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Optimization of Backpropagation (BP) Weight Values Using Particle Swarm Optimization (PSO) to Predict KIP Scholarship Recipients

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Abstract

The Indonesia Smart Card (KIP) Lecture program aims to improve the quality of human resources by providing educational assistance to students from underprivileged families. However, the distribution of KIP Lecture in Palembang still faces problems, such as inaccurate targeting and lack of public understanding of this program. The selection process for scholarship recipients is not optimal, causing students who should be prioritized to be overlooked. In addition, decision-making takes a long time due to the many variables that must be considered and the lack of transparency in data processing. This research discusses the Backpropagation (BP) method for predicting KIP College scholarship recipients, which has previously been applied to the classification of educational aid recipients with high accuracies results. However, BP has disadvantages such as minimum local risk and long training time. To overcome this, the Particle Swarm Optimization (PSO) algorithm is used to optimize the weights of the BP artificial neural network. PSO is a simple but effective optimization algorithm to find optimal weights more quickly and accurately. The results of previous studies show that the combination of BP with PSO can improve prediction accuracy compared to using BP alone. Therefore, this research aims to develop a more efficient and targeted prediction model for KIP College scholarship recipients through BP optimization using PSO, so that the selection process can be carried out more quickly and accurately.

Keywords: Backpropagation (BP), Particle Swarm Optimization (PSO), Prediction Model, Smart Indonesia Card (KIP).

1. INTRODUCTION

Smart Card is a very good program for help study in cash from governments that giving to children who at school's age from 6 to 21 years old and originating from family that have poor economy condition. The goal is for increase level source Power humans in Indonesia with access education made easy, helping lighten up cost education as well as prevent the occurrence separated school. KIP College Program The year 2024 has reaching 101,000 students or by 50 percent of the total quota, namely 200,000 students [1]. Scholarship mission official replaced by the Smart Indonesia College Card (KIP- College) based on Budget State Revenue and

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Expenditure (APBN) [2]. KIP college distributed throughout college state universities and colleges tall private. However, there is distribution problem.

Indonesia Smart Card for College that is not appropriate target as well as Still low knowledge public about the Smart Indonesia Card College program. Network Indonesian Education Monitor (JPPI) stated that KIP-K case misdirected No only happen in One college tall only, but already happen in scope national. According to him, the factor main from error This caused by the KIP-K selection process which is not transparent and not accountability. Lack of selection. good on the recipient KIP College Scholarship result in Lots students in dire need help and should more prioritized become neglected. Attitude in accuracy related eligible students accept KIP College scholarship. So that There is opportunity big for a real student need for Can join become student recipient KIP Scholarship. Withdrawal decision for determine a real student worthy accept KIP College Scholarship need a long time because lots variable determinant. The existence of data processing that is not transparent on recipient data KIP College scholarship because of That need determine classification for determination recipient KIP college scholarships that can be help party institution in take decision with fast and precise so that the KIP College scholarship can distributed in accordance target.

Study about KIP College assistance program classification discuss about Backpropagation method for predict distribution Smart Indonesia Card (KIP) scholarship previously with research that will be done. Like study [3], for prediction student recipient KIP assistance. For determination student not enough capable with application of JST backpropagation developed can walk with good. JST backpropagation is used For practice JST training for get balance on the network For recognize the pattern used in the training process [4]. Learning process adapt weight in direction step back based on error value in the learning process [5]. Research the second one discusses about Use of JST Backpropagation for predict mark students conducted by [6] show Learning Rate value of 0.2, with epoch repetition 1000 times, obtained results the RMSE value is 0.040929 and the MSE is 0.001675 and level accuracy by 93.43%. Meanwhile, in the research [7] which discusses about Design system Supporter decision For prediction recipient scholarship use The Neural Network Backpropagation method produces mark highest average accuracy by 99.00% and lowest average error value result of 0.000101.

One of problem main is inaccuracy target recipient assistance, where still there is case the recipient who came from from family able, while more students need precisely no get assistance. In addition, data inaccuracy and suboptimal selection processes often lead to distribution help No evenly. Another problem arose is misuse of aid funds, where some recipient use funds for non- academic needs are lacking in accordance with program objectives. Phenomenon this is also made worse with emergence pattern consumerism and hedonism among recipient scholarships, which reflect existence challenge in management finance they.

In addition, the delay disbursement of funds often becomes constraint for student in fulfil need academic appropriate time. Other issues is lack of transparency in system selection and distribution assistance, which causes emergence injustice in reception scholarship. Recently This is a disruption to the KIP College system consequence The hacking of the National Data Center (PDN) in 2024 also worsened the selection, registration and verification process for candidate data. recipient scholarship. For overcome problem this, is required system more selection efficient, accurate, and objective. One of approaches that can applied is use network nerve artificial (Artificial Neural Network/ANN) with Backpropagation (BP) algorithm for predict candidate recipient scholarship based on criteria that have been determined. However, BP performance is greatly influenced by the weight frequently initialized start in a way random, which can cause the learning process become slow or trapped in a local.

However a number of study stated in its application Backpropagation algorithm has one of the shortcomings do optimization weight network nerve imitation in avoid the occurrence local minimum, time long training for reach convergence and the process of determining the right parameters (learning rate and momentum) in the training process [3], [8]. Problems This can overcome with optimized use Particle Swarm Optimization (PSO) algorithm which is algorithm simple and reliable optimization for finish problem optimization [8]. algorithm search using Lots individual, or particles, and grouped to in a swarm is understanding from Particle Swarm Optimization (PSO) Where each particle will represent solution candidate For optimization problem [9].

Research using the Particle Swarm Optimization (PSO) model is used for optimizing Backpropagation in get mark weight the ideal. In the research [8]which discusses about particle swarm optimization on improvement prediction with backpropagation method using rapidminer software for data processing using principles and algorithms of data mining [10]. Using the amount of data index development humans, implementation of Backpropagation + particle swarm optimization is better compared to only use Backpropagation implementation.

For increase BP performance, the Particle Swarm Optimization (PSO) method can used for optimize weight beginning. PSO is algorithm optimization based on a population that mimics behavior social flock, such as bird or fish, in look for solution best. With combining PSO and BP, it is expected that the learning process network nerve imitation become more optimal, improve accuracy prediction, and speed up time convergence [11] and PSO is used For solve problem optimization [12]. Therefore that, research This aiming for optimize mark Backpropagation

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weights with Particle Swarm Optimization (PSO) in predict recipient KIP College Scholarship. With approach this, it is expected system selection recipient scholarship become more efficient, precise targets, and transparent, so that can minimize existing inefficiencies in system selection moment this.

2. METHODS

Methodology Chapter study This discuss about the method used in research consisting of from data analysis, particle swarm optimization, kip student data, backpropagation, value accuracy, analysis results processing, compilation report.

Figure 1. Methodology of research

2.1. Literature Study

This method was used to obtain foundational theories as source references for report writing and research development. The approach focused on gathering theoretical data through a literature review and relevant observations. During this stage, references were collected from books, academic journals, and other literature closely related to the research problem [13].

2.2. Data collection

Study this own data source that available from Kaggle that is in the form of recipient data scholarship KIP students- Lecture as training data and test data. From these data before the data is processed, it requires data analysis for get good and clean data. Recipient data scholarship KIP students- Lecture will shared become a number of parts based on weight on the data. Features or indication on the receiver data set scholarship KIP students- Lecture Enough many things this will influence with the amount indications that must be checked when determine recipient scholarship KIP- students who are eligible or No.

2.3. Normalization

Normalization for equalize scale feature input. Where method for change data value to in existing range of 0 and 1 feature said. Data normalization is done with method look for minimum and maximum values moreover formerly as well as difference mark maximum with minimum value of the data [14]. The data normalization process is carried out use equation 1. With use method the can produce mark new range between 0 and 1 [15]. The purpose of normalization in

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PSO-BP is for increase performance and efficiency of prediction models with ensure optimization and learning processes in progress in a way effective, stable and controlled.

2.4. KIP Prediction with PSO-BP

College data that has been normalized furthermore done optimization use Particle Swarm Optimization (PSO) method for optimize mark weight of data before modeled. The purpose of Particle Swarm Optimization is used For solve problem optimization with optimize minimum error value on the network so that got weight network nerves ideal [16]. For find optimal solution, each particle move to direction the best position previous and position best globally [17]. The optimized method This can produce more models accurate [18]. Optimization is a process for to obtain One optimal value with search One or more related solutions with values from One or more function objective on a problem [19]. After the optimization process on the KIP College data use Particle Swarm Optimization (PSO) method, then the data processed with Backpropagation method. The purpose of Backpropagation is For predict recipient KIP scholarship with count mark weight from student data that has been optimized with The Particle Swarm Optimization (PSO) method used For effectiveness time and level high accuracy [20].

This stage using integrated Particle Swarm Optimization (PSO) with Backpropagation (BP) for do KIP College prediction. Backpropagation has point weak that is speed slow convergence consequence from election non - optimal [21], where output and target values are interrelated far apart [22]. This is can cause failure in search optimal [21]. Weaknesses the can overcome with algorithm approach optimization such as Particle Swarm Optimization (PSO) [23]. PSO is used for optimization of parameters in the Backpropagation Neural Network model, which aims for increase accuracy prediction. Particle Swarm Optimization (PSO) is algorithm easy optimization understood, enough simple, and has For work that has been done proven reliable [24]. PSO-Backpropagation is the best model and has performance best with smallest MSE and MAPE values compared only BP and NW-BP [25]. At stage this, the data that has been normalized previously will entered to in the developed model. Stages research conducted in prediction recipient KIP College Scholarship with hybrid Backpropagation and Particle Swarm Optimization divided in a number of stages in the training process and stages in the testing process. Stages in the training process prediction recipient KIP College Scholarship using hybrid network nerve imitation of backpropagation and particle swarm optimization, as shown in Figure 2.

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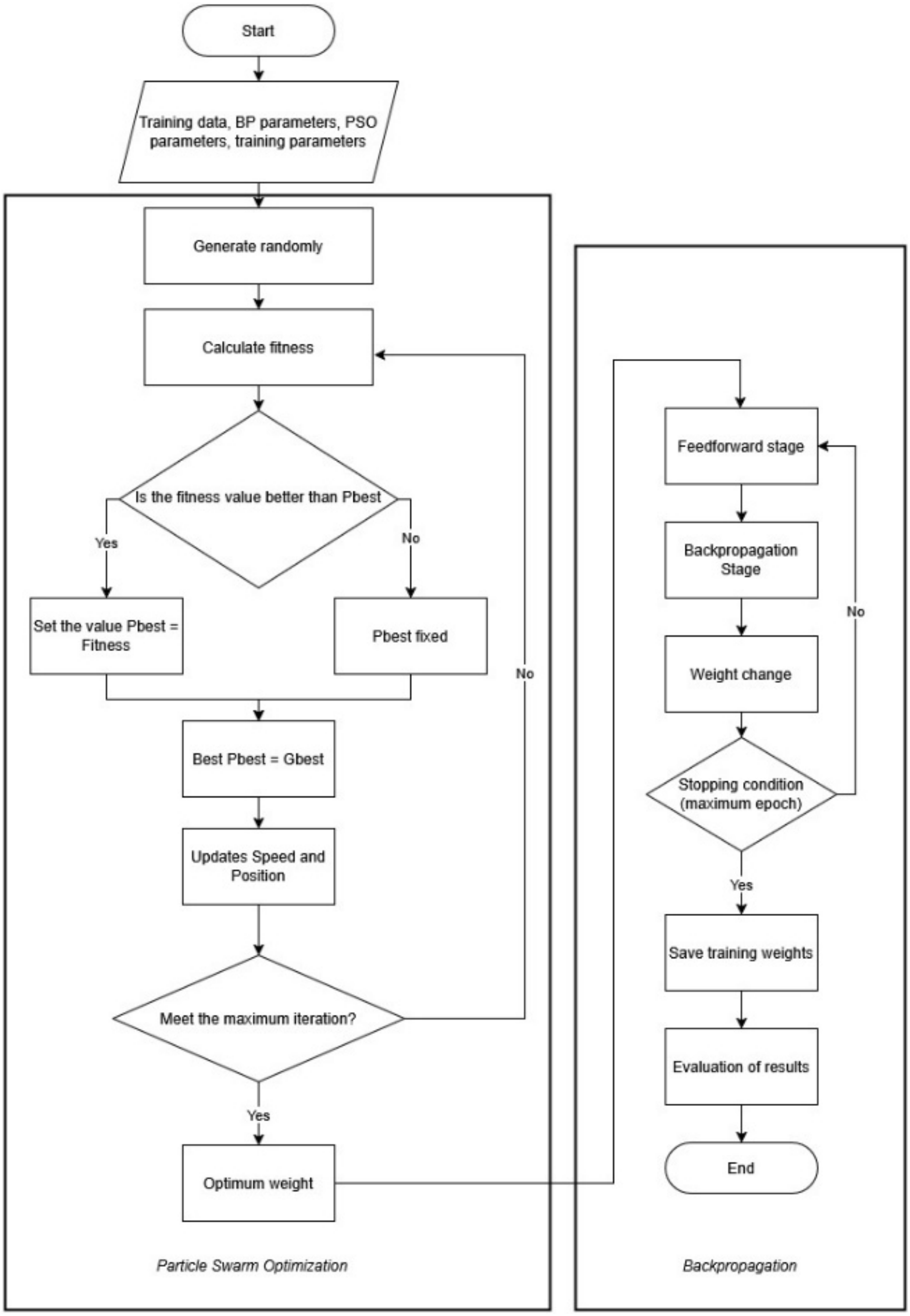

Figure 2. Flowchart of Hybrid PSO and BP KIP Lecture Recipient Prediction Training

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Stages in the testing process prediction recipient KIP college scholarship use network nerve imitation of backpropagation and particle swarm optimization, as shown in Figure 3.

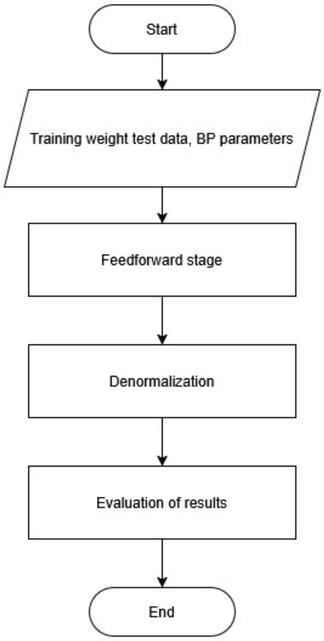

Figure 3. Flow diagram Testing Prediction Hybrid PSO and BP KIP Lecture recipients

2.5. Prediction Analysis

Final result from the process above from student data recipient KIP Scholarship - College will obtained Prediction of the names of students who are eligible and worthy for accept KIP College Scholarship. Prediction student KIP College recipients is a process that aims for manipulate and analyze recipient data KIP College Scholarship with help computer. The data modeling process begins after normalization on recipient data KIP College Scholarship, Optimization Process with particle swarm optimization (PSO) method. Until prediction process is carried out with Backpropagation method. The prediction results obtained will analyzed for get accuracy and speed from the optimization and prediction process. At this stage This analysis count results performance obtained in the form of MAPE and epoc values in the training process and testing process. Percentage error in the results prediction with mark the actual in a way general shown with MAPE [26], [27]. In the study for evaluate performance from various types of prediction models often used MAPE. For count MAPE value with use Equations 1 and 2.

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$$\text{MAPE}= \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t\text{-}\hat{Y}_t|}{Y_t} \tag{1}$$

Information:
n = amount of data
y = mark results current
$\hat{y}$ = mark results prediction

$$\text{MSE}= \frac{1}{n}\sum_{t=1}^{n}(Y_t\text{-}\hat{Y}_t)^2 \tag{2}$$

Information:
n = number of data
yt = value results current
$\hat{y}\ t$ = value results prediction

The more both prediction models used so the smaller MAPE value. After the prediction process done, the results obtained from the PSO-BP model were analyzed. Analysis This usually involving measurement model performance, such as count level accuracy, precision, recall, F1-score, or metric evaluation others. Prediction results can also be compared to with method prediction other for see superiority or PSO-BP shortcomings.

3. RESULTS AND DISCUSSION

3.1. PSO Implementation – BP

The implementation of the Backpropagation Neural Network optimized with Particle Swarm Optimization (PSO) was conducted using the RapidMiner software platform. This software was selected due to its intuitive drag-and-drop interface, support for advanced machine learning algorithms, and seamless integration of various data processing and modeling steps. The goal of this implementation was to enhance the performance of the Backpropagation algorithm by using PSO to optimize weight values during the training phase, thereby increasing model accuracy and minimizing errors.

The process began by launching the RapidMiner application and initializing a new project by selecting the “New Process” workspace. The dataset was then imported using either the Read CSV or Read Excel operators, depending on the file format. The data used for this study was structured in tabular form and included both input features and output labels, suitable for supervised learning tasks. Before building the model, it was essential to ensure the dataset was properly preprocessed. This stage included several key steps such as handling missing values, converting categorical data if necessary, and verifying attribute types. Following that, the dataset was normalized using the Data Normalization operator, which scaled all feature values to a range between 0 and 1. Normalization is a crucial step when

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working with neural networks, as it ensures that features are on a similar scale and prevents the dominance of attributes with larger numeric ranges.

To assess the model's performance reliably, the dataset was split into training and testing sets, with 70% allocated for training and 30% for testing. This division was performed using the Split Data operator, which allows randomized partitioning. A balanced split ensures that the model is trained on a sufficient amount of data while being evaluated objectively on unseen data. The core of the model was built using the Backpropagation algorithm combined with the Optimize Weights (PSO) operator. This combination leverages the strength of neural networks in learning complex patterns and enhances them through global optimization using Particle Swarm Optimization. The PSO algorithm mimics the behavior of a swarm—such as birds flocking or fish schooling—to explore the search space and find optimal weight configurations for the neural network. When executed, this operator iteratively searches for the best weight values that minimize the error function across multiple neural network models.

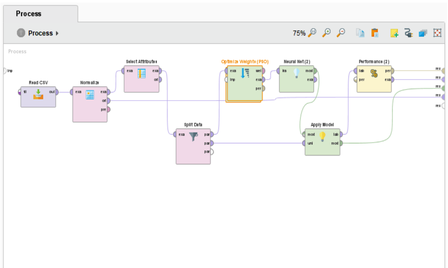

Figure 4. Backpropagation Model with Particle Swarm Optimization

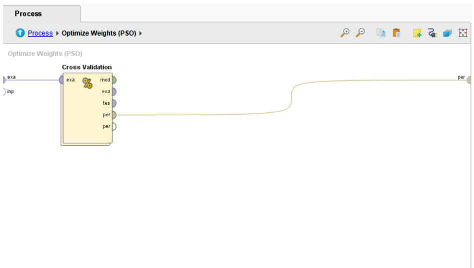

Figure 5. Performance Evaluation Architecture on Optimize Weights (PSO)

As shown in Figure 4, the model architecture included an Optimize Weights (PSO) block that wraps around the neural network and feeds into the X-Validation operator for performance evaluation. By double-clicking the Optimize Weights (PSO) operator, we gain access to the cross-validation architecture, as seen in Figure 5. This design allows the model to be evaluated using k-fold cross-validation, which ensures robust and unbiased performance metrics by rotating training and test data across multiple folds.

Further examination of the X-Validation operator (Figure 6) reveals the use of the Neural Network operator, which builds a feedforward neural network trained using the Backpropagation algorithm. This network was configured with various hyperparameters that play a significant role in the learning process. These include the Training Cycles set to 1000, which defines how many iterations the model goes through during training. The Learning Rate, which controls the step size during

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weight updates, was set to 0.1. Meanwhile, the Momentum, set to 0.2, helps smooth out the updates by including a fraction of the previous weight change, thereby accelerating convergence and avoiding local minima.

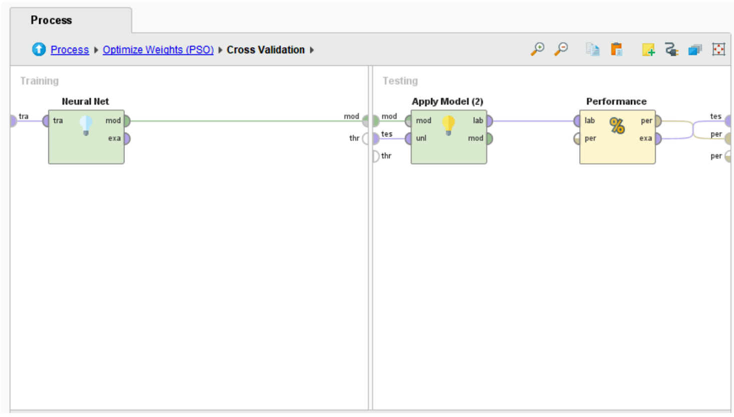

Figure 6. Backpropagation architecture on the x-validation operator

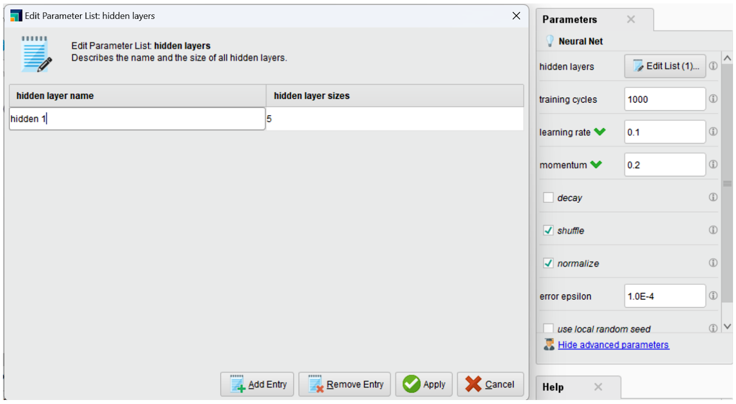

Figure 7. Neural Network Parameters

The architecture also includes the use of hidden layers, which introduce non-linearity into the network and allow the model to learn more complex representations. In this experiment, 1 hidden layer was used, and its size was varied across different configurations using 5, 7, 9, 11, and 13 neurons, as shown in Figure 7. These configurations were tested to identify the architecture that provided the best learning performance. Additional layers could also be added using the Add Entry function within the Neural Network operator's parameter editor.

The full list of parameters used in the Backpropagation neural network with PSO optimization includes as follow.

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1) Input nodes: 2
2) Hidden layers: 1 (with 5, 7, 9, 11, or 13 neurons)
3) Output nodes: 1
4) Training cycles: 1000
5) Learning rate: 0.1
6) Momentum: 0.2
7) Cross-validation folds: 10

Once all parameters were set, the model was executed by clicking the Start button in RapidMiner. The system then initiated the training process, iteratively adjusting the neural network weights using PSO to minimize classification errors. The integration of PSO allowed for global exploration of the weight space, leading to better initialization and overall convergence compared to standard Backpropagation alone. The implementation process successfully demonstrates how hybrid optimization techniques such as combining Backpropagation with Particle Swarm Optimization can be effectively utilized within visual platforms like RapidMiner. This not only enhances model performance but also provides transparency and control in each stage of the machine learning pipeline.

3.2. KIP Prediction with PSO

To evaluate the effectiveness of the Backpropagation algorithm when optimized using Particle Swarm Optimization (PSO), a dataset consisting of 1,000 scholarship recipients of the KIP program was obtained from Kaggle. The dataset was divided into two subsets: 700 records were used as training data and 300 records as testing data. This experiment was designed to identify the most effective neural network structure for predicting scholarship eligibility. To achieve this, five different neural network architectural models were tested, namely: 2-5-1, 2-7-1, 2-9-1, 2-11-1, and 2-13-1. These notations represent the number of neurons in the input layer, hidden layer, and output layer, respectively.

Each of these models was trained using 1,000 training cycles, with a learning rate of 0.1 and a momentum value of 0.2. The performance of each model was measured using the Root Mean Square Error (RMSE) and Squared Error, two standard evaluation metrics used to determine prediction accuracy. The results are summarized in Table 1, which shows that the 2-13-1 architecture yielded the lowest RMSE value of 0.354 ± 0.000 and a squared error of 0.125 ± 0.174. This indicates that this model was the most effective in learning from the training data and making accurate predictions. The highest RMSE was recorded in the 2-9-1 model, which achieved a value of 0.393 ± 0.000, suggesting it was less capable of generalizing patterns from the data. As RMSE measures the average magnitude of the error between predicted and actual values, lower values indicate better model performance.

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Table 1. Root Mean Square Error (RMSE) results with Backpropagation Algorithm

No.	Architectural Model	Training Cycles	Learning Rate	Momentum	RMSE	Squared Error
1	2-5-1	1000	0.1	0.2	0.360 +/- 0.000	0.129 +/- 0.210
2	2-7-1	1000	0.1	0.2	0.367 +/- 0.000	0.135 +/- 0.186
3	2-9-1	1000	0.1	0.2	0.393 +/- 0.000	0.155 +/- 0.262
4	2-11-1	1000	0.1	0.2	0.362 +/- 0.000	0.131 +/- 0.192
5	2-13-1	1000	0.1	0.2	0.354 +/- 0.000	0.125 +/- 0.174

To further assess the impact of PSO in optimizing neural network weights, a comparison was made between models trained using Backpropagation only and those trained using Backpropagation combined with PSO. The results of this comparison are presented in Table 2. It can be observed that, in most cases, the hybrid Backpropagation + PSO approach yielded lower RMSE values compared to Backpropagation alone. For example, in the 2-13-1 model, the RMSE decreased from 0.371 ± 0.000 using Backpropagation alone to 0.354 ± 0.000 with PSO optimization—resulting in an improvement of 0.017. Similarly, in the 2-5-1 model, PSO optimization reduced the RMSE from 0.378 ± 0.000 to 0.360 ± 0.000, an improvement of 0.018.

Table 2. Root Mean Square Error (RMSE) results with Backpropagation Algorithm

No.	Model	Training Cycles	Learning Rate	Momentum	Model	RMSE	Interlude
1	2-5-1	1000	0.1	0.2	BP + PSO	0.360 +/- 0.000	0.018
					BP	0.378 +/- 0.000	
2	2-7-1	1000	0.1	0.2	BP + PSO	0.367 +/- 0.000	0.012
					BP	0.355 +/- 0.000	
3	2-9-1	1000	0.1	0.2	BP + PSO	0.393 +/- 0.000	0.008
					BP	0.385 +/- 0.000	
4	2-11-1	1000	0.1	0.2	BP + PSO	0.362 +/- 0.000	0.002
					BP	0.364 +/- 0.000	
5	2-13-1	1000	0.1	0.2	BP + PSO	0.354 +/- 0.000	0.017
					BP	0.371 +/- 0.000	

However, it is worth noting that in the 2-7-1 architecture, the RMSE slightly increased when using PSO from 0.355 ± 0.000 with Backpropagation alone to

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0.367 ± 0.000 with PSO. This suggests that while PSO generally enhances performance, the effect may vary depending on the architecture and data characteristics. In most cases, however, the inclusion of PSO resulted in consistent improvements, supporting the conclusion that PSO effectively optimizes the initial weight values and accelerates convergence in training.

The experimental results in both Table 1 and Table 2 provide strong evidence that combining Backpropagation with Particle Swarm Optimization improves model accuracy in predicting KIP scholarship recipients. The 2-13-1 architecture emerged as the most effective model, and the integration of PSO contributed to a measurable reduction in prediction error. These findings confirm the potential of hybrid metaheuristic-neural network approaches in solving complex classification problems involving real-world educational data.

3.3. Discussion

The implementation of the Backpropagation Neural Network enhanced with Particle Swarm Optimization (PSO) demonstrates the effectiveness of combining traditional supervised learning techniques with metaheuristic optimization methods. By leveraging the Optimize Weights (PSO) operator within RapidMiner, the training process was guided toward more optimal weight configurations, resulting in better model performance compared to standard Backpropagation alone. This was evident both in the system architecture and in the experimental results across different neural network configurations.

The design of the model allowed for global exploration of the solution space, where PSO played a crucial role in finding a better starting point for training. Unlike traditional Backpropagation, which often suffers from issues such as slow convergence and entrapment in local minima, the swarm-based search mechanism of PSO allows the model to overcome these challenges by adjusting weights based on both individual experience and collective knowledge. This approach led to more stable learning dynamics and improved predictive accuracy, particularly evident in models using a larger number of hidden neurons.

From the comparative analysis in Table 1, it is clear that the architecture with more hidden neurons (specifically the 2-13-1 model) achieved the lowest RMSE of 0.354 ± 0.000 and a squared error of 0.125 ± 0.174. These values indicate that the model was better at minimizing prediction errors and generalizing to unseen data. In contrast, the 2-9-1 model showed the highest RMSE, suggesting that the selection of architectural complexity directly influences model performance. This reflects the importance of not only optimizing training methods but also carefully selecting model architecture for each specific problem domain.

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The findings in Table 2 further support the advantages of PSO in neural network training. In most configurations, integrating PSO led to a measurable reduction in RMSE values compared to Backpropagation alone. For instance, in the 2-5-1 model, the RMSE decreased from 0.378 ± 0.000 to 0.360 ± 0.000, while in the 2-13-1 model, the improvement was from 0.371 ± 0.000 to 0.354 ± 0.000. These improvements demonstrate that PSO successfully complements the gradient descent mechanism by optimizing initial weight values, which leads to a more efficient convergence path during training. Such improvements, although numerically moderate, are statistically meaningful in predictive modeling, especially in sensitive applications like scholarship eligibility classification.

However, it is important to acknowledge that the performance gain from PSO is not universally consistent across all configurations. In the 2-7-1 architecture, for example, the RMSE slightly increased when PSO was applied. This anomaly suggests that the benefits of PSO may be architecture-dependent and that, in some scenarios, standard Backpropagation might be more effective or sufficient. Therefore, selecting the appropriate optimization strategy should be informed by experimentation and empirical validation. Another critical factor contributing to the overall performance was the use of data preprocessing techniques, such as normalization and data splitting. These steps ensured that the model was trained on high-quality input data, which is essential for the effectiveness of both Backpropagation and PSO. The adoption of a 70:30 training-to-testing ratio further ensured that the model was trained on a representative dataset while preserving sufficient test data to evaluate generalization capability.

Collectively, these findings illustrate the value of hybrid models in machine learning workflows. The integration of PSO with Backpropagation not only improved model accuracy but also introduced robustness and adaptability in the learning process. Such hybrid models are especially useful in cases where traditional optimization techniques fall short or where solution landscapes are complex and non-linear. In the context of educational data mining, particularly for tasks like predicting KIP scholarship eligibility, precision in prediction is vital. Misclassification could lead to incorrect allocation of educational resources. Therefore, the observed reduction in RMSE through PSO-enhanced training can translate into more trustworthy and equitable decision-making systems.

This study highlights that the Backpropagation + PSO hybrid model provided notable improvements in prediction performance across various network architectures. While the results support the adoption of PSO in neural network training, they also underscore the importance of architectural tuning and experimental validation. Future research could explore the integration of other metaheuristic algorithms such as Genetic Algorithms or Differential Evolution, and compare their performance against PSO in similar classification tasks.

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4. CONCLUSION

Based on the results of this study, it can be concluded that the Backpropagation algorithm optimized with Particle Swarm Optimization (PSO) performs significantly better than using Backpropagation alone. The experimental results show that the most effective neural network architecture is the 2-13-1 model, which achieved a Root Mean Square Error (RMSE) of 0.371 ± 0.000 with standard Backpropagation, and improved to 0.354 ± 0.000 after applying PSO—resulting in an enhancement of 0.017. These experiments were conducted using RapidMiner software, and the results confirm that a lower RMSE value indicates better model performance. The optimization of weight values using PSO enables the Backpropagation model to learn more efficiently, leading to better accuracy, faster convergence, and more robust predictions. As a result, this optimization technique can contribute to a more accurate, efficient, and transparent scholarship selection system, particularly for the KIP program. By ensuring that scholarship recipients are selected based on data-driven models with higher precision, this approach supports fairer allocation of educational funding, specifically targeting students who truly meet the eligibility criteria. Consequently, the use of Backpropagation + PSO not only improves system performance but also enhances the overall effectiveness and impact of the KIP-K program in expanding access to education for underprivileged communities and ensuring that public funds are utilized optimally in alignment with the program's objectives.

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