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DYNAMIC ANALYSIS OF EEG TIME SERIES DISTINGUISHES PATIENTS WITH PARKINSON'S DISEASE FROM HEALTHY INDIVIDUALS USING MODEL-LEVEL GRAPH TRIPLET NEURAL NETWORK OPTIMIZED WITH CRAYFISH OPTIMIZATION ALGORITHM

[1]K S Ranjith, [2]Bhanu Prakash Reddy Rella, [3]Manoj Kumar Sah, [4]Dr. Vandana Vijaykumar Hanchate, [5]Shameem Ansar A, [6]Praveena Nuthakki

[1]Associate Professor, Artificial Intelligence and Data Science

Mother Theresa Institute of Engineering and Technology

ksranjith2000@gmail.com

[2]Student (Doctor of business administration), Golden Gate university

27rellaprakash@gmail.com

[3]Assistant Professor, Computer Science and Engineering

Government Engineering College Vaishali

emanojcse@gmail.com

[4]Assistant Professor, Electronics and Telecommunication

PES'S Modern college of engineering

vandana.hanchate@moderncoe.edu.in

[5]Assitant Professor, Computer Science and Engineering, TKM College of Engineering,

shameemansar@gmail.com

[6]Assistant professor, Computer science and engineering

Koneru lakshmaiah education foundation

praveena.4u@gmail.com

Abstract— Parkinson's Disease (PD), a degenerative neurologic disorder, has a marked impact on motor and cognitive skills. Early and correct diagnosis is key to successful treatment and disease management. In light of limitations inherent in existing EEG-based PD classification techniques like insufficient feature representation, poor classification efficiency, and inadequate generalization a new dynamic analysis of EEG time series method using a Model-Level Graph Triplet Neural Network optimized with Crayfish Optimization Algorithm (MLGTNN-COA) is introduced. The approach starts with EEG signals from San Diego EEG dataset are first preprocessed with a Deformable Kernel Network (DKN) to eliminate artifacts and cluster the signals into 10 brain regions to perform localized analysis. A Fast hybrid Vision Transformer (FhVT) is then employed to extract discriminative spatial-temporal features from preprocessed EEG signals. For classification, the architecture uses a Model-Level Graph Triplet Neural Network (MLGTNN), which integrates a Model-Level Graph Network for learning inter-region dependencies with a Triplet Attention Network (TAN) for improvement on attention on salient features. The architecture works well in classifying EEG data into three binary PD diagnostic tasks: healthy vs. PD, PD-on medication vs. PD-off medication and healthy vs. PD-off medication. For further improvement in performance, weight and loss values are optimized by applying Crayfish Optimization Algorithm (COA). The developed model has better classification metrics: accuracy (99.93%), recall (99.74%), precision (99.83%), specificity (99.59%), F1-score (99.67%), and high area under

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the ROC curve, indicating robustness and diagnostic accuracy. The complete pipeline shows great promise for clinical application in diagnosing Parkinson's conditions based on non-invasive EEG recordings.

Keywords— Parkinson's Disease, San Diego, electroencephalogram, Deformable Kernel Networks, neurodegenerative disorder.

I. Introduction

PD is a prevalent chronic, age-related neurodegenerative disease, due to progressive nervous system degeneration, and with increased prevalence in the older population [1]. Currently, it is the second most common neurodegenerative disease with an estimated worldwide prevalence of about 0.1-0.5%, and a total of more than 2 million patients with PD in China alone [2]. Onset occurs with a mean age of about 60 years, and incidence rises markedly with age. PD is clinically defined primarily by motor impairments including bradykinesia/akinesia, resting tremor, rigidity, gait impairment, and postural instability, but similarly frequent non-motor symptoms include cognitive impairment, autonomic dysfunction, and psychiatric disturbance [3]. The pathophysiology of PD is degeneration of dopaminergic neurons within substantia nigra pars compacta and accumulation of Lewy bodies. The human brain exists as a highly interconnected system of neurons and areas, and the heterogeneity of symptoms of PD is thought to be caused by disturbances in specific neural circuits [4].

Cognitive impairment that antecedes motor symptoms and increases with disease progression means that timely detection is essential [5]. The identification of valid biomarkers is necessary for early diagnosis and customized neuroprotective treatment, which can potentially retard disease progression through therapy and lifestyle modification [6]. Here, the electroencephalogram (EEG) is emerging as a promising tool, being non-invasive, portable, low-cost, and highly accessible. It may be able to follow the course of PD and identify neurophysiological indicators for early identification [7].

PD is a neurodegenerative disease that worsens with time and is typified by both motor and non-motor symptoms, frequently accompanied by initial cognitive impairment. Timely therapeutic intervention may be initiated by early and correct diagnosis. EEG has emerged as a possible tool in this regard as a non-invasive, cost-effective, and readily available technique for identifying neurophysiological biomarkers. Utilizing EEG signals for early PD detection and monitoring has the promise to improve diagnosis and facilitate personalization of treatment approaches toward better patient outcomes.

Contributions

The key contributions of the proposed work is given below,

- **Dataset Utilization**: EEG signals from San Diego dataset are employed, comprising both healthy individuals and PD patients under resting-state conditions.
- **Pre-processing**: EEG data are pre-processed using a Deformable Kernel Network (DKN), which adaptively refines the signals by learning spatial sampling offsets and kernel weights. This step denoises the EEG and clusters signals into 10 brain regions for structured analysis.
- **Feature Extraction**: A Fast hybrid Vision Transformer (FhVT) extracts spatial-temporal features from the pre-processed EEG data, efficiently capturing both local and global neural dynamics.
- **Classification**: The model employs the Model-Level Graph Triplet Neural Network (MLGTNN), which first utilizes the Model-Level Graph Network (MLGNN) to capture inter-regional dependencies and structural relationships within EEG signals. Then, Triplet Attention Network (TAN) is applied to enhance discriminative feature learning by emphasizing relevant temporal and spatial regions. This architecture classifies EEG data across three binary PD tasks: healthy vs. PD, PD-on vs. PD-off medication, and healthy vs. PD-off.
- **Optimization**: Crayfish Optimization Algorithm (COA) is applied to minimize classification loss and optimize network weights, enhancing convergence and model generalization.

The paper is structured as follows: Section 1 contains introduction; Section 2 contains literature review; Section 3 contains methodology; Section 4 contains results; and Section 5 concludes the study.

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II. Literature Survey

Below is a summary of recent studies of PD classification using EEG signal analysis.

In 2021, Khare, S.K. et.al, [8] presented an automated PD detection using smoothed pseudo-Wigner Ville distribution (SPWVD) coupled with convolutional neural networks (CNN), named Parkinson's disease CNN (PDCNNet). EEG signals underwent SPWVD to generate time-frequency representations (TFRs). These two-dimensional plots fed into a CNN. The model developed using two public datasets: San Diego and UNM.

In 2024, Siuly, et.al, [9] introduced a TFR based AlexNet Convolutional Neural Network (CNN) model to analyse EEG channels and identify critical brain regions for Parkinson's disease diagnosis. The Wavelet Scattering Transform (WST) was used to capture temporal and spectral characteristics, while AlexNet CNN detected complex spatial patterns. San Diego and Iowa dataset were utilized.

In 2022, Aljalal, et.al, [10] introduced a popular spatial pattern-based method for both on- and off-medication PD detection. Metrics including energy, entropy, variance, and band power are used to extract characteristics from EEG signals after they have been pre-processed to eliminate significant artifacts. The collected characteristics are classified using machine learning methods such as k-nearest neighbour, support vector machine (SVM), random forest, and linear/quadratic discriminant analysis. Two EEG datasets San Diego and UNM datasets were used to assess methodologies.

In 2024, Li, et.al, [11] presented a multi-scale fuzzy entropy fusion method for EEG features to quantify complexity and irregularity of EEG signals. A 2 Dimensional Multiple Dual Attention Gated Temporal Separable (2D-MDAGTS) model was developed for automatic Parkinson's disease detection. To improve detection performance, the model used a dual attention network, a gated recurrent unit, and temporal separable convolution. The methods achieved high accuracy on San Diego and UNM dataset in classifying both drug-free PD patients and healthy patients.

A. Problem statement

Even with advancements in neuroimaging, early and correct diagnosis of PD is still problematic because of the heterogeneous symptoms of PD and similar features shared with other diseases. EEG based analysis provides a non-invasive, low-cost means of identifying neurophysiological biomarkers. Nevertheless, strong feature extraction and classification methods are necessary for effective PD detection. This research fulfils the requirement for enhanced diagnosis accuracy by utilizing time-frequency analysis, deep learning, and attention-based models on EEG San Diego dataset to identify PD patients versus healthy controls.

III. Proposed Methodology

San Diego EEG dataset is preprocessed with DKN, in which signals are purified and grouped into 10 regional brain regions. Features are extracted with FhVT, which records spatio-temporal patterns. Following this, classification is done with MLGTNN, which combines a Model-Level Graph Network for encoding EEG topologies and TAN to improve spatial discrimination. This architecture classifies EEG data into three binary Parkinson's tasks: healthy vs. PD, PD-on vs. PD-off and healthy vs. PD-off. COA optimizes the loss and weight of the network. The proposed method's block diagram is shown in Figure 1.

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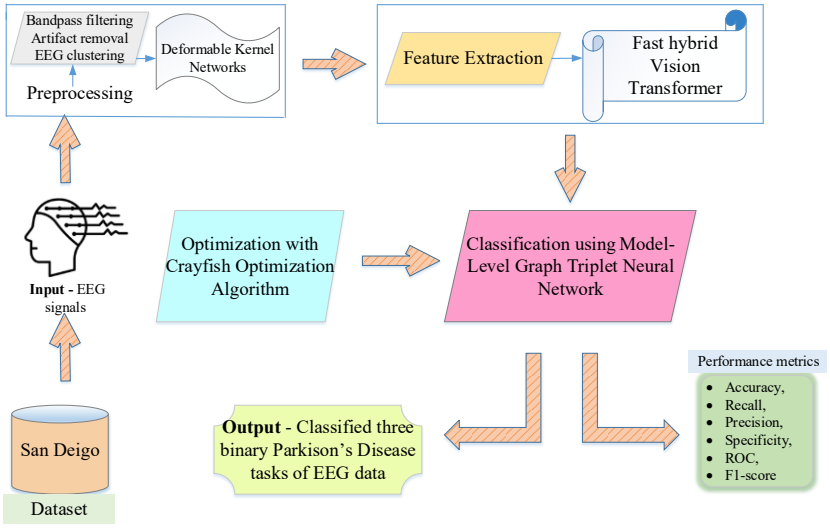

Fig.1. Proposed Methodology MLGTNN-COA's block diagram.

A. Dataset description

San Diego EEG dataset [12] includes recordings from two groups: 16 healthy control (HC) subjects (9 females, 7 males; mean age 63.5 ± 9.6 years) and 15 Parkinson's disease (PD) patients (8 females, 7 males; mean age 63.2 ± 8.2 years). All were right-handed and matched across age, gender, and cognitive capacity, as determined by Mini-Mental State Examination and the North American Adult Reading Test. In acquiring the data, participants sat at ease and gazed at a cross appeared on a screen to maintain minimal movement and eye movement. The collected data are fed into pre-processing stage.

B. Preprocessing using Deformable Kernel Network

Raw EEG signals from San Diego dataset were first pre-processed using Deformable Kernel Network (DKN) to enhance signal quality and preserve meaningful neural patterns [13]. A 1-55 Hz band pass filter was applied to eliminate high-frequency noise and baseline drift. DKN adaptively learned spatial sampling offsets and kernel weights to effectively suppress noise while preserving critical neural structures. This structure-aware refinement improved the clarity of EEG signals for downstream analysis. The process is mathematically expressed as in eq. (1),

$$\tilde{e}_q = e_q + \sum_{w \in M(q)} L_{qt}(e,h) e_{t(w)} \quad (1).$$

where $M(q)$ is a local 3×3 window connected to q, $\tilde{e}_q$ denotes updated feature vector, e_q is the original feature vector, h represents a context vector used in computing the weighting function, $e_{t(w)}$ is a transformed feature. To enable Neighbour Feature Transformation, each pixel (or EEG point) aggregates contextual information from its neighborhood using a learned kernel using eq. (2),

$$e_{t(w)} = \sum_{u \in T(t(w))} F(t,u) e_s \quad (2).$$

where $F(t,u)$ is a learned kernel weights. These kernels adapt spatially to align and enhance features in the vicinity of each location, ensuring robustness against EEG variability across trials. The residual-free form of adaptive filtering is given in eq. (3),

$$\tilde{e}_q = \sum_{w \in M(q)} L_{qt}(e,f) e_{t(w)} \quad (3).$$

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where $L_{qt}(e,f)$ represents learned weighting function. Once the data are cleaned, EEG signals were clustered into 10 regional groups (covering frontal, central, parietal, and occipital lobes), each combining 2-6 electrodes. This regional abstraction provided robust features for downstream analysis (time-frequency decomposition or classification). Thus, DKN-based pre-processing not only denoises the EEG but also reconstructs meaningful local temporal dynamics crucial for PD classification. Thus, the pre-processed EEG signals were then used to extract regional features from 10 clustered brain areas for further analysis.

C. Feature Extraction using Fast hybrid Vision Transformer (FhVT)

Each 1-second EEG trial, preprocessed and grouped clusters, was fed into Fast hybrid Vision Transformer (FhVT) for robust feature extraction. FhVT combines convolutional layers and transformer blocks to capture both local spatial dependencies and long-range temporal dynamics efficiently [14]. The FhVT enables efficient feature extraction by combining convolutional and transformer-based mechanisms for better spatial and contextual understanding as given in eq. (4),

$$G = AQ(\omega(ERConv(Y))) + Y \quad (4).$$

where AQ Layer of Normalization of the Batch, ω is an activation function that is not linear, $ERConv$ is a convolutional layer of depth. The non-linear transformation is removed from this mixing block and operations are reorganized for simplicity and faster inference. The updated design is expressed as follows in eq. (5),

$$G = ERConv(QW(Y)) + Y \quad (5).$$

The block can be reparameterized during deductions into a single depth wise convolutional layer to this structural rearrangement, which lowers memory overhead and latency. The efficient form that is produced is in eq. (6),

$$G = ERConv(Y) \quad (6).$$

The resulting feature maps from all EEG clusters were extracted as compact, discriminative representations encoding the nonlinear dynamics of brain activity, which were subsequently passed to the classification module for PD diagnosis.

D. Classification using Model-Level Graph Triplet Neural Network

Upon completion of feature extraction, classification is carried out using Model-Level Graph Triplet Neural Network (MLGTNN). This integrates Model-Level Graph Neural Network (MLGNN) to learn structural relationships from EEG representations. It captures inter-regional dependencies through graph-based message passing and embedding updates.
Subsequently, the Triplet Attention Network (TAN) refines spatial features, enhancing classification performance.

a. Model-Level Graph Network

Classification of features derived from FhVT was initially performed using MLGNN, offering high-level interpretability by identifying influential graph components [15]. MLGNN was trained to distinguish between three binary classification tasks: (i) PD off medication vs. controls, (ii) PD on medication vs. PD off, and (iii) PD on medication vs. controls. The initial representation of images is given by eq. (7),

$$J^0 = MLP(Z) \quad (7).$$

where MLP denotes Multilayer Perceptron that projects raw features into a lower-dimensional latent space, Z denotes original feature matrix extracted from MRI slices, J^0 represents initial representations of images. To

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capture spatial relationships across multiple neighborhood levels, the image features are propagated through tree-structured sub graphs with multi-hop dependencies as by eq. (8),

$$J^{l} = \left(M^{l} \Theta H^{l,L}\right) J^{0}, l = 1,2,...., K \quad (8).$$

where M^{l} is the adjacency matrix of l^{th} layer, $H^{l,L}$ represents Multi-hop edge importance from diffusion up to hop L, Θ represents element-wise product, L is the maximum depth. Each M^{l} sub-graph represents the tree-structured L hop neighbourhood centred on a brain region. The classification loss A is given as per eq. (9),

$$A = -\sum_{c_j \in U_1} \sum_{i=1}^{V} Y_{ji} \log \widetilde{Z}_{ji} \quad (9).$$

where $\widetilde{Z}$ denotes probability distribution of each image, $U_1 \in U$ indicates a collection of training images with previously established label information, V represents all of the classes that need to be anticipated. Thus, classification using MLGNN enables multi-scale structural regions, followed by TAN for enhanced classification.

b. Triplet Attention Network

Following MLGNN, Triplet Attention Network (TAN) was employed for further classification to improve discrimination between the three binary PD tasks [16]. TAN enhanced extracted features by learning to focus on the most relevant spatial or frequency regions in EEG data. The attention mechanism began with a pooling operation across the width expressed in eq. (10),

$$E - pool(\delta) = [RTU_{0e}(\delta), RIU_{0e}(\delta)] \quad (10).$$

where, $E - pool(\delta)$ **i**ndicates a pooling operation across width dimension (E). The input to the function is γ, 0_e is the 0^{th} dimension across $RTU_{0e}(\delta)$ and $RIU_{0e}(\delta)$ operations are performed. Convolution and sigmoid activation are used by each branch to produce attention weights in (11),

$$x = \frac{1}{3}\left(\overline{y_{0G} e_1} + \overline{y_{1G} e_2} + \overline{y e_3}\right) = \frac{1}{3}\left(\overline{x_1} + \overline{x_2} + \overline{x_3}\right) \quad (11).$$

where e_1, e_2, e_3 are the triplet attention's cross-dimensional attention weights, y_1, y_2 are the 90^0 clockwise rotation. The distance computes as in eq. (12),

$$f_i = \frac{b_i . y}{\|b_i\|} \quad (12).$$

where $b_i \in S^{1 \times K}$ indicates the i^{th} vector's weight vector. The classification probability $soft\max$ is expressed in eq. (13),

$$\vec{x_i} = soft\max(v_i) = \frac{e^{vi}}{\sum_{i=1}^{L} g^{vi}} \quad (13).$$

where $\vec{x_i}$ refers to the classified binary tasks and satisfies $\sum_{i=1}^{L} \vec{x_i} = 1$. Thus, classification of the three binary PD tasks is performed using the MLGTNN, combining structural and spatial attention mechanisms. The resulting class-wise loss and learned weights are then fed into an optimization module to refine model

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parameters for improved accuracy. The COA adaptively explores and exploits the solution space to achieve optimal performance.

E. Optimization with Crayfish Optimization Algorithm (COA)

Subsequent to classification, COA is used to optimize loss and weight and to enhance overall model accuracy. COA is a swarm intelligence system that draws inspiration from the way crayfish naturally react to their surroundings [17]. It models three distinct phases: summer heat escape for global exploration, competition for local refinement, and predation for exploitation. Crayfish seek shaded caves when temperatures are high, compete for limited resources, and use strategic movements to capture food. These behaviours guide the optimization process across the solution space. COA dynamically transitions between phases based on a simulated temperature, enhancing both convergence and diversity.

Step 1: Initialization

The population initialization is the first step of the population based algorithm known as COA, focusing on candidate solutions with G dimensions, H and crayfish locations as a group of solutions. eq. (14) shows the expression of population location,

$$Y=\begin{bmatrix} Y_{1,1} & \cdots & Y_{1,j} & \cdots & Y_{1,G} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ Y_{j,1} & \cdots & Y_{j,i} & \cdots & Y_{j,G} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ Y_{H,1} & \cdots & Y_{H,i} & \cdots & Y_{H,G} \end{bmatrix}_{H\times G} \quad (14).$$

where Y represents the location of initial crayfish population, H indicates number of crayfish population, G denotes dimension of problem, $Y_{j,i}$ denotes initial location of j^{th} crayfish in i^{th} dimension. The populations are initialized and randomly generated.

Step 2: Fitness Evaluation:

A crucial component of COA for assessing the caliber of potential solutions during optimization process is the fitness function. By striking a balance between two crucial factors accuracy and loss it directs the search toward the best categorization performance. The fitness function, FF is evaluated and is given as in eq. (15),

$$FF=\min\left[A,b_i\right]+\max\left[acc\right] \quad (15).$$

where A denotes the loss function, b_i represents weight parameter and acc is the accuracy. After calculating fitness, it moves towards exploration.

Step 3: Summer (Exploration)

Crayfish will go through several phases depending on the surrounding temperature. The crayfish will enter the summer stage when the temperature is above 30^0 C. When it is above 30^0 C crayfish chooses Y_{shade} . The new position update for a crayfish escaping the heat is given by eq. (16),

$$Y_{j,i}^{s+1}=Y_{J,I}^{s}+W_2\cdot t\cdot\left(Y_{shade}-Y_{j,i}^{s}\right) \quad (16).$$

where s denotes current number of iterations, $s+1$ represents number of iterations of next generation, t refers to random number and W_2 decreases with increase in iterations.

Step 4: Competition (diversification)

When the temperature rises beyond 30^0 C and the number chosen at random rand reaches 0.5, many crayfish will vie for a cave and go on to competition stage. At this point, eq. (17) displays the revised crayfish position.

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$$Y_{j,i}^{s+1} = Y_{j,i}^{s} - Y_{x,i}^{s} + Y_{shade} \quad (17).$$

where x is a random crayfish in population.

Step 5: Predation (Exploitation):

The crayfish in the COA proceed into the food seeking and ingestion phase (exploitation) when the temperature reaches 30^0 C. The size of the food, represented by Q, which is a function of the crayfish's fitness in relation to the global best (food) fitness, affects this behavior. The simulated process is given in eq. (18),

$$Y_{j,i}^{s+1} = Y_{j,i}^{s} + Y_{food} \cdot Q \cdot (\cos(2 \cdot \pi \cdot s) - \sin(2 \cdot \pi \cdot s)) \quad (18).$$

where Q denotes the intake of food and s is the random number.

Step 6: Termination:

The algorithm stops when it reaches maximum number of iterations or if fitness function converges to a threshold value, indicating optimal or near-optimal parameter tuning. Thus, the loss and weight are optimized using COA, ensuring optimal parameter adjustment through adaptive exploration and exploitation. As a result, the overall classification accuracy and model robustness are significantly enhanced.

IV. Result

This section presents the evaluation and outcomes of the MLGTNN-COA method's performance in distinguishing PD patients from healthy individuals using dynamic analysis of EEG time series.

A. Performance Analysis of Proposed Model

The performance of the model suggested for dynamic analysis of EEG time-series to differentiate between PD and normal individuals is assessed by using San Diego dataset based on key performance measures. Recall, accuracy, F1-score, precision, specificity, and the Receiver Operating Characteristic (ROC) curve are used to gain a thorough understanding of the model. These metrics show how efficiently the model can distinguish between PD and normal EEG signals, correctly identify pathological patterns, and provide stable convergence and generalization during training.

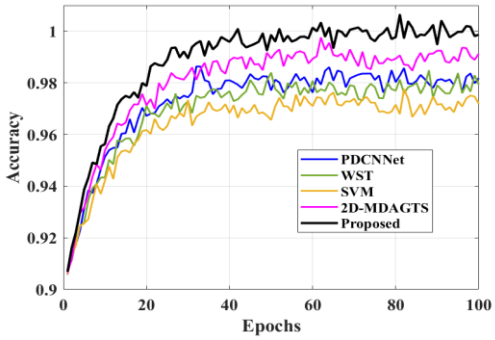

Fig.2. Accuracy vs. Epochs Comparison of PD Classification Models

The figure 2 shows the accuracy performance after 100 training epochs for five PD classification models: PDCNNet, WST, SVM, 2D-MDAGTS, and the proposed method. The proposed approach (black line) outperforms all baselines consistently, exhibiting faster convergence and improved accuracy, stabilizing above 0.99. Conversely, PDCNNet, WST, and SVM plateau at below 0.98, and 2D-MDAGTS performs reasonably but remains suboptimal. This underscores the efficiency and stability of the proposed MLGTNN based approach in classifying PD from EEG data.

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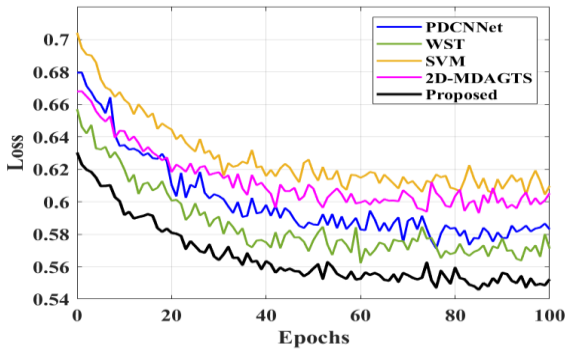

Fig.3. Loss vs. Epochs Comparison of PD Classification Models

The figure 3 shows loss curves after 100 training epochs for five models: PDCNNet, WST, SVM, 2D-MDAGTS, and the proposed method. The proposed model (black line) has the lowest and most stable loss, reflecting better convergence and generalization. It starts at a lower initial loss and continues to descend steadily, surpassing all baseline approaches. On the other hand, SVM (orange) holds the maximum loss, and PDCNNet, WST, and 2D-MDAGTS have moderate decreases. This indicates the excellence of the proposed model in reducing the classification error of PD EEG analysis.

B. Comparative analysi

The most important metrics utilized in the assessment of performance of the proposed architecture for Parkinson's disease diagnosis from EEG signals are F1-score, accuracy, sensitivity, specificity, and ROC. Comparative evaluation is done with previous models PDCNNet [8], WST [9], SVM [10], and 2D-MDAGTS [11], based on benchmark EEG dataset San Diego. A detailed performance comparison is presented in Table 1, which demonstrates the superior predictive ability and robustness of the proposed MLGTNN-COA model in identifying Parkinson's patients versus healthy subjects for early diagnosis.

TABLE I. EVALUATION OF PD CLASSIFICATION MODEL'S PERFORMANCE USING SAN DEIGO DATASET

Methods	**Accuracy (%)**	**Recall (%)**	**F1-Score (%)**	**Specificity (%)**	**Precision (%)**
PDCNNet [8]	84	83	82	85	78
WST [9]	82	88	74	86	84
SVM [10]	87	74	87	73	87
2D-MDAGTS [11]	75	77	79	87	83
MLGTNN-COA (proposed)	**99.93**	**99.74**	**99.67**	**99.59**	**99.83**

The table 1 summarizes a comparative assessment of different approaches to PD detection based on EEG signals. Moderate performance is observed for PDCNNet, WST, SVM, and 2D-MDAGTS based on F1-score, recall, and accuracy. The proposed MLGTNN-COA approach, however, performs far better than all others, with near perfect measures across all the evaluation metrics such as accuracy (99.93%), recall (99.74%), precision (99.83%), and specificity (99.59%), F1-score (99.67%). This emphasizes the superior discriminatory power of the method in separating Parkinson's patients from normal subjects with high sensitivity and reliability in dynamic EEG signal classification.

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V. Conclusion

The research introduced a new deep learning architecture for accurate classification of PD from EEG signals recorded from San Diego dataset. First, EEG data are preprocessed using a Deformable Kernel Network (DKN), which provides robust signal scrubbing and segmentation of EEG signals into 10 spatial brain areas. It is followed by feature extraction using Fast hybrid Vision Transformer (FhVT), which extracts both spatial and temporal EEG dynamics. For classification, the suggested architecture utilizes Model-Level Graph Triplet Neural Network (MLGTNN), which initially uses a Model-Level Graph Network to learn global EEG region pairwise relationships, then a Triplet Attention Network (TAN) to improve inter-feature interdependencies. This configuration allows for accurate classification among three binary PD tasks: (i) healthy and PD, (ii) PD-on medication and PD-off medication, and (iii) healthy and PD-off medication. Lastly, the model is optimized by Crayfish Optimization Algorithm (COA) to adjust loss functions and model weights for steady convergence and good generalization. Experimental results demonstrate that proposed MLGTNN-COA model considerably outperforms state-of-the-art methods in accuracy, precision, sensitivity, and F1-score. This paper provides a solid and interpretable EEG based PD diagnosis tool with the ability to distinguish medication states and healthy controls, providing promising potential for clinical neurodiagnostic use.

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