Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 9, No. 1, March 2026, pp. 104 – 113
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Comparative Study of PSO-Based Machine Learning Models for Early Warning of Student Failure

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Article Info

Article history:
Received Jan 22th, 2026
Revised Mar 02nd, 2026
Accepted Mar 14th, 2026

Keyword:
Feature Selection
K-Nearest Neighbor
Machine Learning
Neural Network
Particle Swarm Optimization

ABSTRACT

Student academic failure is a critical issue in higher education, as it affects graduation rates and the overall quality of an institution. Early recognition of students at risk is essential to enable timely academic interventions. This study proposes to develop a predictive model to recognition students vulnerable to academic failure using machine learning techniques. A dataset collected from the UCI Machine Learning Repository was used in this study and includes students' demographic, socio-economic, and academic attributes. This study applies Particle Swarm Optimization integrated with Mutual Information (PSO-MI) as a feature selection method. It compares the performance of K-Nearest Neighbor (K-NN) and Neural Network (NN) classification algorithms. The feature selection process identified 12 relevant features related to students' academic performance and administrative information. Model performance was assessed using two validation approaches, namely split validation with an 80:20 ratio and k-fold cross-validation, and performance was assessed using precision, recall, and F1 Score metrics. The experimental evaluation reveal that the Neural Network model with PSO-MI-based feature selection consistently outperformed theK-NN model under both validation schemes. In the cross-validation experiment, the Neural Network model achieved an accuracy of 0.91, a precision of 0.91, a recall of 0.89, and an F1-score of 0.90, indicating better performance in identifying students at risk of dropout. The findings reveal the effectiveness of integrating PSO-based feature selection with Neural Network classification offers a promising approach to predicting academic failure. The proposed framework can support the development of early detection systems to help educational institutions recognition at-risk students and implement timely academic interventions.

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DOI: http://dx.doi.org/10.24014/ijaidm.v9i1.39201

1. INTRODUCTION

The increasing rate of academic failure has become a significant concern in higher education institutions worldwide. This issue affects not only students' academic progress and future opportunities but also the institution's performance and reputation. Various academic, social, and economic factors contribute to students' difficulties in achieving academic success. Not all students can complete their studies within the expected time frame. Therefore, early prediction of student academic performance is essential to prevent potential academic failure. Academic performance is also closely associated with institutional accreditation and overall educational quality. Universities face ongoing challenges in identifying effective strategies to ensure that students graduate as competent individuals within the designated study period. As student is affected by both academic and non-academic factors, early detection of students at risk plays an important role in reducing failure rates [1].

Therefore, higher education institutions must develop reliable systems for predicting student performance as an early intervention strategy to prevent academic failure. Such systems can assist institutions in improving learning of learning processes and making more informed decisions. One commonly used approach for analyzing educational data is Educational Data Mining (EDM), which utilizes data mining techniques to uncover meaningful patterns within educational datasets for informed decision-making [2]. Student academic records, including examination scores, demographic information, and attendance data, provide valuable inputs for implementing EDM to predict academic performance and identify students with potential academic failure risk [3].

A considerable number of previous research has examined the implementation of machine learning approaches to predict student academic outcomes and identify potential dropout risks. Previous studies have evaluated several classification algorithms, such as Decision Tree, Naive Bayes, Random Forest, Logistic Regression, Support Vector Machine, and Neural Network, to identify the most accurate predictive model [4], [1], [5], [6], [7], [8]. While these approaches report promising results, the comparisons are often conducted among algorithms with similar learning characteristics or within conventional evaluation settings. In addition, model evaluation in several studies remains primarily centered on accuracy as the main performance metric [1], which may not fully capture predictive robustness on imbalanced educational datasets.

Several studies have attempted to improve prediction performance through optimization techniques. One commonly used approach is Particle Swarm Optimization (PSO), which has been incorporated into student performance prediction models, for purposes such as feature selection and hyperparameter tuning [4][9]. However, in many cases, PSO is primarily employed to optimize individual classifiers or ensemble weights rather than to construct a systematic feature selection framework within a broader comparative paradigm study. As a result, the use of PSO as an integrated component in a unified experimental setting remains relatively limited.

In terms of validation strategies, most existing studies rely on a single evaluation scheme, predominantly k-fold cross-validation, which provides reliable performance estimation. Limited attention has been given to evaluating model stability under multiple validation approaches within the same study. In addition, several studies focus on improving or evaluating a single classification algorithm without conducting broader comparative analyses across fundamentally different learning paradigms [10], [9], [11], [12]. While these approaches may achieve competitive performance, they provide limited insight into how different modeling paradigms behave under consistent experimental conditions.

Despite these advancements, comprehensive comparative investigations involving fundamentally different learning paradigms, such as distance-based methods like K-Nearest Neighbor and model-based approaches like Neural Network, are still limited. This limitation is especially evident in studies that integrate PSO-based feature selection, multiple evaluation metrics, and multiple validation schemes within a single experimental framework. Therefore, a more structured and comprehensive evaluation approach is needed for predicting academic failure.

To address this gap, this study compares K-Nearest Neighbor (K-NN) and Neural Network (NN) models under a unified experimental setting. PSO-based feature selection is applied, with Mutual Information serving as the fitness function to determine the optimal subset of features before classification. The performance of the models is measured using multiple metrics, including accuracy, precision, recall, and F1-score, under both split-validation and cross-validation schemes. This proposed framework is designed to provide a more reliable, stable, and comprehensive evaluation to identify at-risk students at an early stage of academic failure.

2. RESEARCH METHOD

This study compares K-Nearest Neighbors (K-NN) and Neural Network (NN) algorithms, combined with Particle Swarm Optimization (PSO), for feature selection to predict student academic failure. The research procedure comprises data collection, data preprocessing, PSO-based feature selection, data splitting, classification algorithm implementation, and model performance evaluation, as illustrated in Figure 1.

2.1. Data Collection

The dataset employed in this study was retrieved from the UCI Machine Learning Repository, titled “Predict Students Dropout and Academic Success,” developed by Martins et al. [5]. In the educational context, Educational Data Mining (EDM) can be defined as the application of traditional data processing and analysis techniques to educational data to obtain meaningful insights for solving educational problems [13]. The knowledge derived from such data processing can be utilized for various purposes, including validating and evaluating educational systems, improving the quality of learning processes, and developing learning strategies that align with students' needs and capabilities [14]. The dataset consists of 4,424 instances with 37 input features and one target variable. Among these features, 19 are categorical, and 18 are numerical. The original dataset contains three class labels: dropout, enrolled, and graduate. However, in this study, only two classes (dropout and graduate) were considered for the binary classification of students' academic status.

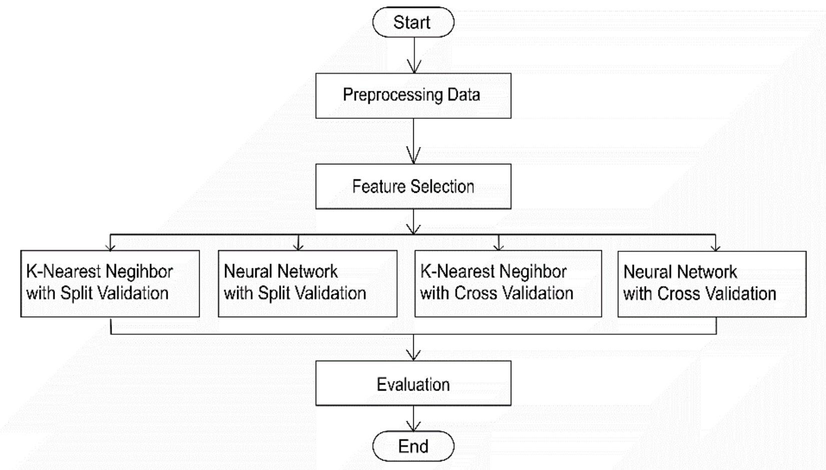

Figure 1. Research Methodology Framework

2.2. Data Pre-processing

Data preprocessing was conducted before feature selection to ensure data consistency and compatibility with the modeling process. The dataset was filtered to focus on two primary classes: graduate and dropout. The dataset was examined for missing values, and no case were detected. Categorical variables were converted using Label Encoding to transform non-numeric attributes into numerical representations suitable for classification models. Numerical features were standardized using the StandardScaler method before model training to ensure comparable feature scales across variables. No resampling technique was applied to address class imbalance. The processed dataset was subsequently used for feature selection and model training.

2.3. Feature Selection using PSO

Feature selection in this study was performed using a Particle Swarm Optimization (PSO) approach with Mutual Information (MI) employed as the fitness function to evaluate feature relevance. Recent studies indicate that PSO remains a competitive optimization method due to its ability to achieve fast convergence with relatively few parameters compared with alternative algorithms such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO) [15]. Furthermore, various follow-up studies have developed PSO variants that demonstrate improved accuracy, stability, and efficiency across different domains, including academic prediction and machine learning modeling [16]. Through this process, the most relevant features influencing the target variable are identified, allowing the classification models to achieve improved performance with a reduced feature set.

The main PSO parameters used in this study were 5 particles and 5 iterations. The inertia weight (w) was set to 0.72, while the cognitive (c1) and social (c2) coefficients were both set to 1.49. A relatively small number of particles and iterations were selected to maintain computational efficiency while ensuring convergence during the optimization process. Each particle was defined using a binary vector, where 1 represents a selected feature and 0 indicates an excluded feature. The initial positions and velocities of the particles were generated randomly and subsequently updated at each iteration based on the fitness evaluation results.

The dependency of each selected feature on the target variable was measured using Mutual Information (MI) to determine the fitness value. Particle positions were updated in accordance with the personal best (pbest) and global best (gbest) solutions using a sigmoid function. This iterative process produced an optimal subset of features with the optimal fitness value. From the initial set of 36 features, PSO selected 12 optimal features. The selected features were subsequently applied in the classification stage using the K-Nearest Neighbor (K-NN) and Neural Network (NN).

2.4. Data Splitting

After feature selection, the data were split into two subsets for training and testing to develop and evaluate the model. Two data splitting strategies were employed in this study. In the split-validation approach, 80% of the data was used for training, while the remaining 20% was used for testing. Data separation was conducted using the train_test_split function from the scikit-learn library, by setting a fixed random_state to ensure reproducibility of the experimental results.

The second strategy was k-fold cross-validation with k = 5. In this approach, the dataset was partitioned into five subsets while maintaining a balanced class distribution between the dropout and graduate categories. During each iteration, four subsets were utilized for training and the other subset was utilized for testing. The procedure was executed until every subset was allocated to the testing set. A stratified cross-validation scheme was adopted to preserve the original class proportions in each fold, given that the dataset was not perfectly balanced. This strategy enables a more representative and unbiased evaluation of model performance.

2.5. Application of Classification Algorithms

The next stage involved comparing two classification algorithms to evaluate their performance in predicting the risk of student academic failure, namely K-NN and NN. K-NN was selected to represent a distance-based lazy learning algorithm that performs classification based on similarity between instances [17], while a neural network was employed as a model-based learner capable of capturing complex nonlinear patterns in educational datasets [18]. Comparing these two algorithms enables the study to analyze the performance differences between instance-based and model-based learning approaches in predicting academic failure. Both models were evaluated using two validation schemes: split validation with an 80:20 training-testing ratio and stratified k-fold cross-validation with k = 5.

In the split-validation scheme, the K-NN model was configured with k = 5 nearest neighbors, and the Euclidean distance was used to measure similarity between instances. The model was first trained on the training dataset and then assessed on the testing dataset to measure accuracy and other performance metrics. The Neural Network model was implemented using a Multilayer Perceptron (MLPClassifier) with a single hidden layer consisting of 100 neurons, a logistic sigmoid activation function, and a maximum of 500 training iterations. These parameter settings were selected to balance model complexity and training stability.

In the stratified k-fold cross-validation scheme, the dataset was split into five folds, and the training and testing process was repeated five times. In every iteration, four folds were used for training, and the remaining fold was allocated for testing. This procedure was applied to both the K-NN and Neural Network models, with performance metrics recorded for each fold. The final model's performance was determined by averaging the accuracy across all folds.

The evaluation result obtained using the k-fold cross-validation approach is more stable, as each data instance has the opportunity to be used as both training and testing data. Consequently, this approach enables a fair comparison of the two algorithms by assessing their consistency in performance across all validation folds.

2.6. Model Evaluation

At this stage, the performance of the applied classification algorithms was evaluated. Four primary evaluation metrics were used to assess the performance of the K-NN and Neural Network models. The metrics were computed using the classification_report function from the scikit-learn library, which provides a detailed comparison of model predictions against the actual class labels. The results from each validation scheme were subsequently analyzed to identify the model that produced the best overall performance.

The evaluation process was conducted after model training using two validation strategies: split validation and stratified k-fold cross-validation. In the split validation scheme, 80% of the dataset was used for training and the remaining 20% for testing. In contrast, the stratified k-fold cross-validation scheme distributed the dataset into five folds, ensuring balanced class distributions during both training and testing. This evaluation strategy enables a more reliable assessment of the model’s predictive performance across different data partitions.

3. RESULTS AND ANALYSIS

3.1. Data Preprocessing Result

The dataset used in this study was retrieved from the UCI Machine Learning Repository, titled "Predict Students' Dropout and Academic Success". The dataset consists of three target classes, namely dropout, enrolled, and graduate, with a total of 18 categorical features, 18 numerical features, and one target variable. It contains information on students’ demographic, socioeconomic, and academic performance characteristics.

Demographic features describe students' personal attributes, including gender, age at enrollment, marital status, and nationality. Socio-economic features are associated with students' financial and administrative conditions, registration status, such as course type, previous qualifications, scholarship status, tuition fee payment status, debtor status, educational special needs, and indicators of economic hardship. Academic performance features from the first and second semesters are numerical variables that describe students' academic activities, learning outcomes, and progress during their studies. These features include the number of enrolled courses, credit load, number of evaluations, grade point average, and the number of courses completed or not evaluated. Table 1 summarizes the dataset attributes implemented in this study.

Table 1. The original dataset used in this study

Marital Status	Application Mode	Application Order	Previous Qualification	Course	…	Curricular Units 2nd Semester	Label
1	17	5	1	171	….	0	Dropout
1	15	1	1	9254	….	0	Graduate
1	1	5	1	9070	….	0	Dropout
2	17	2	1	9773	….	0	Graduate

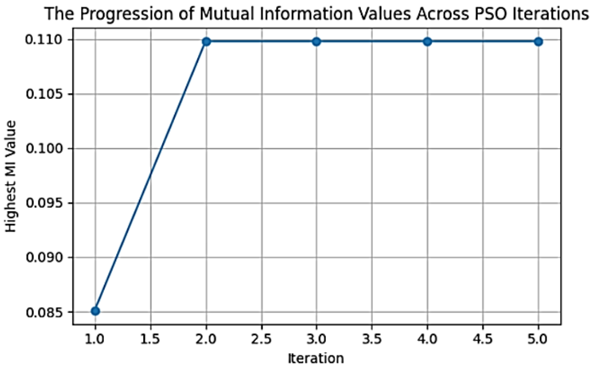

Figure 2. The Progression of Mutual Information Values Across PSO Iterations

In this study, data cleaning was conducted by filtering the dataset and removing instances with the target label enrolled, allowing the analysis to focus on students who completed their studies (graduate) and those who did not (dropout). This step ensured that the classification task was formulated as a binary prediction problem aligned with the research objective.

Subsequently, all categorical features were encoded as numerical values using label encoding. Through this process, the target labels were encoded into binary values, with dropout represented as 0 and graduate represented as 1. This transformation enabled the dataset to be processed effectively by the classification algorithms. After converting categorical attributes into numerical form, feature normalization was applied to ensure that all variables were represented on a comparable scale. This step is especially important for distance-based and gradient-based learning algorithms because it reduces the dominance of features with larger numerical scales from dominating the training process [19].

3.2. Feature Selection Results

Feature selection in this study was coducted using Particle Swarm Optimization (PSO) integrated with Mutual Information (MI). Mutual Information values were used to identify features most relevant to the target label, to improve prediction accuracy by retaining only informative features. The feature selection process began by defining the main PSO parameters, namely the number of particles and the number of iterations. In this experiment, PSO was configured with 5 particles and executed for 5 iterations. Each particle was represented as a binary vector, where the value of each particle was computed as the average Mutual Information score of the selected features.

During the optimization process, particle positions were updated iteratively based on the individual best solution (personal best) and the global best solution of the swarm (global best). This iterative mechanism enabled the algorithm to converge toward an optimal subset of features with the highest MI value, which was subsequently used in the classification stage [20][21]. The final output of the PSO-MI feature selection process was an optimal subset of features, which was subsequently used in the classification modeling stage, employing the K-NN and Neural Network algorithms. To analyze the behavior of the process of selecting relevant features, the progression of Mutual Information (MI) values across PSO iterations is presented in Figure 2.

Figure 2 illustrates the progression of Mutual Information (MI) values across PSO iterations. As shown in the figure, the MI value increased to 0.1098 in the second iteration, then remained stable through the fifth iteration. This behavior indicates that the PSO algorithm converged early, with particle movements converging toward the same solution, and no feature subset with a higher MI value was identified. Consequently, the selected features at this iteration were deemed the most informative combination and served as the basis for subsequent modeling. To further analyze the behavior of the PSO-MI feature selection process, the number of features selected across iterations is shown in Figure 3.

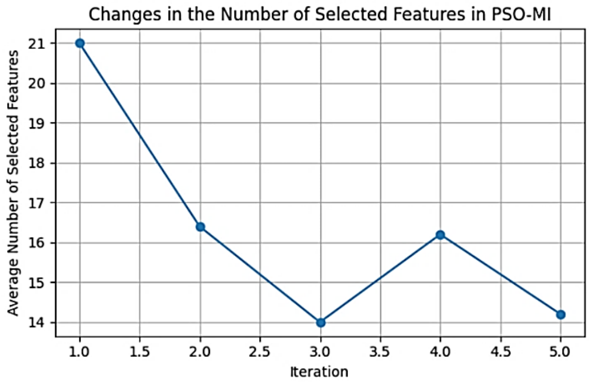

Figure 3. Changes in the Number of Features Selected in PSO-MI

Figure 3 presents the variation in the number of selected features during the PSO-MI optimization process. The average number of selected features changed across iterations, with a relatively larger number of features selected in the initial iteration. In contrast, the number of selected features tended to decrease in the third and fifth iterations. This pattern indicates that PSO effectively balances between maximizing MI values and minimizing the number of selected features. Ultimately, the PSO-MI approach selected 12 features that contributed most significantly to the target variable, thereby aligning with the goal of identifying an informative yet efficient feature subset.

3.3. Classification Modeling Results

After the PSO-MI feature selection stage, the optimal subset of features was used in the classification modeling process. The final selected features consisted of application order, previous qualification, tuition fees up to date, scholarship holder, age at enrollment, curricular units 1st semester (enrolled), curricular units 1st semester (approved), curricular units 1st semester (grade), curricular units 2nd semester (credited), curricular units 2nd semester (approved), curricular units 2nd semester (grade), and curricular units 2nd semester (withoud evaluations). Both K-NN and Neural Network models were evaluated using two validation schemes: stratified 5-fold cross-validation and an 80:20 split validation. Consequently, four experimental scenarios were conducted in this study:

1. K-NN with 5-fold cross-validation
2. Neural Network with 5-fold cross-validation
3. Neural Network with split validation, and
4. K-NN with split validation.

Model performance was evaluated using four evaluation metrics to distinguish between the dropout and graduate classes.

Table 2. The Classification Result of the K-NN Model using 5-Fold Cross Validation

Label	Precision	Recall	F1-Score	Support
Dropout	0.91	0.80	0.85	1421
Graduate	0.88	0.95	0.91	2209
Accuracy			0.89	3630

Table 2 illustrates the classification results of the K-NN model evaluated using 5-fold cross-validation. The analysis results indicate stable performance across all folds, achieving a mean accuracy of 0.8926. The results demonstrate that the K-NN model achieves a satisfactory classification performance after the PSO-based feature selection process.

Based on the aggregated classification report across all folds, the dropout class achieved a precision score of 0.91, a recall of 0.80, and an F1 Score of 0.85 on 1421 samples. Meanwhile, the graduate class achieved a precision of 0.88, indicating that the K-NN model tends to detect graduating students more accurately than students who fail academically.

Table 3. The Classification Result of the Neural Network Model Evaluated using 5-Fold Cross Validation

Label	Precision	Recall	F1-Score	Support
Dropout	0.92	0.83	0.87	1421
Graduate	0.90	0.96	0.93	2209
Accuracy			0.91	3630

Table 3 illustrates the neural network model's prediction results, assessed using 5-fold cross-validation. Compared to K-NN, the Neural Network reached the highest average accuracy of 0.9069, the highest among all experimental scenarios in this study.

The classification report shows that the Neural Network achieved a precision of 0.92, a recall of 0.83, and an F1 Score of 0.96 on 2209 samples for the dropout class. The overall accuracy reached 0.91, indicating a consistent improvement over the K-NN model. Both the micro-average and weighted-average values ranged between 0.90 and 0.91, demonstrating the Neural Network model’s performance to capture complex data patterns more effectively. The high recall value for the graduate class further indicates that the Neural Network is particularly effective in recognizing students who complete their studies successfully.

Table 4. Classification Report of the K-NN Model Based on Split Validation

Label	Precision	Recall	F1-Score	Support
Dropout	0.93	0.79	0.85	284
Graduate	0.87	0.96	0.91	442
Accuracy			0.89	726

The next experimental scenario used split validation with an 80:20 training-to-testing ratio, employing stratified sampling to maintain class proportions. Table 4 illustrates the classification effectiveness of the K-NN model under this validation scheme. The K-NN model achieved an accuracy of 0.8912. For the dropout class, the model achieved precision of 0.93 and recall of 0.79, while for the graduate class, it achieved precision and recall of 0.87 and 0.96, respectively. The corresponding F-scores were 0.85 for the dropout class and 0.91 for the graduate class. The macro-average and weighted-average values ranged from 0.88 and 0.89, indicating that the K-NN model maintained stable performance despite a slight class imbalance in the dataset.

Table 5. Classification Report of the NN Model with Split Validation

Label	Precision	Recall	F1-Score	Support
Dropout	0.92	0.84	0.88	284
Graduate	0.90	0.95	0.93	442
Accuracy			0.91	726

Table 5 shows the classification result of the Neural Network model assessed using split validation. The Neural Network reached an accuracy of 0.9091, outperforming the K-NN model under the same validation scheme. For the dropout class, the model recorded a precision of 0.92 and a recall of 0.84, in the graduate class, the precision and recall were 0.90 and 0.95, respectively. The resulting F1-scores were 0.88 for the dropout class and 0.93 for the graduate class. Both macro-average and weighted-average values were between 0.90 and 0.91, indicating that the Neural Network model demonstrated robust, consistent performance on unseen test data generated via random data splitting.

Across all experimental scenarios, the evaluation results indicate that the Neural Network model consistently outperformed the K-NN algorithm under both validation schemes, namely split validation and stratified cross-validation. This performance gap may be due to several key factors, including model characteristics, generalization capability, and the nature of the features selected using PSO.

The features selected by the PSO-MI method, such as the number of enrolled courses, approved courses, semester grades, and administrative variables, exhibit interdependent relationships rather than acting as independent predictors. Neural Network are capable of capturing such complex relationships through hidden layer representations and nonlinear activation functions. In contrast, K-NN relies solely on distance-based similarity, which limits its flexibility when feature interactions do not form clearly separable clusters in the feature space.

The difference between the two models becomes more evident when analyzing performance on the dropout class. Although feature normalization was applied, K-NN remains sensitive to the data distribution and the dominance of the majority class. Although K-NN is easy to implement and can produce satisfactory results on large datasets, it has limitations in computational efficiency because it requires distance calculations against all training instances, and it is also sensitive to irrelevant features and noise [22]. Given that the number of graduate instances exceeds that of dropout instances, K-NN often exhibits bias toward the dominant class, resulting in lower recall for the dropout class. This indicates that a substantial portion of dropout cases are misclassified as graduates. Neural Networks, on the other hand, mitigate this issue by iteratively adjusting weights during training, allowing the model to assign more balanced importance to both classes and improve recognition of students likely to experience academic failure.

Furthermore, the use of stratified cross-validation highlights the superior stability of the Neural Network model. Its performance remains relatively consistent across different folds, indicating strong generalization capability despite variations in data composition. In comparison, the K-NN algorithm exhibits higher variability, as it does not involve an explicit learning process and instead depends directly on the structure of the training data. When combined with the multidimensional feature subset selected by PSO, Neural Networks can exploit the available information more effectively. Overall, these findings suggest that Neural Networks achieve higher accuracy, greater stability, and better suitability for predicting the risk of academic failure in the given dataset.

From a practical perspective, the results of this research provide important consequences for educational institutions. The superior performance and stability of the Neural Network model indicate that machine-learning-based early-warning systems can be utilized to identify students at risk of academic failure at an early phase. By utilizing such predictive models, universities can design targeted academic interventions, such as mentoring programs, academic counseling, or personalized educational support to improve students' academic achievement and reduce dropout rates.

These findings are in line with several previous studies that reported the effectiveness of Neural Networks in capturing complex patterns in educational datasets. For instance, Martins et al. [5] and Suleyman et al. [8] also found that Neural Network models achieved competitive performance in predicting student outcomes. The ability of Neural Networks to model nonlinear relationships enables them to better capture interactions among demographic, academic, and socioeconomic variables compared to distance-based algorithms such as K-NN. These results further demonstrate the effectiveness of Neural Network-based methods in academic performance prediction, particularly when the dataset includes complex, interdependent features.

Table 6. Comparison of Accuracy, Precision, Recall, and F1-Score across Experimental Scenarios

Experimental Scenario	Model	Accuracy	Precision	Recall	F1-Score
Split Validation (80:20)	K-NN	0.89	0.90	0.87	0.88
Split Validation (80:20)	NN	0.91	0.91	0.90	0.90
5-Fold Cross Validation	K-NN	0.89	0.90	0.88	0.88
5-Fold Cross Validation	NN	0.91	0.91	0.89	0.90

Table 6 summarizes the performance comparison of the Neural Network and K-Nearest Neighbor models across all experimental scenarios. The results imply that the NN consistently provides better, more stable performance under both split-validation and cross-validation schemes. The accuracy, precision, recall, and F1-score metrics of the NN model are consistently higher than those of K-NN, reflecting stronger generalization and a more balanced sensitivity across both classes. Although the K-NN model also demonstrates satisfactory performance, it is more sensitive to variations in data distribution, resulting in slightly lower consistency than the NN model.

4. CONCLUSION

This study assessed the performance of machine learning approaches for predicting students' graduation status (dropout and graduate) by integrating Particle Swarm Optimization (PSO) in feature selection with two classification algorithms: K-Nearest Neighbor (K-NN) and Neural Network (NN). The experimental results demonstrate that PSO-based feature selection effectively identified the most informative features, particularly those related to early academic performance and student administrative records. These findings indicate that early academic indicators play a critical role in detecting students with a high risk of academic failure. The experiment also found that the Neural Network model consistently outperformed the K-NN algorithm under both split-validation and stratified k-fold cross-validation schemes. NN achieved higher accuracy, precision, recall, and F1-score, particularly for detecting dropout cases, which are generally more difficult to detect. This suggests that Neural Networks are more effective at capturing complex relationships among student-related features than distance-based methods such as K-NN.

Overall, this research demonstrates that combining PSO-based feature selection with neural network classification provides a promising approach for predicting student academic failure. Such predictive models have the potential to support higher education institutions in implementing early warning systems that identify students at risk and provide timely academic support. For future research, several directions can be explored to further improve model performance and practical implementation. Future studies may investigate more advanced Neural Network architectures or ensemble learning methods. In addition, applying data imbalance handling techniques, such as SMOTE, may improve the detection of at-risk students. Finally, implementing the proposed model in a real-world early warning system could help educational institutions deliver more effective, timely academic interventions.

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