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Predicting financial distress of property and real estate companies using optimized support vector machine - particle swarm optimization (SVM-PSO)

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ABSTRACT

Financial distress is a critical phenomenon in a company that has significant implications for the business itself, employees, investors, and creditors, and can also impact a country's economy. Predicting a company's financial distress, including property and real estate companies, becomes one crucial thing to be studied. Support Vector Machine (SVM) is said to be one of the most powerful model for prediction among other methods. However, it is difficult to determine the parameters of the SVM model. Thus, the SVM parameters must be improved for higher accuracy. This research aims to increase the performance of SVM in financial distress prediction of property and real estate companies. Particle Swarm Optimization (PSO) is used to optimize the previous model. The PSO approach takes cues from how a group of insects or birds interacts to maintain life. The PSO algorithm uses a population of random particles as points initialized in a D-dimensional search space. Each particle modifies its direction using the best experience it discovers (p-best) and the best value discovered by all other members (g-best) to arrive at the ideal outcome. As a result, throughout the search process, particles will move through multidimensional space to more advantageous locations. This research showed that SVM produced the greatest accuracy at 80.47% while when the PSO method was implemented in the SVM model, the accuracy increased to 83.16%. It can be concluded that the PSO method successfully optimized the parameters and increased the accuracy of SVM in the financial distress prediction for property and real estate companies listed on the Indonesian Stock Exchange.

1. Introduction

The sustainability of a corporation is greatly influenced by its financial situation. Therefore, the primary responsibility of corporate management is to maintain the company's financial health continuously and even improve its condition. Early detection and accurate bankruptcy indicators can assist businesses in taking the required steps to address their financial difficulties [1]. Financial distress is a critical phenomenon in a company that has significant implications for the business itself, employees, investors, and creditors, and can also impact a country's economy. Financial distress refers to a condition when a company faces financial difficulties, such as the inability to pay debt obligations, declining operating profit, declining net income, declining working capital, and potential insolvency. According to [2] financial distress arises when a company's cash flow is insufficient to cover the amount of matured long-term debt, suggesting that the company is not able to make its payments. The insolvency of a company can have a negative financial impact on business management, workers, investors, suppliers, creditors, and even the stability of the national economy. Thus, one of the most crucial elements in preventing a company's financial difficulty is its ability to forecast it [3].

The property and real estate sector is one of the numerous corporate sectors in Indonesia that has a significant effect on other company sectors. The property and real estate sectors can significantly impact the material, logistics, services, financial, and banking stores [4]. Because of this, many governments pay close attention to changes in the real estate and property industries.

The Chinese real estate company Evergrande, towards the end of 2021startled the world economy owing to financial trouble. The fundamental issue is that Evergrande, like other businesses in the real estate sector, operates primarily on debt [5]. The data of 2021's second quarter showed that The total debt of Evergrande hit 1.96 trillion including the interest on debt of 571.8 billion. This value is a large amount comparing the existing physical worth of just 86.7 billion [6]. The research of [6] also stated that other property and real estate companies should avoid falling into financial difficulties by being aware of diversifications, controlling the leverage ratios, and balancing the speed of development. This financial crisis brought on by debt default is a brand-new global concern.

Several statistical techniques, such as the Altman Z-Score [7], Logistic Regression [8], and Factor Analysis [9], are the basic method in financial distress prediction. Then, during the 1990s, statistical techniques started to be coupled with artificial intelligence, particularly machine learning [3]. Decision trees, employing k-nearest neighbors, evolutionary algorithms, artificial neural networks, and support vector machines are methods that integrate statistics and machine learning. The Support Vector Machine (SVM) model was created by Vapnik and Cortes [10]. Within the literature, SVM is said to be the most frequently applied machine learning technique in the prediction and classification of financial distress [11].

Support Vector Machine (SVM) is a statistical learning theory-based supervised machine learning language that is primarily used for regression analysis and data classification [12]. Additionally, SVM employs the Structural Risk Minimization (SRM) principle to determine the optimum hyperplane that divides two categories in the input space. The ideal hyperplane is the one that lies in the middle of two categories of objects belonging to different categories. The optimal hyperplane between the two categories can be identified by calculating its most significant point and assessing its margin. The margin is the separation of the hyperplane and the closest pattern. The closest pattern is known as a support vector [13].

SVM's fundamental premise is a linear-classifier, but the development of SVM makes it able to be applied to non-linear issues by using trick kernels in high dimensional workspaces [11]. Radial Basis Function (RBF), polynomial, and sigmoid kernels are examples of non-linear SVM kernels [14]. Using a support vector to calculate distance is one of the benefits of SVM, as it speeds up processing [9]. SVM is a classifier that has the benefit of processing high-dimensional data without noticeably degrading performance. It also researches the SVM approach, which can lower the misclassifications and deviations from training data [15]. Numerous research studies have demonstrated that SVM is an effective strategy and claimed that SVM is more appropriate than traditional Statistical Methods [16]–[18].

Selecting the optimal value of the parameters is a fundamental step in SVM as these parameters have a huge impact on the power of SVM [19]. According to Saikin et al. [20], model optimization enhances the model's usefulness and the accuracy value it generates. Therefore, it is essential to study SVM model optimization. To choose the best parameter and increase its accuracy, some previous researchers have applied Particle Swarm Optimization (PSO) to the SVM [19], [21]–[26].

The PSO approach which was first developed by Eberhart and Kennedy [27] draws inspiration from how organisms like insects, fish, and birds work together to hunt food and maintain life. PSO refers to the population as a swarm and the individuals as particles. In multidimensional space, the many particles initially lie at random locations. Each particle modifies its path using the best experience it discovers (p-best) and the best experience discovered by all other members (g-best) to arrive at the ideal outcome. As a result, throughout the search process, particles will move through multidimensional space to more advantageous locations. By exchanging social and historical knowledge with one another, these particles look for the best locations. Position and speed are two features of PSO; if a particle finds the appropriate and quick path while traveling to a food supply, it will signal other particles to quickly follow that path, even if the destination is far away.

Previous research has demonstrated that the PSO approach can determine the ideal parameters to increase forecast accuracy. Some of these come from [28], which compared the SVM method to the

SVM technique optimized with the PSO algorithm. According to this study, it has been demonstrated that the PSO approach produces a greater performance compared with the classic SVM Model by improving the model's accuracy. Additionally, the research of [19] also testified that in their study PSO-SVM has an outstanding classification precision.

PSO has been used in SVM optimization in several disciplines. Furthermore, several research studies used PSO-SVM in economics, particularly when analyzing company financial distress, as done by [28]–[30]. Although the property and real estate companies are the sector that have a great impact to the global economy, none of these researches have employed PSO-SVM to predict company financial distress.

This study builds a financial distress prediction model for the property and real estate sector companies utilizing SVM parameter optimization using the PSO method, drawing on prior research. This model was created to get higher accuracy results than the traditional SVM model the author had created the year prior [31] so that it might serve as a guide for decision-makers, including management, investors, and banking institutions.

2. Method

This research uses financial ratios of financial reports of the companies in the property and real estate sector that were listed in the Indonesia Stock Exchange from 2018 to 2022. The sample are the company that have a complete financial report from 2018 through 2022. The total data used in this study are 267 cases. The company that fit at least one of these criteria will be categorized as financial distress [32], [33]:

- The Value of working capital is negative.
- The profit of operating is negative
- or The net income of the company is negative.

The predictors variables used to predict the financial distress are 5 (five) financial ratios which are:

- Ratio of Liquidity (consists of 5 variables). These liquidity ratios help assess a company's ability to meet short-term obligations and manage its current assets efficiently. By analyzing these ratios together, investors and creditors can gain a comprehensive understanding of a company's liquidity position.
- The second financial ratio is the ratio of Solvability (consists of 2 variables). Ratio of solvability is a measure of how easily a problem can be solved compared to other problems. It helps determine the complexity and feasibility of finding a solution within a given time frame.
- The third is the Profitability ratio (consists of 5 variables) which the ratio that measures the ability of a company to generate profit relative to its revenue. It is an important metric for investors to assess the financial health and performance of a company.
- Ratio of Asset Utilization (consists of 3 variables) is a key financial metric that measures how efficiently a company is using its assets to generate revenue. A higher ratio indicates better utilization of assets, leading to increased profitability and overall financial health of the company
- Ratio of Investor (consists of 3 variables) is a comparison of the amount of funds invested by different individuals or entities in a particular investment opportunity. This ratio can help determine the level of risk and potential return associated with the investment.

The data were analysed in four steps which are:

- The data and samples being used are cleaned and transformed at this point. The independent variable is cleaned and transformed before dimension reduction is applied using the Principal Component Analysis (PCA). The variables and features are then chosen from the created Principal Component (P.C.) based on the eigenvectors that match the criteria (the absolute value of the eigenvectors is more significant than 0.3).
- In the stage of modelling, the data is split into two parts: training data and testing data. To build the model, training data is used and to assess the accuracy, the testing data is used. Training and

testing data are distributed by the K-Fold Cross Validation. A10-fold CV tends to produce a less biased estimate of accuracy [34]. A 10-fold CV divides the data into ten similar folds, producing ten subsets of data that can be used to assess the model's performance. For up to ten iterations, CV will alternatively use nine folds for training and one for testing for each of the ten data groups. SVM parameter selection using PSO takes place during the swarming phase. At that point, the PSO parameters—including the maximum iterations, the particle speed limit, the number of particles, their diameters, and weight for fitness calculations—are predetermined. Creation of the SVM model using the best parameters found during the swarming stage.

- The confusion matrix assesses the fitness calculation, as illustrated in Table 1.

Table.1 Confusion Matrix

Category		Real Class		Total
		Yes	*No*	
Prediction Class	Yes	TP (True Positive)	FP (False Positive)	P'
	No	FN (False Negative)	TN (True Negative)	N'
Total		P	N	Total

The following formula can be used to calculate accuracy and error rate:

$$accuracy = \frac{TP+TN}{P+N} \tag{1}$$

$$error\ rate = \frac{FP+FN}{P+N} \tag{2}$$

In addition, the following formula can be used to evaluate the model:

$$precision = \frac{TP}{TP+FP} \tag{3}$$

$$recall = \frac{TP}{TP+FN} = \frac{TP}{P} \tag{4}$$

The amount of financial hardship in the property and real estate sector that the SVM model could accurately anticipate is known as TP (True Positive). The amount of property and real estate companies with no financial distress difficulties is known as TN (True Negative), and the SVM also predicted it. False Positive (FP) and False Negative (FN) are when the SVM could not correctly anticipate the case's condition. High value of accuracy, precision, recall, and a low error rate are the criteria to define the quality of the model.

- Selection of the best model. The k-fold CV procedure is used to choose features for fitness calculations after the PSO iteration is initially set to 0. The local best value (p-best) and global best value (g-best) will then be updated by the PSO system, which will subsequently generate various parameters for each particle. Then, each particle will migrate to the following location. The system will return to the model construction (modeling) step if the requirements have been satisfied or the allotted maximum number of iterations has been reached. The prior stage ultimately determines when the training iteration ends. PSO will subsequently provide the optimal SVM parameter value. If the swarming phase is interrupted, the PSO-SVM system will revert to the model construction phase. The SVM model will also assess the testing data's precision. With the highest testing data accuracy requirements, the best model is chosen.

3. Results and Discussion

3.1. Pre-Processing

Cleaning is done during the pre-processing step to remove incomplete data subsets for all variables. The data transformation was performed by normalizing the attribute data (making the data have a mean of 0 and a variance of 1) to ensure no discernible deviation between the attributes (variables) used. The PCA method was applied to select the variables that will be used in the modes.

Table 2 displays the variance of Principal Component (PC). PC1 was selected since it contains the most significant proportion of variation compared to other PC, making it the best fit. Then, eigenvectors from PC1 that satisfy the requirement (their absolute value is more significant than 0.3) are used to generate a selection of variables.

Table.2 Variance of PC

PC	Std Dev	Proportion of Var	Cumulative Var
PC 1	1.743	0.169	0.169
PC 2	1.544	0.132	0.301
PC 3	1.267	0.089	0.39
PC 4	1.242	0.086	0.476
PC 5	1.111	0.069	0.545

Table 3 reveals that X12 (Return on Assets), X16 (Earning Per Share), X18 (Book Value Per Share), and X10 (Operating Profit Margin), have absolute values of PC1 eigen vectors higher than 0.3. Therefore, the model was built by using these four variables.

Table.3 The Eigen Vector

Variable	Absolute Eigen Vector PC1
X12. Return On Asset	0.476
X16. Earnings per share	0.446
X18. Book Value Per Share	0.399
X10. Operating Profit Margin	0.387
X09. Net Profit Margin	0.270
X05. Inventory TO	0.226
X13. Asset Turnover	0.225
X07. Leverage Ratio	0.100
X01. Working Capital to total Aset	0.069
X15. Fix Asset Turnover	0.068
X11. Return On Equity	0.051
X02. Current Ratio	0.047
X03. Quick Ratio	0.045
X06. Debt to Equity	0.028
X08. Gross Profit Margin	0.012
X04. Account Receivable Turn Over (TO)	0.005
X17. Price Earnings Ratio	0.004
X14. Working capital Turn Over	0.003

3.2. Modeling

- Build the SVM Model

The data were split into training and testing sets using a 10-fold CV as the first step. The SVM model is then created using 3 kernel types: linear, polynomial, and RBF. The parameters used in this research is shown in Table 4.

Table.4 Parameter of SVM

Kernel	Parameter C	Degree	Sigma
Linier	C=0	-	-
	C=0.5		
	C=1.0		
	C=5.0		
Polynomial	C=0	Degree = 2	-
	C=0.5	Degree = 3	
	C=1.0	Degree = 4	
	C=5.0		
RBF	C=0	-	Sigma = 1
	C=0.5		Sigma = 2
	C=1.0		Sigma = 3
	C=5.0		Sigma = 4

The criteria of accuracy, error rate, precision, and recall were used to assess each SVM model. The output of the top SVM model is displayed in Table 5.

Table.5 SVM Model Performance

Kernel and Parameter	Evaluation (%)			
	Accuracy	*Error rate*	*Precision*	*Re call*
Linier Kernel C = 0.0	75.63	24.37	86.27	43.14
Polynomial, degree=2, C = 5.0	72.64	27.36	80.85	37.25
RBF sigma=4, C = 5.0	80.47	19.53	78.41	67.55

Table 5 demonstrates that the Radial Basis Function with sigma=4 and C=5.0 was the optimal kernel for SVM. Among the different SVM models, this one had the highest accuracy (80.47%, 19.53% error rate). This model's recall value was 67.55%, and its precision was also sufficiently good at 78.41%.

- The implementation of PSO

  All SVM models include the PSO method for model optimization. Both the initial population size and the maximum number of generations (iterations) are needed for this procedure. The performance will peak with a swarm population of 70–100 particles [35]. For this reason, the swarm population employed in this study is a maximum of 70 particles, with a maximum of 500 iterations that can be stopped after the particles have been discovered g-best.

  Each SVM Model incorporated the PSO algorithm. The brand-new model's name was PSO-SVM. These PSO Models' accuracy, error rate, precision, and recall were also evaluated. The outcome is displayed in Table 6.

Table.6 PSO-SVM Model Performance

Kernel Type	Evaluation (%)			
	Accuracy	*Error rate*	*Precision*	*Re call*
Linier Kernel C = 5.0	78.29	21.71	86.67	50.98
Polynomial, degree=2, C = 5.0	74.13	25.87	86.67	38.24
RBF sigma=4, C = 7.5	83.16	16.84	82.76	70.59

According to Table 6, the Radial Basis Function with sigma=4 and C=7.5 was the optimum kernel for PSO-SVM. Compared to other PSO-SVM models, this one had the highest accuracy (83.16%) and lowest error rate (16.84%). This model's recall value was 70.59%, and its precision was 82.76%.

- Comparison of the Performance

Fig. 1 represents the comparison of the PSO-SVM and SVM models done to assess the performance of the PSO-SVM model.

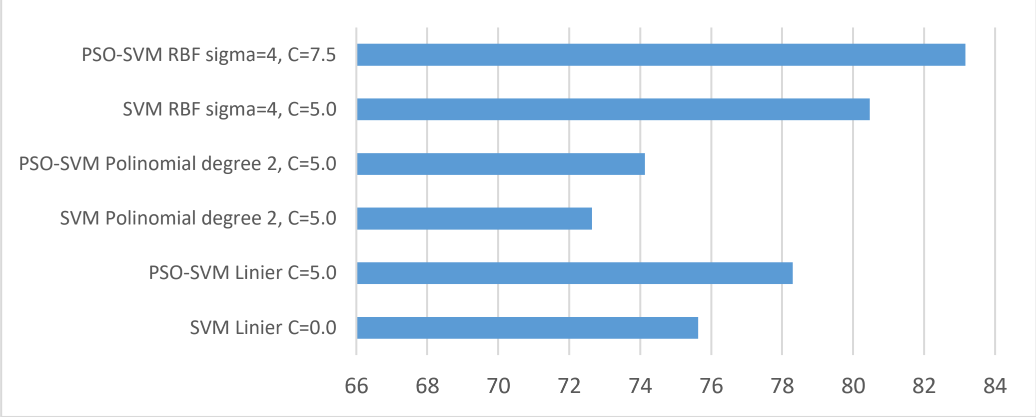

Fig. 1. The Comparison of PSO-SVM and SVM Model Accuracy

The finest SVM models have managed to predict financial distress in the property and real estate sector enterprises with an accuracy of more than 70%. However, with an accuracy rate of 83.16%, the PSO-SVM model with RBF sigma=4 and C=7.5 kernels surpassed the other models. Table 7 displays the Confusion Matrix for this model.

Table.7 The Confusion Matrix of The Best PSO-SVM

Category		True Class		Total
		F.D.	*Not F.D.*	
Pred. Class	F.D.	72	15	87
	Not F.D.	30	150	180
Total		102	165	267

Table 7 displays the confusion matrix that was created using the model. It is demonstrated that out of 102 samples of financial distress in property and real estate enterprises, the best PSO-SVM can correctly predict 72 cases, while the model cannot predict 30 cases. Additionally, just 15 out of 165 cases of non-financial distress were incorrectly predicted by that model, which can reliably predict 150 of those cases. This outcome demonstrates that the PSO-SVM model, based on a Radial Basis Function kernel, accurately identifies financial distress in real estate and property enterprises. As a decision consideration for investments or any other critical decisions, this model can be used to forecast the occurrence of another case of financial difficulty in property and real estate companies listed on the Indonesian Stock Exchange.

Accurate financial distress predictions are crucial for companies' sustainability, particularly those in the property and real estate sectors. Predicting potential financial distress enables companies to take necessary preventive or corrective actions, such as debt restructuring, improving cash management, reducing costs, and making better management decisions. With the ability to predict financial distress, companies can take strategic steps to ensure the continuity of their operations, balance finances, increase liquidity, and manage risks effectively.

Predicting financial distress is crucial not only for companies but also for society as a whole. Financially distressed companies can affect economic stability and lead to layoffs, affecting the livelihoods of their employees. The society also has a role as an investor and creditor for a company. Therefore, early warning signs of financial distress are essential in minimizing the risks of the society's investment. Thus, predicting financial distress is not only a business issue but also has a significant impact on the welfare of society. Understanding and managing financial risks are critical in maintaining economic and social stability.

4. Conclusion

According to the findings of this analysis, Particle Swarm Optimization (PSO) can optimize parameters and increase the predictive power of Financial Distress Support Vector Machine (SVM) in Property and Real Estate Sector Companies. Following the use of Particle Swarm Optimization, the accuracy increases in the PSO-SVM model with the RBF sigma=4.0 and C=7.5 kernels with an accuracy of 83.16%, while the traditional SVM model obtains the highest accuracy with the RBF sigma=4.0 and C=5.0 kernel models with an accuracy of 80.47%..

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