection
Kubota et al. [14]	2016	This work was designed with body Sensor networks to observe movements.	PD was detected using wearable senor data. These sensor were made to find motions of body pats.	Real-Time monitoring mechanism helped to get realistic outcomes
Camps et al. [15]	2017	Freezing gait and waist movement were analyzed using DL techniques.	Freezing gait and motor symptoms were taken to detect PD.	A knowledge based analysis worked well for extracting the Parkinson symptoms.

biochemical features, tremor, ultrasonic features, proteins were effectively analyzed among 196 individuals. They were analyzed around various time spans to know the growth of the abnormalities. Also, the results were produced for each individual separately. However, the study had missed ML and DL impacts in accuracy improvement. Choi *et al.* [10] proposed DL based image analysis techniques using DNN and CNN. This work took dopamine transporter images features and variations for deep analysis. PD was detected and predicted by creating number of CNN and DNN layers between image frames. The image analysis was helpful to identify Parkinson symptoms from the evaluated elements. In this situation, the work concentrated on dopamine image features only.

Abdulhay *et al.* [11] found the new approach for detecting PD from gait and tremor disorders. The disorders were found by analyzing the real-time frequency variations.

This work proposed two separate algorithms such as peak detection algorithm and gait detection algorithm with kinetic feature evaluations. In this work, signaling filters were used with ML techniques for determining cutoff frequency ranges for gait and tremor. Mostly, the work focused on body movement abnormalities from the frequency disorders. The results produced by the techniques were sufficient but learning rate could be improved with more DL training phases. Frid *et al.* [12] proposed natural speech evaluation approaches based on ML techniques. The system found various words pronounced by patients from different ages. The abnormalities in each speech attribute was taken for Parkinson identification. In the same way, several works were implemented using movement detection sensors and pressure sensors. Pereira *et al.* [13] and Kubota *et al.* [14] used various sensors for detecting handwriting abnormalities and movement variations of patients. In the first system, sensors were used in pen for observing writing deviations. In order to detect the handwriting abnormalities, pressure sensors were used in patient's pen. The next technique used motion sensors for monitoring the patient's movement. This work was implemented with body sensors, which were affixed on patient's body. Finally, Camps *et al.* [15] used same motiondetection technology for detecting frozen gait. Even though, these systems produced valuable Parkinson observations,there was a lack in finding the number of patients and abnormalities.

Most of the related works were implemented using limited hidden layer function with less independent analysis procedures. This problem is resolved using MSAEPD system, which attains both dependent and independent nature of dataset features. After finding the research work solutions and the problem, the Proposed MSAEPD techniques are implemented using following algorithms. The algorithms used below represent classless, clustered and multi-perspective auto encoding procedures for predicting Parkinson symptoms.

III. MSAEPD SYSTEM

SAE is technique, which has unsupervised ML construction to maintain three different layers. The layers such as input, output and hidden functions. The auto encoder is working out two processes like encoding and decoding. Encoding process maps the input layer data in to hidden layer constructions. Decoder reforms input data from complex hidden layer representations.

The equations (1) and (2) represent auto encoder structure as follow. In the equation, H^e is encoding vector at hidden layer, w^e is encoding weight matrix, x^n is input layer elements (dataset) and b^e is bias element.

$$H^e = f\left(w^e.x^n + b^e\right) \tag{1}$$

$$x^d \sim= d\left(w^d.H^e + b^d\right) \tag{2}$$

x^d is decoding vector, w^d is decoding weight matrix and b^d is bias element at decoder part. SAE is constructed with the help of multiple auto encoders, which are arranged in stacked format to attain complex data analysis. It has multiple hidden layers for handling complex set of data. These layers are trained and back propagated to optimize overall cost. The proposed work optimizes SAE for handling huge amount of PD dataset. The proposed system is built with both supervised and unsupervised SAE for detecting PD. In addition, it extends SAE complexities to classify Parkinson symptoms using Balanced-SAE and Multi-SAE.

Algorithm 1 gives the procedures related to classless SAE for evaluating and training PD samples collected from various datasets. The datasets are gathered from various resources to build hyperactive heterogeneous dataset. The SAE analyses the data features in terms of various data samples for multiple epochs.

The training procedure is executed with the help of additional parameters such as, learning rate, data bias rate and weight factor matrix. These parameters are applied for multiple Parkinsonfeatures of each dataset. The data items are given in matrix order for evaluation. The data has been identified as either notable states or hidden units. For every state items, the weight factor matrix θ is determined and output sequences O_n are produced under unsupervised training procedures.

The SAE can be integrated with both supervised and unsupervised classification procedures. This provides extended scalability among various types of datasets. Algorithm 2 illustrates clustered SAE, which is supervised training method.

In this approach, the initial training procedures are not modified as much as notable. But algorithm 2 has logistic regression layer as data log layer for better evaluation of data samples at each epoch, α. Both algorithms express the Parkinson dataset training in different ways. The first one is unsupervised learning. The later approach is supervised training procedure. The proposed approach uses these variants of trained Parkinson features (multiple datasets) for deep learning based effective feature classification.

Algorithm 3 describes newly proposed Balanced Multi-SAE (BMSAE). The proposed system assumes that the trained Parkinson features are not balanced with concrete representations. On behalf of the data improvement, BMSAE

Algorithm 1 Hyperactive Classless SAE (HUSAE)

Input: *Sequence of Parkinson data samples*
Output: *Trained data items*

Step 1: *Call the procedure,*

$$P^{DA} = \sum(\alpha, \beta, \mathrm{C}, \gamma, \tau, \theta) \tag{3}$$

$\mathrm{C} = \{a_1, a_2 \ \ldots \ \ldots \ a_n\} \in M(nXm)$, *input matrix*
$a_n \in (0, 1)$ *in the order of* m
τ *is the learning rate*
Step 2: *Compute hidden component sequence,*

$$U = \{u_1, u_2, \ldots . u_n\} \in z^{\tau}$$

Step 3: *Determine Data noise rates,*

$$\gamma = \{\gamma_1, \gamma_2, \ldots . \gamma_n\} \in (0, 1)\, z^{\tau}$$

Step 4: *Do the computations for,* $\theta = \{\theta_1, \theta_2, \ldots \ldots \theta_n\}$; $\theta = \{\omega, \rho\}$
Step 5: *Compute determinations*

$$\text{Output } O_1 = P^{DA}\left(\sum(\alpha, \beta, \mathrm{C}, \gamma, \tau, \theta)\right) \tag{4}$$

Step 6: *For the Parkinson samples,* $i = 1 \ldots . n$

Do
{

$$O_1.i = \sigma\,(a_n\omega_1 + \rho) \tag{5}$$

}
Step 7: *Do the same for computing* O_1, j
Step 8: *End Procedure*
Step 9: *End*

P^{DA}	*Parkinson stacked auto encoder training procedure*
α	*Epochs*
β	*Group factor*
C	*Parkinson data samples*
γ	*Data noise level*
τ	*Learning rate*
θ	*Weight factor matrix*
ω	*Weight component*
ρ	*Bias in data samples*

is used for building well-structured Parkinson feature classification. BMSAE gets inputs from multiple trained Parkinson samples with their weight factor matrix, θ. This must be updated and revised according to balanced data distribution model, $\emptyset$. At the same time, this BMSAE finds the variations in both input and output data sequences with respect to epoch time interval. In this model, the data variants and the bias rates are regularized at different time intervals. Algorithm 3 gives the procedures of BMSAE.

This produces concrete classified results on PD detection. In the same way, Deep Variant Multi-SAE (DVSAE) is proposed for identifying the sub classes in each Parkinson feature

Algorithm 2 A Hyperactive Clustered SAE (HSSAE)

Input: *Sequence of Parkinson data samples*
Output: *Trained data items*

P^{ST} *Supervised auto encoder tuning procedure*

Step 1: *Call the procedure*

$$P^{ST} = \sum(\alpha, \beta, \mathrm{C}, \gamma, \tau, \theta) \tag{6}$$

Step 2: *Compute the procedures of* P^{DA}
Step 3: *Compute hidden and output layers, Un and On*
Step 4: *Compute data log layer, i.e. Logistic Regressed layer*
Step 5: *For every* α, *execute* P^{ST}
Step 6: *End*

Algorithm 3 Balanced Multi-SAE for Parkinson Feature Classification (BMSAE)

Input: *Trained Parkinson data with* θ
Output: *Classified Results*

$\emptyset$	*Balanced data distribution function*
t	*Time intervals*
∂	*balanced Multi-SAE*
∂_α	*Adjustment in* α
∂_0	*Initial seed in* α
dt^α	*Adjustment in* α *at time intervals*
∂O_n	*Adjusted output samples*

Step 1: *Collect outputs,*

$$O_n = P^{\frac{DA}{ST}}\left(\sum(\alpha, \beta, \mathrm{C}, \gamma, \tau, \theta)\right) \tag{7}$$

Step 2: *Compute balanced data distribution,*

$$\emptyset = \frac{exp(\log(a_i + \theta_i)/t))}{\sum(exp(\log(a_n + \theta_n)/t)} \tag{8}$$

Step 3: *Initialize balanced Multi-SAE,*

$$\partial = \left(\frac{\partial_\alpha}{\partial_0}\right) dt^\alpha \tag{9}$$

Step 4: *Determine Samples,*

$$\partial O_n = B(\theta_n, dt^\alpha) \tag{10}$$

Step 5: *Compute layered balanced network,* $f(b)$
Step 6: *Calculate gradient of distortions w.r.t,* θ
Step 7: *Update* a_n *and* O_n
Step 8: *Evaluate* θ_{new} *at* dt^α
Step 9: *Produce iterative classified* O_n.
Ll
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group. This system creates input diminutive sets from input matrix elements. Algorithm 4 provides the details of DVSAE. This SAE identifies deep variants in each Parkinson dataset features.

Algorithm 4 Deep Variant Multi-SAE (DVSAE)

Input: *Trained Parkinson data with* θ
Output: *Classified Results*

C_C	*Input diminutive sets*
δ	*Parkinson attribute gradient*
∂_S	*Change in diminutive sets*
∂_O	*Change in output values*

Step 1: *Get* $C = \{a_1, a_2 \ \ldots\ldots \ a_n\} \in M(nXm)$, *input matrix*
Step 2: *While sample are not deeply converged, then do* $C_C = \{S_1, S_2, \ \ldots\ldots \ S_n\} \in M\ (nXm)$
Step 3: *Compute gradient,* δ *on* ∂_S *and* ∂_O
Step 4: *Update* S_n, θ_n *and* O_n
Step 5: *Set Sample diminutive input samples*
Step 6: *Calculate and Update* δ *for all samples at* τ
Step 7: *Formulate sample states and instant samples at* τ
Step 8: *Train deep variant SAE*$\forall\ C_C$ *w.r.t* θ_n *at* τ
Step 9: *Collect the samples and feed in to deep SAE learning network*
Step 10: *Produce* O_n *at all* τ
Step 11: *Redo iterative SAE for all Parkinson variants and features*

According to that, multiple sub classes are formed for evaluating feature weights. The deep analysis over various state-based input identification has been executed by DVSAE. This gives more relevant and optimal Parkinson data resemblance rate. This proposed approach produces more converged results than other methods in huge data handling systems.

As discussed AEs support dimensionality reductions. This create more sophisticated dataset. In addition, the effective feature reduction helps to improve the DL based PD analysi system. The proposed SAEs are supporting for both dimensionally reduction effective PD recommendation design. The AE stacks extensively classify the clinical PD symptoms. This SAE based PD detection technique uses real-time clinical dataset. These datasets are filled up with both voice and tele monitoring features of multiple patient records.

Figure 1 illustrates the types and functions of proposed system. The first two systems HUSAE and HSSAE are hyperactive SAEs. They are working based on unsupervised and supervised learning methodologies respectively. BMSAE helps to distribute the Parkinson data evenly among all AEs in the stacks. This distributes the load of computational events among all AEs to reduce the complexity. The final version of SAE is trained by more number of sample variants using DNN based SAEs. Comparing to all SAEs, the proposed DVSAE has highest learning rate.

It provides the generic structure of SAE. In this figure SAE has been equipped with more AEs. Each AE in a stacks is constructed using DNN to evaluate Parkinson features. The DNNs in the stacks are getting Parkinson data in a distributed manner for the hidden layer functions

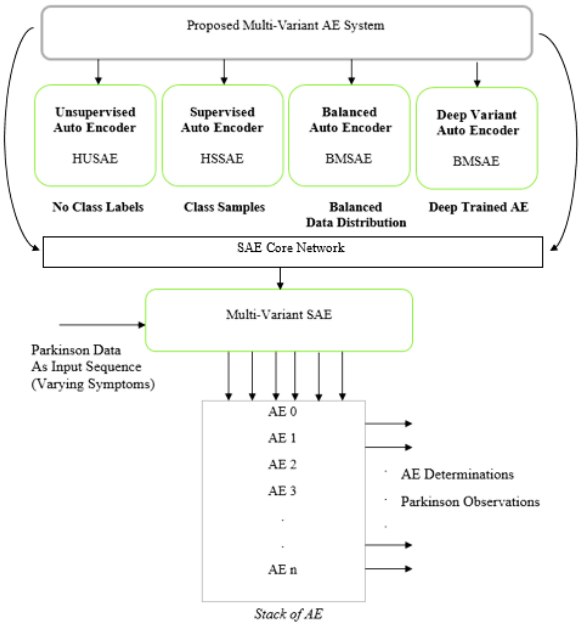

FIGURE 1. Multi-variant SAE on Parkinson Detection.

(Encoding and Decoding). Figure 2 gives the gradient manipulation for the input and output variances at τ_i.

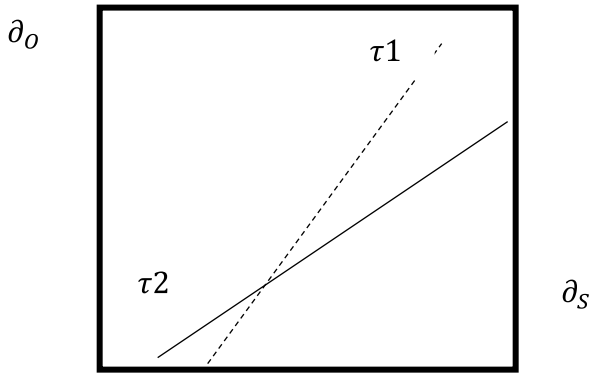

FIGURE 2. Parkinson variance.

The gradient curve output dependency is given in equation (11).

$$O_n = \sum (\theta_n \pm S_n)\ .dt^{\alpha} \tag{11}$$

The proposed techniques are implemented with real-time datasets of Parkinson features. The results section describes the performance evaluation of proposed MVSAEPD system.

IV. UNITS

The Proposed MSAEPD System has been implemented and evaluated under different aspects. There are different types of datasets available for evaluating Parkinson detection techniques. This Proposed MSAEPD System uses real-time Parkinson datasets collected from various patients. The dataset is collected from the Neurological Department of Velammal Medical College Hospital, Madurai, India. The

dataset contains 520 medical records. Among those records, 430 records hold the measurements of Parkinson patients and 90 records belong to normal people. The measurements of Parkinson symptoms are taken from the medical features such as UPDRS scores (motor, voice and total score), voice pitch variations (frequency) and dopamine levels. Also, the real-time dataset contains pain scores, headache scores, falls, tremor scores, cardiac scores, respiratory scores and others. This kind of dataset has more attributes in diversified manner to promote the medications without making any side effects. These measurements are taken from each patient during gradual time phases (40 weeks and 80 weeks).

These values use to create multi-variant dataset, which support for MSAPD evaluation procedures. Based on Proposed MSAPD procedures, these Parkinson scores are classified under three categories such as Normal, Early stage groups and Delayed stage groups. According to that, each Parkinson score has baseline but it can be tolerated depends on patient conditions. MSAPD procedures analyses both UPDRS scores, voice measurements and dopamine levels to provide concrete results to take care of more early stage patients. The better classification accuracy leads the PD detection system to avoid more early stage patients enter in to delayed stage patient list.

The raw dataset may contain missing scores, noise, incomplete data fields, redundant data fields and unrelated data objects. MSAEPD uses Weka 3.0 tool to preprocess the raw dataset using data preprocessing techniques. The preprocessing helps to remove unusable data fields and correlate related data objects. Then the Proposed MSAEPD procedures are implemented to analyze the preprocessed dataset fields using Python 3.7. The Proposed works are evaluated on real-time dataset features. There are many medical based and ML existing techniques available to detect PD [16]–[18].

The Proposed techniques such as, HUSAE, HSSAE, BMSAE and DVSAE are compared with each other on three different datasets. In this performance evaluation section, Multi-Attribute Artificial Neural Network (MANN), Genes - AE (GAE) and Unsupervised ML for Bio variation Detection (UMLBD) are compared with Proposed techniques. Also, the conventional CNN and RNN are taken for performance comparison. In this evaluation, the following parameters are identified for system effectiveness. The evaluation parameters are shown in table 2.

MANN, GAE and UMLBD are existing techniques used to evaluate the real-time dataset as mentioned above. Among the existing techniques, MANN is developed for detecting Parkinson symptoms using pattern-matching techniques. In addition, this approach uses back propagation technique to improve the accuracy. Though the technique is significant to analyze multi-attribute dataset, it has limited ANN layers. This causes reduction in PD classification accuracy [1]. GAE is the technique to handle PD detection and prediction using AE components. AE network of this approach helps to encode and decode Parkinson symptoms genetically. It uses gene patterns for effective coding analysis. However, the technique has restricted AE functions to deal with complex gene patterns [18].

In ML approaches, UMLBD analyses biological information of neural systems. It is a kind of unsupervised ML technique use to randomly classify neural activities and biochemical impacts related to PD [19]. All of these works are motivated to detect PD but with less complexity in their structures [20], [21]. The existing techniques such as UMLBD is evaluating the biochemical variations using multivariable analysis. At the same time MANN is analyzing the PD data using multiple attributes. These two techniques are ML approaches. In contrast, GAE uses AE for evaluating deep genetic structures. This is DL approach. These three techniques are closely related to multi-variant analysis model. Thus the proposed multi-variant SAE is compared with these existing systems.

To handle multi-attribute dataset, the ML system needs more layers of deep analysis such as deep SAE. This produces dynamic range of AE stacks to analyze the data observations effectively. Table 2 shows the results taken for the parameters such as precision, recall, specificity, classification accuracy and Mean Absolute Error (MAE). These performance metrics are observed for various MANN, GAE, UMLBD and the Proposed PD detection procedures.

TABLE 2. Performance comparison of ML strategies.

Parkinson Detection Techniques	Rate of Precision	Rate of Recall	Rate of Specificity	Rate of Accuracy	Mean Absolute Error
MANN	97.52	97.15	96.15	96.42	3.58
GAE	97.01	97.05	96.03	96.11	3.89
UMLBD	96.36	96.45	95.85	95.89	4.11
HUSAE	98.81	98.55	98.98	98.95	1.05
HSSAE	98.78	98.25	98.36	98.56	2.44
BMSAE	98.89	99.07	99.10	98.87	1.13
DVSAE	99.06	99.12	99.02	99.01	0.09

It shows DVSAE holds optimal performance rate than other techniques due to its dynamic adaptation with changes. DVSAE evaluates the observations based on changing sequences using multiple hidden SAE layers. As same as, BMSAE handles the PD dataset in balanced manner for multi-SAE network structure. The other HUSAE and HSSAE are classless and clustered approaches help to provide distinct set of PD detection results. These methods use to analyze the PD results in different aspects. The existing results MANN, GAE and UMLBD are effective related techniques but they lacks with multi-layer neural structures.

Figure 3 illustrates the comparison of all ML techniques in terms of precision rate on increasing sampling rate. Sampling rate critically affects the performance measures of PD detection outcomes. Sampling rate is gradually increasing from 10% to 50% for overall dataset. From 520 patients, the samples are gathered based on PD sensitivity. Particularly, UPDRS scores, dopamine counts and voice samples are taken

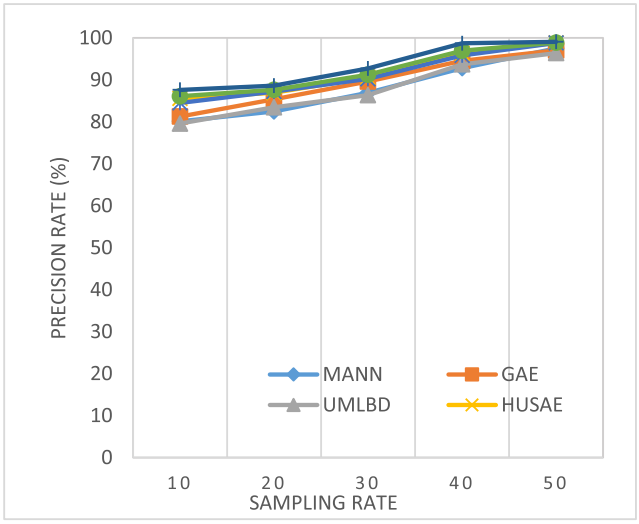

FIGURE 3. Precision rate against data sampling rate.

as samples to the maximum rate of 50%. This rate is common to all patients.

As given in figure4, DVSAE, BMSAE perform with better precision rate than the other existing work. In this performance evaluation, the precision rate increases as samples increases.

Figure 4 and 5 provides PD classification accuracy rate for different experiment phases. The phase one of PD is experimented at the week of 40 and the phase two of PD is conducted at the week of 80.

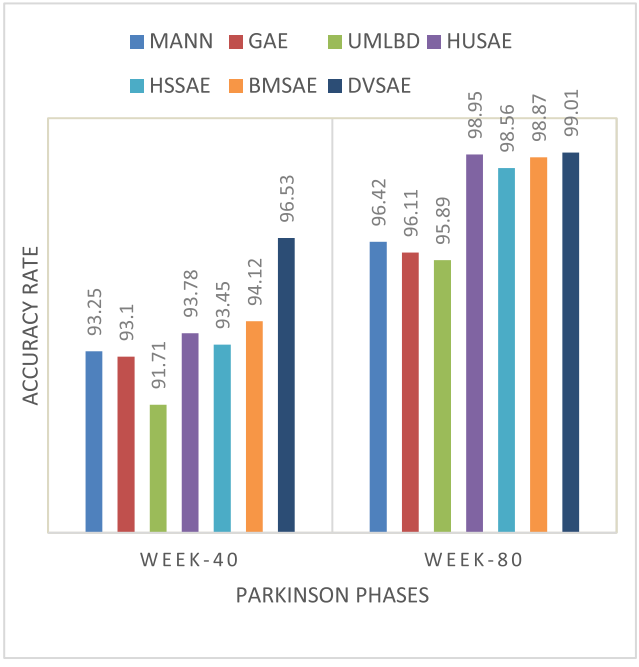

FIGURE 4. Parkinson detection phases and accuracy rate.

In both sections, accuracy rate and MAE are identified for all techniques. Among these various techniques,

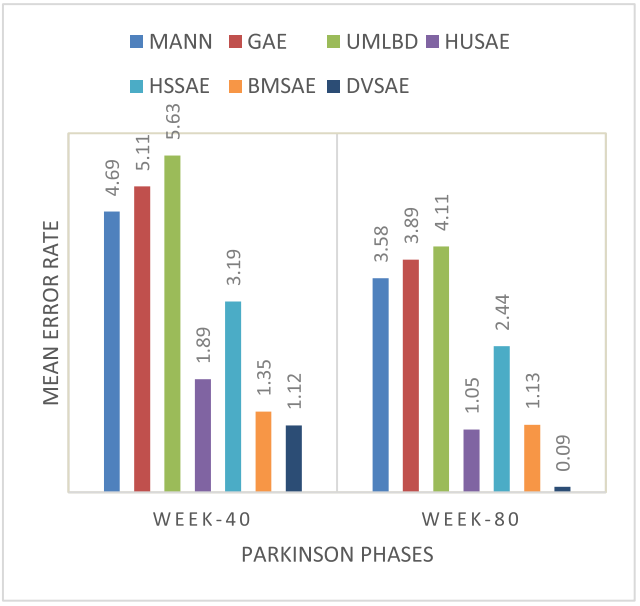

FIGURE 5. Parkinson detection phases and MAE.

the Proposed procedures delivered optimal performances. However, MANN gives slightly better performance than GAE and UMLBD due to its ANN complexities.

Table 3 shows PD score classes and Independent Accuracy Rates. The score classes contain UPDRS motor and non motor scores, voice symptoms and dopamine particulars. The existing and Proposed techniques are evaluated over different set of dataset features independently. The real-time clinical dataset is classified based on UPDRS, voice attributes and dopamine levels as given in Table 3. The Proposed MSAEPD procedures are executed independently for detecting PD symptoms. In this case also, the Proposed MSAEPD procedures outperforms the other techniques. The collective observed results and independent score-based outcomes are used to train the MSAE network continuously to predict the PD easily than other systems [22]–[24].

TABLE 3. Precision rate.

SAMPLES/ PRECISION	MANN	GAE	UMLBD	HUSAE	HSSAE	BMSAE	DVSAE
UPDRS	94.5	93.5	92.1	98.7	97.8	99.2	99.8
Voice Symptoms	93.5	91.2	90.2	96.5	95.5	97.6	97.6
Dopamine	92.5	92.4	90.5	97.5	95.6	98.1	98.3

V. CONCLUSION AND FUTURE SCOPE

The Proposed MSAEPD system was developed to ensure more accurate PD detection and PD optimal treatment assistantship. To achieve accurate PD classification, MSAEPD system used four different strategies with the help of complicated MSAE. In this work, HSSAE, HUSAE, BMSAE and

DVSAE were proposed and examined using real-time Parkinson dataset. The Proposed procedures are compared with MANN, GAE and UMLBD techniques using various critical parameters. In this comparison, MSAEPD system showed notable improvement than existing systems in all aspects. The reason behind the performance is the multiple stacks of SAE and the effective learning approaches [25], [26].

In future, this system is expected to be improved with a greater number of patients and complex biological data analysis techniques. Further this proposed PD data analysis model can be extended using different types AE variances. This variations experiments provides versatile results for PD detection.

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