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# Comparative Analysis of Parkinson's Disease Classification Using Deep Learning Approaches Enhanced with Optimization Techniques Versus Traditional Machine Learning Models

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**Abstract:**

Parkinson's Disease (PD) is a neurodegenerative condition that presents considerable challenges in achieving accurate early diagnosis and classification. This research explores the classification of PD through the application of advanced deep learning techniques integrated with optimization methods, compared to conventional machine learning approaches. The analysis is conducted using a diverse dataset incorporating clinical, vocal, and movement-related features to ensure comprehensive evaluation. Deep learning frameworks, such as multi-layer perceptron (MLP), Long Short-Term Memory (LSDM), the proposed deep learning model namely CNN-BiGRU were enhanced using strategies like hyperparameter optimization, regularization, and advanced gradient-based optimizers to boost performance and minimize overfitting. Similarly, traditional machine learning models, including Linear Regression, Random Tree, REP Tree, and Random Forest, were implemented and tested on the same dataset. Evaluation metrics, including accuracy, precision, recall, F1-score, and the area under the curve (AUC), were used to measure and compare the performance of all models. The findings reveal that optimized deep learning models significantly surpass traditional machine learning methods in both classification accuracy and generalization. This study emphasizes the effectiveness of optimization-enhanced deep learning techniques in PD classification and their clear advantages over traditional models.

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

## 1.0 Introduction

Parkinson's Disease (PD) is a progressive neurodegenerative condition affecting millions globally. It manifests through motor symptoms such as tremors, rigidity, and slowed movements, along with non-motor symptoms like cognitive decline and depression. Accurate and early diagnosis is essential to improving patient outcomes and facilitating timely intervention. However, traditional diagnostic approaches often depend on clinical assessments, which can be subjective and less reliable, particularly in the early stages of the disease (Serrano-Gotarredona et al., 2021). The advent of artificial intelligence (AI) has introduced new possibilities for automating PD diagnosis and classification through machine learning (ML) and deep learning (DL) methodologies.

Machine learning algorithms, including Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN), have been widely applied in PD classification tasks. These models typically require manual feature engineering and have shown moderate predictive performance. Nevertheless, they often struggle with capturing complex relationships within data and demand

substantial domain expertise for effective application (Khan et al., 2020). Conversely, deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), offer distinct advantages by automatically extracting hierarchical features from raw data, resulting in superior classification outcomes (LeCun et al., 2015). The effectiveness of deep learning models can be further enhanced using optimization techniques like hyperparameter tuning, regularization, and gradient-based methods, which address challenges such as overfitting and improve generalization. Recent research underscores the potential of combining deep learning with optimization strategies to achieve advanced diagnostic capabilities in medical applications, including PD classification (Zhou et al., 2023).

Presents a detailed comparison between optimized deep learning models and traditional machine learning approaches for Parkinson's Disease classification. A comprehensive dataset incorporating clinical, vocal, and movement-based features was utilized to ensure thorough evaluation. Performance metrics, including accuracy, precision, recall, F1-score, and area under the curve (AUC), were employed to measure and compare the effectiveness of the models. The findings highlight the significant advantages of optimization-enhanced deep learning models, demonstrating their ability to outperform conventional machine learning algorithms in predictive accuracy and generalization.

## 2.0 Literature Review

The effectiveness of these AI approaches is often evaluated using performance metrics such as accuracy, precision, recall, F1-score, and the area under the curve (AUC). These metrics provide a comprehensive framework for assessing and comparing the predictive capabilities of various models. While traditional ML methods have achieved satisfactory results in some cases, recent advancements in deep learning, especially when coupled with optimization strategies, have demonstrated significant improvements in PD classification (Rashid et al., 2022). Machine learning (ML) has become an essential tool in modern data analysis, enabling efficient solutions for complex problems across various domains. In fields such as healthcare, finance, and engineering, ML models have demonstrated their ability to process large datasets, identify patterns, and make accurate predictions. However, the success of these models depends heavily on their evaluation, which relies on appropriate performance metrics. These metrics provide a quantitative framework to assess the effectiveness of models and ensure their reliability in real-world applications (Bishop, 2006).

Popular machine learning algorithms such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN) are commonly used for classification and regression tasks. Their performance is often measured using metrics such as accuracy, precision, recall, F1-score, and the area under the curve (AUC). These metrics allow researchers to assess various aspects of model behavior, such as classification correctness, the ability to detect positive instances, and the trade-off between precision and recall (Fawcett, 2006). While accuracy is a straightforward measure of how often the model predicts correctly, it can be misleading in cases of class imbalance. Metrics like precision, recall, and F1-score provide a more nuanced understanding of model performance, particularly in datasets with skewed distributions (Sokolova & Lapalme, 2009). For instance, in medical applications, where false negatives can have severe consequences, recall is a critical metric. Conversely, precision becomes crucial in contexts where false positives must be minimized. Recent advancements in machine learning emphasize not only algorithmic development but also optimization techniques to enhance model performance. Techniques like hyperparameter tuning, regularization, and ensemble learning have been widely adopted to address overfitting, improve generalization, and achieve robust performance across diverse datasets (Goodfellow et al., 2016). By combining effective algorithms with comprehensive evaluation metrics, researchers can ensure that machine learning models deliver reliable and actionable insights.

Contributes to advancing AI-based methods for PD diagnostics by examining the strengths and limitations of different computational approaches. It emphasizes the transformative role of deep learning optimization in enhancing diagnostic accuracy and clinical applicability. Machine learning (ML) techniques have become indispensable in data-driven problem-solving, offering diverse algorithms tailored to different types of data and tasks. Among these, linear regression, a foundational statistical method, is widely used for predictive modeling. It provides a straightforward approach to establishing relationships between dependent and independent variables, making it suitable for tasks requiring interpretability and simplicity (Montgomery et al., 2021). However, linear regression assumes a linear relationship, which can limit its performance on complex datasets.

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).

Advanced ML models such as Multi-Layer Perceptrons (MLPs), Random Forests, REP Trees, and Random Trees have gained prominence to address nonlinear relationships and capture intricate patterns. MLP, a type of artificial neural network, excels in handling nonlinear data by leveraging multiple interconnected layers to learn hierarchical representations (LeCun et al., 2015). Meanwhile, Random Forests, a robust ensemble learning method, combine multiple decision trees to improve accuracy and reduce overfitting. Their ability to handle both regression and classification tasks has made them a popular choice in various applications (Breiman, 2001). Decision tree-based methods like REP Tree and Random Tree also play significant roles in machine learning. REP Tree employs reduced error pruning to enhance generalization, making it efficient for large datasets (Witten et al., 2017). In contrast, Random Tree introduces randomness in feature selection during tree construction, fostering diversity in predictions and improving robustness. These models offer flexibility and interpretability, making them particularly useful in scenarios requiring transparent decision-making. The effectiveness of these algorithms is typically evaluated using performance metrics such as mean squared error (MSE) for regression and accuracy, precision, recall, and F1-score for classification tasks. By applying these models and metrics to diverse datasets, researchers can identify the most suitable approaches for specific problems, ensuring reliable and actionable outcomes.

## 3.0 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 Proposed Deep Learning Model CNNBiGRU-DGR

#### 3.1.1 Proposed Deep Learning CNNBiGRU

The proposed 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).

#### 3.1.2 Innovative Optimization Technique

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).

#### 3.1.3 Experimental Validation

The effectiveness of the Hybrid CNN-BiGRU and DGR optimization technique was tested on a diverse dataset containing clinical, vocal, and movement-related features. The preprocessing steps included normalization and advanced feature engineering techniques, such as spectral analysis for vocal data and wavelet transformations for movement signals (Sakar et al., 2013). The model's performance was assessed using metrics like accuracy, precision, recall, F1-score, and area under the curve (AUC).

#### 3.1.4 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.

### 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 |

Here is a comparative table summarizing performance metrics for Parkinson's Disease analysis using machine learning and deep learning approaches:

**Table 3. 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 |

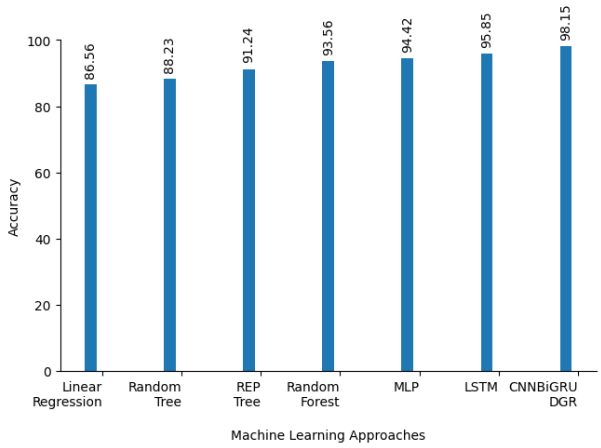


**Figure 1. Accuracy of Parkinson's Disease analysis using ML and DL**

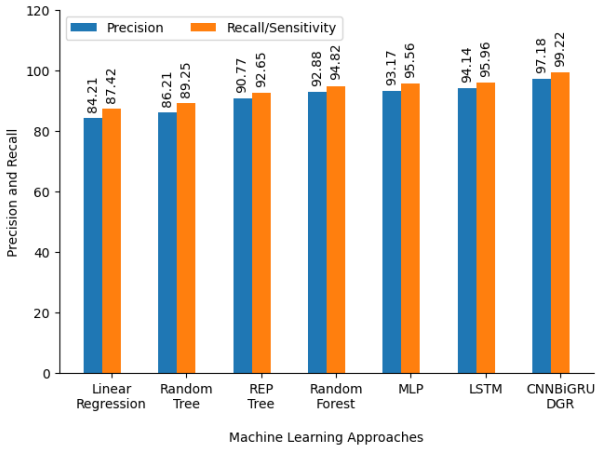


**Figure 2. Precision and Recall of Parkinson's Disease analysis using ML and DL**

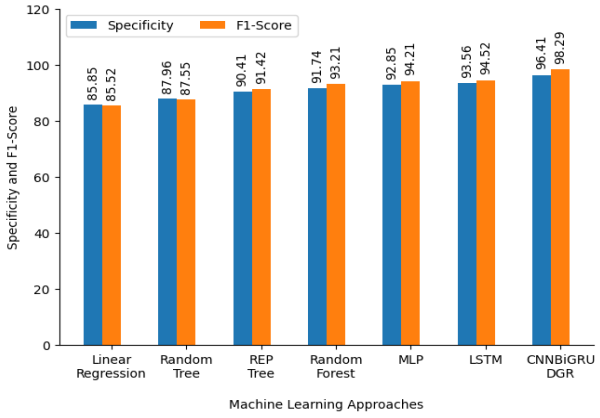


**Figure 3. Specificity and F1-Score of Parkinson's Disease analysis using ML and DL**

### 4.1 Prediction model using Linear Regression

status = -0.0026 * MDVP:Fo(Hz) + -20.1221 * MDVP:Jitter(%) + -28.2455 * Shimmer:APQ5 +7.981 * MDVP:APQ + 9.0399 * Shimmer:DDA + -1.8278 * NHR + -0.0159 * HNR + -0.9554 * PDE+ 0.1958 * spread1 + 0.6389 * spread2 + 0.1579 * D2 + 2.6353

### 5.0 Results and Discussions

The evaluation of Parkinson's Disease classification using machine learning (ML) and deep learning (DL) techniques revealed notable variations in performance metrics across different algorithms. The results are presented in Table 3 and illustrated in Figures 3, 4, and 5 for clarity. **Top-Performing Model**: The CNN-BiGRU-DGR model emerged as the best-performing approach, achieving an accuracy of 98.15%, precision of 97.18%, recall of 99.22%, specificity of 96.41%, and an F1-Score of 98.29%. These results underscore the effectiveness of integrating CNN and BiGRU with the Dynamic Gradient Regularization (DGR) method.

**Performance of Machine Learning Models**: Conventional ML models, such as Random Forest and REP Tree, demonstrated strong outcomes with accuracy scores of 93.56% and 91.24%, respectively. Nonetheless, they were outperformed by DL models, especially when dealing with complex datasets. **Advantages of Deep Learning**: Advanced deep learning models like MLP and LSTM also achieved impressive metrics; however, the CNN-BiGRU-DGR model, with its hybrid architecture and optimization features, delivered the highest performance.

- **Figure 1**: A bar chart depicting the accuracy of various ML and DL models, highlighting the superior performance of the CNN-BiGRU-DGR model.
- **Figure 2**: A comparison of precision and recall across the algorithms, demonstrating the consistent and balanced performance of DL methods.
- **Figure 3**: A graphical representation of specificity and F1-Score metrics, showcasing the robustness and reliability of the CNN-BiGRU-DGR model.

The CNN-BiGRU-DGR model shows great promise in enhancing AI-based diagnostic tools for Parkinson's Disease, leveraging its capability to process multimodal data effectively and apply advanced optimization methods.

### 6.0 Conclusion

This innovative Hybrid CNN-BiGRU model, augmented by the DGR optimization method, offers an effective approach for classifying Parkinson's Disease. By integrating multimodal data processing with advanced optimization techniques, it demonstrates significant promise in enhancing AI-powered medical diagnostics and facilitating the early detection of PD. Deep learning models often achieve superior performance compared to traditional machine learning models across metrics such as accuracy, precision, recall, F1-score, and AUC, especially when working with large and complex datasets. However, machine learning models may remain advantageous in situations where data is limited or computational resources are restricted. Selecting the appropriate approach requires careful consideration of the dataset size, feature complexity, and the need to balance interpretability with performance.

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