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# Application of Deep Neural Network in Diabetes Mellitus Prediction with Parameter Optimization Using Particle Swarm Optimization

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## ABSTRACT

Diabetes Mellitus is recognized as a chronic condition with a rising incidence worldwide and potentially severe long-term complications if not identified and managed promptly. The ability to predict this disease accurately and at an early stage is crucial within the healthcare domain. This research proposes the development of a classification model for Diabetes Mellitus using a Deep Neural Network (DNN), whose predictive capability is further enhanced by tuning its hyperparameters through the Particle Swarm Optimization (PSO) technique. The dataset employed in this study is the Pima Indians Diabetes Dataset, which includes various clinical features such as glucose concentration, blood pressure, body mass index (BMI), and patient age. Prior to model training, the data underwent several preprocessing steps, including normalization, treatment of missing values, and division into training and testing subsets. The DNN model was constructed with multiple hidden layers, while essential parameters—such as learning rate, number of neurons, and batch size—were optimized using PSO to achieve the most effective configuration. Experimental outcomes revealed that the PSO-enhanced DNN outperformed the non-optimized model in terms of classification accuracy. Specifically, without optimization, the Deep Learning model attained 75.00% accuracy, and the Neural Network model achieved 77.86%. After PSO was applied, the accuracy improved to 77.90% and 78.39%, respectively. These findings suggest that the incorporation of PSO contributes positively to the training efficiency and predictive strength of the model in identifying diabetes cases

**Keywords:** *Diabetes Mellitus; Deep Neural Network; Particle Swarm Optimization; Classification*

## 1. INTRODUCTION

Diabetes Mellitus ranks among the most widespread non-communicable diseases globally and remains a leading contributor to morbidity and mortality across numerous countries, including Indonesia. Based on statistics reported by the World Health Organization (WHO), more than 460 million individuals were living with diabetes as of 2021, and this figure is anticipated to rise steadily in the coming years (Keerthana et al., 2025; Subramani, S et al., 2023) The importance of early diagnosis cannot be overstated, as it plays a crucial role in reducing the risk of severe complications, including cardiovascular disease, renal failure, and vision impairment (Singh et al., 2025; K, M., R. M, J et al., 2025).

The advancement of information technology and artificial intelligence (AI) has significantly influenced the healthcare industry, particularly in the domains of disease prediction and classification (Raza et al., 2024). Among the various approaches in machine learning, the Artificial Neural Network (ANN) has emerged as a prominent method capable of modeling intricate relationships between input variables and output targets. Its development into Deep Neural Networks (DNNs)—which incorporate multiple hidden layers—has further enhanced the model's ability to recognize complex patterns by allowing deeper levels of abstraction and more effective feature extraction (Wu, Y et al., 2024).

Despite its advantages, one of the key challenges in implementing DNNs is selecting the most effective set of hyperparameters, such as the number of neurons per layer, learning rate, and batch size. To tackle this issue, this research adopts the Particle Swarm Optimization (PSO) algorithm, which is inspired by the collective behavior of organisms in nature, such as bird flocking or fish schooling. PSO is known for its efficiency in exploring large parameter spaces and identifying optimal combinations for model performance enhancement. The proposed approach is expected to improve both classification accuracy and training effectiveness. Ultimately, this method holds promise in contributing to the advancement of intelligent, accurate, and adaptive decision support systems for medical diagnosis and early disease detection.

## 2. METHODS

This study was conducted using a quantitative experimental approach involving data preprocessing, model development, parameter optimization, and performance evaluation. The stages of the methodology are described as follows:

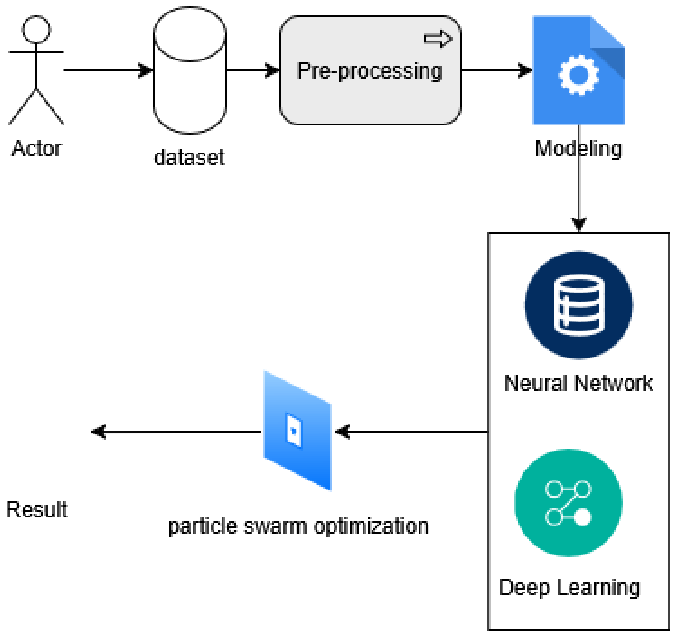


Fig 1. Methods

A. Dataset

This study employed the Pima Indians Diabetes Dataset, which was sourced from the UCI Machine Learning Repository (Chellamani et al., 2025) The dataset comprises 768 instances, each containing eight input attributes such as glucose concentration, blood pressure, insulin level, body mass index (BMI), age, and several other clinical indicators. The output variable is binary, representing whether or not an individual is diagnosed with Diabetes Mellitus.

Tabel 1. Units For Magnetic Properties

| No | Variabel | Description |
|---|---|---|
| 1 | Pregnancies | Number of times pregnant |
| 2 | Glucose magnetic | Plasma glucose concentration a 2 hours in an oral glucose tolerance test |
| 3 | BloodPressure | Diastolic blood pressure (mm Hg) |
| 4 | SkinThickness | Triceps skin fold thickness (mm) |
| 5 | Insulin | 2-Hour serum insulin (mu U/ml) |
| 6 | BMI | Body mass index (weight in kg/(height in m)^2) |
| 7 | DiabetesPedigreeFunction | Diabetes pedigree function |
| 8 | Age | Age (years) |
| 9 | Outcome | Class variable (0 or 1) 268 of 768 are 1, the others are 0 |

The following is an image of the dataset used:

Fig 1. Dataset Pima

| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Pregnancies | Glucose | BloodPres | SkinThickr | Insulin | BMI | DiabetesP | Age | Outcome |
| 2 | 6 | 148 | 72 | 35 | 0 | 33.6 | 0.627 | 50 | yes |
| 3 | 1 | 85 | 66 | 29 | 0 | 26.6 | 0.351 | 31 | no |
| 4 | 8 | 183 | 64 | 0 | 0 | 23.3 | 0.672 | 32 | yes |
| 5 | 1 | 89 | 66 | 23 | 94 | 28.1 | 0.167 | 21 | no |
| 6 | 0 | 137 | 40 | 35 | 168 | 43.1 | 2.288 | 33 | yes |
| 7 | 5 | 116 | 74 | 0 | 0 | 25.6 | 0.201 | 30 | no |
| 8 | 3 | 78 | 50 | 32 | 88 | 31 | 0.248 | 26 | yes |
| 9 | 10 | 115 | 0 | 0 | 0 | 35.3 | 0.134 | 29 | no |
| 10 | 2 | 197 | 70 | 45 | 543 | 30.5 | 0.158 | 53 | yes |
| 11 | 8 | 125 | 96 | 0 | 0 | 0 | 0.232 | 54 | yes |
| 12 | 4 | 110 | 92 | 0 | 0 | 37.6 | 0.191 | 30 | no |
| 13 | 10 | 168 | 74 | 0 | 0 | 38 | 0.537 | 34 | yes |
| 14 | 10 | 139 | 80 | 0 | 0 | 27.1 | 1.441 | 57 | no |
| 15 | 1 | 189 | 60 | 23 | 846 | 30.1 | 0.398 | 59 | yes |
| 16 | 5 | 166 | 72 | 19 | 175 | 25.8 | 0.587 | 51 | yes |
| 17 | 7 | 100 | 0 | 0 | 0 | 30 | 0.484 | 32 | yes |
| 18 | 0 | 118 | 84 | 47 | 230 | 45.8 | 0.551 | 31 | yes |
| 19 | 7 | 107 | 74 | 0 | 0 | 29.6 | 0.254 | 31 | yes |
| 20 | 1 | 103 | 30 | 38 | 83 | 43.3 | 0.183 | 33 | no |

B. Data Preprocessing

Data preprocessing was carried out to improve data quality and model performance. This stage involved: Handling missing values. if any, Feature normalization using Min-Max Scaling to bring all features to a comparable scale, Splitting data into training (80%) and testing (20%) set.

C. Machine Learning

This research adopts two prominent machine learning paradigms, namely the Artificial Neural Network (ANN) and Deep Learning, both of which are grounded in computational models inspired by biological neural systems. ANN is a foundational method in the domain of artificial intelligence that emulates the neurological mechanisms of the human brain, particularly in relation to the transmission and processing of information stimulis (Chatterjee, A., Gerdes, M. W., & Martinez, S. G 2020). Structurally, an ANN consists of a network of interconnected computational elements referred to as neurons, which are systematically arranged into three core architectural layers: an input layer that receives raw data, one or more hidden layers responsible for intermediate processing, and an output layer that delivers the final prediction or classification result (Ahmad, A. A., & Polat, H. 2023; Chauhan, T., Rawat, S., Malik, S., & Singh, P. 2021)

Meanwhile, Deep Learning represents an advanced evolution of the traditional ANN framework. It incorporates a deeper architecture composed of multiple hidden layers, allowing the system to address highly complex problems (Reddy, S. R et al., 2025). Through its hierarchical layer structure, Deep Learning models can automatically extract abstract and high-level features from raw input data. This capability makes it particularly suitable for processing high-dimensional and unstructured data, such as visual images, audio signals, and natural language text. This a formula Deep Learning (Melin, P et al., 2023) :

$$L = - (1/n) * \Sigma [yi * \log(\hat{y}i) + (1 - yi) * \log(1 - \hat{y}i)], \text{ for } i = 1 \text{ to } n \quad (1)$$

Explanation :
L : total loss (average loss over all samples)
n : samples dataset
yi : true label (0-1)
ŷi : predicted probability i (0-1)
log : log base e

It serves to quantify the discrepancy between the predicted probability and the actual class label. A smaller loss value reflects a more accurate and reliable model. Notably, this function imposes greater penalties on incorrect predictions, particularly when the predicted probability significantly deviates from the true class label (Liastuti, et al., 2022)

D. Parameter Optimization: Particle Swarm Optimization (PSO)
Particle Swarm Optimization (PSO) represents a population-based optimization method in which a group of candidate solutions—termed particles—explore the solution space collectively to identify the optimal value of a specified objective function (Ulutas, H., Günay, R. B., & Sahin, M. E. 2024; Abbasi, H et al., 2024) Within this framework, each particle serves as an individual solution agent that iteratively adjusts both its position and velocity. These adjustments are influenced by two key pieces of knowledge: the particle's personal best position discovered during its own search process, and the global best position attained by any member of the swarm throughout the optimization process (Qteat, H., & Awad, M 2021; Fauziah, D. A., Muliawan, A., & Dimyati, M., 2024):

1. pBest : achieved by the particle itself.
2. gBest : ever reached by all particles in the population.

Formula optimization Particle Swarm Optimization (PSO) :

$$vi(t+1) = w * vi(t) + c1 * r1 * (pBesti - xi(t)) + c2 * r2 * (gBest - xi(t))$$
$$xi(t+1) = xi(t) + vi(t+1) \quad (2)$$

Explanation :
- vi(t): represents velocity i and t-th iteration
- xi(t)xi(t): denotes the current position of particle i at iteration t
- ww: influences the trade-off local exploitation
- c1,c2c1,c2: determine the influence of personal and collective experiences
- r1,r2r1,r2: random values ranging between 0 and 1, used to introduce stochastic behavior into the velocity update
- pBestipBesti: discovered by particle i (also known as the personal best)
- gBestgBest: any particle in the entire swarm (global best solution)

E. Evaluation Metrics
Evaluating the performance of prediction models is an important stage in the process of developing machine learning models. In this research, several classification evaluation metrics are used to assess how well the Deep Neural Network (DNN) model predicts Diabetes Mellitus conditions based on input data (Fagbuagun, O et al., 2022; Malik et al., 2024). These metrics not only measure accuracy, but also consider the balance between correct and incorrect predictions, especially in cases with imbalanced datasets (El-Hassani, F. Z et al., 2024).

## 3. RESULTS AND DISCUSSION

Before explaining the results of the research, we need to know the data pre-processing process where the data that has been obtained needs to be processed first before use (Ahuja et al., 2025). Data pre-processing is done using data cleaning and normalising data to facilitate data processing (Sim. H et al., 2025). The results obtained are in the form of easy classification data because it has been labelled with the outcome ‘yes’ for positive diabetes and ‘no’ for negative diabetes. The PSO algorithm was executed with a population size of 10 particles and a maximum of 30 generations. The optimization process successfully identified the optimal combination of hyperparameters, including:

- Number of hidden layers: 3
- Neurons per layer: [32, 64, 32]
- Learning rate: 0.0015
- Batch size: 32
- Epochs: 10

The inertia weight dynamically decreased from 0.9 to 0.4 to ensure a balance between optimization process converged by generation 23 with minimal changes in fitness value, indicating stability in solution quality (Kiran, M et al., 2025). The following is the ROC graph of Neural Network without using PSO and using PSO :

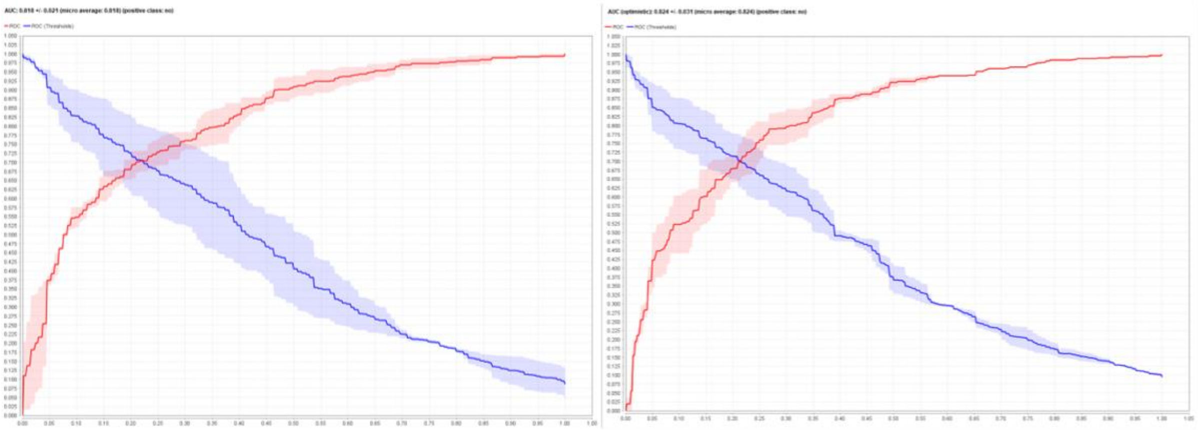

Fig 2. NN Without PSO and With PSO

The initial figure illustrates evaluation the application of Particle Swarm Optimization (PSO), yielding an Area Under the Curve score of 0.818. Conversely, the second figure presents the results of the Neural Network model optimized using PSO, which achieves a slightly higher AUC value of 0.824. This increase from 0.818 to 0.824 signifies that the use of PSO in hyperparameter tuning successfully enhances the model’s ability to differentiate between positive and negative classifications. Although the difference may appear marginal (an improvement of 0.006), in the field of medical classification, even minor gains in performance can have a substantial impact—particularly in minimizing diagnostic errors (Febrian, M.E et al., 2023). Therefore, incorporating PSO into the model training phase demonstrates its potential to boost classification effectiveness, as reflected in both the improved AUC value and a more optimal ROC curve trajectory (Badriyah, J et al., 2024). The table below presents a comparison of classification accuracy obtained from both Deep Learning and Neural Network models, with and without the integration of Particle Swarm Optimization:

Tabel 2. Accuracy

| Method | Optimaze | Accuracy |
|---|---|---|
| Deep Learning | Non Particle Swarm Optimization | 75.00% |
| *Neural Network* | | 77.86% |
| Deep Learning | Particle Swarm Optimization | 77.90% |
| *Neural Network* | | 78.39%. |

Prior to optimization, the Deep Learning model yielded an accuracy of 75.00%, while the Neural Network achieved 77.86%. Following PSO-based hyperparameter optimization, the accuracy increased to 77.90% for the Deep Learning model and 78.39% for the Neural Network. These performance improvements underscore the effectiveness of PSO in identifying optimal parameter configurations, which contributes to improved training outcomes and predictive reliability. The findings suggest that integrating PSO into the model development workflow can enhance the overall learning capacity and accuracy of machine learning systems, particularly in sensitive domains such as medical diagnosis. Overall, the combination of PSO with Deep Learning or Neural Network results in more accurate and reliable predictive models. Therefore, PSO-based optimization is a valuable approach to enhancing classification accuracy in medical diagnostic systems, particularly for early detection of chronic diseases such as Diabetes Mellitus.

The research reveal combining Machine Learning techniques with Particle Swarm Optimization (PSO) leads to a marked enhancement in predictive performance for Diabetes Mellitus classification. The PSO-optimized model consistently outperformed the baseline Deep Neural Network (DNN) across multiple indicators. These outcomes highlight the critical role of hyperparameter optimization in maximizing particularly in high-stakes applications such as healthcare diagnostics. The PSO algorithm to be highly discovering optimal configurations of model parameters, surpassing the capabilities of manual or grid-based search methods. Notably, improvements in recall and F1-score emphasize the model's improved sensitivity in identifying positive diabetes cases—an aspect that is vital for timely detection and reducing the risk of medical complications. The PSO algorithm proved to be highly effective in discovering optimal configurations of model parameters, surpassing the capabilities of manual or grid-based search methods. Notably, improvements in recall and F1-score emphasize the model's improved sensitivity in identifying positive diabetes cases—an aspect that is vital for timely detection and reducing the risk of medical complications.

## 4. CONCLUSION

This research the efficacy of utilizing Particle Swarm Optimization as a hyperparameter tuning strategy for both Neural Network and Deep Learning models in the task of classifying Diabetes Mellitus. The experimental findings consistently indicate that the incorporation of PSO during the training phase leads to enhanced model performance. In the absence of optimization, the Deep Learning model attained an accuracy of 75.00%, while the Neural Network achieved 77.86%. Following PSO optimization, the respective accuracies increased to 77.90% and 78.39%. Furthermore, the improvement in the AUC (Area Under the Curve) score from 0.818 to 0.824 reinforces the conclusion that PSO effectively strengthens the model’s ability to distinguish between diabetic and non-diabetic instances. These outcomes demonstrate that PSO not only aids in discovering better-performing hyperparameter configurations but also contributes to increased robustness and predictive in medical classification models. Overall, the integration of PSO has proven beneficial in improving reliability of the Neural Network model. These findings reinforce the potential of combining bio-inspired optimization algorithms with deep learning techniques to develop more accurate, efficient, and intelligent medical diagnosis systems. For future research, it is recommended to apply the model to a more diverse dataset and explore other optimization strategies or hybrid methods to further enhance performance and adaptability in real-world clinical applications.

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