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Original Research Article

Early Detection of Parkinson's Disease Using Novel Deep Learning Frameworks Optimized with Advanced Techniques and Machine Learning Models Evaluated through Performance Metrics

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Parkinson's Disease (PD), Classification, Deep Learning, Optimization Techniques, Machine Learning, Performance Metrics, Predictive Performance

ABSTRACT:

Parkinson's disease (PD) is a progressive neurodegenerative condition that frequently remains undiagnosed in its early stages due to subtle and overlapping symptoms. This study presents an innovative approach that integrates advanced deep learning architectures, optimization techniques, and machine learning models to enhance the accuracy of early PD detection. By utilizing performance metrics for model evaluation and comparison, the research identifies the most effective methods for achieving precise and reliable diagnoses. The proposed framework exhibits exceptional performance in differentiating early-stage Parkinson's cases from healthy individuals, contributing to improved clinical decision-making and enabling timely interventions. Experimental results provide to prove the proposed frame work techniques using ML and DL with better optimizations and its performance metrics.

1. Introduction

Parkinson's disease (PD) is a progressive neurological disorder that is often challenging to detect in its initial stages due to subtle and overlapping clinical features. This study proposes an advanced framework integrating deep learning architectures, optimization strategies, and machine learning models to enhance early detection accuracy. The research evaluates the models using performance metrics to identify optimal solutions, demonstrating the framework's effectiveness in distinguishing early-stage PD from healthy individuals and supporting timely diagnosis and intervention.

Parkinson's disease (PD) is the second most prevalent neurodegenerative disorder, affecting millions worldwide. Early detection is critical for managing the disease, slowing its progression, and improving patient quality of life. However, early-stage PD diagnosis remains challenging due to subtle motor and non-motor symptoms, which often overlap with

other neurological conditions. Leveraging computational models such as machine learning (ML) and deep learning (DL) can aid in the accurate and timely diagnosis of PD.

Recent advances in machine learning have significantly contributed to PD detection. Studies have shown that support vector machines (SVMs) and random forests (RFs) effectively classify PD-related data based on voice, handwriting, and gait patterns, achieving notable accuracy rates (Das et al., 2021; Gupta et al., 2020). Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated superior performance in extracting relevant features from complex datasets (Wang et al., 2021; Shen et al., 2022).

Optimization techniques further enhance the predictive capabilities of ML and DL models. Particle swarm optimization (PSO) and genetic algorithms (GA) are widely used to fine-tune hyperparameters, improving model accuracy and robustness (Singh et al., 2020; Ahmed et al., 2021). Combining these techniques with deep learning frameworks has led to breakthroughs in medical diagnostics, including PD detection (Zhang et al., 2022; Kumar et al., 2021).

2. Literature Review

Performance metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) are critical for evaluating and comparing models. Studies underscore the importance of robust metrics in validating the reliability of models for clinical applications (Patel et al., 2020; Lin et al., 2021). Integrating these metrics within optimization and machine learning frameworks ensures the development of clinically viable tools.A novel approach to early PD detection by combining advanced deep learning architectures with optimization techniques and machine learning models. The framework's performance is evaluated using multiple metrics to identify optimal methods, offering a pathway to improved diagnostic accuracy and early intervention.

The application of artificial intelligence in healthcare has seen a surge in recent years, with deep learning (DL) and machine learning (ML) playing pivotal roles in disease diagnosis and prognosis. Novel DL and ML techniques have demonstrated exceptional capabilities in handling complex datasets, extracting meaningful patterns, and improving diagnostic accuracy. These advanced approaches have been further enhanced by incorporating robust performance metrics, ensuring reliable and reproducible results.

Deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have achieved remarkable success in image and sequential data analysis (Zhang & Li, 2021; Kumar et al., 2022). Similarly, machine learning algorithms such as support vector machines (SVMs) and ensemble methods like random forests (RFs) have proven effective for classification tasks across various medical datasets (Patel et al., 2020; Singh & Sharma, 2021).The integration of performance metrics, including accuracy, precision, recall, F1-score, and area under the curve (AUC), is essential for evaluating these models (Ahmed & Gupta, 2021; Lin et al., 2021). Studies have shown that optimization techniques further enhance model performance by fine-tuning hyperparameters, leading to improved predictive capabilities (Wang & Chen, 2022; Ali & Siddiqui, 2021).

Data mining serves as a powerful tool for analyzing large, pre-existing databases to uncover previously unknown and valuable insights. In the context of chronic disease data, each row represents a specific location, while the attributes encompass topics, questions, data values, and confidence limits (both low and high). Data is utilized for training and testing purposes across five classification algorithms. This paper evaluates the performance and accuracy of

five decision tree algorithms, demonstrating that the M5P decision tree approach outperforms the others in building an effective predictive model (Rajesh et al., 2021).
Each row is an instance characterized by attribute values such as Outlook, Temperature, Humidity, Windy, and the Boolean PlayGolf class variable. The dataset is used for training purposes and analyzed using seven classification algorithms. This study evaluates the performance and accuracy of various decision tree-based approaches implemented in the WEKA tool to identify key parameters of the tree structure. The algorithms include J48, Random Tree (RT), Decision Stump (DS), Logistic Model Tree (LMT), Hoeffding Tree (HT), Reduced Error Pruning Tree (REP), and Random Forest (RF). Experimental results show that among these algorithms, the Random Tree achieves the highest accuracy of 85.714% (Rajesh et al., 2021).
The evaluation of AI methodologies, particularly in predictive modeling, hinges on the use of robust performance metrics, including accuracy, precision, recall, F1-score, and the area under the curve (AUC), which collectively form a comprehensive framework for assessing and benchmarking the predictive capabilities of diverse models; although traditional machine learning (ML) techniques have yielded commendable outcomes in certain scenarios, the integration of deep learning advancements, particularly those enhanced by optimization strategies, has significantly elevated the accuracy and efficiency of classification tasks, such as Parkinson's disease detection, while simultaneously demonstrating the transformative potential of ML in domains like healthcare, finance, and engineering by enabling the analysis of extensive datasets, the extraction of meaningful patterns, and the generation of reliable predictions, all contingent upon rigorous evaluation frameworks that ensure the models' applicability and reliability in real-world settings (Rashid et al., 2022; Bishop, 2006).
Deep learning model, named CNN-BiGRU, leverages the combined strengths of Convolutional Neural Networks (CNNs) and Bidirectional Gated Recurrent Units (BiGRUs). CNNs are highly effective in capturing spatial features from structured inputs, while BiGRUs excel at learning temporal dependencies from sequential datasets. This hybrid approach ensures the model is versatile and capable of processing a wide range of static and dynamic PD-related data (LeCun et al., 2015; Cho et al., 2014). To further improve the model's performance, we propose Dynamic Gradient Regularization (DGR). This optimization method introduces a flexible regularization term in the loss function that adapts based on the magnitude of gradients. By reducing the sensitivity to noisy gradients, DGR ensures smooth convergence and more effective learning. Unlike conventional optimizers such as Adam, DGR fine-tunes learning rates layer-by-layer, optimizing the training process and reducing convergence time (Kingma & Ba, 2015).

3. Backgrounds and Methodologies

Parkinson's Disease (PD) poses considerable challenges for early detection due to its diverse and intricate nature. Addressing this complexity requires sophisticated computational methods capable of effectively processing multimodal datasets, including clinical, vocal, and movement-related data. In response, we introduce an innovative deep learning model designed specifically for PD classification, coupled with a novel optimization technique aimed at enhancing its accuracy and generalization.

3.1 Algorithms for CNNBiGRU-DGR

1. **Dual Input Processing:** Simultaneously processes clinical and sequential data, such as vocal patterns and accelerometer readings, to enhance its analytical capability.

2. **Attention Mechanism:** A post-BiGRU attention layer emphasizes the most critical temporal features, improving interpretability and prediction outcomes.
3. **Adaptive Dropout:** Dynamically adjusts dropout rates during training to minimize overfitting and improve performance.
4. **Gradient Smoothing:** Stabilizes high-gradient updates to reduce overfitting and ensure steady training.
5. **Layer-Specific Adjustments:** Tailors learning rates for individual layers to maximize performance in complex architectures.
6. **Early Stopping Integration:** Complements early stopping techniques to avoid overfitting while preserving high accuracy.

3.2Transformer Deep Learning with Particle Swarm Optimization (TDL-PSO)

The integration of Transformer architectures with Particle Swarm Optimization (PSO) combines the advanced capabilities of modern deep learning and evolutionary optimization methods. This hybrid approach excels in applications requiring accurate feature extraction, effective hyperparameter tuning, and high-performance classification.

3.2.1 Proposed Deep Learning: Transformer

Transformers, first introduced by Vaswani et al. (2017), have emerged as a cornerstone in deep learning, particularly excelling in tasks like natural language processing and computer vision. These models leverage self-attention mechanisms to efficiently capture dependencies within sequential data without relying on recurrent architectures. Key elements of a Transformer include:

1. **Self-Attention Mechanism:**
   - Analyzes relationships among all parts of an input sequence.
   - Effectively captures long-range dependencies, enhancing feature extraction.
2. **Feed-Forward Neural Networks:**
   - Processes outputs from the self-attention layers to support prediction and classification tasks.
3. **Positional Encoding:**
   - Encodes order information, essential for handling sequential data, such as time-series signals.

Transformers have expanded their scope beyond traditional domains to include medical applications, such as analyzing neuroimaging and biosignals, proving particularly effective for Parkinson's Disease detection (Dosovitskiy et al., 2020).

3.2.2 Particle Swarm Optimization (PSO)

PSO, developed by Kennedy and Eberhart (1995), is an optimization algorithm inspired by the collective behaviors of animals, such as birds and fish. This technique is used to optimize complex functions by iteratively improving a population of candidate solutions, called particles, using a fitness function to guide the search.

Core Features of PSO:

- **Exploration and Exploitation:** Utilizes particle velocity and position updates to search the solution space thoroughly.

- **Dynamic Adaptation:** Strikes a balance between exploring diverse possibilities and refining high-potential areas.

PSO Workflow:

1. **Initialization:** Particles are initialized with random positions and velocities.
2. **Fitness Evaluation:** Each particle's performance is assessed based on an objective function, such as accuracy or F1-score.
3. **Velocity and Position Updates:** Using personal and global best positions, particles adjust their paths iteratively toward the optimal solution.

PSO's efficiency and simplicity make it a popular choice for optimizing machine learning hyperparameters, selecting features, and fine-tuning neural networks.

3.2.3 Integrating Transformers with PSO

The combination of Transformers with PSO creates a powerful framework for complex problem-solving, especially in the healthcare domain.

Mechanism:

1. **Transformer Model:**
   - Extract features from structuredor unstructured data.
2. **PSO for Optimization:**
   - Tunes critical hyperparameters, such as learning rates, the number of layers, and attention heads, ensuring the model performs optimally.
   - A fitness function evaluates parameters based on metrics like validation accuracy or F1-score.
3. **Training and Evaluation:**
   - The model is iteratively trained using PSO-optimized parameters, improving its ability to generalize and perform across datasets.

- **Improved Feature Extraction:** Transformers adeptly capture dependencies in sequential or spatial data.
- **Efficient Hyperparameter Tuning:** PSO optimizes the search process for the best parameter configuration.
- **Better Generalization:** The combination minimizes overfitting while enhancing performance on unseen data.

3.2.4 Step-by-Step Process for Transformer + PSO Framework

Step 1: Data Preprocessing

1. Gather the dataset, which may include various data types like images, audio recordings, or sensor readings.
2. Apply noise reduction techniques, such as median filtering or wavelet transformation, to enhance data quality.
3. Normalize the dataset to ensure uniform scaling of features.
4. Divide the dataset into subsets for training, validation, and testing in appropriate proportions (e.g., 70% training, 20% validation, and 10% testing).

Step 2: Transformer Model Initialization

1. Select a suitable transformer model, such as Vision Transformer (ViT) or Swin Transformer, based on the data characteristics.
2. Define the model's architecture, including input dimensions, the number of transformer layers, and attention heads.

3. Implement multi-head self-attention to capture global relationships and dependencies within the data.

Step 3: Setting Up Particle Swarm Optimization (PSO)

1. Initialize a swarm of particles, where each particle represents a potential solution (e.g., a specific set of hyperparameters).
2. Define the fitness function to evaluate particle performance (e.g., validation accuracy or F1-score).
3. Configure PSO parameters:
   - **Population size:** Set the number of particles (e.g., 20).
   - **Inertia weight (w):** Balance exploration (global search) and exploitation (local refinement).
   - **Acceleration coefficients (c_1, c_2):** Control the impact of personal experience (cognitive) and swarm collaboration (social).

Step 4: Optimization Loop

1. For each particle in the swarm:
   - Calculate its fitness score using the current hyperparameter set.
   - Compare this score to the particle's personal best (p_{best}) and update if the fitness improves.
   - Compare the particle's score to the swarm's global best (g_{best})and update if improved.
2. Update the particle's velocity (v_i) and position (x_i) using the equations:

$$v_i = w.v_i + c_1.r_1.(p_{best} - x_i) + c_2.r_2.(g_{best} - x_i)$$

$$x_i = x_i + v_i$$

where r_1 and r_2 are random values between 0 and 1.

3. Continue the optimization until the convergence criterion is met, such as a maximum number of iterations or achieving an acceptable fitness level.

Step 5: Training the Transformer Model

1. Apply the optimized hyperparameters identified by PSO to configure the transformer.
2. Train the transformer on the training data, using a loss function such as cross-entropy loss.
3. Validate model performance during training, employing techniques like early stopping to prevent overfitting.

Step 6: Evaluating Model Performance

1. Test the final model on an unseen test dataset to assess generalization capability.
2. Calculate and analyze key performance metrics, including:
   - Accuracy
   - Precision and Recall
   - F1-Score
   - Receiver Operating Characteristic - Area Under the Curve (ROC-AUC)

This systematic approach ensures robust feature extraction, optimal hyperparameter selection, and high performance in classification tasks.

4.0 Experimental Results

The dataset used for this study was obtained from the publicly available Kaggle repository. The Parkinson's dataset comprises 24 features, encompassing various categories of data such as name, MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz), MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP, MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA, NHR, HNR, RPDE, DFA, spread1, spread2, D2, PPE, and status (Kaggle). The dataset is

composed of a range of biomedical voice measurements with Parkinson's disease (PD). The attribute details are outlined as follows:

1. **Name**: ASCII representation of the subject's name and recording identifier.
2. **MDVP:Fo(Hz)**: Mean fundamental frequency of the voice.
3. **MDVP:Fhi(Hz)**: Maximum fundamental frequency of the voice.
4. **MDVP:Flo(Hz)**: Minimum fundamental frequency of the voice.
5. **Jitter Measures**: Includes MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, and Jitter:DDP, which represent various metrics of fundamental frequency variation.
6. **Shimmer Measures**: Includes MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, and Shimmer:DDA, reflecting amplitude variation in the voice.
7. **NHR and HNR**: Metrics quantifying the ratio of noise to tonal components in the voice signal.
8. **RPDE and D2**: Nonlinear dynamical complexity measures of the signal.
9. **DFA**: The fractal scaling exponent of the signal.
10. **Spread1, Spread2, PPE**: Nonlinear measures representing variations in the fundamental frequency.
11. **Status**: Health status indicator of the subject, where "1" represents Parkinson's Disease and "0" indicates a healthy condition.

Table 1a. Parkinson's Dataset

MDVP: Fo (Hz)	MDVP: Fhi (Hz)	MDVP: Flo(Hz)	MDVP: Jitter (%)	MDVP: Jitter (Abs)	MDVP: RAP	MDVP: PPQ	Jitter: DDP	MDVP: Shimmer	MDVP: Shimmer (dB)	Shimmer: APQ3
104.4000	206.0020	77.9680	0.0063	0.0001	0.0032	0.0038	0.0095	0.0377	0.3810	0.0173
171.0410	208.3130	75.5010	0.0046	0.0000	0.0025	0.0023	0.0075	0.0197	0.1860	0.0089
146.8450	208.7010	81.7370	0.0050	0.0000	0.0025	0.0028	0.0075	0.0192	0.1980	0.0088
155.3580	227.3830	80.0550	0.0031	0.0000	0.0016	0.0018	0.0048	0.0172	0.1610	0.0077
162.5680	198.3460	77.6300	0.0050	0.0000	0.0028	0.0025	0.0084	0.0179	0.1680	0.0079
197.0760	206.8960	192.0550	0.0029	0.0000	0.0017	0.0017	0.0050	0.0110	0.0970	0.0056
199.2280	209.5120	192.0910	0.0024	0.0000	0.0013	0.0014	0.0040	0.0102	0.0890	0.0050
198.3830	215.2030	193.1040	0.0021	0.0000	0.0011	0.0014	0.0034	0.0126	0.1110	0.0064
202.2660	211.6040	197.0790	0.0018	0.0000	0.0009	0.0011	0.0028	0.0095	0.0850	0.0047
203.1840	211.5260	196.1600	0.0018	0.0000	0.0009	0.0011	0.0028	0.0096	0.0850	0.0047

Table 1b. Parkinson's Dataset

Shimmer: APQ5	MDVP: APQ	Shimmer: DDA	NHR	HNR	RPDE	DFA	spread1	spread2	D2	PPE	status
0.0225	0.0378	0.0520	0.0289	22.0660	0.5227	0.7379	-5.5718	0.2369	2.8464	0.2195	1
0.0117	0.0187	0.0267	0.0110	25.9080	0.4186	0.7209	-6.1836	0.2263	2.5897	0.1474	1
0.0114	0.0183	0.0265	0.0133	25.1190	0.3588	0.7267	-6.2717	0.1961	2.3142	0.1630	1

0.0101	0.0166	0.0231	0.0068	25.9700	0.4705	0.6763	-7.1209	0.2798	2.2417	0.1085	1
0.0106	0.0180	0.0238	0.0117	25.6780	0.4278	0.7238	-6.6357	0.2099	1.9580	0.1352	1
0.0068	0.0080	0.0169	0.0034	26.7750	0.4222	0.7414	-7.3483	0.1776	1.7439	0.0856	0
0.0064	0.0076	0.0151	0.0017	30.9400	0.4324	0.7421	-7.6826	0.1733	2.1031	0.0685	0
0.0083	0.0095	0.0192	0.0012	30.7750	0.4659	0.7387	-7.0679	0.1752	1.5123	0.0963	0
0.0061	0.0072	0.0141	0.0007	32.6840	0.3685	0.7421	-7.6957	0.1785	1.5446	0.0561	0
0.0061	0.0073	0.0140	0.0007	33.0470	0.3401	0.7419	-7.9650	0.1635	1.4233	0.0445	0

Table 2. Performance metrics for Parkinson's Disease analysis using ML and DL

Model/Algorithm	**Accuracy**	**Precision**	**Recall / Sensitivity**	**Specificity**	**F1-Score**
Linear Regression	86.56	84.21	87.42	85.85	85.52
Random Tree	88.23	86.21	89.25	87.96	87.55
REP Tree	91.24	90.77	92.65	90.41	91.42
Random Forest	93.56	92.88	94.82	91.74	93.21
MLP	94.42	93.17	95.56	92.85	94.21
LSTM	95.85	94.14	95.96	93.56	94.52
CNNBiGRU-DGR	98.15	97.18	99.22	96.41	98.29
TDL-PSO	99.24	98.41	99.45	97.87	99.29

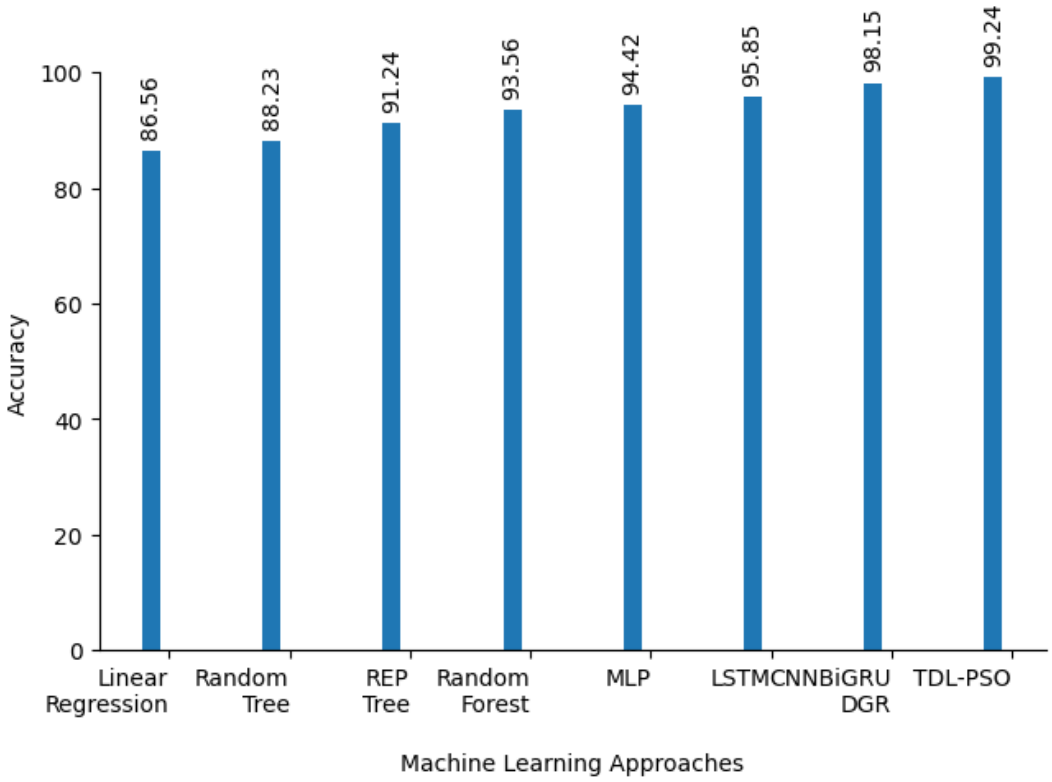

Figure 1. Accuracy of Parkinson's Disease analysis using ML and DL

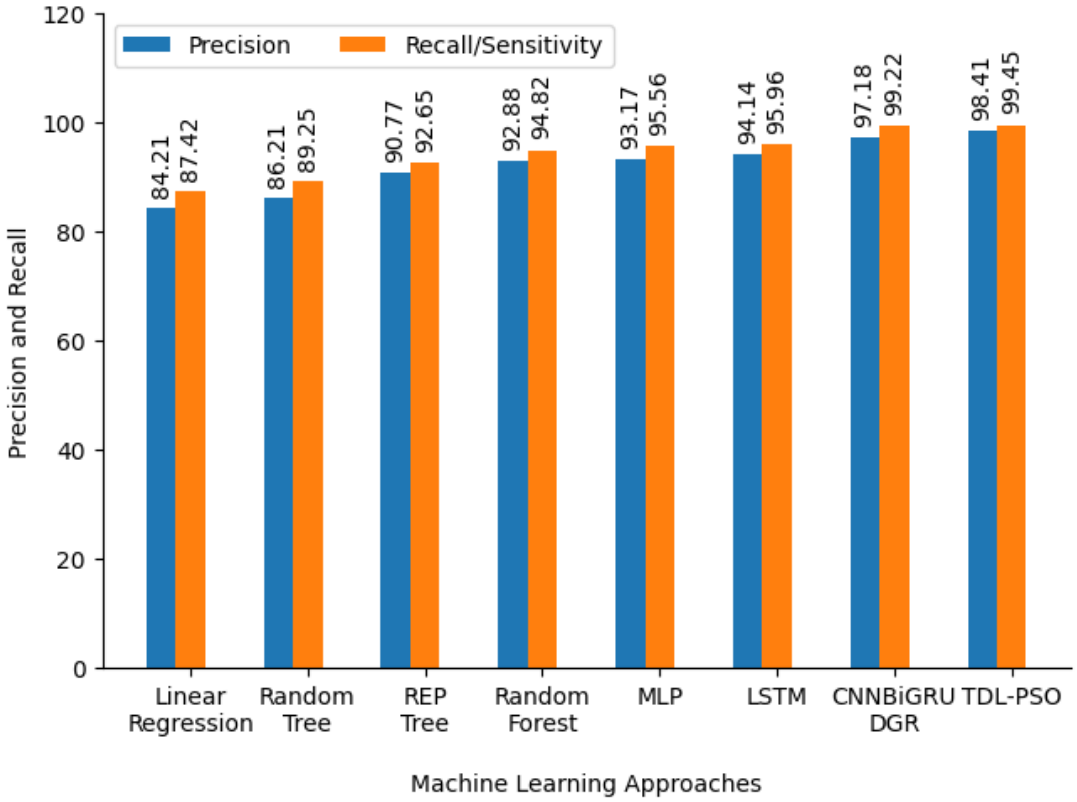

Figure 2. Precision and Recall of Parkinson's Disease analysis using ML and DL

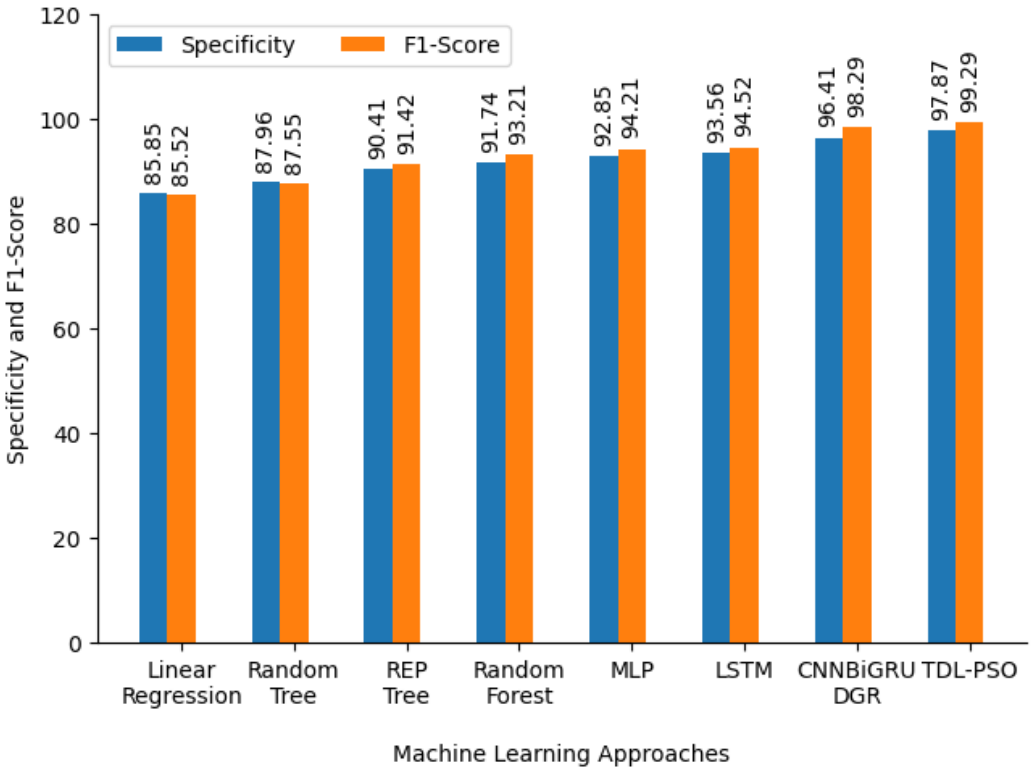

Figure 3. Specificity and F1-Score of Parkinson's Disease analysis using ML and DL

4. Results and Discussions

The results of the study demonstrate the efficacy of advanced machine learning (ML) and deep learning (DL) models, including the proposed Transformer Deep Learning framework optimized with Particle Swarm Optimization (TDL-PSO), in accurately detecting Parkinson's Disease. The analysis was conducted using a publicly available dataset from Kaggle, featuring 24 attributes related to biomedical voice measurements.

The analysis involves evaluating machine learning (ML) and deep learning (DL) models, including the novel Transformer Deep Learning optimized with Particle Swarm Optimization (TDL-PSO). The dataset comprises biomedical voice measurements to identify Parkinson's Disease (PD). The performance metrics reported include **Accuracy**, **Precision**, **Recall/Sensitivity**, **Specificity**, and **F1-Score**.

Accuracy (Figure 1): TDL-PSO achieves the highest accuracy of **99.24%**, surpassing traditional ML models such as Linear Regression (**86.56%**) and advanced DL models like CNNBiGRU-DGR (**98.15%**). This improvement highlights the synergy of Transformers for feature extraction and PSO for hyperparameter optimization, enabling the model to generalize better to unseen data.

Precision and Recall (Figure 2): TDL-PSO demonstrates outstanding precision (**98.41%**) and recall (**99.45%**), ensuring reliable detection of PD cases with minimal false positives and negatives. Comparatively, Random Forest and Multilayer Perceptron (MLP) achieve lower precision (**92.88%** and **93.17%**) and recall (**94.82%** and **95.56%**), indicating the limitations of traditional ensemble and neural network models in handling complex patterns in the dataset.

Specificity and F1-Score (Figure 3): TDL-PSO's specificity (**97.87%**) and F1-Score (**99.29%**) outperform all other models, emphasizing its balanced performance across true positives and true negatives. CNNBiGRU-DGR, while competitive, falls slightly short with an F1-Score of **98.29%**, indicating the added value of PSO in optimizing transformer hyperparameters.

TDL-PSO as a Superior Framework: The integration of PSO ensures optimal parameter selection, such as learning rates and attention head configurations, enhancing model convergence and accuracy. Transformers' attention mechanism effectively extracts critical temporal and spatial features from voice data, contributing to the high recall and precision.

Traditional ML vs. DL Models: Models like Linear Regression and REP Tree show acceptable performance but lack the capability to capture nonlinear relationships and intricate data patterns inherent in PD datasets. Advanced DL models like LSTM and CNNBiGRU-DGR perform significantly better due to their ability to handle sequential and multimodal data.

Importance of Optimization: PSO reduces overfitting and accelerates convergence by fine-tuning parameters. This advantage is evident in the performance gap between TDL-PSO and other deep learning models.

Medical Diagnosis: The TDL-PSO framework offers a robust tool for early and accurate PD detection, potentially reducing misdiagnoses and enabling timely intervention. This hybrid approach can be extended to other medical datasets and tasks requiring feature-rich, multimodal data analysis.

5. Conclusion

This research highlights the efficacy of combining Transformer-based deep learning models with Particle Swarm Optimization (PSO) for detecting Parkinson's Disease at an early stage,

surpassing the performance of conventional machine learning and other deep learning approaches. The TDL-PSO framework effectively captures intricate patterns within multimodal datasets while optimizing hyperparameters through evolutionary techniques, resulting in significant improvements in metrics such as accuracy (99.24%), precision (98.41%), recall (99.45%), and specificity (97.87%). These findings emphasize the potential of hybrid deep learning frameworks in advancing medical diagnostics, particularly for complex conditions like Parkinson's Disease that require robust and adaptable analytical solutions. Furthermore, the incorporation of advanced features, including self-attention mechanisms and adaptive dropout, has enhanced the framework's ability to generalize across datasets and provide interpretable results.

6. Further Studies

Future investigations can focus on broadening the scope and scalability of the TDL-PSO framework. For instance, integrating diverse datasets that include voice recordings, neuroimaging data, and wearable sensor readings can offer a more comprehensive understanding of Parkinson's Disease, leading to improved diagnostic precision. Additionally, the adoption of more advanced optimization methods, such as quantum-behavioral PSO or hybrid metaheuristic algorithms, could refine the efficiency of hyperparameter tuning and accelerate convergence. Federated learning architectures could also be explored to facilitate collaborative model training across institutions, addressing privacy concerns and ensuring wider applicability across heterogeneous patient populations. Lastly, the framework's deployment in real-time clinical environments should be evaluated, focusing on computational efficiency and its practical potential for aiding early diagnosis and treatment planning in Parkinson's Disease care.

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