# CCZO Residual GhostNet: Parkinson Disease Classification using Optimized Deep Learning Technique

Original Scientific Paper

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***Abstract*** *– Parkinson's disease (PD) classification plays a crucial role in medical diagnosis and patient management. Identifying Parkinson's disease at an early stage can lead to more effective treatment and improved patient outcomes. However, existing methods for Parkinson's disease classification face several limitations. The foremost limitation is the need for accurate and reliable diagnostic tools, as misdiagnosis can lead to inappropriate treatments and unnecessary stress for patients. Thus, a hybrid deep learning model is introduced in this research. The proposed model involves the utilization of EEG signals obtained from a publicly available dataset. Key features are extracted from the EEG signals using a bandpass filter, and every feature is associated with specific brainwave frequencies and cognitive states. The feature mapping and classification are executed through the Chaotic Chebyshev Zebra optimization-based Residual GhostNet (CCZO_Residual_GhostNet). This hybrid classifier, Residual GhostNet, combines ResNet-152 with GhostNet, enhancing classification precision. Furthermore, the CCZO algorithm optimizes the loss function, introducing elements of chaos and Chebyshev mapping to improve classification accuracy. The assessment based on accuracy, sensitivity, specificity, and F-score acquired 98.76%, 98.59%, 98.95%, and 99%, respectively.*

***Keywords***: *EEG signal, hybrid deep learning, Parkinson's disease classification, Feature extraction, GhostNet, ResNet-152.*

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## 1. INTRODUCTION

People get older, and their neurons decline along with a decrease in the connections between brain cells. Nerve cells cannot replenish themselves, in contrast to other cell types in the body [1]. Neurons can get damaged or degenerate over time. Neurodegenerative illnesses are a group of disorders characterized by the progressive degeneration of the structure and function of the nervous system. These conditions often result in the gradual loss of cognitive and motor functions. Some common neurodegenerative illnesses include Alzheimer's disease, Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis (ALS). Parkinson's disease (PD) is a neurodegenerative illness that primarily affects neurons in the brain's substantia nigra. These neurons are essential for the synthesis of dopamine, which is a neurotransmitter that connects neurons in the brain [2]. Dopamine helps messages go from the brain to other regions of the body, especially when it comes to speech articulation and physical motions. When a considerable proportion of dopaminergic neurons degenerate or when dopamine levels in the brain diverge from normal, Parkinson's disease symptoms become apparent [3]. Statistics from the World Health Organization indicate that about 10 million people suffer from the effects of this illness. It is more common in older adults, affecting those in their fifties and older. Males are 1.5 times more prone to PD than females, and around 4% of cases are identified before the age of fifty [4]. The initial symptoms could be difficult to notice and modest at first, but they get worse over time. Dyskinesia, syncope, exhaustion, tremors, stiffness, dystonia, hypomimia, diarrhea, poor smell or taste, and loss of weight are examples of both

motorized and non-motorized symptoms. Because PD is untreatable, early diagnosis is essential for patients to take proactive steps for managing the condition, which allows them to continue with their regular activities [5].

Depending on how Parkinsonism is classified, many imaging modalities are used to diagnose PD [6]. There are different kinds of Parkinsonism, and this study focused on the most common kind, idiopathic PD, usually referred to as PD, which has an unclear etiology [7]. As part of the diagnostic procedure for PD, PET (positron emission tomography) and SPECT (single photon emission computed tomography) show exceptional sensitivity in detecting dopamine shortages [8]. However, the high cost and specialized equipment required for these imaging modalities limit their broad use in routine clinical diagnosis [9]. In addition to imaging techniques, 90% of patients who undergo the olfactory dysfunction test are utilized as a preliminary clinical sign of PD. Techniques based on biomarkers include quantifying biological markers found in different parts of the body and blood to provide information on the existence and severity of illness. Another potential diagnostic method for PD is electroencephalography (EEG) [10]. EEG-based treatments have several benefits with respect to other diagnostic techniques, such as cost-effectiveness, non-interfering, and better resolution, as they are non-invasive. The number of studies utilizing EEG technology is increasing [11, 12].

Many different methods are presented in this field; most of them use speech signals, handwriting signals, gait signals, MRI, and very few use EEG. One of the most effective methods for diagnosing PD is electroencephalography (EEG) [13]. Since EEG technology is portable and affordable, its value is demonstrated by its capacity to record brain activity in real-world settings [14]. Moreover, EEG-record-based brain activity occurs faster than other modalities and for longer periods. Thus, the analysis of EEG integrated with machine learning techniques has already proven to be useful in the diagnosis of a number of neurological disorders, including epilepsy, major depressive disorder, schizophrenia, Alzheimer's disease, autism spectrum disorder, and dementia [15, 16]. The amount of medical data that is being recorded has grown to incredible heights; signals and photographs in particular have amassed gigabytes and even terabytes of data. It is a laborious undertaking to process these enormous datasets and extract valuable insights from them. One aspect of artificial intelligence called machine learning gives machines the ability to anticipate outcomes based on data analysis, teaching them to mimic human intellect [17]. Thus, a novel deep learning-based framework is introduced in this research. The major contributions of the research are:

- Design of CCZO Algorithm: The proposed CCZO algorithm is designed by integrating the chaotic Chebyshev mapping with zebra optimization to enhance the randomization criteria for obtaining the global best solution.
- Design of hybrid Residual_GhostNet: The hybrid deep learning by integrating the ResNet-152 with the GhostNet to improve the classification accuracy.
- Design of CCZO-Residual_GhostNet for PD classification: The PD classification is employed using hybrid Residual_GhostNet, wherein the loss function optimization is employed using the CCZO algorithm.

The organization of the research is: Section 2 details the related works and Section 3 explains the Proposed PD classification. Section 4 elaborates the experimental outcome and Section 5 concludes the research.

## 2. RELATED WORKS

This section offers a survey of the literature on machine learning-based Parkinson disease classification. The EEG signal was used by [18] to distinguish between individuals with PD who were taking medication and those who were not. Pre-processing of the signals was done in order to remove significant artifacts. Based on the collected characteristics, [19] created a collection of machine learning methods for classifying Parkinson's illness. These methods make it possible to automatically classify EEG data into those with PD and those without it. In this case, the discriminative characteristics of Parkinson's illness were improved by the use of spatial filtering. Analyzing variables such as frequency bands, segment lengths, and feature reduction numbers provides valuable information for improving the suggested approaches' efficiency and versatility. Complexity may be introduced by utilizing various machine learning algorithms and feature extraction metrics, which can make the models difficult to comprehend and use in clinical contexts. To accurately classify PSD and healthy control (HC) participants, a convolutional neural network (CNN)-based classification model with seven hidden layers and various filter sizes was suggested [20]. Three-dimensional data was transformed into a one-dimensional tensor flow using a flattening layer. In order to determine the initial danger of PSD patients, the dense layer finally outputs a categorization of HC and PSD patients depending on the strength of their tremors. With a tremor detection rate of 92.4%, it surpassed the conventional models. In order to demonstrate the value of deep learning-driven voice recognition as a diagnostic instrument for Parkinson's disease (PD), a speech signal processing technique was suggested [21]. It was explored if voice recordings could offer a straightforward, inexpensive approach to assessing and testing for Parkinson's disease, utilizing deep learning to forecast and assess expert scores. As a result, a modified Hybrid Mask U-Net architecture with an adaptive custom loss function called the Deep U-lossian model was developed for PD assessment and recognition, aiming toward an improved ratio of recall and precision in handled speech.

It is discussed how to classify the high-dimensional PD data [22]. In order to create effective ML classifiers to classify Parkinson's disease (PD), the best subset of features from the PD data set is chosen using a bio-inspired feature selection strategy. Eleven machine learning classifiers (ML) were used in the study: LR, lSVM, rSVM, GNB, GPC, kNN, DT, RF, MLP, AB, and QDC. Two bioinformatics techniques (GA and BPSO) were used for feature selection. The PD data set is split into training and testing sets in the ratio of 0.7:0.3 to train and test all 11 ML classifiers. Based on numerous classification assessment measures, the effectiveness of these ML classifiers is assessed both prior to and following the selection of bioinspired features. The presented results indicate that three of the best BPSO-inspired classifiers, BPSOMLP, and three of the best GA-inspired classifiers, GAMLP, GAGPC, and GALR, can be suggested for categorizing the PD data.

### 2.1. PROBLEM STATEMENT

PD is a crippling neurological ailment that has several negative consequences. It mostly affects the motor function of the person, resulting in symptoms like tremors, muscular stiffness, and postural instability. As the illness worsens, mobility issues may arise, increasing the risk of falls and associated injuries. PD can also include non-motor symptoms such as anxiety, sadness, insomnia, and cognitive decline. Difficulties with swallowing and speech might also occur, making everyday living even more challenging. PD can have a significant emotional and social impact on a person, sometimes resulting in social disengagement, a decline in daily functioning, and a breakdown of relationships.

Various methods are currently used for PD diagnosis, but they come with their own set of challenges. Imaging techniques like MRI and DaTscan can visualize brain changes, but they are costly and not always readily available. Biosensors offer continuous monitoring but struggle to distinguish PD from other movement disorders. Genetic testing can identify rare mutations linked to PD, but most cases do not involve these mutations. EEG-based methods can detect brain activity changes but require advanced data analysis and interpretation.

The hybrid Residual_GhostNet model represents a promising approach to overcome these challenges. By using deep learning and neural networks, this model can analyze EEG data, identifying patterns associated with PD more objectively and efficiently. It leverages a data-driven approach for automatic extraction of relevant features from EEG signals, reducing the need for manual feature engineering and human interpretation. Loss function optimization technique using CCOZ fine-tunes the model's parameters, enhancing its ability to classify PD accurately. With the automation and efficiency of deep learning models, the Hybrid Residual_GhostNet can analyze large datasets rapidly, offering a potential solution to the challenges of subjectivity in clinical assessments, early-stage PD detection, and the requirement for cost-effective and non-invasive diagnostic tools. This model represents a significant advancement in the field of Parkinson's disease detection, potentially leading to more timely diagnoses and improved patient care.

## 3. PROPOSED METHODOLOGY

The proposed PD classification is presented in Fig. 1, wherein the input EEG signal is acquired from the publicly available dataset. Initially, the essential features are extracted from the EEG signal by the bandpass filter. From the extracted features, feature mapping and classification are employed using the proposed Chaotic Chebyshev Zebra optimization-based Residual GhostNet (CCZO_Residual_GhostNet). Here, the hybrid classifier Residual GhostNet is designed by integrating ResNet-152 with GhostNet. Besides, the loss function optimization is employed using the CCZO algorithm designed by incorporating the chaotic Chebyshev with the conventional zebra optimization algorithm for enhancing the classification accuracy.

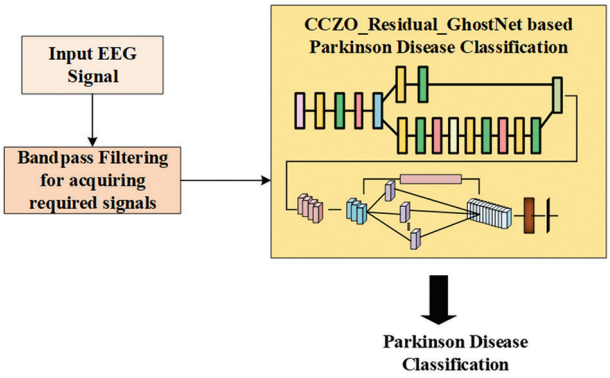


**Fig. 1.** Workflow of proposed PD classification

### 3.1. DATA ACQUISITION

The input data for processing the PD classification is acquired from the publically available dataset named the UCSD dataset.

### 3.2. FEATURE EXTRACTION

The acquired EEG signal is filtered using the bandpass filter to acquire the required features alpha, beta, gamma, delta, and theta.

Delta Waves (0.5-4 Hz): Delta oscillations manifest as the most languid cerebral frequencies, intimately entwined with profound slumber, tranquility, and states of subliminal awareness. They organize the symphony of physical and psychological rejuvenation.

Theta Waves (4-8 Hz): Theta waves find their similarity with profound serenity, dream, and the primary phases of inactivity. These waves are also patrons of ingenuity and transcendental contemplation.

Alpha Waves (8-13 Hz): Alpha rhythms take centre stage when one is in an awakened yet tranquil disposition.

They often grace us when our eyelids are shut, heralding a composed and vigilant mentality.

Beta Waves (13-30 Hz): Beta frequencies accompany lively, conscious cogitation and acumen. They flourish during periods of vigilance, attentiveness, and cognitive riddles.

Gamma Waves (30-100 Hz and beyond): Gamma waves, the swiftest of neural harmonics, intertwine with loftier cognitive faculties, perception, and cognizance. They partake in the orchestration of informational processing and may be linked with epiphanies.

From the acquired signal, the PD classification is employed.

### 3.3. PD CLASSIFICATION USING IMPROVED RESIDUAL_GHOSTNET

The Parkinson's disease classification is employed using the proposed Improved Residual_GhostNet. Here, the ResNet-152 is integrated with the GhostNetto enhance the disease classification precision. Besides, the loss function optimization is devised using the CCZO algorithm for enhancing the classification accuracy further.

#### 3.3.1. Architecture of ResNet

ResNet architectures are known for their skip connections, also called residual connections. These connections enable the network to skip over one or more layers and add the output from a previous layer to the output of a subsequent layer. This is done through element-wise addition. The key criteria for a skip connection are that the dimensions of the feature maps must match. ResNet-152 is a deep convolutional neural network with 152 layers. It comprises various components, including convolutional layers, residual blocks, maxpooling, fully connected layers, and activation functions. These components work together to map the features from the input features to perform the classification more accurately. The architecture of the ResNet-152 is depicted in Fig. 2.

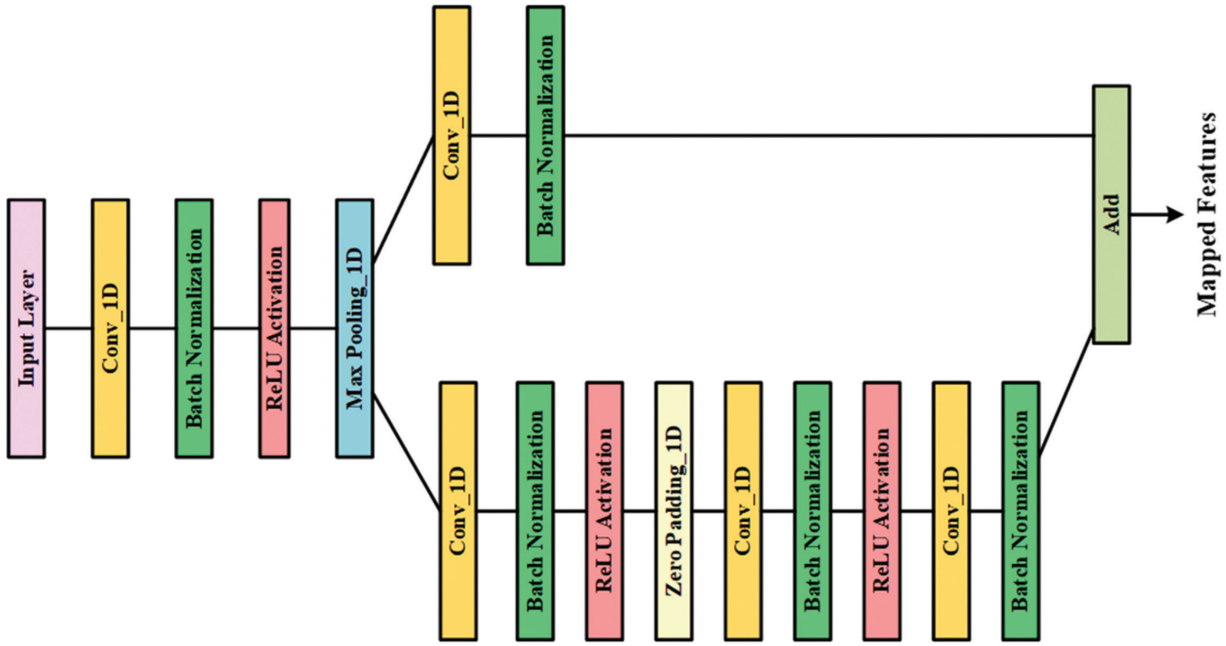


**Fig. 2.** Architecture of ResNet-152

#### 3.3.2. Architecture of GhostNet

Using the features mapped by ResNet-152, the PD classification is employed using GhostNet. The utilization of GhostNet for PD classification offers a range of significant benefits. GhostNet, renowned for its efficiency and compact architecture, stands out as an optimal choice in the field of disease diagnosis and classification. Its lightweight design and reduced computational requirements result in faster inference times, making it ideal for real-time or near-real-time applications. This attribute is particularly crucial in the context of healthcare, where swift diagnosis and monitoring are paramount. The architecture of GhostNet is depicted in Fig. 3.

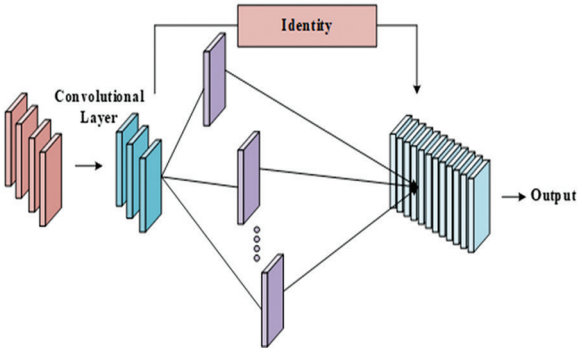


**Fig. 3.** Architecture of GhostNet

The two various paths utilized by the GhostNet are the:

**Convolutional Layer**: The Convolutional Path is the primary pathway in GhostNet for processing input data. It consists of standard convolutional layers, which are fundamental in deep learning for feature extraction. The Convolutional Path plays a critical role in capturing low- and high-level features from the data, gradually building a hierarchical representation of the input. The outcome of the Convolutional layer is represented as:

$$CL = D * b + f \tag{1}$$

where, refers the outcome of the convolutional layer, bias is notated as, the input data is represented as, and defines the conventional filters.

**Ghost Layer**: The Ghost Path is a distinctive aspect of GhostNet's architecture. It complements the Convolutional Path to improve feature representation and model performance. The Ghost Path consists of ghost modules, which are essentially lightweight versions of standard convolutional layers. These ghost modules are created by using depth-wise separable convolutions. In the Ghost Path, the ghost modules are designed to capture additional features and patterns in the input data. They operate in parallel with the Convolutional Path.

$$GL = D * f' \tag{2}$$

where, the filter utilized in the ghost path is denoted as and the outcome of the Ghost module is defined as.

The outputs from the ghost modules are then combined with the outputs from the Convolutional Path. This fusion of information enhances the network's ability to learn discriminative features while maintaining efficiency.

#### 3.3.3. Architecture of Residual_ GhostNet

The proposed Residual_GhostNet is designed by integrating the conventional ResNet-152 with the GhostNet for enhancing the classification accuracy, which is depicted in Fig. 4. In this the outcome of the GhostNet is connected with the fully connected layer and the softmax layer for classifying the PD.

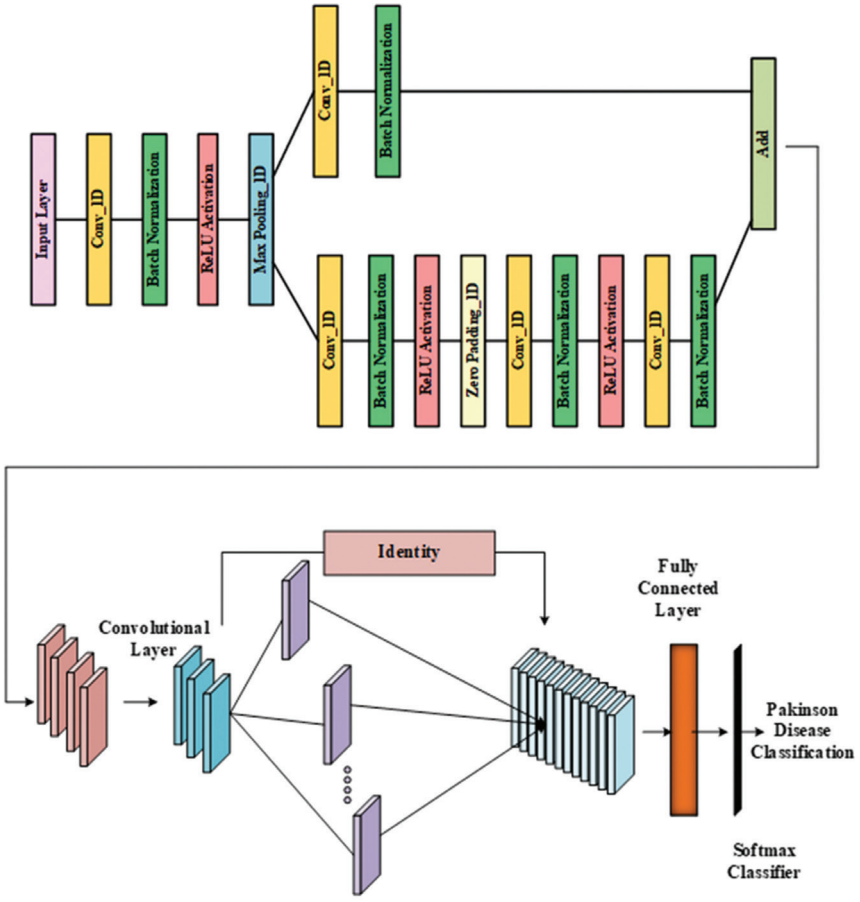


**Fig. 4.** Architecture of Residual_GhostNet

Here, the proposed PD model is tuned optimally using the CCZO algorithm for enhancing classification accuracy.

**Loss Function Optimization**: The loss function optimization is devised using the proposed Chaotic Chebyshev Zebra Optimization (CCZO) algorithm. In this, the solution trapping at the local optima is eliminated by incorporating the randomness criteria in the exploration phase using the Chaotic Chebyshev mapping.

**Initialization**: Each zebra in this population is like a potential solution to a problem that the algorithm is trying to solve. The location of each zebra on the search space represents a set of values for the decision variables related to the problem. Essentially, the zebra's

positions correspond to different potential solutions. This randomness is part of the algorithm's exploration of several solutions. The initialization of the population is stated as:

$$A = \begin{bmatrix} A_1 \\ \vdots \\ A_k \\ \vdots \\ A_G \end{bmatrix} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,l} & \cdots & a_{1,b} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ a_{k,1} & \cdots & a_{k,l} & \cdots & a_{k,b} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ a_{G,1} & \cdots & a_{G,l} & \cdots & a_{G,b} \end{bmatrix}_{G \times b} \quad (3)$$

Here, the population of the zebra is denoted as $A$, and $A_k$ refers to the $k^{th}$ zebra in the search space. The total count of zebras considered in the algorithm is denoted as $G$, and $a_{k,l}$ represents the $k^{th}$ zebra with the solution dimension $l$. After placing the population, the feasibility of the solution is evaluated.

**Feasibility Evaluation**: The feasibility of the solution is estimated for every zebra to identify the closeness of the solution to the required target. In the proposed disease detection, the mean square error is considered for evaluating the feasibility and is stated as:

$$F = \frac{1}{T}\sum_{x=1}^{T}(O_x - T_x)^2 \quad (4)$$

where, the fitness is $F$, overall samples is denoted as $T$, the observed value is $O_x$ and the target value is denoted as $T_x$.

**Randomization**: The randomization of the algorithm utilizes the foraging behaviour, wherein the food searching is employed. A specific type of zebra grasses in the plains and is named as Pioneer zebra that leads the group members to get the food and updates the solution as:

$$a_{k,l}^{R} = a_{k,l} + q \cdot \left(DE_l - H \cdot a_{k,l}\right) \quad (5)$$

Here, the zebra that guides the team members in obtaining the food is denoted as $DE_l$ and the value [0,1] is the limit for the arbitrarily chosen variableq. The expression for identifying the factor $H$ is expressed as:

$$H = round(1 + d) \quad (6)$$

Here, random number denoted as dhas the limit [0,1] and hence, the range of the factor $H$ is varies from {1,2}. After evaluating the solution for the zebras, the updation of the acquired solution is devised by:

$$A_k = \begin{cases} A_k^R F_k^R < F_k \\ A_k Otherwise \end{cases} \quad (7)$$

The solution accomplished by the zebra in the randomization phase is denoted as $a_{k,l}^{R}$, and the fitness for this phase is defined as $F_k^R$.

Here, in the randomization phase, the chaotic chebychev randomization is incorporated with the foraging behaviour of the zebra for enhancing the exploration strategy to obtain the global best solution. The expression that represents the chaotic chebyshev randomization is expressed as:

$$A_k^R = cos(J.cos^{-1} A_k) \quad (8)$$

$$A_k^R = 0.5[A_k^R]_{Zebra} + 0.5[A_k^R]_{chaoticchebyshev} \quad (9)$$

$$A_k^R = 0.5\left[a_{k,l} + q \cdot \left(DE_l - H \cdot a_{k,l}\right)\right] + 0.5[cos(J.cos^{-1} A_k)] \quad (10)$$

Thus, using the equation (10), the solution updation is devised using the CCZO algorithm and assist to obtain the global best solution.

Escaping Capability: In this phase, the zebra tries to escape from the predator like the lion. Similarly, zebras offend some predators like dogs and hyena's. Thus, the solution updation devised by the zebra in both the escaping and offending capability is expressed as:

$$a_{k,l}^{R2} = \begin{cases} a_{k,l} + Q \cdot (2q - 1) \cdot \left(1 - \frac{\tau}{\tau_{max}}()_{k,l_s}\right) \\ a_{k,l} + q \cdot \left(R_l - H \cdot a_{k,l}\right), otherwise \end{cases} \quad (11)$$

Here,

$$A_k = \begin{cases} A_k^{R2} F_k^{R2} < F_k \\ A_k Otherwise \end{cases} \quad (12)$$

Thus, using the evaluation of the fitness, the solution updation is devised.

Stoppage: The acquisition of the targeted solution or the completion of the iteration stops the iteration processing.

## 4. RESULT AND DISCUSSION

The implementation of the proposed PD classification is performed using the PYTHON programming language. Besides, the comparison with the conventional PD classification methods likes 2D-CNN [22], CSP+KNN [19], DWT+SVM [18] and Channelwise CNN [20] for depicting the superiority of the proposed model.

### 4.1. DATASET DESCRIPTION

The dataset comprises of various EEG signal, where in each EEG recording in the dataset is associated with a label indicating the presence or absence of Parkinson's disease. These labels are essential for supervised machine learning tasks, where the goal is to classify EEG signals as either Parkinson's disease or non-Parkinson's disease.

### 4.2. PERFORMANCE ANALYSIS

The performance evaluation of the proposed CCZO-Residual_GhostNet model for various iterations is visualized in Fig. 5. When using 100 iterations with 50% of the data allocated for training, the model achieves an accuracy of 95.12%. However, when the model is evaluated with 80, 60, 40, and 20 iterations, the accuracy decreases to 92.33%, 91.23%, 89.42%, and 88.37%, respectively. This analysis reveals that the model performs better with a higher number of iterations and a larger percentage of training data.

The superior outcomes in these scenarios are attributed to the use of the CCZO algorithm for loss function optimization. This optimization enhances the model's

generalization capability, allowing it to achieve higher accuracy and better performance.

### 4.3. COMPARATIVE ANALYSIS

The comparative assessment of PD classification is visualized in Fig. 6. In this assessment, the accuracy achieved by the CCZO_Residual_GhostNet model is 96.01%. This accuracy outperforms the 2D-CNN, CSP+KNN, DWT+SVM, and Channelwise-CNN methods by margins of 1.40%, 2.00%, 4.10%, and 5.79%, respectively, when 80% of the data is used for training. Likewise, when considering sensitivity, the CCZO_Residual_GhostNet model demonstrates a sensitivity of 94.21%. This sensitivity surpasses the 2D-CNN, CSP+KNN, DWT+SVM, and Channelwise-CNN methods by margins of 3.16%, 5.40%, 6.00%, and 7.18%, respectively, when 70% of the data is allocated for training.

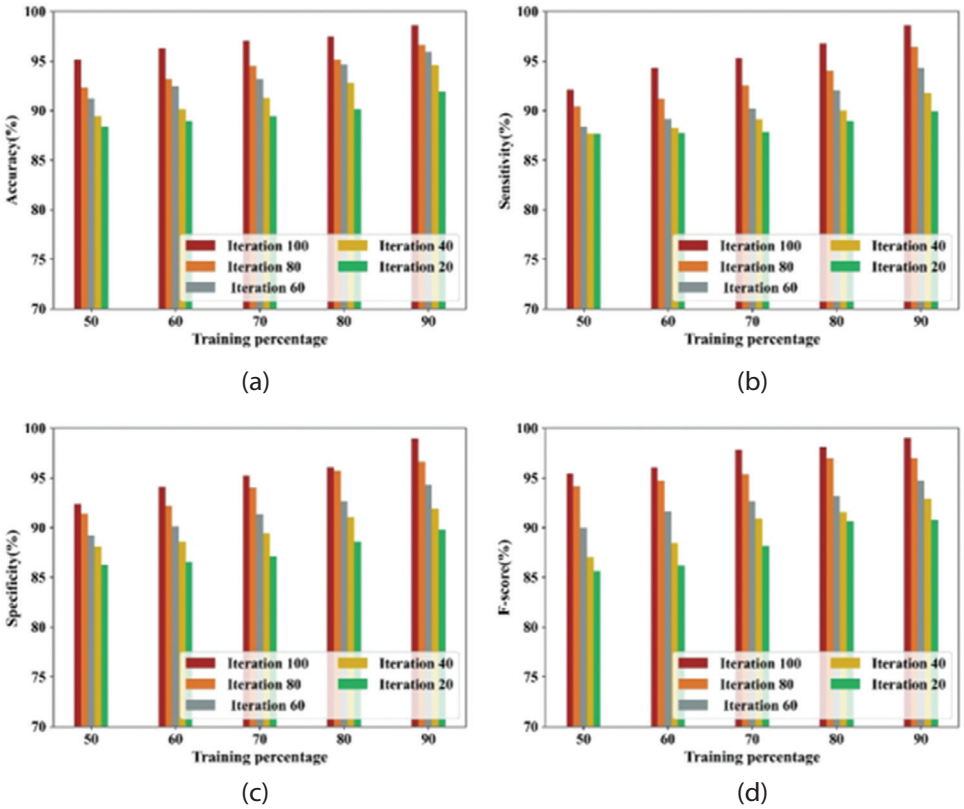


**Fig. 5.** Analysis of Improved Residual_GhostNet (a) accuracy, (b) Sensitivity, (c) Specificity and (d) F-Score

The analysis provided in the table offers insights into how the hybrid deep learning model excels in classifying the disease with minimal complexity. This efficiency is attributed to the model's minimal number of layers, which effectively capture essential features for accurate classification.

The accuracy-loss analysis of the proposed PD classification method is presented in Fig. 7. The accuracy analysis depicts the superior outcome for the training data compared to the testing data. Similarly, the loss function is higher for the testing data. But the performance is closer to the training data.

### 4.4. COMPARATIVE DISCUSSION

The precision ascertained through the adept CCZO_Residual_GhostNet achieves a remarkable 98.76%, bestowing a substantial superiority of 2.18%, 2.74%, 4.13%, and 6.96% in contrast to the 2D-CNN, CSP+KNN, DWT+SVM, and Channelwise-CNN techniques. Further delving into the assessment, the sensitivity estimations courtesy of the CCZO_Residual_GhostNet reveal a remarkable edge. The metrics stand at 98.59%, eclipsing their counterparts by margins of 2.20%, 4.37%, 6.94%, and 8.77% when juxtaposed with 2D-CNN, CSP+KNN, DWT+SVM, and Channelwise-CNN, respectively. It is paramount to elucidate the specificity aspect, where the CCZO_Residual_GhostNet truly excels. Recording an estimable score of 98.95%, it soars above the 2D-CNN, CSP+KNN, DWT+SVM, and Channelwise-CNN by significant differentials of 2.32%, 4.68%, 7.13%, and 9.26%. To further enhance the narrative, the F-Score, a comprehensive metric of precision and recall, is a standout. The CCZO_Residual_GhostNet attains an impressive 99%, accentuating its dominance over its peers. These achievements underscore the model's superiority, boasting advantages of 2.02%, 4.31%, 6.17%, and 8.29% compared to the 2D-CNN, CSP+KNN, DWT+SVM, and channelwise-CNN methods, respectively.

Here, the analysis depicts the superior outcome in terms of all assessment measures by the proposed model. Several real-world applications of Parkinson's disease classification using deep learning are emerging, showing promise for improving diagnosis, treatment, and patient care.

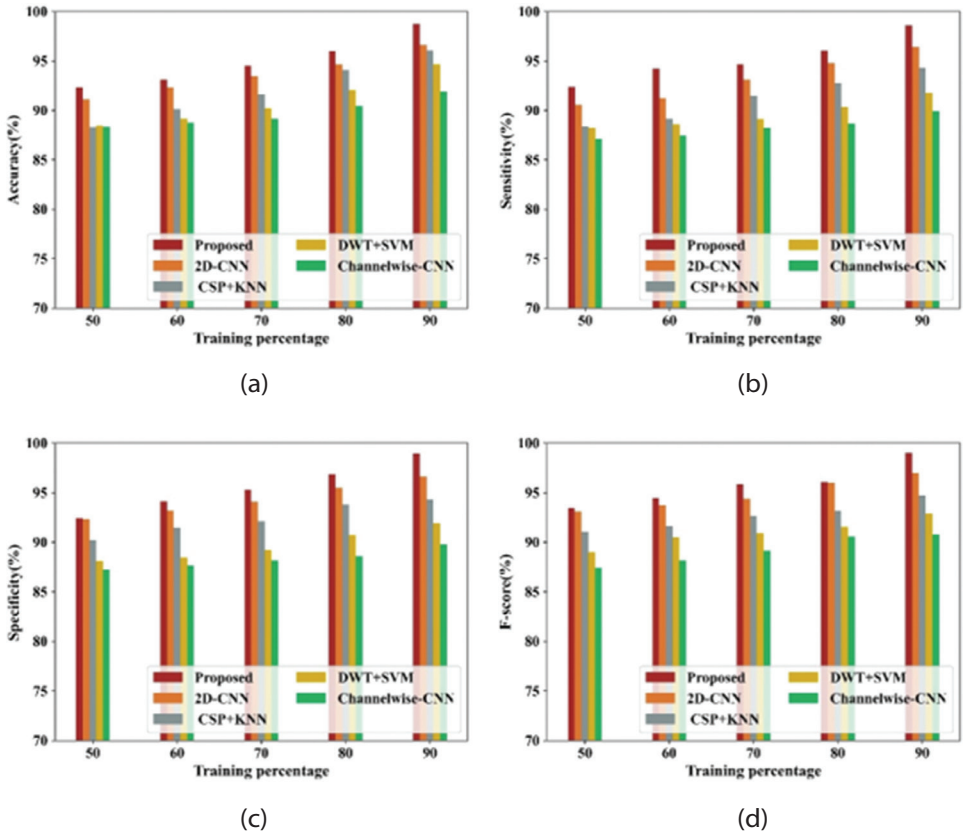


**Fig. 6.** Comparative Analysis (a) accuracy, (b) Sensitivity, (c) Specificity and (d) F-Score

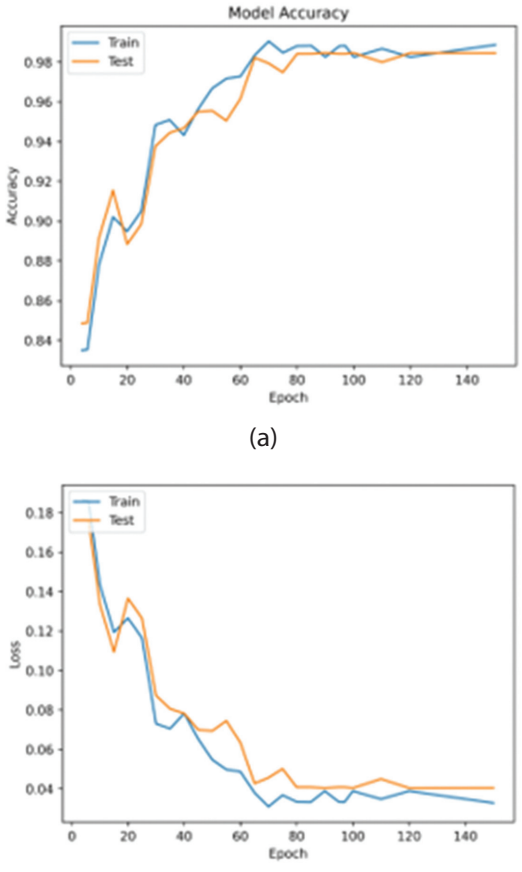


**Fig. 7.** Accuracy-Loss Analysis: (a) Accuracy and (b) Loss

## 5. CONCLUSION

In summary, this research presents a robust method for PD classification. By employing the CCZO_Residual_GhostNet model, we achieve superior accuracy, sensitivity, specificity, and F-Score compared to conventional methods such as 2D-CNN, CSP+KNN, DWT+SVM, and Channelwise-CNN. The utilization of ResNet-152 with skip connections, coupled with GhostNet's efficient architecture, ensures an efficient tool for disease classification. The incorporation of the CCZO algorithm further refines the model's performance, eliminating local optima and enhancing global optimization. This method offers a promising approach for accurate and efficient PD classification using EEG signals, contributing to advancements in the field of medical diagnosis and treatment. In the future, it might be helpful to recognize present clinical data sets that have been utilized that could help the clinical classification of the illness, like DaTscan, or to capitalize on information set methods such as sleep EEGs, which could help with the possible rapid detection of biological indicators of PD and its associated issues, such as MCI and dementia.

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