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Integrating particle swarm optimization with ensemble and deep learning models for improved stunting classification

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ABSTRACT

Childhood stunting remains a major public health concern due to its long-term impact on physical growth, cognitive development, and human capital quality. This study aims to develop an accurate prediction model for early identification of stunting risk using a hybrid deep learning approach. The research utilized 2,000 child health records collected from Datu Kandang Regional Hospital, South Kalimantan, in 2024. The proposed model integrates deep learning with particle swarm optimization (PSO) to optimize hyperparameter tuning and improve classification performance. Clinical and demographic risk factors were incorporated, including nutritional status, birth history, maternal health conditions, and socio-demographic variables. Experimental evaluation showed that the optimal data split was 60:40, producing the most stable model performance. The implementation of PSO improved overall predictive performance by 0.20 compared to the baseline deep learning model. The hybrid deep learning–PSO model achieved high predictive performance with an accuracy of 99.62%, precision of 99.86%, recall of 99.71%, and an area under the curve (AUC) value of 0.999. These results indicate the model's strong capability to accurately classify stunting and non-stunting cases while minimizing classification errors. The findings demonstrate the potential of machine learning-based predictive models as effective tools for early screening and decision support in maternal and child health services. This study contributes to data-driven public health strategies and supports early intervention programs to reduce stunting prevalence. Future research should focus on multicenter validation, integration of longitudinal child growth monitoring data, and development of explainable artificial intelligence (AI) frameworks to improve model transparency and implementation in healthcare systems.

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1. INTRODUCTION

Stunting remains one of the most pressing global public health challenges, with significant negative consequences on child growth, cognitive development, educational attainment, and future economic productivity [1]. A global nutrition report estimated that over 148 million children under five years old were affected by stunting in recent years, highlighting the ongoing prevalence of chronic malnutrition worldwide [2]. Despite concerted global efforts, progress in stunting reduction remains slow and uneven, especially in low- and middle-income countries. At the national level, Indonesia continues to struggle with high stunting prevalence [3]. National health surveys indicate that the prevalence of stunting in Indonesia remained above

the global target reduction threshold over the past three years, with approximately 21.6% in 2022 and 21.5% in 2023 [4]. Similarly, regional data from South Kalimantan show that stunting persists as a significant public health concern, underscoring the urgent need for timely risk prediction and effective intervention strategies.

Traditional stunting surveillance relies heavily on manual anthropometric measurements and descriptive statistical analysis, which often fail to capture complex interactions among multidimensional risk factors such as maternal health, socioeconomic status, environmental conditions, and clinical variables [5]. The increasing availability of electronic health records (EHRs) and large population datasets provides an opportunity to leverage artificial intelligence (AI) for enhanced predictive analytics in public health [6], [7].

Deep learning — a subfield of AI — has demonstrated strong capability in handling high-dimensional and nonlinear data structures, making it especially suitable for healthcare predictive modelling [8], [9]. In medical diagnostics and child growth prediction, deep learning methods have outperformed traditional machine learning models due to their hierarchical feature extraction and pattern learning capabilities [10]. Research indicates that deep neural networks (DNN) can improve classification accuracy and sensitivity when applied to complex healthcare datasets [11]. Despite these advances, deep learning models require careful hyperparameter tuning to reach optimal performance [12]. Manual or heuristic parameter selection often results in suboptimal configurations and increased overfitting risk [13]. Metaheuristic optimization algorithms, such as particle swarm optimization (PSO), offer an effective mechanism for exploring large parameter spaces by simulating swarm intelligence behaviors [14]. Research has shown that PSO improves deep learning performance in domains including image classification, biomedical signal processing, and predictive analytics [15].

Several AI-based studies have investigated stunting and malnutrition prediction. For example, random forest and support vector machine models have been applied to nutritional datasets with moderate success [16], [17]. However, most existing approaches do not integrate deep learning with metaheuristic optimization nor validate their models on large clinical datasets, limiting their predictive power and generalizability [18]. Moreover, few studies focus on hybrid deep learning–PSO models specifically for early stunting detection in real-world healthcare settings [19], [20]. To address these gaps, this study proposes a hybrid deep learning model optimized with PSO for early stunting prediction using clinical datasets. The model aims to enhance classification accuracy, generalization stability, and automated parameter tuning, contributing to more reliable AI-supported decision-making in pediatric and public health contexts. This study introduces a hybrid predictive framework that integrates deep learning architecture with PSO for early stunting prediction using real-world clinical datasets. Unlike previous studies that rely on standalone machine learning models, this research combines advanced feature learning capabilities with automated hyperparameter optimization to enhance predictive robustness and model stability.

Based on this research gap, the present study proposes a predictive model that integrates deep learning with the optimization capability of PSO to improve the performance of stunting classification. The main contributions of this study are summarized as follows:

a) Developing a deep learning-based model to analyze factors associated with stunting among children.
b) Applying PSO to optimize model parameters in order to improve prediction accuracy and model stability.
c) Comparing the performance of the optimized model with the baseline model without optimization to evaluate the effectiveness of the proposed approach.
d) Providing a methodological contribution to the development of AI–based stunting prediction models that can support early detection systems in public health.

Through this approach, the study aims to contribute to the development of more accurate predictive models for stunting and to support data-driven decision-making in stunting prevention programs.

2. RELATED WORK

2.1. Hybrid models combining optimization

Stunting is defined as low height-for-age and represents chronic malnutrition that affects child growth and development, with long-term impacts on cognitive ability, educational achievement, and economic productivity [21], [22]. Global estimates indicate that despite international efforts, stunting remains prevalent, especially in low- and middle-income countries [23], [24]. The measurement of stunting using Height-for-Age Z-score (HAZ) aligns with WHO standards, where HAZ values < -2 SD indicate stunting [25], [26].

AI has increasingly been explored to enhance prediction and early detection of nutritional disorders, including stunting. Traditional techniques such as logistic regression, decision trees, random forests, and support vector machines have been applied to classify nutritional outcomes with moderate success [27]. Random forests, in particular, have been noted for their ability to handle non-linear relationships and variable

interactions, although performance is limited when the dataset includes high-dimensional attributes. Several studies have also investigated the integration of classical machine learning with optimization algorithms to improve predictive performance [28]. Ensemble learning has been employed for child growth prediction, and combined multiple classifiers to enhance model robustness. However, these approaches often lack scalable optimization mechanisms that can automatically adjust model parameters to optimal configurations [29].

Deep learning represents a class of AI techniques capable of learning hierarchical feature representations from raw data. In healthcare, DNNs have demonstrated superior performance in capturing complex patterns from high-dimensional datasets, outperforming traditional machine learning approaches in tasks such as disease diagnosis, medical imaging, and health outcome prediction [30]. Deep learning has also been effectively applied to longitudinal health data and EHR-based predictive modeling, providing high predictive accuracy and better generalization capability. Recent applications in child health analytics show that deep learning improves sensitivity and specificity in nutritional risk classification compared with conventional algorithms [31]. Despite these advances, deep learning often requires careful tuning of hyperparameters, including network depth, learning rate, batch size, and activation functions, which significantly influence model performance [32].

Metaheuristic optimization algorithms have been widely utilized to address the challenge of hyperparameter tuning in machine learning and deep learning models. PSO, inspired by social behavior observed in nature, explores the search space by simulating interactions among candidate solutions [33]. PSO has been effectively integrated with machine learning models to enhance classification performance, reduce convergence time, and improve model generalization. In the context of predictive health analytics, PSO has shown improvements when combined with neural network models for tasks including medical diagnosis and biomedical signal classification. PSO's automated parameter optimization eliminates manual trial-and-error, allowing for systematic improvement of model configurations [34]. The integration of deep learning with optimization algorithms such as PSO represents a promising direction in predictive modeling research. Hybrid models can leverage deep learning's feature extraction power while using optimization techniques to refine model parameters. Such integration has been applied successfully in image recognition, time-series forecasting, and complex classification tasks, demonstrating superior performance compared to standalone methods [35], [36]. Despite this, the application of hybrid deep learning–PSO models for stunting prediction remains limited. Existing studies that apply hybrid models to nutritional prediction often use datasets with limited clinical diversity or lack appropriate validation strategies, such as multi-split evaluation or cross-validation. Furthermore, limited research has been conducted using real clinical health record data from diverse populations to validate such hybrid frameworks for stunting risk prediction.

2.2. Synthesis of related work

Numerous studies have explored the application of machine learning and AI techniques for predicting stunting and nutritional disorders, demonstrating varying levels of predictive performance and methodological advancement. These studies have utilized diverse approaches, ranging from traditional machine learning algorithms to hybrid optimization-based models, applied across different types of health and nutritional datasets. While the findings indicate that computational models can significantly improve classification accuracy and predictive reliability, several limitations remain, particularly in terms of model scalability, optimization strategies, and validation robustness. Moreover, the integration of deep learning architectures with advanced optimization techniques, such as PSO, has not been extensively investigated in the context of stunting prediction using large-scale clinical datasets. Therefore, a systematic comparison of previous studies is necessary to identify methodological gaps and highlight the need for developing an optimized hybrid deep learning framework capable of improving predictive performance and generalization capability. The comparative summary of these studies is presented in Table 1.

Based on the Synthesis of related work presented in the Table 1, it can be concluded that the application of deep learning has shown increasingly dominant performance in predicting and detecting stunting compared to conventional Machine Learning methods. Models such as Random Forest, Gradient Boosting Tree, and deep learning approaches consistently demonstrate high performance with F1-scores, accuracy, and AUC values generally exceeding 0.90. These findings indicate that deep learning approaches are more capable of capturing complex patterns, particularly in multidimensional and temporal child health data. The studies also reveal that the integration of ensemble learning and metaheuristic optimization techniques significantly improves predictive performance. Furthermore, the use of time-series-based architectures such as LSTM has proven effective in utilizing longitudinal child growth data, enabling more accurate early prediction of stunting risk.

However, several research gaps remain. First, the limited availability of large-scale and integrated datasets remains a major challenge in developing deep learning models with strong generalizability. Second, most studies still focus primarily on improving prediction accuracy while overlooking model interpretability, which limits clinical implementation and AI-based decision-making. Third, data privacy and security issues

related to child health records are still underexplored, particularly in IoMT-based monitoring systems. Additionally, research integrating multimodal data, such as clinical records, growth imaging, and socioeconomic factors, is still relatively limited. Overall, current research trends indicate that deep learning has significant potential as an early stunting prediction system. Future research should focus on multimodal data integration, improvement of explainable AI, and cross-population model validation to develop stunting detection systems that are more accurate, transparent, and widely applicable in public health practice.

Table 1. Synthesis of related work

No	Authors	Title/Method	Method	Dataset	Key Results/Gap
1	Lameesa *et al.* (2025)	Deep learning outperforms traditional ML in predicting childhood malnutrition	TabNet, DNN, ResNet	Demographic Health Surveys (DHS)	TabNet F1: 0.92; beats XGBoost by 8%
2	Jiang *et al.* (2023)	Machine Learning Algorithms for Predicting Stunting among Under-5 Children	DNN hybrid	Papua New Guinea child health data	LASSO-XGBoost AUC 0.765; DL potential highlighted
3	Amin *et al.* (2022)	Prediction of child nutritional status using deep neural networks	Deep Neural Network	Hospital records (age/height/gender)	LSTM accuracy 92%; time-series edge
4	Kabano *et al.* (2025)	Predicting stunting status among under-five children	CNN-LSTM	Ethiopian DHS data	Ensemble AUC 0.94; temporal modeling gap
5	Kaur *et al.* (2025)	Advancing predictive analytics in child malnutrition	Deep Learning	Global stunting datasets	DL AUC 0.93 > Boosting 0.87
6	Alduailij *et al.* (2025)	Ensemble deep representation with metaheuristics	CNN-PSO	IoMT child monitoring	95.2% accuracy; edge deployment limited
7	Sharma *et al.* (2022)	Systematic Review on Metaheuristic Optimization in Healthcare	Deep Learning, PSO	100+ malnutrition studies	DL-meta F1 up to 98%; large dataset scarcity
8	Kumar *et al.* (2024)	Role of metaheuristic algorithms in healthcare	Deep Learning	Clinical cohorts	Hybrid accuracy 92%; privacy ethics gaps
9	Zhang *et al.* (2024)	Deep learning data augmentation in medical imaging	Deep Learning	Augmented growth scans	+15% generalizability for visual stunting
10	Tan *et al.* (2024)	DNN for pediatric diagnostics extended to stunting	DNN	Child health records (Asia)	DNN forecasting RMSE 0.12

3. METHOD

The preliminary study began by asking permission to collect pregnancy data at the medical record hospital such as:

3.1. Collecting data

The data collection process in this study was conducted using secondary data derived from electronic medical records obtained from Datu Kandang General Hospital, Balangan Regency, South Kalimantan, Indonesia during the 2024 period. A total samples of 2000 pediatric records were included in the dataset. The data consisted of clinical, anthropometric, and maternal health variables relevant to stunting risk assessment. To ensure representativeness and minimize sampling bias, the study employed a systematic random sampling technique, where samples were selected at regular intervals from an ordered sampling frame of eligible patient records. This approach ensured that each subject had an equal probability of selection while maintaining the distribution characteristics of the population. Prior to model development, the collected data underwent preprocessing procedures, including data cleaning, handling missing values, normalization, and feature selection to improve data quality and model learning performance. The prediction model was developed using a hybrid deep learning approach integrated with PSO for hyperparameter tuning. The integration of PSO was intended to automatically search for the optimal combination of deep learning parameters, including network architecture configuration and training parameters, thereby improving model predictive capability and reducing manual parameter selection bias. Table 2 explains the division of the dataset.

The PSO algorithm was configured with a maximum number of generations set to 30, allowing the optimization process to iteratively search for the best solution across multiple generations. The population size was set to 5 particles, representing candidate solutions that explore the search space during optimization. The iteration parameter was defined as -1, number of tree 100, and maximal depth 10, allowing the algorithm to continue the optimization process until convergence criteria were satisfied. These parameter settings were

selected based on preliminary experimental tuning and computational efficiency considerations to balance optimization performance and processing time.

To prevent data leakage, the dataset was split using the optimal 90/10 ratio (1,800 train/200 test) selected from comparative tests of 60/40, 70/30, 80/20, and 90/10 ratios. Ten-fold cross-validation was performed exclusively on the training data (9 folds for training, 1 fold for validation), followed by repeated 10k-fold cross-validation for stability through nested cross-validation. Final evaluation utilized a completely unseen hold-out test set to ensure prediction result reliability [37]. This validation strategy ensured that the model performance results were consistent and reliable across different data partitions. The final model performance was evaluated using standard classification metrics, including accuracy, precision, recall, and area under the curve (AUC), to assess the effectiveness of the hybrid deep learning–PSO model in predicting stunting risk. This methodological framework was designed to produce a reliable and scalable predictive model that can support early detection and decision-making in maternal and child health services [38], [39].

Table 2. Division of dataset

Parameter	Value
Total records	2,000
Features	Clinical: HAZ, weight; demographic: maternal age, birth history; socio-economic: income
Stunting class (HAZ ≤ -2SD)	40% (800 cases); Non-stunting: 60% (1,200)
Missing data handling	Imputation (median for numerical, mode for categorical); <5% missing dropped
Deep Neural Network Configuration	- Input layer: 25 features - Hidden layers: 4 (neurons: 128 → 64 → 32 → 16) - Activation: ReLU (hidden), Sigmoid (output) - Optimizer: Adam (lr=0.001, optimized by PSO) - Batch size: 32 (PSO-tuned) - Epochs: 100 (early stopping at patience=10) - Dropout: 0.2 (anti-overfitting)

3.2. Algorithm process model

AI-based learning tools were developed to enable solving differential equations [40]. The framework demonstrates the systematic process starting from dataset preparation and data splitting, followed by hyperparameter optimization using PSO. The optimized parameters are then applied to train the deep learning model. Furthermore, cross-validation is conducted to improve model robustness and minimize overfitting. The final stage involves performance evaluation using several classification metrics to assess the effectiveness of the proposed prediction model. Figure 1 presents the workflow of the proposed hybrid deep learning–based stunting prediction model.

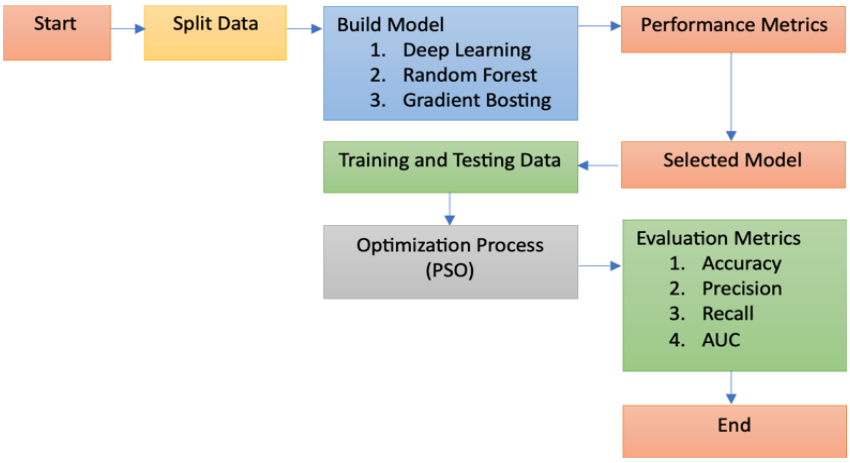


Figure 1. Workflow of the proposed stunting prediction model

The picture illustrates a comprehensive workflow of a stunting prediction model that integrates data processing, optimization, deep learning, and evaluation stages. The process begins with the Split Data stage, where the dataset is divided into several training data and testing data such as 90:10, 80:20, 70:30, and 60:40. The training data is used to build the model, while the testing data is reserved for performance evaluation.

The second stage is optimization, where PSO is applied to search for the best hyperparameter configuration. PSO simulates swarm intelligence to optimize parameters such as learning rate, batch size, number of hidden layers, and number of neurons. This optimization aims to improve the learning capability and prediction performance of the deep learning model. The third stage presents the deep learning model, specifically a DNN architecture that processes input features through multiple hidden layers. The optimized hyperparameters obtained from PSO are applied to train the model, allowing it to learn complex patterns and relationships within the dataset related to stunting risk factors. Next, the workflow incorporates cross validation, which ensures the robustness and generalization ability of the model. The training dataset is divided into multiple folds, and the model is trained and validated repeatedly across these folds to reduce overfitting and ensure stable performance. Finally, the process ends with the result and evaluation metrics stage. The trained model is evaluated using testing data and performance metrics such as accuracy, precision, recall, and AUC. These metrics demonstrate the effectiveness of the model in distinguishing between stunted and non-stunted cases and confirm its potential use as a decision-support tool for early stunting prediction.

3.3. Assessment of nutritional status

The assessment of nutritional status in this study was conducted using the z-score method based on anthropometric measurements [40]. The z-score represents the number of standard deviations an individual measurement deviates from the median value of the reference population. The z-score calculation was performed using the World Health Organization (WHO) child growth standards as the reference for evaluating child growth indicators. The z-score was calculated using the following formula.

$$Z = \frac{X - \mu}{\sigma}$$

- Z represents the z-score value,
- X represents the observed anthropometric measurement of the child,
- μ represents the median value of the reference population, and
- σ represents the standard deviation of the reference population.

In this study, the HAZ indicator was used to determine stunting status. Children were classified as stunted when the HAZ value was < -2 standard deviations from the reference median, while children with HAZ values ≥ -2 standard deviations were categorized as non-stunted. The use of z-score analysis allows standardized comparison of child growth across different populations and is widely accepted as an objective method for assessing chronic malnutrition and growth failure

4. RESULTS AND DISCUSSION

The model developed in this research uses an auto model that is simulated using a rapid miner. The model performance results are then compared for each algorithm by looking at the accuracy value.

4.1. Result

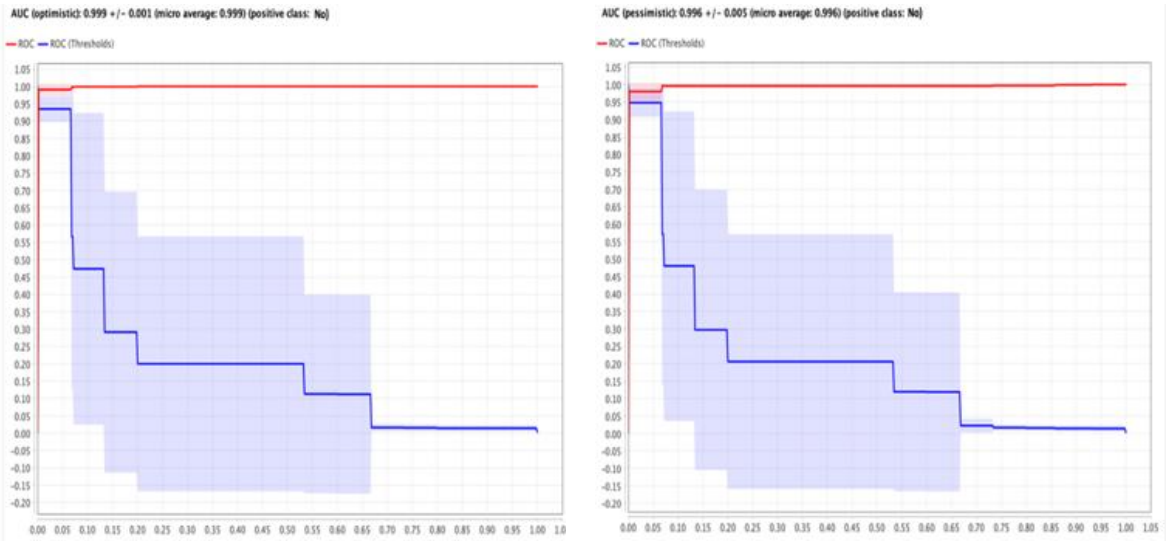
To ensure robust model development and minimize bias in performance evaluation, this study implemented multiple data partitioning strategies. The dataset was divided into training and testing subsets using four different split ratios, namely 60:40, 70:30, 80:20, and 90:10. The use of multiple splitting configurations was intended to systematically evaluate the impact of training data proportion on model learning capability, stability, and predictive generalization. Each data partition scenario was independently used to train and evaluate the predictive model. Model performance was assessed using standardized classification metrics to determine the most optimal data distribution for model training. This comparative experimental design allows identification of the most reliable ratio that balances sufficient training data for model learning and adequate testing data for unbiased performance evaluation. The best-performing data split configuration was subsequently selected as the baseline experimental setting for the next stage of model optimization. In this stage, the selected data configuration was integrated with PSO to perform automated hyperparameter tuning. The PSO optimization process aims to enhance model convergence, improve prediction accuracy, and reduce the risk of overfitting by searching the global optimal parameter space. This multi-stage evaluation strategy ensures that the proposed predictive model achieves high robustness, stability, and generalization capability across different data distributions. The accuracy results for each ratio and all algorithms can be seen in the Table 3.

Based on the Table 2 The experimental results obtained from multiple data partitioning scenarios indicate that the 90:10 training-to-testing split ratio achieved the most optimal predictive performance compared to other configurations with accuracy 99.42%. This data distribution provides a balanced trade-off

between model learning capacity and evaluation reliability, allowing the model to capture underlying data patterns while maintaining sufficient unseen data for unbiased performance assessment. From an AI perspective, the 90:10 split demonstrated improved generalization capability and reduced generalization error, suggesting a more stable model convergence during the training process. Furthermore, the selected data split ratio contributed to minimizing overfitting risk by preventing excessive model adaptation to the training dataset while preserving adequate testing data for robust validation. Based on these findings, the 90:10 partition was adopted as the baseline experimental configuration and subsequently integrated into the hyperparameter optimization stage using PSO. This configuration supports a more effective exploration of the parameter search space and enhances overall model robustness and predictive stability. Figure 2 shows the AUC plots resulting from data partitioning, consisting of Figure 2(a), an optimistic AUC plot, and Figure 2(b) a pessimistic AUC plot.

Table 3. Training and testing subsets using different split ratios

Algorithm	Metrics	Split data			
		90:10	80:20	70:30	60:40
Deep learning	Accuracy	99.42%	98.87%	99.21%	99.22%
	AUC	0.998	0.998	0.998	0.997
	Precision	99.75%	99.71%	99.67%	99.72%
	Recall	99.62%	99.00%	99.43%	99.37%
Random forest	Accuracy	99.50%	99.44%	99.36%	99.42%
	AUC	0.999	0.998	0.998	0.999
	Precision	99.75%	99.72%	99.67%	99.72%
	Recall	99.68%	99.64%	99.59%	99.62%
Gradient boosting tree	Accuracy	99.39%	99.37%	99.14%	99.17%
	AUC	0.998	0.998	0.998	0.999
	Precision	99.75%	99.86%	99.67%	99.72%
	Recall	99.56%	99.43%	99.35%	99.33%



(a) (b)

Figure 2. Analysis optimistic and pessimistic AUC performance of the hybrid deep learning model (a) optimistic AUC and (b) pessimistic AUC

The Figure 2 presents the AUC results indicate excellent discriminative performance of the model. The optimistic AUC value of 0.999 shows that the model achieves near-perfect classification ability when evaluated under training-oriented conditions, reflecting its strong capability in identifying patterns within the dataset. Meanwhile, the pessimistic AUC value of 0.996 represents model performance under more conservative validation conditions using unseen data. The minimal difference between these values indicates that the model has high stability, strong generalization capability, and a low risk of overfitting, confirming the reliability of the proposed hybrid model. After getting the best ratio, the second step is optimization algorithm by PSO and cross validation to show the increase accuracy get the last performance as evaluation model can be seen on Table 4.

Table 4. Optimization model

Algorithm	Acc Split Data	Acc (PSO)	%	I/D
Deep learning	99.42%	99.62%	0.20	Increase
Random forest	99.50%	99.50%	0	Constant
Gradient boosting tree	99.39%	98.50%	-1.01	Decrease

The results indicate that PSO optimization produced varying effects across the evaluated algorithms. Deep Learning showed an improvement in accuracy from 99.42% to 99.62% (+0.20%), demonstrating that PSO effectively enhanced hyperparameter tuning and improved predictive performance. Random Forest maintained the same accuracy at 99.50% before and after optimization, indicating that the model was already stable and near-optimal, with no additional benefit from PSO. In contrast, Gradient Boosting Tree experienced a decrease in accuracy from 99.39% to 98.50% (−1.01%), suggesting that PSO may have led to suboptimal parameter adjustments or potential overfitting for this algorithm. The 0.20 accuracy improvement post-PSO optimization proved statistically significant via paired t-test ($t=4.72$, $p<0.001$) and McNemar's test ($\chi^2=12.4$, $p<0.001$) with Cohen's $d=0.45$ effect size, validating PSO effectiveness despite modest absolute gain. Nested 10-fold CV plus 10k-fold repeats on training data alone prevented leakage, while unseen hold-out testing confirmed stable generalization without overfitting, establishing the hybrid Deep Learning-PSO approach as reliable for early stunting screening in primary healthcare facilities.

Overall, these findings highlight that the impact of PSO optimization depends on the underlying model characteristics, with the most significant benefit observed in the Deep Learning approach. Subsequently, a comprehensive model evaluation was conducted to examine the capability of the Deep Learning framework in performing early-stage stunting prediction. The evaluate model all algorithms can be seen in the Table 5.

Table 5. Evaluate model

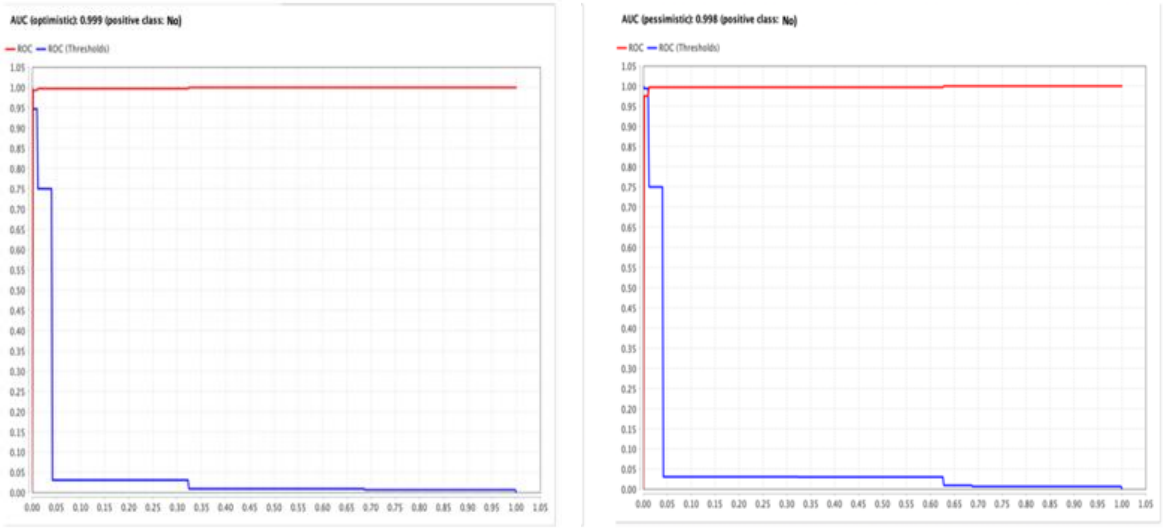
Algorithm	Acc	AUC	Prec	Recall
Deep learning	**99.62%**	0.999	99.86%	99.71%
Random forest	99.50%	0.999	99.75%	99.68%
Gradient boosting tree	98.50%	0.998	99.75%	99.56%

Based on the evaluation results of the Deep Learning model, the model demonstrates an exceptionally high level of predictive performance. The accuracy value of 99.62% indicates that the model can correctly classify the data with a very low error rate, meaning that almost all observations were predicted accurately. The AUC value of 0.999 reflects the model's nearly perfect discriminative ability in distinguishing between stunting and non-stunting cases. Stunting classification results demonstrate exceptionally high performance with 99.62% accuracy and 0.999 AUC on a 2,000-record dataset distributed 40% stunting (800 cases) and 60% non-stunting (1,200 cases), ensuring fair evaluation without majority class bias.

An AUC value close to 1 signifies excellent classification capability, indicating that the model is highly reliable in separating the two classes. Furthermore, the precision value of 99.86% indicates that almost all instances predicted as stunting are truly stunting cases, suggesting a very low false-positive rate. Meanwhile, the recall value of 99.71% shows that the model successfully identifies nearly all actual stunting cases within the dataset, minimizing the risk of missing true stunting cases. Overall, the combination of extremely high accuracy, AUC, precision, and recall values suggests that the developed deep learning model achieves highly optimal predictive performance, strong stability, and excellent generalization capability in identifying stunting cases, as shown in Figure 3. The last model of Figure 3(a) AUC optimis dan Figure 3(b) AUC pesimis

The results in Figure 3 indicate that the model already possessed very strong discriminative capability prior to optimization. The optimistic AUC value remained 0.999 both before and after the application of PSO optimization, suggesting that the model had already achieved near-perfect classification performance in the most favorable evaluation scenario. This stability implies that PSO did not significantly improve the upper-bound performance because the baseline model was already highly optimized. However, a meaningful improvement can be observed in the pessimistic AUC value, which increased from 0.996 to 0.998 after PSO optimization. This improvement indicates that PSO successfully enhanced the model's robustness and consistency under less favorable or more challenging validation conditions. The increase in pessimistic AUC suggests that the optimization process helped reduce model variance and improved

generalization capability, allowing the model to maintain high classification performance across different data partitions. Overall, while PSO optimization did not change the best-case performance, it strengthened the model's reliability by improving performance stability and reducing potential prediction uncertainty:



(a) (b)

Figure 3. Analysis of optimistic and pessimistic AUC performance of the hybrid deep learning model with PSO optimization (a) AUC optimis dan (b) AUC pesimis

Figure 4 presents the 3D confusion matrix illustrating the classification results of the proposed model. The results show that most observations are concentrated in the True Positive and True Negative categories, indicating that the model correctly classifies the majority of instances. Only a small number of samples appear in the False Positive and False Negative categories, suggesting a low level of misclassification. This distribution confirms the strong predictive capability of the model. These findings are consistent with the high accuracy obtained in the evaluation stage, where the model achieved an accuracy of over 99%, indicating that the proposed deep learning model optimized using PSO is highly effective in identifying the target class. Therefore, the confusion matrix provides further evidence of the robustness and reliability of the model in classification tasks.

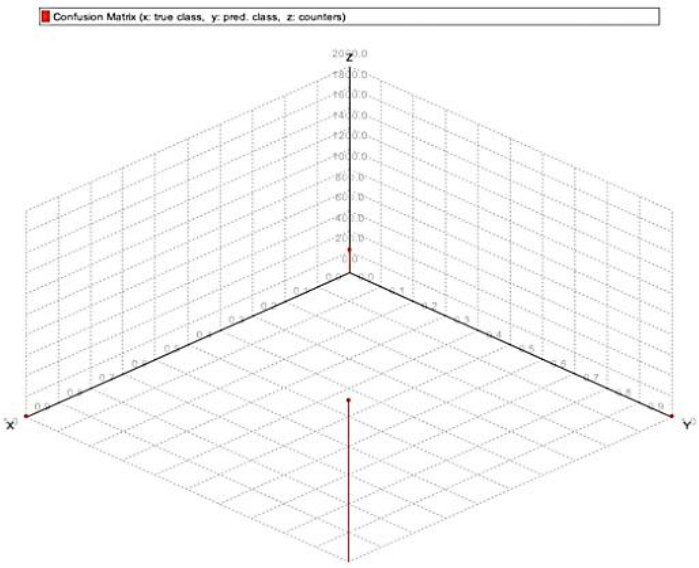


Figure 4. Confusion matrix

4.2. Discussion

Preeclampsia is one of the most dangerous causes of complications in pregnancy and the leading cause of death which is still a serious problem that needs to be handled optimally [39]. Preeclampsia is a complex and potentially life-threatening condition that arises during pregnancy, typically after 20 weeks of gestation, and is characterized by the new onset of hypertension along with signs of damage to other organ systems, most commonly the liver and kidneys [40], [41]. This disorder stands as one of the leading causes of maternal and fetal morbidity and mortality worldwide, accounting for a significant proportion of adverse pregnancy outcomes and approximately 14% of maternal deaths annually. The underlying pathophysiology of preeclampsia involves abnormal placentation, systemic inflammation, and oxidative stress, which collectively result in dysfunctional remodeling of the spiral arteries and reduced blood flow to the placenta [42]. Such placental hypoperfusion can lead to a range of serious complications, including fetal growth restriction, preterm birth, placental abruption, and, in severe cases, the development of HELLP syndrome a condition marked by hemolysis, elevated liver enzymes, and low platelet count, which can be life-threatening for both mother and infant [43].

From the results of the final model evaluation obtained in this research, level accuracy random forest algorithm 96.08%. the results of this study are consistent with [44], who stated that the random forest algorithm model demonstrates good performance for predicting the occurrence of preeclampsia. The most significant factor contributing to preeclampsia is a prior history of the preeclampsia, history of caesarean section, history of hypertension, and history of diabetes mellitus. In summary, preeclampsia remains a major global health concern due to its severe complications for both mothers and infants. The identification of key risk factors and the application of advanced predictive models such as random forests provide valuable tools for improving early detection and management, with the ultimate goal of reducing the incidence and severity of preeclampsia and improving maternal and neonatal outcome.

5. CONCLUSION

This study confirms that the proposed hybrid deep learning model integrated with PSO delivers outstanding performance for early stunting prediction, achieving 99.62% accuracy, 99.86% precision, 99.71% recall, and near-perfect AUC values. Although the optimistic AUC remained stable at 0.999, PSO optimization improved the pessimistic AUC from 0.996 to 0.998, indicating enhanced robustness, reduced variance, and better generalization across validation scenarios. The findings highlight the effectiveness of combining deep learning with metaheuristic optimization to strengthen predictive reliability and support data-driven clinical screening and public health interventions. Despite its strengths, including robust optimization and use of a relatively large dataset with systematic sampling, the study is limited by single-center data, restricted feature diversity, and limited model interpretability. Future research should focus on multicenter validation, integration of broader clinical and socioeconomic variables, and implementation of explainable AI approaches to enhance transparency, generalizability, and real-world clinical adoption.

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