An efficiency metaheuristic model to predicting customers churn in the business market with machine learning-based

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ABSTRACT

Metaheuristics is an optimization method that improves and completes a task in a short period of time based on its objective function. The goal of metaheuristics is to search the search space for the best solution. Machine learning detects patterns in large amounts of data. Machine learning encourages enterprise automation in a variety of areas in order to improve predictive ability without requiring explicit programming to make decisions. The percentage of customers who leave the company or stop using the service is referred to as churn. The purpose of this research is to forecast customer churn in the market business. Particle swam optimization (PSO) was used in this study as a metaheuristic method to provide a strategy to guide the search process for new customers and obtain parameters for processing by support vector regression (SVR). SVR predicts the value of a continuous variable by determining the best decision line to find the best value. The number of transactions, the number of periods, and the conversion value are the parameters that are visible. Efficiency models are added to improve prediction results through two optimizations: prediction flexibility and risk minimization. The findings demonstrate the effectiveness of prediction in reducing customer churn.

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1. INTRODUCTION

The goal of metaheuristics is to solve problems faster and to be able to solve complex problems. Algorithms are used in metaheuristics to solve optimization problems [1]. The metaheuristic algorithm combines natural phenomena's rules and randomness to find the best result globally. Its application in various cases demonstrates metaheuristics efficiency and effectiveness in solving large and complex problems [2].

Machine learning benefits businesses by accelerating growth, generating new revenue streams, and resolving issues. Data is an important driver in business decisions, but companies have traditionally used data from a variety of sources, including customer, employee, and financial feedback [3], [4]. Machine learning automates and optimizes the process of rapidly analyzing large amounts of data, allowing businesses to achieve results faster [5]. Churn customers can have a significant impact on a business because acquiring new users costs more money and effort than retaining existing ones. So, it is preferable if you can maintain customer loyalty by taking preventive measures against churn [6].

In this study, churn refers to customers who no longer make transactions within a specific time frame. Customer churn is an important factor to consider when evaluating a company or business. This is because the company's goal is to acquire as many customers as possible, and retaining customers is more difficult. If the company is unable to retain customers, it will fall behind, and the cycle of company performance will decrease and decline [7], [8].

Predictions are estimates based on past and present data. The goal of prediction is to gather information about future changes that will affect policy and its impact [9]. The prediction of churn customers provides the outcome of whether or not the customer will churn. Predictions are made by analyzing customer behavior over time and transactions. This study forecasts customer churn at merchants.

Particle swarm optimization (PSO) is used in this study to search for criteria parameters based on transaction, environmental, and social behavior criteria [10], [11]. PSO is a collective behavioral intelligence stochastic population-based algorithm. PSO generates global solutions in the search space via individual particle interactions [12]. Each particle communicates information to other particles in the form of its best position and adjusts its respective velocity position based on information about the best position. Furthermore, support vector regression (SVR) is used to solve multi-purpose optimization uncertainty problems for predictive decision making [13]. SVR is a supervised learning algorithm that predicts the values of continuous variables [14]. The SVR algorithm's goal is to find the best decision line. SVR works to find the best value within a certain margin by adjusting the best line in the threshold value [15]. In this study, efficiency is achieved by incorporating predictive flexibility features and minimizing risk.

2. METHOD

The first stage is data collection, followed by preprocessing in two stages, namely data selection and cleaning of data that has no value (null). Furthermore, data processing is done using the PSO method, namely initialization, three stages of weighting, and finding the best position. The value of the best position will be re-evaluated with SVR through the process of calculating the error value, calculating the delta value, de-normalizing, and calculating the regression function. The decision results are tested and re-evaluated to get a new model for making predictions. Thus, the result of optimization is a standard combination model of renewal. The stages of the research method can be seen in Figure 1.

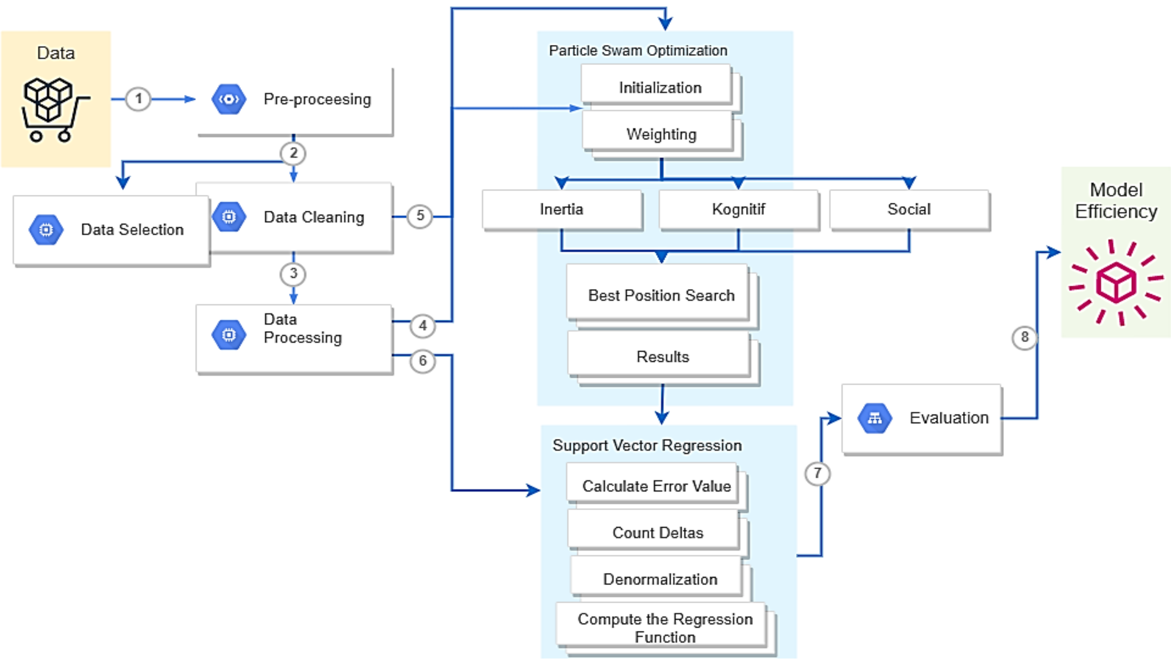


Figure 1. State of the art

2.1. Datasets

Variable data consists of ID, age, customer, income, value, purchase, and category. Data is used as much as 35,000 times in the market business. Previously, the data cleaning process was carried out to find null data. An example of data can be seen in Table 1.

Tables 2 and 3 are descriptions of Table 1, explaining the information from customers and the value of the category. Table 2, Customers who make transactions in the market business are initialized with 0 and 1. Table 3, the number of periods when customers make transactions, is initialized based on segments 1 to 4.

Table 1. Sample data

ID	Age	Customer	Income	Value	Purchase	Category
00001GDJD	45	0	452572	439	0	3
0000BDKSO	35	1	343656	283	0	2
0000HJSKSF	60	1	454525	390	1	3
0000JHDKSP	44	0	235666	475	0	3
0000GDJDJK	48	0	254646	497	1	3
00007I26OR	26	1	254525	443	1	3
000DJDJKSK	51	0	235325	425	0	3
00020GDKJS	27	1	252525	173	0	1
00020GDJHJ	24	1	354464	300	0	2
00022GDJSJK	44	0	454354	474	1	3
00026GDJSJI	65	0	545455	210	0	2
00031VDJDB	36	1	324245	100	1	1
00032DGDJD	49	0	343435	329	1	2
00033DBDJD	23	1	343432	430	1	3
00034HDJDK	44	0	343435	492	1	3
00038HDJDK	50	1	266565	585	1	4
00039DHDJD	22	0	668688	23	0	1
00040GDHDJ	47	0	565656	356	0	2
00040OHJDKJ	36	0	456456	536	1	4
00045GDJUJO	55	1	456564	876	1	4

Table 2. Customer

Customer	Information
Female	1
Male	0

Table 3. Categories

Categories	Information
1	<300
2	300-560
3	760-900
4	>900

2.2. Particle swam optimization

The PSO optimization paradigm mimics human knowledge processing ability. Life (such as flocks of birds) and evolutionary computing are the two major components [16], [17]. This trait consists of one person's behavior and influence on other people in the population [18]. Other components include particle, cognitive and social, and particle speed. Each particle represents a problem solution. Particle learning is the combination of particle experience and swarm learning [19]. Cognitive learning seeks the best position of a particle, whereas social learning seeks the best position of all particles in a swarm. Cognitive and social learning parameters are used to calculate the particle's speed and the speed of calculating the position of the next particle [20]. PSO algorithm steps [21]: i) assign random positions to all initial particles, ii) calculating the weights of the criteria (inertia, cognitive, and social), and iii) the number of repetitions for each particle is the process of finding the best solution. PSO in training the performance of multi-layer ceptrons, in (1) [22], position represents the best fitness value for each particle, in (2) [23].

$$M_i = \{M_i^{|1|}, M_i^{|2|}\} \quad (1)$$

$$S_i = \{S_i^{|1|}, S_i^{|2|}\} \quad (2)$$

Looking for the best particle index at *x*, with (3) [24]. The velocity of particle *i* in (4) [25], in (5) and (6), a and b represent the row and column indices of the matrix in particle manipulation, respectively [26].

$$A_x = \{S_x^{|1|}, S_x^{|2|}\} \quad (3)$$

$$L_i = \{L_i^{|1|}, L_i^{|2|}\} \tag{4}$$

$$L_i^r(a,b) = L_i^r(a,b) + \{h \propto [S_i^{|r|}(a,b) - M_i^{|r|}(a,b)] + c\beta[S_x^{|r|}(a,b) - M_i^{|r|}(a,b)]\}/p \tag{5}$$

$$M_i^{|r|} = M_i^{|r|} + L_i^r p \tag{6}$$

According to (4) is used to calculate the particle's new velocity based on its previous velocity and the distance from its current position to the group's best fitness value based on social and cognitive behavior. The collaboration of particles as a group is depicted in (5). In (6) calculates the new position based on the new velocity. A nonlinear variable inertia weight model is used to increase PSO work, and M increases PSO performance in (7) [27]:

$$M = M_{max} - \frac{(M_{max} - M_{min})}{1+e} * e\left(\frac{i}{i_{max}}\right) \tag{7}$$

Where M_{max} and M_{min} are the minimum and maximum values of M, i is the iteration number, and i_{max} is the maximum iteration number. As i increases, M decreases nonlinearly, and e increases to ensure that the local algorithm is optimized. To ensure that the scope of the log parameter is at a definite value, the input data is normalized to (0.1), as shown in (8) [28]. Where f^* is normalized data, f_i are input data, $min_{1<i<n}\{f_j\}$ is the minimum data value, and $max_{1<i<n}\{f_j\}$ is the maximum value of the data.

$$f^* = \frac{f_i - min_{1<i<n}\{f_j\}}{max_{1<i<n}\{f_j\} - min_{1<i<n}\{f_j\}} \tag{8}$$

2.3. Support vector regression

The goal of the SVR algorithm is to find the best dividing line. The best dividing line can be found by measuring the margin on that dividing line. The margin is the distance from the dividing line to the closest data point. The SVR model in this study can be seen in (9)-(12) [29], [30].

$$a_x[b^T \emptyset(f_k) + y] \geq 1 \tag{9}$$

$$a_x[b^T \emptyset(f_k) + y] \geq 1 - \xi_k \tag{10}$$

$$min_{b,y} \frac{1}{2} \|b\|^2 + Q \sum_{k=1}^{m} \xi_k \tag{11}$$

$$\begin{Bmatrix} a_i - b^T \Phi(x_i) - g \leq \varepsilon + \xi_i^+ \\ b^T \Phi(x_i) - g - a_i \leq \varepsilon + \xi_i^+ \\ \xi_i^+, \xi_i^- \quad \geq 0, \end{Bmatrix} \tag{12}$$

Information: f is predictor variable vector, a : sample classification, T is weight vector, y is constant, and Q is model parameters. SVR in non-linear predictions as in (13) [31].

$$a(x) = \sum_i (\propto_i^- - \propto_i^+) s\langle x_i . x\rangle + g \tag{13}$$

2.4. Improvement model

The improvement model is used to optimize system, process, and performance components. This model provides a methodology for identifying development opportunities, implementing changes, and measuring progress. Here is the employed optimization model, index: business market (X); time (a); customer (b); product (c); distance (p); transaction (i); and habit (r). Improvements to predictive flexibility:

$$\frac{\sum_x (DET_x)}{|X|} \tag{14}$$

minimize risk:

$$\sum_a \sum_b \sum_c (ar_{abc} \ x \ cs_{bc}) + \sum_i \sum_t \sum_p (qwe_{itp} \ x \ ss_{tp}) + \sum_a \sum_b \sum_c (cs_{abc} \ x \ qwe_{bc}) \tag{15}$$

Parameter:
1. DET_x Overall flexibility of customer habits to -i
2. ar_{abc} Product input risk to -a from market business to -b in period to -c
3. cs_{bc} 1, if the market business to -b produce products in period t -c; if not, 0.
4. qwe_{itp} Product production risk to -i from market business to - t in period to - p
5. ss_{tp} 1, if the market business to - t produce products in period t - p; if not, 0
6. cs_{abc} Product risk to - a from market business to - b in period to - c
7. qwe_{bc} 1, if the market business to - b distribute products in period to - c; if not, 0

2.5. Assessment of models

Assessing the superiority of the model is done with several indices, namely regression coefficient (R^2), the R^2 is calculated by dividing the covariance of the two variables by the variance of the independent variable. Root mean square error (RMSE) measures the accuracy of the regression model, measuring the difference between the predicted value and the actual value of the dependent variable (y), or the square root of the average squared difference between the predicted and actual value of the dependent variable. Mean absolute percentage error (MAPE) measures the accuracy of a forecasting model, measuring the average absolute percentage difference between the actual value and the predicted value of the time series [32]–[34].

$$R^2 = \left\{1 - \frac{\sum_{b=1}^{a}\left(X_{obs,b} - X_{sim,i}\right)^2}{\sum_{b=1}^{a}\left(X_{obs,b} - X_{obs}\right)^2}\right\} \tag{16}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{X}\|a(i) - a(i)\|^2}{X}} \tag{17}$$

$$MAPE = \left(\frac{1}{x}\sum_{i=1}^{x}\left|\frac{a_i}{b_i}\right|\right) \times 100\% \tag{18}$$

3. RESULTS AND DISCUSSION

3.1. Particle swam optimization analysis results

The PSO method aligns the parameters based on the optimization criteria in (1) and (2). In (3) and (4), the linear combination of the radial basis function is used to map the number of purchases, customers, and time scale (4). The number of base functions and population size are determined by the customer. The number of purchases and the time period are used to calculate the individual fitness value for each learning particle. This procedure chooses the variables that will aid the model-building process as in (5) and (6). As in (6) shows the behavior of functions in age categories does not differ significantly. As see in Table 4. Each objective function pair exhibits behavior. The value of the customer's habit of using the product demonstrates behavior. Table 5 shows the performance of PSO in determining the best results based on behavior in (7) and (8).

Table 4. Process optimization criteria

Customers	Purchase amount	Number of periods	Conversion rate
0	9746	16273	45.53
1	24236	22637	58.31

Table 5. Value of customer habits

Categories	Purchase amount	Number of periods	Conversion rate
1	2351	6459	36.40
2	7023	16545	42.45
3	9208	11697	78.72
4	4449	5299	83.96

3.2. SVR analysis results

After the PSO indicator is calculated and normalized, the SVR model is optimized for prediction. The optimal parameters for each function in (9)-(12), are given in Table 6, for the class 0 and 1 period indicating predictive SVR. Classes 0 and 1 denote customers who are churn or not churn. The predicted value is illustrated in Figure 2.

Table 6. Predictions

Conversion matrix		
Actual	Predicted	
	Class 0	Class 1
Class 0	6473	5537
Class 1	3747	12643

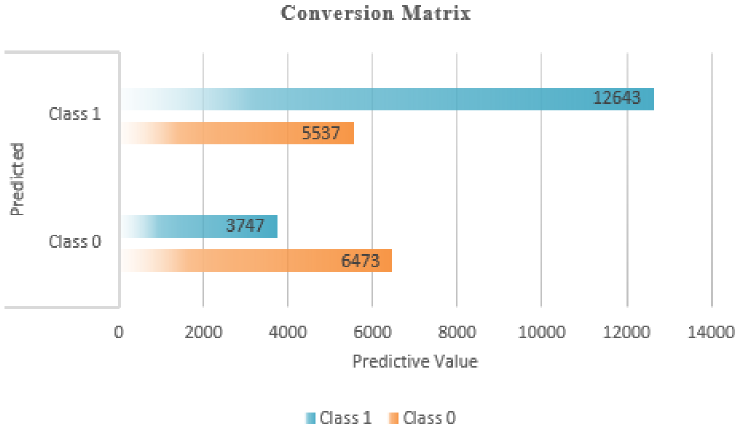


Figure 2. Predicted value based on conversion matrix

3.3. Efficiency of hybrid models

After processing the PSO and SVR with different structural parameters, the increase in predictive flexibility is carried out based on (14). This model considers all the minimum and maximum complexity between behavior objects. It can be seen in Table 7 object 1 represents the value of behavior based on the number of purchases, and object 2 represents the number of periods.

Minimizing risk is carried out as an evolutionary weight optimization for each solution to improve further. Precision is determined after 50 iterations and five sections. The classification accuracy results are shown in section 5 with a value of 0.9500, as shown in Table 8, and the increase in classification accuracy is shown in Figure 3. The vertical line represents the iteration value, while the horizontal line represents section repetition.

Table 7. Predictive flexibility

Objective	Min	Max	Range	Mean
1	0.126474	0.84637	0.72369	0.33534
2	0.027585	0.23537	0.18464	0.07252

Table 8. Classification accuracy minimizes risk

Iteration	Section 1	Section 2	Section 3	Section 4	Section 5
1	0.12748	0.033738	0.016474	0.11345	0.026382
2	0.12343	0.03363	0.016374	0.11345	0.026382
3	0.1187	0.031638	0.016449	0.11345	0.026382
4	0.1187	0.036389	0.016483	0.10537	0.026382
5	0.11647	0.033849	0.016483	0.10537	0.026382
10	0.11678	0.037489	0.016483	0.10537	0.026547
15	0.11044	0.026373	0.064748	0.10763	0.026547
20	0.11044	0.026474	0.015347	0.10763	0.026547
25	0.11044	0.029634	0.016648	0.10527	0.026547
50	0.10536	0.029634	0.016764	0.096373	0.026547
Classification accuracy	0.8100	0.8800	0.8200	0.8600	0.9500

3.4. Model validation

Validation is carried out using R^2, RMSE, and MAPE. After training the model, it will run performance tests on test data. The analysis results aim to determine whether the efficiency model is working properly or not. Table 9 explains the validation results, where the higher the ratio, the better the results and accuracy. It uses precision, recall, F1-score, sensitivity, specificity, and accuracy values to understand the performance of the research algorithm. This evaluation was conducted on a 65%:35% data distribution, which was deemed to be the best splitting data, and Table 10 shows this.

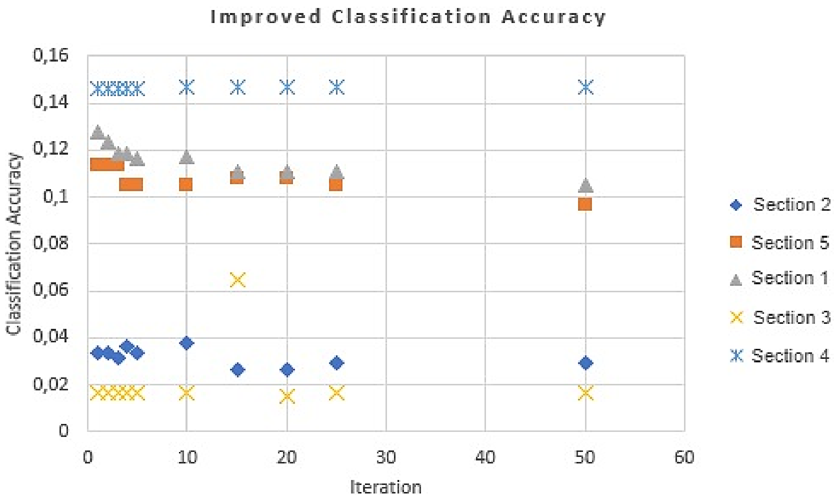


Figure 3. Improved classification accuracy

Table 9. Model validation

Validation (%)	R^2 (%)	RMSE	MAPE (%)	N
1	22.34	11.24	60.60	9
2	36.34	35.45	81.48	16
3	34.39	12.65	85.83	17
4	45.38	17.53	86.44	21
5	43.58	23.12	85.16	98
10	50.36	23.45	88.66	46
15	64.12	33.12	91.91	78
20	56.15	12.46	97.77	88
25	45.55	23.45	92.66	89
50	60.34	19.35	91.35	99

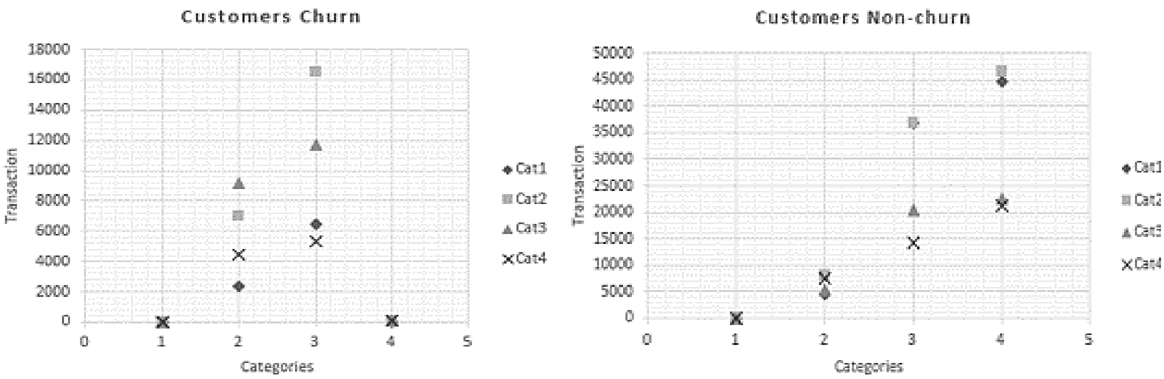
Table 10. Model validation value measurement

	Value
Accuracy	0.677
Precision	0.580
Recall	0.665
F1-score	0.630
Sensitivity	0.677
Specificity	0.443
TPR	0.667
FPR	0.457

3.5. Implementation of the efficiency model

Here we conducted research, shown in Figure 4 showing the output of the simulated model from test data based on Table 3. Explaining predictions of churn and non-churn customers from the behavior of the transaction time period, Figure 4(a) churn, it can be seen that 1,000 customers from ≤ 16,000 time periods (hours, days, weeks, and months) did not make transactions and Figure 4(b) did not churn, 21,000 customers from ≤ 50,000 time periods made transactions.

Figure 5 shows a graph of the conversion rate of the 4 categories: category 1 in red, category 2 in orange, category 3 in purple, and category 4 in blue. Based on the conversion value of the validation value, it appears that each category shows the value of customer habits in increasing predictive flexibility and minimizing risk, which can be effective in predicting churn and non-churn customers.



(a) (b)

Figure 4. Customers of (a) churn and (b) non-churn

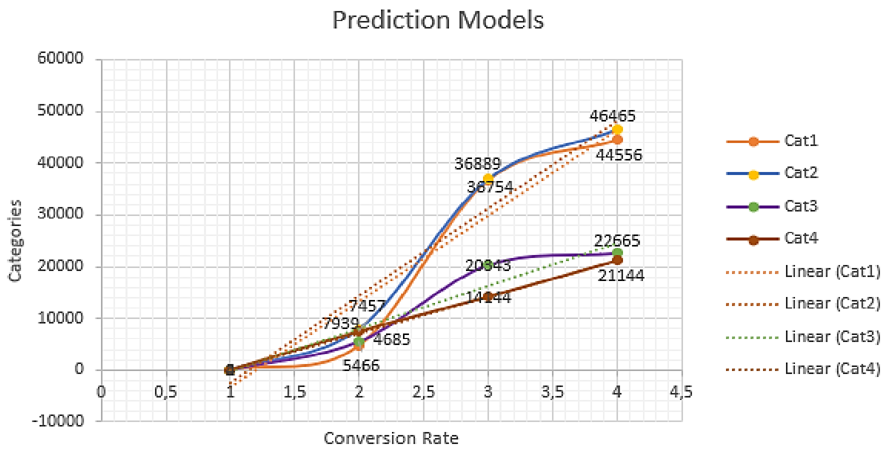


Figure 5. Model effectiveness in predicting churn and non-churn customers

4. CONCLUSION

Every multi-objective optimization is distinct in that includes a number of solutions as goals. A meta-heuristic algorithm is implemented in PSO in this work. PSO empirical comparison results in terms of precision and execution time. Furthermore, when the obtained results are processed with SVR, the model demonstrates a significant, consistent, and stable increase in customer behavior predictions. This efficiency is also seen through the addition of an increased model of predictive flexibility and minimizing risk. In conclusion, this study provides several contributions to improving and optimizing the prediction results of churn and non-churn customers. Where these results can be used as a reference in minimizing customers who want to churn.

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