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K-Nearest Neighbors Optimization using Particle Swarm Optimization in Selection Digital Payments

RIDWANSYAH[1], RESTI LIA ANDHARSAPUTRI[2], YUDHISTIRA[3], IRMAWATI CAROLINA[4], SUHARJANTI[5]

[1,2,3,4,5]Universitas Bina Sarana Informatika, Jakarta, Indonesia

CORRESPONDING AUTHOR: RIDWANSYAH (ridwansyah.rid@bsi.ac.id)

ABSTRACT Fintech developments have increased the use of digital payment systems such as OVO and GoPay. However, selecting a payment method that suits user preferences is still a challenge. This research proposes a combination of K-Nearest Neighbors (KNN) and Particle Swarm Optimization (PSO) to improve the classification accuracy of digital payment systems. The dataset used comes from a survey of Fintech users with factors such as ease of application, data security, cashback and customer service. KNN is used as a classification method, while PSO is applied for feature selection to improve model efficiency. Evaluation is carried out using accuracy, precision, recall, and AUC. The research results show that accuracy increased from 94.00% to 95.47% after optimization with PSO. The most influential factors are customer service, user employment and cashback. However, the AUC value remains 0.500, which shows that the model still has limitations in optimally differentiating categories. Further research is recommended to explore other algorithms such as Random Forest and SVM, as well as developing a machine learning-based digital payment recommendation system.

KEYWORDS: Digital Payments, Fintech, KNN, PSO.

I.INTRODUCTION

The development of information technology has brought significant changes in various aspects of life, including digital payment systems [1]. This advancement allows transactions to be carried out more quickly, safely and efficiently compared to conventional payment methods. The phenomenon of shifting from cash to non-cash transactions is increasing along with the adoption of Financial Technology (Fintech) services that offer convenience in digital payments, such as e-wallets and mobile banking [2]. The rapid growth of Fintech services is driven by the increasing need of users for convenience and speed in digital transactions [3]. However, this growth also presents various challenges in optimizing digital payment systems, especially in increasing the accuracy of selecting payment methods that best suit user needs [4].

One of the main challenges in digital payment systems is how to increase the accuracy of classification and recommendation of optimal payment methods [5]. Factors such as data security, convenience, transaction speed, as well as incentives in the form of cashback and discounts are the main considerations for users when choosing digital payment services [6]. Therefore, an optimization method is needed that is able to increase accuracy in the classification and recommendation of digital payment systems [7].

Various previous studies have been carried out to improve classification accuracy in digital payment systems. Previous research used various classification methods such as Naïve Bayes Classifier [8], K-Nearest Neighbors (KNN) [9], and Support Vector Machine [10]. However, most of these studies focus on text mining or sentiment analysis [11]. Meanwhile, research in the field of data mining has been carried out using classification algorithms such as Decision Tree (C4.5) to measure accuracy and Particle Swarm Optimization (PSO) to increase accuracy in selecting digital payment systems [12]. However, this method still has limitations in processing complex data and searching for optimal parameters. To overcome these limitations, this research proposes a combination of the KNN algorithm with PSO to improve classification performance in digital payment systems.

The KNN algorithm is known as a simple but effective classification method, especially in processing data that does not have certain distribution assumptions [13]. KNN works by comparing the distance between the data being tested and data that has been previously classified, so that it can provide predictions based on similar characteristics [14]. Meanwhile, PSO is a metaheuristic-based optimization algorithm that is able to find optimal parameters in a classification model with fast and stable convergence [15]. PSO works by adjusting the position of particles in a search space to find the best solution based on individual and group experience [16].

This research aims to optimize the digital payment system by implementing a combination of the KNN and PSO algorithms in the classification process. The proposed approach will identify important attributes in the selection of digital payment services and increase accuracy in optimal payment system recommendations. The main contribution of this research is to develop a KNN-based classification model that is optimized using PSO to improve accuracy in selecting digital payment methods and identify the main factors that influence user preferences in choosing digital payment services.

It is hoped that the results of this research can contribute to the development of a more accurate and efficient digital payment system, as well as support innovation in the Fintech sector to improve the user experience in digital transactions.

II.METHOD

This research focuses on analyzing the performance of the KNN algorithm which has been proven effective in classification tasks and improving its performance through the application of the PSO algorithm with data on Fintech determinations in the form of service applications found on Ovo or Gopay. Each stage in this research includes steps that are systematically designed to achieve the research objectives. In order for the research process to run optimally, a structured and methodological approach is needed. The series of stages in this research can be represented visually through the research flow diagram shown in Figure 1.

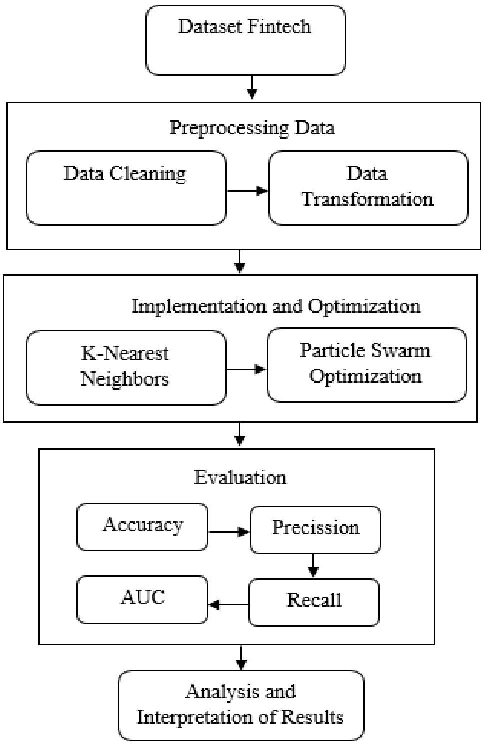

FIGURE 1. Research Flow Diagram

In Figure 1, it is explained that the fintech dataset used in this research consists of digital money users who utilize Ovo and GoPay payment services. Data was collected from various respondent sources using a questionnaire method, including direct surveys of digital payment service users. The questionnaire was designed in the form of a comparison of the advantages between the Ovo and GoPay applications, taking into account various main attributes such as ease of use of the application, data security, and the quality of customer service in handling complaints.

After the data has been successfully collected, the next stage is data preprocessing, which aims to improve the quality of the data before it is used in the model training and testing process. This preprocessing stage includes several important steps, including data cleaning to remove invalid or missing values, normalization so that the data scale is more uniform, and feature selection to select the most relevant and influential attributes in classification analysis. With preprocessing, data quality becomes more optimal so that it can improve the performance of the model to be applied.

After completing the data preprocessing stage, the next step involves implementing the K-Nearest Neighbor (KNN) algorithm for classification of digital payment preferences. KNN is a non-parametric, instance-based learning algorithm that classifies a new data point such as a user's preference for OVO or GoPay based on the majority label of its 'k' nearest neighbors in the feature space. In this research, the proximity between users is calculated using a distance metric, typically the Euclidean distance, which measures the similarity based on selected attributes like application usability, transaction speed, and customer service satisfaction. Choosing an appropriate value of 'k' is critical, as a small 'k' may be overly sensitive to individual variations, while a large 'k' could obscure meaningful user preference patterns in digital payment behavior [17]. However, to increase the effectiveness of the KNN model, optimization was carried out using the PSO method [18].

This PSO method mimics the behavior of a collection of particles that dynamically adapt to find the best combination of parameters with each particle in the PSO updating its position based on its own best experience as well as information from other particles in the population [19]. In this context, PSO is utilized to optimize the hyperparameters of the KNN model, primarily focusing on: The optimal value of 'k' and The selection of appropriate features to be included in the distance calculation. In the PSO process, each particle represents a potential solution a specific combination of hyperparameters (e.g., a certain value of 'k' and a subset of features). Each particle moves through the search space by adjusting its position according to two main factors Personal Best (pBest) Pbest and Global Best (gBest).

After the KNN model has been optimized using PSO, an evaluation process is carried out to measure its performance in classifying data. The assessment is carried out by observing the level of prediction accuracy and the balance between positive and negative errors in classification [20]. Some of the indicators used include how accurate the model is in recognizing each category, the extent to which the model is able to identify the correct class without many errors, and the level of balance between success in detecting positive and negative classes.

It is hoped that KNN optimization with PSO can increase the accuracy and stability of the model in classifying digital transaction patterns. PSO allows adaptive selection of optimal parameters, so that the model is more efficient than conventional approaches and to what extent PSO optimization contributes to improving classification performance and whether this method is superior to KNN without optimization.

III.RESULT AND DISCUSSION

The dataset used in this research is the result of a survey of Fintech service users, especially OVO and GoPay. This dataset covers various important aspects that influence users' decisions in choosing digital payment services. The factors are collected in the dataset in Table 1.

TABLE 1. KEY ATTRIBUTES

Variable	Value
Gender	M: Male; F: Female.
Job Category	Self-employed; Civil Servant; Laborer; Student; Private sector employee.
Ease of Application	Yes; No.
Data Security	Safe; Not safe.
Trust in Comfort	Yes; No.
Increase Maximum Balance	There is; No.
Discount	Low; Currently; Tall.
Cashback	Low; Currently; Tall.
Topup Facilities	Yes; No.
Merchant Coverage	A little; currently; Lots.
Refunds	Yes; No
Customer service	slow; currently; fast.

Table 1 provides a broad and detailed overview of the key attributes or variables that play a major role in the dataset used for this study. These variables have been carefully selected based on their relevance to user behavior such as satisfaction level, and perception towards financial service platforms particularly digital wallets or similar financial applications. Each variable carries meaningful information, when analyzed collectively can reveal important patterns and insights into user preferences and system performance. The gender variable differentiates users based on their biological sex, categorized into Male (M) and Female (F) allowing the model to capture any potential gender-based behavioral patterns or preferences. The job category variable includes five detailed categories such as Self-Employed, Civil Servant, Laborer, Student, and Private Employee offering insights into how job roles influence adoption and use of financial services. The Ease of Application variable indicates whether users find the application process simple or complicated which is an important factor in user orientation. The data security variable reflects users' perceptions regarding the security of personal and financial information which is crucial in fostering trust in digital platforms. The trust in comfort variable indicates whether users feel comfortable and confident using the application for their financial needs. The increase maximum balance variable reflects whether the platform allows users to increase their balance limits, which may be attractive to users with higher transaction needs. In addition, variables such as discounts and cashbacks are categorized into levels (low to high) that provide an overview of the benefits currently offered. The topup facilities variable indicates the ease of adding funds to the wallet, while the merchant coverage variable assesses the usability of the platform across vendors classified as Few, Medium, and Many indicating the stage of expansion. The refunds and customer service variables (ranging from slow to fast) are also considered important indicators of user experience and satisfaction.

Before data processing, the dataset was still in raw form with format variations and some incomplete data. Therefore, data cleaning was carried out by removing duplicate data and invalid data so as not to influence the analysis. As well as data transformation by changing the data into a format that is more suitable for the classification model to be used. After processing, the final dataset has a cleaner structure and is ready for analysis. The following is the appearance of the dataset after going through the preprocessing stages.

Gender	Job Category	Ease of Application	Data Security	Trust in Comfort	Increase Max Balance	Discount	Cashback	Topup Facilities	Merchant Coverage	Refunds	Customer Service	Fintech
M	Self-employed	Yes	Safe	Yes	No	High	Low	Yes	Medium	No	Medium	OVO
M	Civil Servant	Yes	Safe	Yes	Yes	Low	Medium	Yes	Many	Yes	Fast	GOPAY
F	Entrepreneur	Yes	Safe	Yes	Yes	Medium	Low	Yes	Many	No	Slow	GOPAY
F	Civil Servant	Yes	Safe	Yes	Yes	Medium	Low	Yes	Many	Yes	Fast	OVO
F	Civil Servant	Yes	Safe	Yes	No	Low	Medium	Yes	Few	Yes	Medium	GOPAY
M	Laborer	Yes	Safe	Yes	Yes	Medium	High	Yes	Few	No	Medium	GOPAY
M	Student	Yes	Safe	Yes	Yes	Low	Medium	Yes	Medium	No	Medium	GOPAY
F	Civil Servant	Yes	Safe	Yes	No	Medium	High	Yes	Few	No	Fast	OVO
F	Laborer	Yes	Safe	Yes	Yes	Low	Medium	Yes	Few	Yes	Fast	GOPAY
F	Civil Servant	Yes	Safe	Yes	Yes	Low	Medium	Yes	Medium	No	Fast	OVO
M	Civil Servant	Yes	Safe	Yes	Yes	Medium	Low	Yes	Many	Yes	Slow	GOPAY
M	Student	Yes	Safe	Yes	No	Medium	High	Yes	Many	No	Fast	OVO
F	Private Employee	Yes	Safe	Yes	No	High	Medium	Yes	Many	Yes	Medium	GOPAY
F	Civil Servant	Yes	Safe	Yes	No	Medium	Medium	Yes	Medium	Yes	Slow	GOPAY

FIGURE 2. Dataset after processing

Figure 2 shows the final view of the dataset after going through a series of comprehensive preprocessing steps, including cleaning, transformation, and formatting. These steps are important to ensure that the data used in this study meets the criteria of consistency, accuracy, and compatibility with the classification model to be applied. As explained in Chapter 2, the data was analyzed using the KNN classification method.

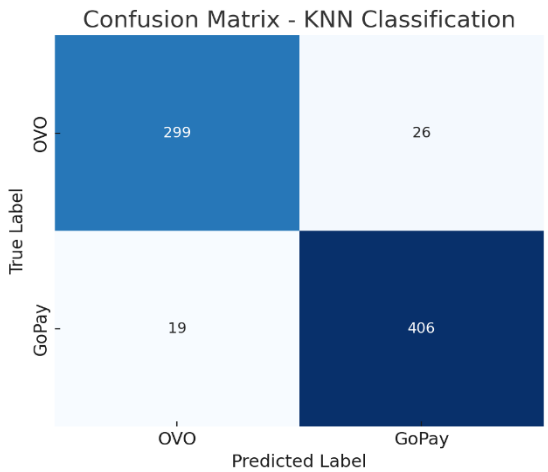

FIGURE 3. Confusion Matrix KNN

Figure 3 presents the Confusion Matrix resulting from the classification process using the KNN algorithm, which is applied to digital payment transaction data. The matrix illustrates the model's performance in classifying two leading digital payment platforms, namely OVO and GoPay. The actual label is represented on the vertical axis (Y) which indicates the actual data class, while the predicted label is on the horizontal axis (X) which shows the classification results predicted by the model. Entries on the main diagonal (i.e., values 299 and 406) represent the number of examples correctly classified for each class. In this case, it is a case where the predicted label matches the actual label. In contrast, values outside the diagonal (i.e., values 26 and 19) represent misclassifications. Where the model incorrectly predicts one class as another. From this confusion matrix, we observe that the KNN model achieves high classification accuracy because the majority of predictions are on the main diagonal. The relatively small number of off-diagonal values indicates that the algorithm performs well in distinguishing between OVO and GoPay user data. This indicates that the feature patterns used in the model are relevant to support accurate classification. These findings support the potential of KNN as a lightweight yet effective algorithm in digital payment analysis.

Apart from using the confusion matrix, model performance can also be evaluated using the Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC). ROC Curve is a graph that depicts the balance between True Positive Rate (TPR) and False Positive Rate (FPR) at various thresholds. The closer it is to the top left corner (the AUC value is closer to 1), the better the model is at differentiating between different classes. Figure 4 below shows the ROC Curve classification results using the KNN method.

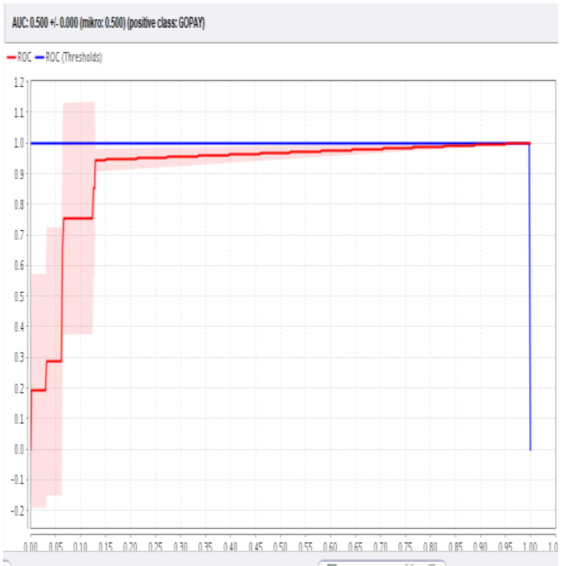

FIGURE 4. ROC Curve K-NN

Based on Figure 4, the model produces an AUC of 0.500 indicating that its performance is equivalent to random guessing. According to the AUC classification, a value below 0.6 reflects poor or failed classification ability. Therefore, the model requires further improvement to achieve acceptable and reliable classification performance. Given the AUC value of 0.500, it is clear that the current KNN model configuration does not have the ability to effectively distinguish between the two classes. This result indicates that the model fails to establish a meaningful decision boundary for accurate classification. Such performance can be attributed to suboptimal parameter settings in the KNN algorithm such as feature weighting, rather than issues related to data quality or model complexity. Therefore, substantial improvements are needed to improve the predictive ability of the model. In the next stage, the model will be optimized using the PSO algorithm to fine-tune the KNN parameters, such as relevant feature weighting. This optimization aims to improve classification accuracy by guiding the model towards a more effective decision boundary. The integration of KNN with PSO is expected to overcome the limitations observed in the initial results and provide a more robust approach to classifying digital payment user behavior.

After evaluating the model with the confusion matrix and ROC Curve, the classification results show that the model performance can still be improved. One way to increase model accuracy is by feature selection, namely selecting the features that have the most influence in determining classification results. In this research, feature selection was carried out using PSO. By using PSO, less significant features can be removed, so that the model becomes simpler and more efficient without losing important information. Table 2 below shows the attribute weights obtained after optimization using the PSO method on the same dataset.

TABLE 2. ATTRIBUTE WEIGHT PSO

Attribute	Weight
Gender	0.623
Job Category	0.863
Ease of Application	0.565
Data Security	0.069
Trust in Comfort	0.221
Increase Maximum Balance	0.485
Discount	0.182
Cashback	0.968
Topup Facilities	0.562
Merchant Coverage	0.937
Refunds	0.062
Customer service	0.693

Based on Table 2, the attributes with the highest weight are customer service (0.693), job (0.683), and gender (0.623). This shows that these three factors have a greater influence in determining user preferences for OVO and GoPay Fintech services. In contrast, attributes such as data security (0.069) and refund (0.062) have lower weights, indicating that these factors may not contribute significantly to the model classification.

The feature selection results provide some important insights to improve the performance of the classification model. However, features with lower weights are still used in the KNN testing process optimized with PSO, because weights that are still above zero can still affect the optimization results. This allows for further analysis of the influence of these features on user decisions in choosing Fintech services, without sacrificing model accuracy.

After optimization using the PSO algorithm, the performance of the KNN classification model has increased significantly compared to the model before optimization. This optimization process has succeeded in increasing the classification accuracy of the model by adjusting important parameters that affect the performance of KNN. By using PSO, the search for the model parameter space is carried out efficiently to find the optimal parameter set that leads to more precise prediction improvements. To analyze and compare the changes that occur, the following is a further evaluation based on the results of the Confusion Matrix after optimization.

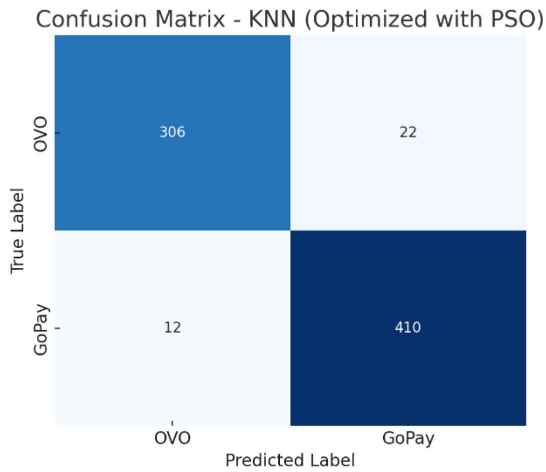

FIGURE 5. Confusion Matrix KNN-PSO

Figure 5 illustrates the Confusion Matrix after optimization with PSO applied to the KNN method. In this matrix, True Label is represented on the Y-axis which corresponds to the original class label (OVO or GoPay), while Predicted Label is displayed on the X-axis which represents the model prediction after the optimization process. The main diagonal of the matrix (values 306 and 410) shows the number of correct predictions made by the model. These values represent instances when the model accurately classifies the data as OVO or GoPay. On the other hand, the values outside the main diagonal (values 22 and 12) represent the number of incorrect predictions, when the model makes a mistake in classifying the data. When compared to the Confusion Matrix before optimization, a marked improvement is observed. The number of correct predictions has increased significantly, while the number of incorrect predictions has decreased. This shows the effectiveness of the optimization process using PSO in improving model accuracy and reducing classification errors, thus showing better overall performance after the optimization phase.

After optimizing the model with PSO and analyzing the results using a Confusion Matrix, the next crucial step is to evaluate the model's performance further by utilizing the ROC curve and the AUC. As shown in Figure 6, the ROC curve provides a graphical representation of the model's ability to distinguish between the positive and negative classes at various threshold settings. The AUC, which quantifies the overall ability of the model to correctly classify the instances, will help in assessing the effectiveness of the optimization. A higher AUC value indicates a better-performing model, capable of making more accurate predictions.

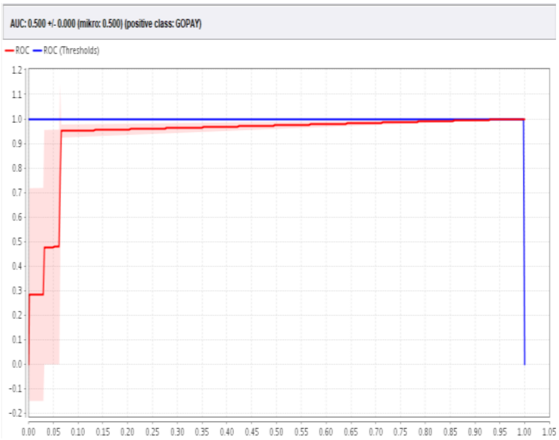

FIGURE 6. ROC Curve KNN-PSO

From Figure 6, it can be seen that the AUC value remains at 0.500, which shows that the model still has performance equivalent to random guessing. Even though PSO optimization succeeded in increasing accuracy and reducing the number of classification errors based on the previous confusion matrix, this improvement was not significant enough to affect model performance on the ROC Curve.

After the KNN model was optimized using PSO, an extensive evaluation process was conducted to assess its performance in classifying data effectively. The evaluation focused on measuring the model's ability to make accurate predictions and the balance between positive and negative errors in classification. Several key performance indicators (KPIs) were utilized to provide a comprehensive analysis of the model's effectiveness. These indicators include accuracy, which measures the overall percentage of correct predictions. Precision, which indicates the accuracy of positive predictions. Recall, which evaluates the model's ability to identify all positive instances, and the AUC, which summarizes the model's ability to distinguish between the positive and negative classes across different thresholds. By assessing these metrics, the optimization process with PSO could be fully evaluated in terms of its impact on the model's classification performance.

Table 3 below presents a comparative analysis of the model evaluation results before and after the optimization process using PSO. The table highlights the key performance metrics, such as accuracy, precision, recall, and AUC, for both the pre-optimization and post-optimization stages. By comparing these metrics, we can clearly observe the improvements in model performance, particularly in terms of classification accuracy and error reduction. This comparison serves to demonstrate the effectiveness of PSO in optimizing the KNN model, leading to better overall performance in data classification.

TABLE 3. COMPARISON OF KNN MODEL EVALUATION RESULTS

Evaluation Metrics	KNN	KNN+PSO
Accuracy	94.00%	95.47%
Precision	95.61%	97.20%
Recall	93.99%	94.90%
AUC	0.500	0.500

Based on Table 3, there is an increase in performance after the KNN model was optimized using PSO. Accuracy increased from 94.00% to 95.47%, indicating that the model was better at correctly classifying the data. Where the accuracy results are obtained based on images 3 and 5 with TP = True Positive, TN = True Negative FP = False Positive FN = False Negative.

Based on Figure 3 to obtain the following accuracy values.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Accuracy = \frac{299 + 406}{299 + 406 + 26 + 19} = 94.00 \quad (2)$$

Based on Figure 5 to get the following accuracy values.

$$Accuracy = \frac{306 + 410}{306 + 410 + 12 + 22} = 95.47 \quad (3)$$

Precision increased from 95.61% to 97.20%, this improvement shows that the optimized model is better able to avoid errors in predicting certain classes. Recall increased from 93.99% to 94.90%, which means the model is better at identifying data. The AUC value remains 0.500, which indicates that although accuracy has increased, the model is still not effective enough in optimally differentiating classes at various classification thresholds.

Based on the results of model evaluation before and after optimization using PSO, there are several important findings that can be analyzed further.

The increased accuracy and precision indicate that PSO effectively optimizes the model's parameter space, resulting in better classification performance. That the model is better able to identify transactions that truly fall into that category without much misclassification in selecting more relevant features, so the model can make more accurate predictions.

Increased recall indicates the model is more sensitive in detecting transactions and can ensure that more users are classified correctly without being missed.

The AUC did not increase, indicating that the model still has limitations in optimally differentiating between the two categories.

IV.CONCLUSION

Based on the objectives, research results, and evaluations that have been carried out, the KNN algorithm has been successfully applied to classify Fintech service users based on critical influencing factors. Initially, the KNN model, without optimization, achieved a classification accuracy of approximately 94.00%, indicating good performance in identifying user preferences for digital payment platforms such as OVO and GoPay. To further enhance model performance, Particle Swarm Optimization (PSO) was implemented to perform feature selection and optimize the hyperparameters of KNN. After applying PSO, the classification accuracy increased to 95.47%. This improvement demonstrates that PSO effectively identifies the most relevant features, removes irrelevant or redundant information, and assists in tuning the KNN model to better fit the underlying data patterns. The PSO-based feature selection process revealed that the most influential factors in determining users' choice of digital payment services were customer service quality, user employment status, and the availability of cashback promotions. These features significantly contributed to distinguishing between users who preferred OVO and those who preferred GoPay. The increase in accuracy from 94.00% to 95.47% reflects the model's improved capability in minimizing classification errors, making the system more reliable for predicting user preferences in the digital payment landscape. Thus, optimizing KNN with PSO not only improves predictive accuracy but also provides valuable insights into the dominant attributes influencing digital payment method selection.

Although this research has shown an increase in classification accuracy in digital payment systems, there are still several aspects that can be further developed by exploring other classification algorithms, such as Random Forest, Support Vector Machine or Deep Learning to compare classification performance with the KNN+PSO model that has been applied in this research.

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