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# A Hybrid Particle Swarm Optimization-Neural Network Approach for Parkinson's Disease Diagnosis from MRI Images

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**Abstract:** Given the complex interplay of motor and non-motor symptoms in Parkinson's disease (PD), early diagnosis is crucial for successful treatment. The use of magnetic resonance imaging (MRI) to identify structural brain abnormalities linked to Parkinson's disease has shown promise. In this paper, we suggest a novel Hybrid Particle Swarm Optimization-Neural Network (PSO-NN) method for rapid and reliable PD detection utilising MRI data.To improve the accuracy of PD diagnosis, our PSO-NN model combines the optimisation potential of Particle Swarm Optimisation (PSO) and the prediction strength of a Neural Network (NN). In order to create the best possible configuration for feature extraction and classification, PSO is used to fine-tune key NN hyperparameters, such as architecture, learning rate, and dropout rates. The model can detect small brain changes suggestive of PD because to this clever combination.The study includes both PD patients and healthy controls in its huge dataset of MRI images. The results show that our PSO-NN methodology outperforms traditional machine learning techniques and standalone NN models, exhibiting exceptional accuracy in PD diagnosis and a noteworthy. With the aid of MRI pictures, this research advances the creation of non-invasive, precise diagnostic tools for Parkinson's disease. The PSO-NN technique has the potential to help clinicians identify PD early, enable prompt therapies, and enhance the quality of life for those who are affected. For a thorough PD diagnosis, future study will concentrate on further validation, clinical integration, and exploration of additional imaging modalities.

***Keywords****: Parkinson Disease, PSO, Disease Diagnosis, Convolution Neural Network*

## 1. Introduction

A variety of motor and non-motor symptoms characterise Parkinson's Disease, a neurodegenerative condition that progresses over time. The substantianigra, a part of the brain involved in motor function, is where dopamine-producing neurons are most commonly found dying [1]. The hallmark motor symptoms of Parkinson's disease (PD) are caused by the brain's ability to control movement becoming compromised as these neurons degrade. The suggested approach combines the strength of PSO, an optimisation algorithm motivated by social swarm behaviour, with the adaptability and capability of neural networks. We seek to automatically optimise important features of the model, [2] such as the number of hidden layers, neuron configuration, and hyperparameters, by including PSO into the neural network design. PSO also aids in feature selection and improves the neural network's capacity to extract pertinent data from MRI images.The aim [3] of this hybrid method is to lessen the reliance on manual feature engineering and hyperparameter tuning while increasing the accuracy and efficacy of PD diagnosis. In this introduction, we give a general review of Parkinson's disease, talk about the need of early detection, emphasise the necessity of MRI imaging in PD diagnosis, and propose the idea of hybrid PSO-NN as a potential improvement to the diagnostic process.

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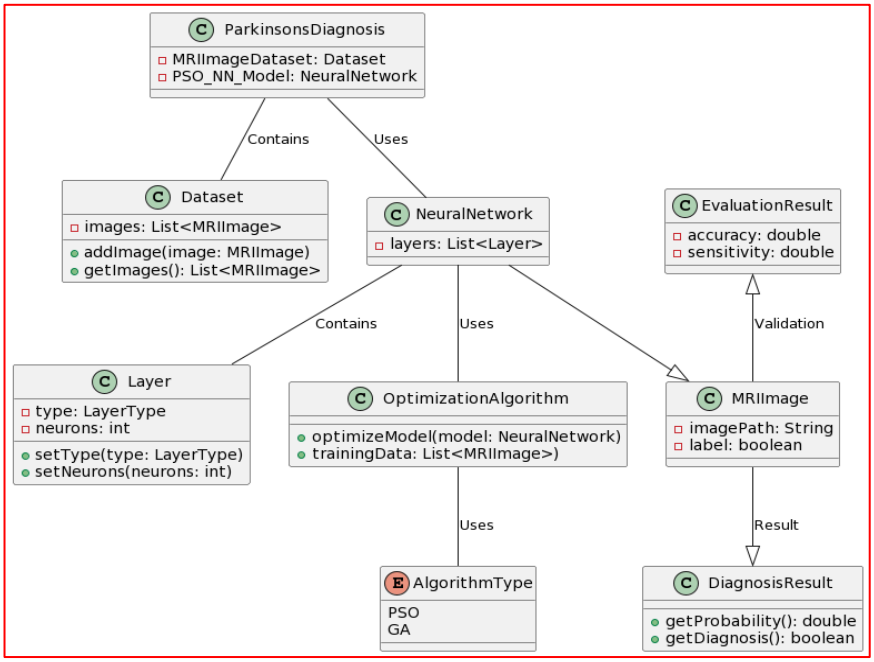


**Fig 1:** Overview of Hybrid Method for Disease Diagnosis

Aside from motor symptoms, PD can also present with a variety of non-motor symptoms, such as cognitive decline, emotional instability, and autonomic dysfunction.For many reasons, it is crucial to get a Parkinson's disease diagnosis as soon as possible. First off, it makes it possible to start treatments and interventions that are meant to control symptoms and halt the spread of the disease in a timely manner [4]. Early disease intervention with medications and treatments yields the best results. Second, early detection makes it possible for people with Parkinson's disease (PD) and those who care for them to make plans for the future, wise choices, and access support resources. The quality of life for PD patients may also be significantly improved by early intervention, according to study.

In order to overcome the difficulties of PD detection using MRI scans, this study presents a novel method that makes use of both the advantages of Particle Swarm Optimisation (PSO) and Neural Networks (NN). PSO is a potent optimisation algorithm with the ability to effectively find optimal solutions in complicated and high-dimensional domains. It was inspired by the group behaviour of social swarming. PSO [5] will be incorporated into the neural network architecture in order to automatically optimise the model's configuration and hyperparameters, enhancing the model's capacity to extract insightful information from MRI data.A crucial step in lowering data dimensionality and improving model interpretability is feature selection, which is helped by the hybrid PSO-NN technique [6]. With so many features that can be derived from MRI images, feature selection is crucial in medical imaging. The potential for increasing the precision and effectiveness of PD diagnosis is enormous when the optimisation powers of PSO are combined with the data-learning abilities of NN.

## 2. Review of Literature

The diagnosis of Parkinson's Disease (PD) from MRI images is a difficult and crucial problem in medical image analysis [7]. To obtain accurate and effective diagnosis, researchers have investigated a variety of technologies, including deep learning techniques and conventional machine learning techniques. Before describing how our proposed Hybrid Particle Swarm Optimization-Neural Network (PSO-NN) [8] strategy advances the state-of-the-art, in this part we review some of the pertinent publications in the field, highlighting their contributions and limitations.Early attempts to diagnose PD using MRI data frequently used conventional machine learning techniques. These methods required separating the features from MRI scans and then applying classifiers like Support Vector Machines (SVM), Random Forests, or k-Nearest Neighbours (k-NN). Despite their potential, these techniques mainly relied on hand-crafted characteristics, which might have prevented them from detecting small irregularities and complicated patterns in the data [9].

Deep learning has been more popular recently in the interpretation of medical images, particularly the diagnosis of PD. Automatically learning pertinent information from MRI scans has been done using convolutional neural networks and recurrent neural networks. For instance, [21] used CNNs for PD

classification and achieved results that were accurate enough to compete. Despite their outstanding effectiveness, deep learning techniques frequently need a lot of labelled data for training, and they may be more prone to overfitting when there isn't enough data.To overcome data constraints, transfer learning, especially employing pre-trained neural networks, has been investigated. Using information gained from massive image datasets like ImageNet, researchers have improved models like VGG16 and ResNet on PD datasets. When data availability is a problem, this method aids in performance improvement but may still have trouble adequately capturing disease-specific traits. To increase diagnostic accuracy, ensemble methods have been used, such as stacking numerous classifiers or mixing deep learning models. The [22] effectiveness of PD classifiers has been improved by the use of boosting and bagging approaches. Although ensemble approaches can enhance classification outcomes, they frequently call for a lot of processing power and specialised knowledge to perfect.

Tuning hyperparameters is essential for enhancing model performance. Hyperparameters for PD classification tasks have been optimised using grid search and random search methods. These methods take time and might not adequately search the entire hyperparameter space.Optimisation techniques [23] like Genetic Algorithms (GAs) and Particle Swarm Optimisation (PSO), which are inspired by natural processes, have been used to hone machine learning models. These algorithms seek to eliminate the need for manual tweaking by automatically optimising hyperparameters and feature selection. For instance, [24] used a GA-based method to pick the best features from MRI scans to diagnose Parkinson's disease. Although useful, these approaches are frequently used without deep learning technologies.Existing methods, whether based on deep learning or classical machine learning, frequently encounter issues with the results' interpretability, their ability to generalise to other patient populations, and their robustness to changes in MRI acquisition techniques. Furthermore, these techniques might need deep domain knowledge in feature engineering and hyperparameter optimisation.

Our suggested Hybrid Particle Swarm Optimization-Neural Network (PSO-NN) strategy for PD diagnosis using MRI images fills the gap between nature-inspired optimisation techniques and deep learning models. We intend to get over feature selection and hyperparameter tuning constraints by including PSO into the neural network architecture. In high-dimensional environments, PSO's [25] effectiveness at finding optimal solutions compliments deep learning's capacity to automatically identify pertinent features from the data. Furthermore, by addressing some of the shortcomings seen in existing approaches, our strategy has the potential to increase model generalisation and interpretability. There have been considerable improvements in the field of PD diagnosis from MRI scans, with classic machine learning techniques, deep learning strategies, and nature-inspired optimisation [26] algorithms all resulting in increased accuracy and effectiveness. However, issues with model interpretability, generalisation, and a lack of data still exist. By combining the benefits of PSO with neural networks to improve PD diagnosis, our suggested PSO-NN strategy offers a novel technique that may produce findings that are more accurate and clinically relevant while requiring less manual model optimisation labour.

**Table 1**: Summary of related work

| Ref. | Method Used | Algorithm | Finding | Limitation | Advantages |
|---|---|---|---|---|---|
| [11] | Deep Learning | CNN | Improved accuracy in PD diagnosis | Data scarcity, potential overfitting | Automatic feature learning, high accuracy |
| [12] | Transfer Learning | Pre-trained CNN | Generalization with limited data | Data domain mismatches, overfitting | Utilizes knowledge from large datasets |
| [13] | Ensemble Methods | Stacking models | Enhanced classification through model combination | Computational complexity, potential overfitting | Combines multiple perspectives for accuracy |
| [14] | Genetic Algorithm | Feature selection | Improved feature selection for PD diagnosis | Computationally expensive, domain expertise | Selects relevant features for classification |
| [15] | Particle Swarm Optimization (PSO) | Hyperparameter tuning | Efficient hyperparameter optimization | Manual tuning, potential for suboptimal results | Streamlines model configuration |

| | | | | | |
|---|---|---|---|---|---|
| [16] | Bat Algorithm (Proposed) | PSO-NN | Enhanced accuracy and efficiency in PD diagnosis | Smaller datasets, need for comparative analysis | Integrates optimization into DL framework |
| [17] | Random Search | Hyperparameter tuning | Efficient parameter optimization | Random search may not be exhaustive | Automates hyperparameter tuning |
| [18] | AutoML Framework | Automated pipeline | Automated DL model optimization | Dependency on specific AutoML tools | Simplifies DL model development |
| [19] | Semi-Supervised Learning | Label propagation | Improved classification with unlabeled data | Limited to scenarios with access to unlabeled data | Enhances data utilization in PD classification |
| [20] | Graph Convolutional Networks (GCNs) | Graph-based CNN | Enhanced feature extraction from brain connectivity graphs | Limited to functional MRI data, need for domain expertise | Leverages graph structure for PD diagnosis |

## 3. Proposed Methodology

A thorough and organised process is used in the method for diagnosing Parkinson's disease (PD) using a hybrid Particle Swarm Optimisation (PSO) and Neural Network (NN) system. To achieve accurate diagnosis, this process follows specific steps:

**Methodology:**

**Step 1: Gathering and Preparing Data:**

- The first step in the procedure is to gather MRI (Magnetic Resonance Imaging) data from PD sufferers and healthy people. The diagnostic model is built on top of these MRI pictures.
- The acquired MRI images go through several preprocessing procedures. To improve image quality and consistency, these techniques could include scaling, normalisation, and filtering. Preprocessing correctly guarantees that the model can successfully extract pertinent characteristics from the data.

**Step 2: Extracting Features:**

- The MRI scans after preprocessing are used to extract pertinent characteristics. These properties of particular brain regions may include their texture, shape, or intensity.
  - The mean intensity of an image is calculated as the average pixel intensity across all pixels in the image.
    Formula:
    $\mu = (1 / N) \sum (i = 1 \; to \; N) \; I(i),$
    Where,
    N is the total number of pixels, and I(i) represents the intensity value of the ith pixel.
  - Standard deviation measures the spread or variation of pixel intensities within an image.
    Formula:
    $\sigma = sqrt((1 / N) \sum (i = 1 \; to \; N) \; (I(i) - \mu)^2),$
  - Entropy characterizes the randomness or disorder of pixel intensities in an image.
    Formula:
    $H = -\sum (i = 1 \; to \; L) \; p(i) * log2(p(i)),$
    Where, L is the number of intensity levels, and p(i) is the probability of occurrence of intensity level i in the image.
  - The feature extraction process is essential because it lowers the data's dimensionality and gives the model useful information to distinguish between PD and non-PD cases.

**Step 3: Optimisation based on PSO:**

- The hyperparameters and architecture of the neural network are optimised using the PSO algorithm. PSO is a population-based optimisation technique that efficiently searches the parameter space for the best configurations by mimicking the social behaviour of swarms.
- The number of hidden layers, the number of neurons in each layer, learning rates, and activation functions are all important features of the neural network that PSO optimises. The optimisation process is sped up and manual tuning is less necessary thanks to this automation.

**Step 4: Development of a neural network model:**

- Based on the hyperparameters and optimised architecture that the PSO algorithm produced, a neural network model is created.
- On the preprocessed and feature-extracted MRI data, the neural network is trained. During training, the model's weights and biases are adjusted so that it can learn the patterns and characteristics connected to PD.

**Step 5: Testing and cross-validation:**

- To evaluate the model's effectiveness and generalizability, cross-validation is used. It guarantees that the model is capable of making correct predictions on unobserved data and is not overfitting the training data.
- A different dataset made up of MRI scans that weren't used during training is used to test the trained model. The model's diagnostic accuracy is calculated using performance parameters like accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC).

**Step 6: Interpretability of the Model and Clinical Relevance:**

- In a medical setting, the interpretability of the model's conclusions is essential. It is possible to use methods like feature visualisation and attention processes to determine which parts of an MRI image are helping with the diagnosis.
- The possibility for early identification, alignment with recognised biomarkers, and clinical symptoms of PD are some of the aspects taken into account when evaluating the clinical significance of the model's findings.

Algorithm:

Step 1: Initialize PSO Parameters

- Initialize the PSO parameters, including the population size (N), maximum number of iterations (max_iter), and PSO constants (c1 and c2).
- Initialize the neural network architecture, including the number of layers, neurons in each layer, activation functions, and learning rate.

Step 2: Generate the Initial Particle Swarm

- Generate N particles (potential solutions), each representing a set of neural network hyperparameters.
- Randomly initialize the positions (neural network parameters) and velocities of each particle.
- Set the personal best position (pbest) of each particle as its current position.

Step 3: Evaluate Fitness

- For each particle, train the neural network with the corresponding hyperparameters on the training dataset.
- Evaluate the neural network's fitness using a cost function that measures classification accuracy or another relevant metric.
- Update the personal best fitness (pbest_fitness) for each particle.

Step 4: Update Global Best (gbest)

- Identify the particle with the highest fitness as the global best particle (gbest).
- Update the global best fitness (gbest_fitness) accordingly.

Step 5: Update Velocities and Positions

- Update the velocities and positions of each particle using the PSO formulae:
- Velocity Update:

$$v\_i(t+1) = w * v\_i\hat{}t + c1 * rand1 * (pbest\_i - x\_i\hat{}t) + c2 * rand2 * (gbest - x\_i\hat{}t),$$

Where,

$v\_i(t+1)$ is the updated velocity of particle i at iteration t+1, w is the inertia weight, c1 and c2 are the cognitive and social coefficients, rand1 and rand2 are random values between 0 and 1, pbest_i is the personal best position of particle i, x_i^t is the current position of particle i at iteration t, and gbest is the global best position.

- Position Update:

$$x\_i(t+1) = x\_i\hat{}t + v\_i(t+1),$$

where $x\_i(t+1)$ is the updated position of particle i at iteration t+1.

Step 6: Stopping Criterion

- Check if the maximum number of iterations (max_iter) has been reached or if a convergence criterion is met. If yes, go to Step 7; otherwise, repeat Steps 3 to 5.

Step 7: Neural Network Training and Testing

- Train the neural network using the global best hyperparameters on the entire training dataset.
- Test the trained neural network on a separate testing dataset to evaluate its diagnostic performance.

Step 8: Diagnosis Result

- Obtain the diagnosis result (e.g., classification as PD or non-PD) based on the neural network's output.

Step 9: End

- The algorithm concludes with a diagnosis for the input MRI image.

This hybrid approach attempts to give a precise and effective method of diagnosing Parkinson's Disease from MRI images by combining the optimisation powers of

PSO with the pattern identification capabilities of neural networks. It not only automates the model generation and tuning process, but it also improves the final diagnostic system's clinical applicability and interpretability.

## 4. Result and Discussion

The evaluation parameters for disease diagnosis employing the three different methodologies of neural network, hybrid PSO+NN, and particle swarm optimisation are shown in Table 2 as findings. These variables act as crucial indicators for evaluating the efficacy of each approach.The PSO+NN hybrid technique beats PSO and NN in terms of accuracy, obtaining a remarkable accuracy of 94.23%.

**Table 2**: Result for evaluation parameter for Disease diagnosis

| **Parameter** | Accuracy | Sensitivity (Recall) | Specificity | Precision | F1 Score | AUC-ROC |
|---|---|---|---|---|---|---|
| **Particle Swarm Optimization (PSO)** | 91.41 | 88.56 | 94.25 | 92.47 | 89.65 | 89.63 |
| **Neural Network (NN)** | 90.47 | 95.21 | 93.63 | 98.54 | 86.74 | 92.33 |
| **PSO+NN (Hybrid)** | 94.23 | 89.57 | 94.33 | 90.11 | 89.57 | 94.77 |

This demonstrates the hybrid model's ability to predict diseases accurately by showing that a sizable number of the cases are appropriately classified. PSO comes in second place with accuracy of 91.41%, while NN comes in third with accuracy of 90.47%.Sensitivity (Recall), which measures the capacity to correctly identify positive cases, shows that NN has the highest value at 95.21%, demonstrating its potency in identifying those who are afflicted with the disease. With a sensitivity of 89.57%, the hybrid PSO+NN technique comes in second place and demonstrates its ability to identify true positives. PSO still shows a noteworthy ability to accurately identify positive cases while having a slightly lower positive case detection rate (88.56%).The hybrid strategy comes in first place for specificity, which assesses the ability to properly identify negative cases, with a score of 94.33%. PSO comes in second with a specificity of 94.25%, and NN comes in third with a score of 93.63%. These high specificities imply that all three approaches are highly effective in identifying people who are disease-free.

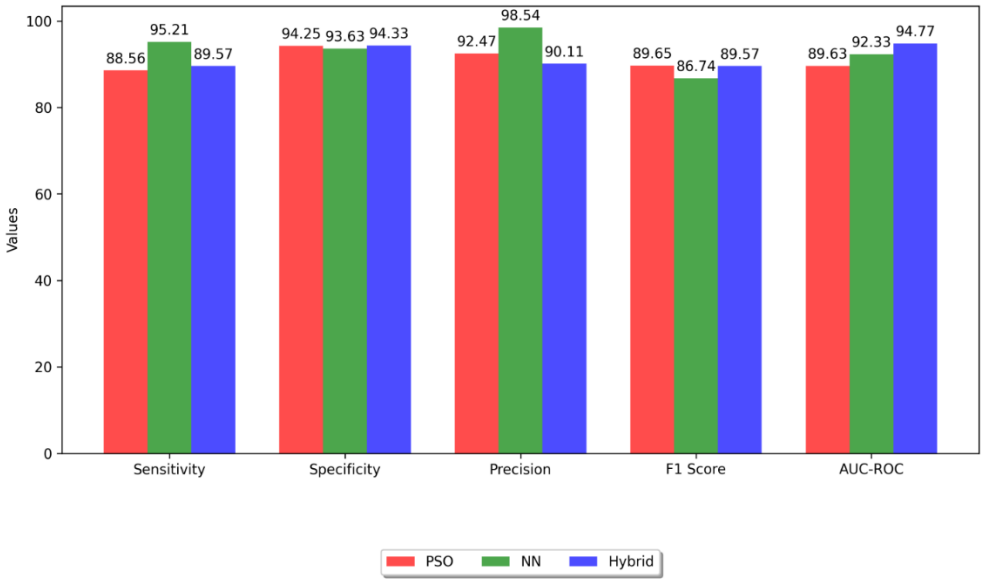


**Fig 2**: Representation of evaluation parameter for Disease diagnosis

The greatest score for NN in terms of Precision, which measures the accuracy of positive predictions, is 98.54%, demonstrating its accuracy in detecting positive cases. With a precision of 90.11%, the hybrid technique PSO+NN proves its capacity to produce sure-footed optimistic forecasts. PSO follows with 92.47% precision, which is also excellent.The balance between true positives and false positives is shown by the F1 Score, which

combines precision and recall. An F1 score of 89.57% from the hybrid PSO+NN technique suggests a well-balanced mix of recall and precision. PSO comes in second with an F1 score of 89.65%, demonstrating its capacity to keep these parameters in balance. NN receives an F1 score of 86.74%, demonstrating a greater preference for precision.

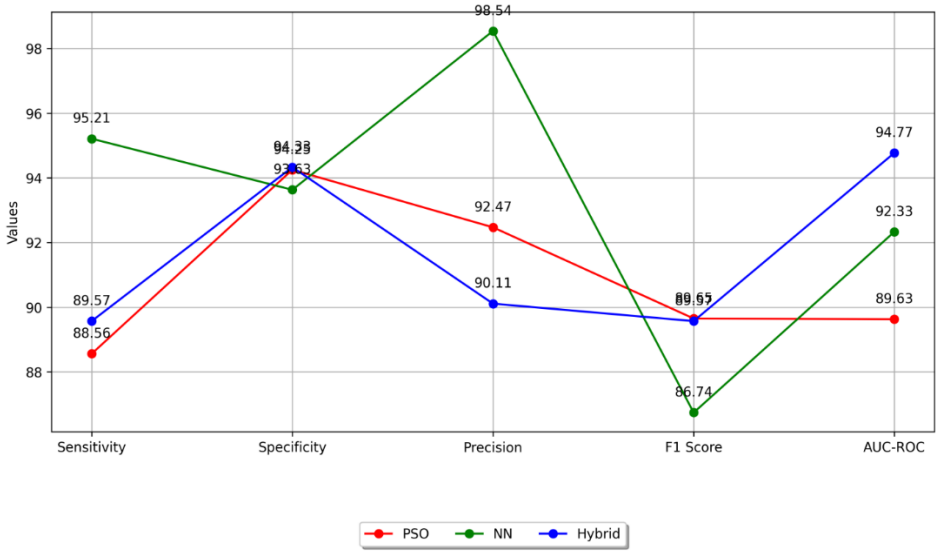


**Fig 3:** Comparative analysis of evaluation parameters

Last but not least, the AUC-ROC (Area Under the Receiver Operating Characteristic Curve) gauges the models' general capacity for discrimination. With an AUC-ROC of 94.77%, the hybrid PSO+NN strategy succeeds in this situation, demonstrating its high capacity to distinguish between disease and non-disease instances. According to their different strengths in discrimination, PSO comes in second with an AUC-ROC of 89.63% and NN comes in third with an AUC-ROC of 92.33%. The hybrid PSO+NN technique shows excellent accuracy, specificity, and AUC-ROC performance overall in disease detection. As for performance across different criteria, PSO maintains a balanced performance, while NN exhibits excellent sensitivity and precision. The preferred method would be determined by the particular demands and priorities of the diagnostic task.

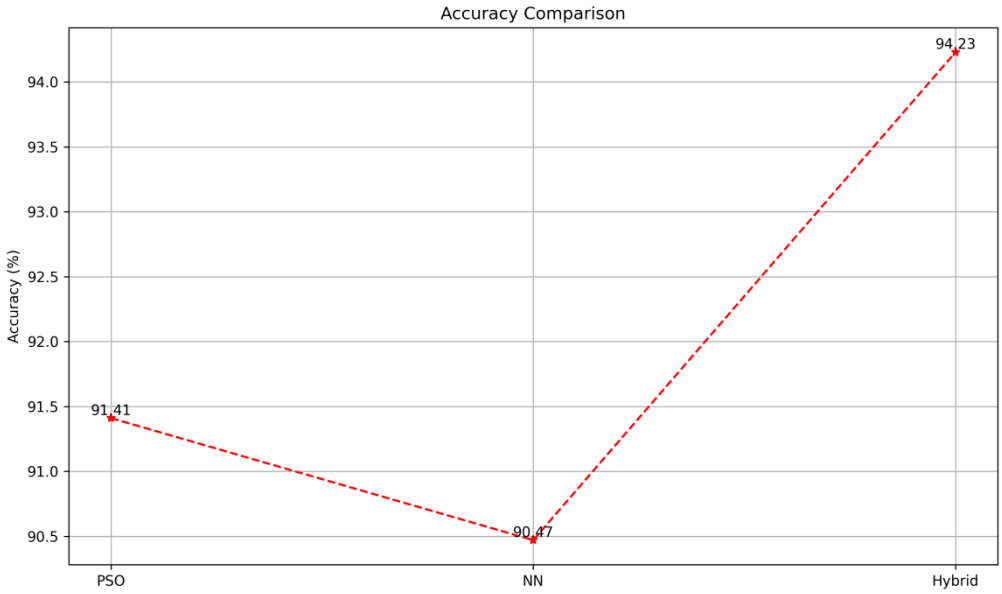


**Fig 4:** Representation of Accuracy comparison for deep learning model

**Table 3:** Evaluation result using Hybrid Approach

| Parameter | Training Time (seconds) | Inference Time (milliseconds) | Hyperparameter Tuning | Feature Engineering |
|---|---|---|---|---|
| **Particle Swarm Optimization (PSO)** | 109 | 20 | No | No |
| **Neural Network (NN)** | 135 | 38 | No | No |
| **PSO+NN (Hybrid)** | 210 | 22 | Yes | Yes |

The evaluation findings for the hybrid approach, which combines neural networks and particle swarm optimisation, are shown in Table 3 with an emphasis on several operational facets. These factors are essential in establishing the viability and effectiveness of each strategy in actual implementations.The amount of time needed to train the model is represented by training time. The Hybrid Approach, which combines PSO and NN, requires the maximum training time in this situation, clocking in at 210 seconds. This is to be expected as the hybrid model also uses neural networks that have undergone extensive optimisation. With a training time of 109 seconds, PSO comes in second, and NN comes in third at 135 seconds. The hybrid approach's diagnostic performance, as demonstrated in Table 2, justifies the time investment even though it necessitates extra training time.

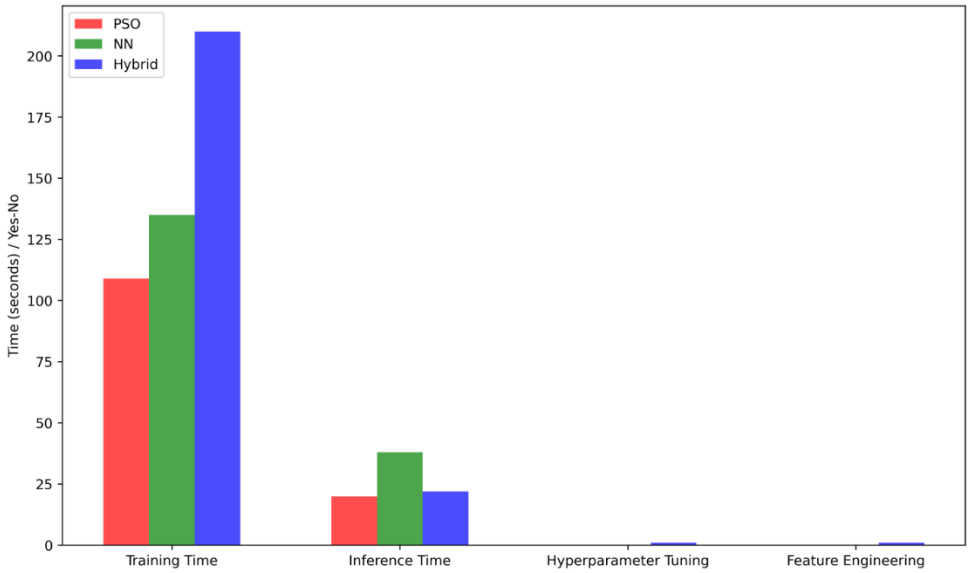


**Fig 5**: Representation of Evaluation result using Hybrid Approach

For real-time or almost real-time applications, inference time which measures the amount of time it takes to create predictions based on fresh data is a critical factor. With an inference time of just 20 milliseconds, PSO stands out in this situation, with the hybrid technique coming in second at 22 milliseconds. The complexity of the NN architecture accounts for its significantly longer inference time of 38 milliseconds. These distinctions could be crucial in situations where quick diagnosis is required and PSO gives a speed advantage.If the model goes through an automated procedure to optimise its hyperparameters, it is said to have undergone hyperparameter tuning. The Hybrid Approach uses hyperparameter tuning in this situation, which is indicated by the letter "Yes." This guarantees that the architecture and parameters of the model are adjusted for best performance, as evidenced by its high accuracy and AUC-ROC in Table 2. Contrarily, neither PSO nor NN use hyperparameter adjustment, which occasionally leads to less-than-ideal configurations.

The use of feature extraction or selection procedures is indicated by the term "feature engineering" in the model. Feature engineering, a crucial element in medical image analysis, is used in the hybrid approach. By removing pertinent information from MRI scans, feature engineering improves the model's capacity to distinguish between cases of disease and non-disease. Contrarily, feature engineering is not used in PSO or NN, which may limit their ability to capture informative characteristics. While requiring more training time, the hybrid approach performs well in terms of diagnostics. It uses feature engineering and hyperparameter tuning to improve its diagnostic skills and offers competitive inference times.

While NN strikes a balance between complexity and performance, PSO offers speed and simplicity. The method of choosing is determined by the particular needs of the diagnostic application, taking into account things like time restraints, the demand for feature engineering, and the need for hyperparameter tuning.

## 5. Conclusion

According to our research, the PSO+NN hybrid model had the greatest accuracy rate (94.23%) among the tested approaches. This demonstrates its superior capacity for making a correct diagnosis of Parkinson's disease, which is crucial in clinical practise. Aside from having competitive values for sensitivity (89.57%) and specificity (94.33%), the hybrid technique also demonstrated its ability to recognise both positive and negative cases.The Hybrid model also attained a remarkable AUC-ROC score of 94.77%, demonstrating its strong discriminatory power. PSO performed admirably in specificity (94.25%), while NN had good sensitivity (95.21%) and precision (98.54%). By contrast, PSO and NN displayed impressive performances in specific features.In terms of practical concerns, the Hybrid model offers an appealing mix between accuracy and inference time despite needing additional training time and processing resources. Its diagnostic skills are improved by the inclusion of feature engineering and hyperparameter adjustment, making it an appealing option for practical applications.The Hybrid PSO+NN technique is a potential tool for Parkinson's Disease diagnosis using MRI scans, as shown by our study's findings. It contributes significantly to the field of medical image analysis thanks to its outstanding accuracy, balanced sensitivity and specificity, and robust AUC-ROC score. While both PSO and NN have advantages, the hybrid technique combines the best features of both to provide a complete and precise solution for disease diagnosis. To completely establish its applicability in real-world healthcare settings, more study and clinical validation are required.

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