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RESEARCH ARTICLE

EEG-Centered Parkinson's Disease Prediction System Using Gaussian Kernel Discrete Wavelet Transform and Leaky Single Peak Triangle Context Convolutional Neural Network Deep Learning Technique

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Abstract: Parkinson's disease (PD), a neurodegenerative illness where dopamine-producing brain cells are destroyed, slows down motor performance. To identify PD, numerous techniques have recently been established. In this research, a novel idiosyncratic Gaussian Kernel Discrete Wavelet Transform (GKDWT) and a Leaky Single Peak Triangle Context Convolutional Neural Network (LeakySPTC-CNN)-centered effective Deep Learning (DL) model have been developed for the prediction of PD. The Electroencephalogram (EEG) signal is first acquired and then divided into one-second segments. The model then carried out signal filtering and spectrogram conversion. The features are then extracted with the support of GKDWT, and feature selection and ranking are carried out using the Quadratic Chimp Optimization Algorithm (QChOA). The LeakySPTC-CNN is used to categorize both ill and healthy people. The model has a promising future, according to the experiential evaluation, and it also offers a better way to *diagnose Parkinson's disease (PD) early.*

Keywords: *Parkinson's disease (PD), Electroencephalogram (EEG), Convolutional Neural Network (CNN), Gaussian Kernel function (GK), Wiener Filter (WF).*

1. INTRODUCTION

Currently, Parkinson's disease (PD) is deemed to be a critical generative disease; it mainly targets the body's central nervous system and affects millions of elderly persons all over the world[1]. A person is infected by PD when the dopamine neurons in the substantia nigra are damaged and die[2]. The Parkinson's association says that an average of 10 million people will be affected by PD[3]. PD-infected patients undergo '5' stages. At stage 1, a person will suffer minor symptoms like tremors and rigidity[4,5]. Patients at stage 2 will have decreased facial expression and write in tiny letters[6]. With the loss of balance, this disease is marked in a patient at stage 3[7]. At last, a dangerous symptom termed FOG (Freezing of Gait) is experienced by the patient at stages 4 and 5[8]. The consequences of FOG are fear of falling, loss of independence, injuries, a lack of activity leading to social isolation, and an elevated risk of osteoporosis [9,10].

This disease pessimistically influences the quality of life since it is progressive; thus, detecting the in the earlier stage is highly significant[11]. Therefore, by utilizing an automated system like EEG, Computer-Aided Diagnosis (CAD) systems are adopted[12]. EEG-centric diagnosis is non-invasive; moreover, it is incredibly effortless to set up[13]. Generally, the sum of post-synaptic potential synchronization of numerous neural tissues is gauged[14]. The EEG signals' spatial, spectral, and temporal features are utilized for detecting PD[15]. Enhanced EEG activity with specific frequency bands is wielded to monitor ongoing motor tasks. Exclusively, during motor preparation, it includes beta activity; at the time of motor gating, it subsumes gamma activity; eventually, during the processing of conflict-related signals, it encompasses the beta activity[16]. EEG signals are of two types; (i) the background EEG, here, during the rest state, the signal is gathered; in addition, it includes the brain's regular activity even when it is not activated; (ii) Event-Related Potential (ERP), here, the changes in the background EEG, caused by a particular stimulus, are marked[17]. Spectral analysis and microstate analysis, which specify merely the brain's current topographical activity, are the advantages of EEG[18]. EEG has disordered elements with dynamic properties; by utilizing these properties, the on and off-medication states of patients suffering from PD are differentiated[19]. In classifying the patient's condition, specific classifiers like K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) is utilized[20]. Although there are various machine learning methodologies along with classifiers to predict the disease, the signal quality will be influenced by certain factors like eye-blinking, signal distortion, and noise included in the signal as a consequence of the environment. To solve this problem, a modified CNN termed LeakySPTC-CNN has been suggested. The paper's remaining parts are structured as follows: the related works are reviewed in section 2; the proposed methodology is explicated in section 3; the results and discussions are demonstrated in section 4; lastly, the paper is concluded with suggestions for future research in section 5.

2. LITERATURE SURVEY

Smith K. Khare *et al.*[21] presented a model for PD diagnosis grounded on automated Tuneable Q wavelet transform (A-TQWT) by utilizing EEG signals. Initially, the EEG signals being adapted were tuned and decomposed into various Sub Bands (SBs). After that, using Least Square Space Vector Machine (LSSVM), '5' features were extracted, tested, classified, and analyzed as of every SB. The experiential outcomes displayed that the presented model, then the manual EGG system, achieved a higher accuracy. However, in this model, the sensitivity was augmented to outliers; also, it lacks sparseness.

Erfan Nagsh et al. [22] introduced a lower-cost biomarker by employing EEG signals to detect PD, named PD Stage Detection (PDSD). Primarily, the signals were pre-processed by utilizing a notch filter along with ICA (Independent Component Analysis). After that, the blind source separation system was utilized for extracting the neuronal source data with a minor dependency. Eventually, the source identification was performed with the aid of the Brain Electrical Source Analysis Algorithm (BESA). A significantly this model possessed an extremely lower cross-validation error. However, this model did not utilize multi-modal measurements, thus mitigating the system's accuracy.

Ana Paula S. de Oliveira et al.[23] suggested a biomarker of PD by utilizing EEG signals, photic stimulation, and Partial Directed Coherence (PDC). Firstly, on EEG signals, artifact removal and feature extraction were performed; then, using a genetic algorithm, the feature selection was made. Next, various classifiers were adopted to classify the healthy or PD individual. The experiential outcomes demonstrated that the presented system achieved higher performance. Nevertheless, this model could have been more effective for real-time applications as it was prolonged.

Soojin Lee et al.[24] recommended a lightweight amalgamation of CNN, Recurrent Neural Network (RNN), and Gated Recurrent Units (GRU) for classifying the EEG signals' resting state. To extract spatiotemporal features across EEG channels, 1D-CNN layers were designed; subsequently, the extracted features were applied to the GRU to perform the temporal features' proper classification. In the process of classifying PD as Healthy Controls (HC), a higher precision, together with the recall, was achieved by the combinational DL methodology. However, here, the PD prediction was influenced owing to the existence of artifacts in the EEG.

Md Fahim Anjum et al.[25] presented a Linear-predictive-coding Algorithm (LEAPD) to differentiate betwixt PD and normal patients. To capture PD-related changes, Linear Predictive Coding (LPC) was utilized. Then, for classification, single-channel and multi-channel tuning classifiers were wielded. The presented LEAPD classifier mitigated generality and high complexity when analogized with the prevailing model. This model utilized higher classifiers for adoption; however, this model did not provide precise data about the gold-standard PD diagnosis.

3. PROPOSED PARKINSON'S DISEASE PREDICTION SYSTEM

Here, to predict PD, a unique GKDWT, as well as LeakySPTC-CNN model-centric effectual DL technique, has been proposed. The block diagram for this system is exhibited in figure 1.

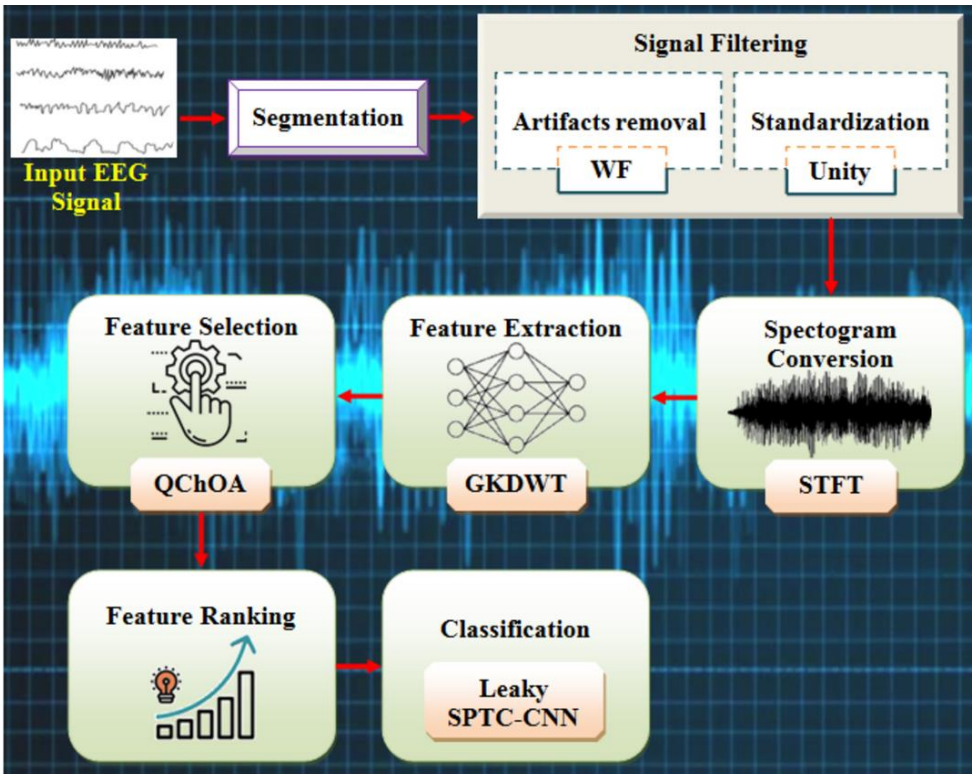

Figure 1: Block diagram of the proposed framework

3.1 Segmentation

The input EEG signal in this proposed model is initially initialized using data from freely accessible databases. The signal is then divided into a number of segments, each of which has a period and shares a similar statistical properties with the signal's amplitude and frequency.For practical analysis, the signals being utilized here are partitioned into segments of one second duration. The segmented signals are expressed as,

$$y(k) = y(1), y(2), \ldots\ldots, y(\mathrm{K}) \quad (1)$$

Where, the number of segmented signals is specified as $k = 1,2,\ldots\ldots,K$.

3.2 Signal Filtering

3.2.1 Artifacts removal

The analysis of an electroencephalogram (EEG) is highly challenging since physiological signals can vary widely. Therefore, the noise removal procedure has a significant role in assessing the EEG signal. Here, the raw waveform is transformed into noise-free with the usage of a Weiner Filter (WF). The segmented EEG $(y(k))$ with a noisy component (N_o) is modelled as,

$$y(k) = y_i(k) + N_o \quad (2)$$

The WF transfer function is analyzed as,

$$y'''(k) = mean(N_o) + \frac{Var^2(y_i(k))}{Var^2(y_i(k)) + \text{var}^2(N_o)}\{y(k) - mean(y_i(k))\} \quad (3)$$

Where, the mean and variance of (N_o) are symbolized as $mean(*), Var(*)$, the noise-free component is notated as $(y_i(k))$, and the noise-removed signal is signified as $y'''(k)$.

3.2.2 Standardization

Normalize a signal at a similar level; the signals are standardized following the completion of artifact removal. The signals are scaled in a uniform range by performing standardization to obtain better outcomes. The signal is rescaled by establishing unity normalization regarding the percentage or weight of every single segment. It is formulated as,

$$x(n) = \frac{y'''(k)}{\sum y'''(k)} \quad (4)$$

Here, the filtered standard EEG signal is denoted as $x(n)$.

3.3 Spectrogram Conversion

Here extracting the time-frequency features $x(n)$ is transmuted into a spectrogram. The spectrogram provides an extraordinary level of information as of the signals. This conversion is performed by utilizing Short-Time Fourier Transform (STFT). To assess only a smaller section of the signal at a time, the signal spectral content variations are captured by the STFT; in addition, it also adapts Fourier Transform (FT). It is highly suitable for a non-stationary signal; moreover, it also provides information about both the time-frequency domain simultaneously. By exploiting a sliding window of constant length along the signal time, the STFT partitions $(x(n))$ into fixed segments; subsequently, to those segments, the FT is applied; thus, bringing about a planar graph termed spectrograms. In the spectrogram graph, the signal's time-frequency information is specified on the horizontal and vertical axis. The STFT is expressed as,

$$z^M(u,v) = \sum_{n=0}^{N-1} x(v+n)W(n)\exp\left(-\frac{j2\pi un}{N}\right) \quad (5)$$

Here, the window function is specified as W, and $0 \le u \ge N-1$. Consequently, the attained spectrogram of $(x(n))$ turns into z^M; from this, the features are extracted for further evaluation.

3.4 Feature Extraction by Gaussian Kernel Discrete Wavelet Transform

Distinguishing properties, a recognizable measurements, and functional component are the features of classifying PD. The EEG dynamics' visual inspection for feature extraction is highly challenging. Therefore, the GKDWT is espoused in the proposed system to extract the features. The DWT is a wavelet transform methodology; here, the wavelets are sampled at discrete intervals. The amalgamation of the analysis filter bank and the decimation operation can be utilized for evaluating the signal. The wavelet decomposition includes low-pass and high-pass filters to extract the approximate information and details. However, in DWT, computing the mother wavelet function is complicated as it influences the complete

feature extraction procedure. Therefore, the GK function is utilized in this proposed work to evaluate the mother wavelet. Let z^M the EEG signal's spectrogram; then, the GKDWT decomposition level is represented as,

$$\varphi^{\mathrm{E}} = \sum_{M} z^M \cdot \varphi(2\mathrm{E} - M) \quad (6)$$

$$\gamma^{\mathrm{E}} = \sum_{M} z^M \cdot \lambda(2\mathrm{E} - M) \quad (7)$$

Where, the signals' details and approximation (outputs of high pass and low pass filters) are specified as φ^E, γ^E, respectively. Furthermore, GKDWT is scaled as well as translated as,

$$GKDWT(g,h) = \Re_0^h \sum_{M} \left\| z^M \right\| * GK\left(\frac{\tau - h\mu_0 \Re_0^h}{\Re_0^h} \right) \quad (8)$$

Where, the translation coefficient and scaled parameters are signified as $\mu_0, \Re_0^h$, the scale and shift parameter are indicated as g, h, respectively, the discrete-time interval is proffered as t, and $GK(\bullet)$ is the mother wavelet, which is determined by utilizing the GK function; it is expressed as,

$$GK\left(z^M\right) = \frac{1}{\left(2\pi {S_D}^2\right)^{1/2}} * \exp\left(- \frac{{z^M}^2}{2{S_D}^2} \right) \quad (9)$$

Thus, the extracted $n-$signal features like mean, standard deviation (S_D), energy, kurtosis, skewness, et cetera are specified as,

$$\ell^i = \ell^1, \ell^2, \ldots\ldots, \ell^n \quad (10$$

3.5 Feature Selection using Quadratic Chimp Optimization Algorithm

Using QChOA, the most relevant features are selected after extracting all the time-frequency EEG features. The chimp Optimization Algorithm (ChOA) is a recently developed meta-heuristic model; in this model, the individual intelligence, along with the sexual motivation of chimps, is mimicked. Attacker, chaser, barrier, and driver are the strategies with which every chimps group discovers the search space independently. Nevertheless, the chimp population converges faster towards the best chimp in the system while updating the position, thus, weakening the global search ability. Consequently, a Quadratic interpolation (Q) model is adopted in ChOA to enhance the solution accuracy. The chimps are made to explore the optimal global solution by this Q; in addition, it also diverges the population. Therefore, the proposed strategy is termed QChOA. The following are the phases undergone by this model.

Initialization

Let the initial chimp population (extracted features) in the $D-$dimensional search space be $\ell^i = \ell^1, \ell^2, \ldots\ldots, \ell^n$. Next, to detect the fittest one, the fitness of every single chimp is gauged. Here, the maximum classification accuracy turns into the fitness measure. It is expressed as,

$$fit\left(\ell^i\right) = \sum_{i=1}^{n} \max_{acc}\left(\ell^i\right) \quad (11)$$

Where, the fitness function is specified as $fit\left(\ell^i\right)$. By employing $fit\left(\ell^i\right)$, the best chimp is exhibited as ${\ell^i}_{best}$.

Driving and chasing behavior

The chimps' driving and chasing behaviour wielded for attacking the prey is illustrated as,

$$\xi_{driv} = \left(\left(\kappa \cdot \rho^t - \upsilon \cdot \ell^{i,t} \right)^2 \right)^{0.5} \quad (12)$$

$$\ell^{i,t+1} = \rho^t - \eta \cdot \xi_{driv} \quad (13)$$

Where, the chimps' driving behaviour is signified as ξ_{driv}, the iteration number is proffered as $t, t+1$, the preys' position vector is notated as ρ^t, and the coefficient vectors of prey formulated further are symbolized as κ, υ, η,

$$\eta = 2\delta \cdot R_1 - \delta \quad (14)$$

$$\kappa = 2R_2 \quad (15)$$

$$\upsilon = \varepsilon \ell^i \left(1 - \ell^i\right) \quad (16)$$

Where, the non-linear function, which decreases from 2.5 to 0, is depicted as δ, the random numbers in the range [0, 1] are defined as R_1, R_2, and the mapping betwixt 2 to 4 is indicated as ε.

Regarding the chimps' exploration behaviour of prey like driving, blocking, and chasing, along with encircling behaviour around the prey, their attacking behaviours are modelled.

Exploration

Let the prey's position and the chimp's (attacker) position be the same. The driver, barrier, and chaser positions are updated by employing this position as,

$$\xi_A = \left(\left(\kappa_1 \cdot \rho_A - \upsilon_1 \ell^1\right)^2\right)^{0.5} \quad (17)$$

$$\xi_B = \left(\left(\kappa_2 \cdot \rho_B - \upsilon_2 \ell^2\right)^2\right)^{0.5} \quad (18)$$

$$\xi_C = \left(\left(\kappa_3 \cdot \rho_C - \upsilon_3 \ell^3\right)^2\right)^{0.5} \quad (19)$$

$$\xi_D = \left(\left(\kappa_4 \cdot \rho_D - \upsilon_4 \ell^4\right)^2\right)^{0.5} \quad (20)$$

Here, the position of attacker, barrier, chaser, and driver chimps selected regarding $fit\left(\ell^i\right)$ and corresponding prey are represented as $\xi_A, \xi_B, \xi_C, \xi_D, \rho_A, \rho_B, \rho_C, \rho_D$, respectively. Hence, the chimps' subsequent location might be anywhere in the search space within its current location along with the prey's location. It is modelled as,

$$\ell^1 = \rho_A - \eta_1 \xi_A \quad (21)$$

$$\ell^2 = \rho_B - \eta_2 \xi_B \quad (22)$$

$$\ell^3 = \rho_C - \eta_2 \xi_C \quad (23)$$

$$\ell^4 = \rho_D - \eta_4 \xi_D \quad (24)$$

$$\ell^{i,t+1} = \frac{1}{4} * \left(\ell^1 + \ell^2 + \ell^3 + \ell^4\right) \quad (25)$$

Exploitation

Here, regarding the chimps' attacking techniques, their location is updated in the search space. For the updation process, quadratic interpolation is utilized; thus, ameliorating the exploitation capability as well as the solution accuracy. The best chimps $\ell^{i}{}_{best}$ and 2 other best search agents $(\hbar, \wp)$ in ℓ^i are chosen by the quadratic interpolator. Next, the best search agent $\left(\rho^{best}\right)$ is engendered as,

$$\rho^{best} = \frac{1}{2}\left(\frac{\left(\hbar^2 - \wp^2\right) \cdot f\left(\ell^{i}{}_{best}\right) + \left(\wp^2 - \ell^{i}{}_{best}{}^2\right) \cdot f\left(\hbar\right) + \left(\ell^{i}{}_{best}{}^2 - \hbar^2\right) \cdot f\left(\wp\right)}{\left(\hbar - \wp\right) \cdot f\left(\ell^{i}{}_{best}\right) + \left(\wp - \ell^{i}{}_{best}\right) \cdot f\left(\hbar\right) + \left(\ell^{i}{}_{best} - \hbar\right) \cdot f\left(\wp\right)}\right) \quad (26)$$

At last, the position is updated as,

$$\ell^{i,t+1} = \begin{cases} \rho^{best} - \eta\xi & \chi < 0.5 \\ \upsilon & \chi > 0.5 \end{cases} \quad (27)$$

Where, the random number [0, 1] is exhibited as χ. Eventually, the obtained optimal solution in every single iteration turns into the selected $m-$best features, which is signified as,

$$\mathrm{Y} = \langle y_1, y_2, \ldots\ldots, y_m \rangle \quad (28)$$

Figure 2 demonstrates the flowchart of the proposed feature selection technique.

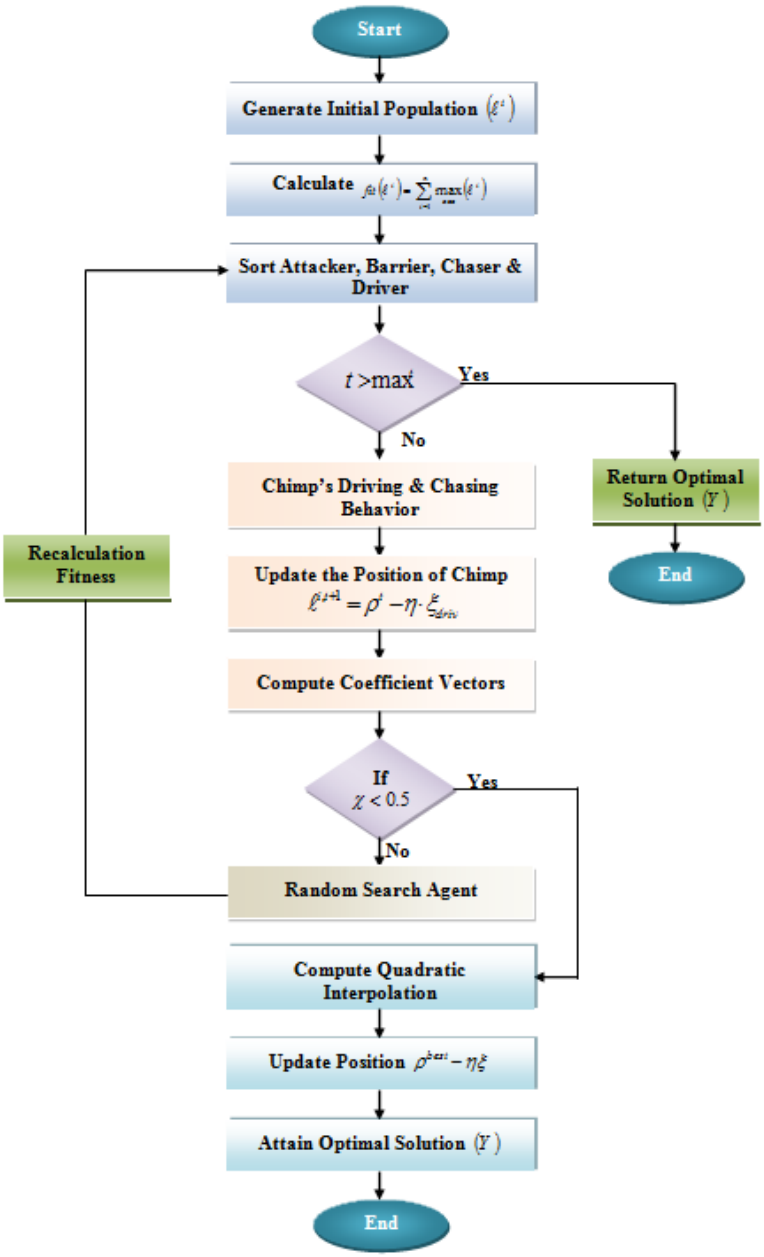

Figure 2: Flowchart of the proposed feature selection model

3.6 Feature Ranking

Next, the feature ranking process is performed to the set of optimal features, which abates the computational complexity along with the time needed by the classifier. In this process, the score value is defined for every feature regarding their entropy measure. The entropy calculation betwixt every single optimal feature is formulated as,

$$Ent = -\sum P(Y) * \log\langle P(Y)\rangle \quad (29)$$

Here, the features' probability value is symbolized as $P(Y)$. In accordance with this measure, the ranked features (R^j) are expressed as,

$$R^j = R^1, R^2, \ldots\cdots, R^m \quad (30)$$

3.7 Classification with Leaky Single Peak Triangle Context Convolutional Neural Network

Here, the ranked features are fed into the proposed Leaky SPTC-CNN classifier to classify regular and PD patients. CNN is a deep neural network; moreover, the input layer, convolutional layer, pooling layer, and fully connected layer are included. Every single layer comprises several neurons; the outputs are obtained by embedding weight and bias vectors. In CNN, the Rectified linear unit (ReLu) activation function is utilized; the drawback of this ReLu is that in this function, the units will not activate once gradients reach zero; in addition, the CNN will not have the dynamic information memory ability while utilizing this function. Thus, in the proposed LeakySPTC-CNN, a Leaky Single-Peaked Triangle Linear Unit (LSPTLU) activation function is an amalgamation of the actual activation function, and biological neuron properties are utilized to trounce the gradient problem. Furthermore, a context layer is added to accumulate the preceding layer's output information. Figure 3 exhibits the architecture of LeakySPTC-CNN.

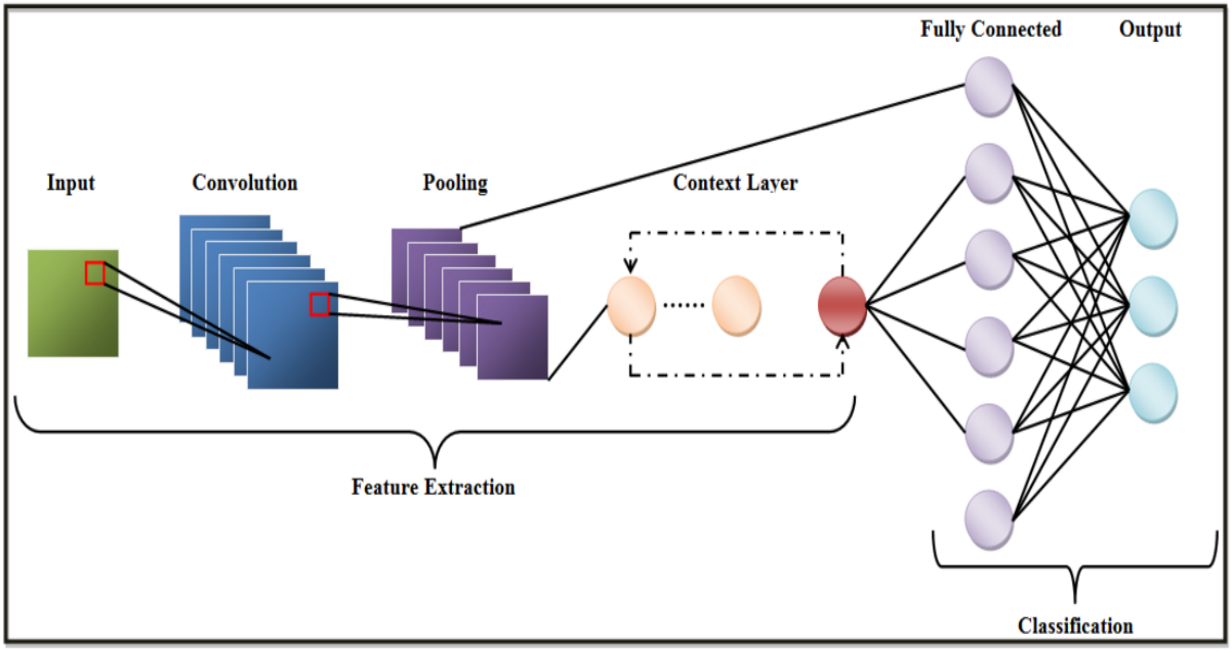

Figure 3: LeakySPTC-CNN architecture

Step 1: The ranked features $\left(R^{j}\right)$ are fed to the LeakySPTC-CNN's input layer; here, it is processed with the weight along with biases; subsequently, it is transferred to the convolutional layer. To execute convolution operations, the convolution layer is comprised of 256 filters with 5*5 convolutional kernels. The output generated by this layer $\left(\lambda^{(k)}\right)$ is,

$$\lambda^{(k)} = \psi\left(\varpi^{(k)} R^{j} \otimes K + b^{(k)}\right) \quad (31)$$

Where, the number of neurons in the convolution layer is specified as $k = 1,2,\ldots\ldots,N$, the weight and bias values are signified as $\varpi^{(k),b^{(k)}}$, the kernel size is notated as K, and the LeakySPTC-CNN activation function is symbolized as $\psi(\bullet)$, which is computed as,

$$\psi\left(\lambda^{(k)}\right) = \begin{cases} 0.2\lambda^{(k)} & \lambda^{(k)} < 0 \\ \lambda^{(k)} & 0 \le \lambda^{(k)} \le \nu \\ 2\nu - \lambda^{(k)} & \nu < \lambda^{(k)} \le 2\nu \\ 0 & \lambda^{(k)} > 0 \end{cases} \quad (32)$$

Here, the constant value is depicted as ν.

Step 2: Next, to compress the number of parameters and abate the network's computational cost, the pooling operation is conducted whilst maintaining the required features. After that, the data is sent to the context layer $\left(\Gamma_c\right)$; this layer subsumes merely the relevant information feedback of the pooling layer at the preceding moment; thus, analyzing the sample data more comprehensively, which is more helpful for the final classification. It is mathematically formulated as,

$$\Gamma_c = S_c \cdot po^{(k)}{}_{k-1} + \lambda^{(k)}{}_{k-1} \quad (33)$$

Here, a scalar constant, which controls the weight of information feedback as of the context unit at the preceding moment, is denoted as S_c, and the pooling and convolution outputs are described as $po^{(k)}{}_{k-1}, \lambda^{(k)}{}_{k-1}$.

Step 3: Lastly, the data is inputted to the fully connected layer $\left(F^{(k)}\right)$. Here, the final features initiated as of the processing of multiple convolutional as well as pooling layers could be well-classified as,

$$F^{(k)} = \psi\left(R^{j} \varpi^{(k)F} po^{(k)}{}_{k-1} \lambda^{(k)}{}_{k-1} + b^{(k)F}\right) \quad (34)$$

Thus, the classification result is produced by the classifier as normal and PD.

4. RESULTS AND DISCUSSION

To evaluate the effectiveness of the suggested model, its results are compared with those of other widely used approaches. This model is implemented in Python, and publically available EEG signal datasets are used for evaluation.

4.1 Performance analysis of proposed Leaky Single Peak Triangle Context Convolutional Neural Network

CNN, RNN, Long Short Term Memory (LSTM), and ANN (Artificial Neural Network) are the prevailing models with which the proposed system is analogized regarding the performance metrics like accuracy, precision, F-measure, recall, False Negative Rate (FNR), along with False Positive Rate (FPR).

Table 1: Performance analysis in terms of accuracy and precision

TECHNIQUES	ACCURACY (%)	PRECISION (%)
Proposed Leaky SPTC-CNN	98.3155	97.2254
CNN	95.3255	94.5455
LSTM	92.7415	90.4574
RNN	88.5845	88.5547
ANN	82.5685	86.2454

Regarding accuracy and precision, the proposed LeakySPTC-CNN's performance is compared with the prevailing methodologies in table 1. It is established that the accuracy and precision obtained by the proposed model are 98.3155% and 97.2254%, respectively. In contrast, the accuracy and precision values attained by the prevailing CNN, LSTM, RNN, and ANN are 95.3255% and 94.5455%, 92.7415% and 90.4574%, 88.5845%, 88.5547%, and 82.5685% and 86.2454%, in that order, which is lower than that of the proposed one. Thus, it is clear that the proposed model achieved superior performance to the other conventional methodologies.

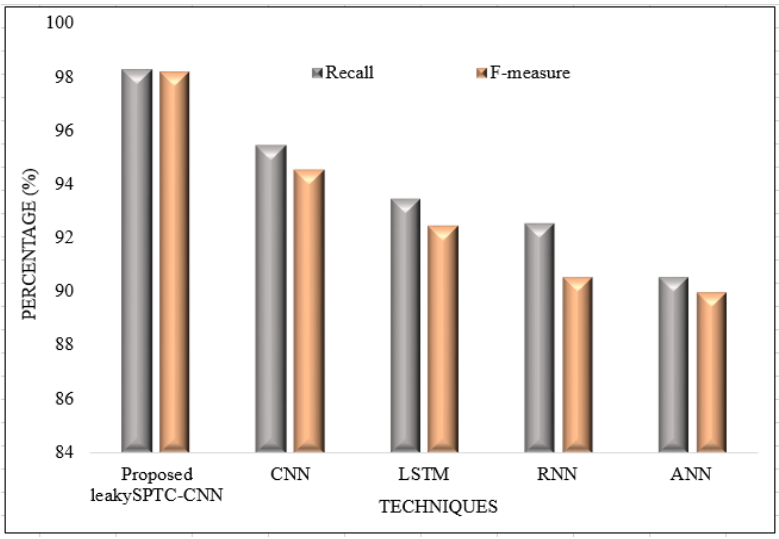

Figure 4: Performance comparison based on recall and F-measure

The proposed methodology's performance is evaluated concerning recall and F-measure in figure 4. The rise in the graph demonstrates the proposed system's supremacy. The proposed Leaky SPTC-CNN attained a recall of 98.2545%, significantly higher than the value of 90.5545% obtained by the traditional ANN. Similarly, the F-measure values attained by the proposed model and the prevailing ANN are 98.1454% and 89.9877%, respectively. In the same manner, a lower value was obtained by the other conventional models also. Thus, it is evident that the

proposed technique achieved a higher recall and F-measure performance.

Table 2: FNR and FPR assessment

TECHNIQUES	FNR	FPR
Proposed Leaky SPTC-CNN	0.0015	0.0145
CNN	0.2545	0.3788
LSTM	0.5988	0.5052
RNN	0.6558	0.6875
ANN	0.9877	0.7445

In table 2, the proposed model's performance regarding FNR and FPR is analogized with other prevailing classifiers. The proposed model attained a lower FNR of 0.0015. Similarly, the proposed one obtained a lower FPR of 0.0145, whereas the prevailing CNN, LSTM, RNN, and ANN models attained a higher value of 0.3788, 0.5052, 0.6875, and 0.7445, respectively. Thus, it is confirmed that the proposed methodology achieved better performance in terms of FNR and FPR.

4.2 Performance analysis of proposed Quadratic Chimp Optimization Algorithm

Regarding fitness vs. iteration, the proposed QChOA's performance is analogized with the prevailing methodologies like ChOA, Firebug Optimization Algorithm (FSO), Whale Optimization Algorithm (WOA), and Particle Swam Optimization (PSO) in figure 5.

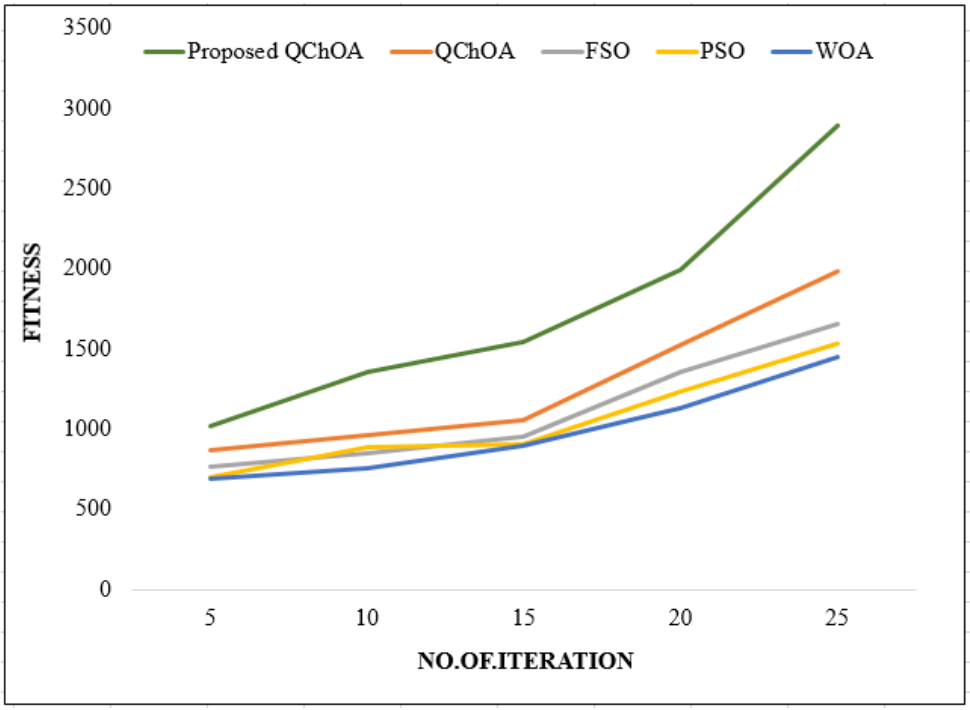

Figure 5: Performance evaluation via fitness vs iteration

The proposed system's fitness values gradually rise from 1021 to 2894 when the number of iterations increases from 5 to 25. Similarly, for the prevailing WOA classifier, the fitness values increase from 689 to 1452, which is lower than the proposed system. Thus, it is evident that the proposed model achieved a better performance in terms of fitness vs. iteration.

5. CONCLUSION

The LeakySPTC-CNN model is suggested in this research as a way to forecast PD disease earlier. Noise reduction and spectrogram conversion are carried out using a novel idiosyncratic Gaussian Kernel Discrete Wavelet Transform (GKDWT) and a Leaky Single Peak Triangle Context Convolutional Neural Network (LeakySPTC-CNN)-centered effective Deep Learning (DL). Furthermore, the Quadratic Chimp Optimization Algorithm (QChOA) feature selection optimization model is provided. The LeakySPTC-CNN is used to classify both ill and healthy people. When compared to other widely used approaches, the experiential result showed that the proposed model achieved accuracy, recall, and F-measure values of 98.3155%, 98.2545%, and 98.1454%, respectively. In the future, the work can be expanded using advanced DL techniques to identify freezing of gait signs in Parkinson's disease.

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