Support Vector Machine (SVM) as Financial Distress Model Prediction in Property and Real Estate Companies

Ni Wayan Dewinta Ayuni
Department of Accounting
Politeknik Negeri Bali
Badung, Indonesia
dewintaayuni@pnb.ac.id

Ni Nengah Lasmini
Department of Accounting
Politeknik Negeri Bali
Badung, Indonesia
nengahlasmini@pnb.ac.id

Agus Adi Putrawan
Department of Electrical Engineering
Politeknik Negeri Bali
Badung, Indonesia
putrawanagusadi@pnb.ac.id

***Abstract*— Financial distress prediction is an interesting topic to be studied because of its significant impact on various stakeholders. Various methods have been developed to predict the company's financial distress. Among the famous models, the Support Vector Machine (SVM) is claimed to be the most successful model in prediction and classification. SVM is a machine learning method that works on the principle of Structural Risk Minimization (SRM) with the aim of finding the best hyperplane that separates two classes in the input space by maximizing the hyperplane margin and obtaining the best support vector. This study applies the SVM model in predicting the financial distress of property and real estate companies listed on the Indonesia Stock Exchange. There were 18 variables of financial ratios used in this study. By Using Principal Component Analysis (PCA) in feature selections there are five variables selected in this study, namely Return on Assets, Return on Equity, Net Profit Margin, Earning Per Share, and Operating Profit Margin. The SVM model is formed by dividing the training and testing data with 10-fold cross-validation and using three kernels: linear kernel, polynomial, and Radial Basis Function (RBF). The best SVM model formed is the SVM model with RBF kernel type with parameters sigma = 1 and C = 1.0 which can predict financial distress with an accuracy value of 82.99% and an error rate of 17.01%.**

Keywords*— *financial distress, machine learning, support vector machine, property and real estate companies

I. Introduction

Financial distress is a stage of the company's financial condition where there is a decline before the company faces bankruptcy or liquidation [1]. The bankruptcy of a company can cause economic disruption for the company's management, investors, creditors, suppliers, employees, and can even destabilize the economy of a country. Thus the prediction of financial distress becomes one of the most important parts in evaluating the prospects for the company's sustainability and has a significant impact on various parties [2].

According to [3] internal factors that can cause a company to be in financial distress are poor management, autocratic leadership, and the company's inability to adapt and compete in the market. However, apart from that, external factors can also be a significant cause of a company being in a state of financial distress. One of them is the Covid-19 Pandemic that hit the world at the beginning of 2020. The pandemic has disrupted lives across all countries and communities and negatively affected global economic growth in 2020 beyond anything experienced in nearly a century [4]. Various social restrictions and several prohibitions related to preventing the Covid-19 pandemic by various countries around the world, including in Indonesia, caused almost 80 percent of companies to experience a drastic decline in income [5]. According to data from the Central Statistics Agency or Badan Pusat Statistik (BPS) on September 15, 2020, 82.85% of companies in Indonesia were affected by the Covid-19 pandemic. Reporting from CNBC Indonesia [6] data from the Association of Indonesian Issuers or Asosiasi Emiten Indonesia (AEI) stated that more than 50 companies listed on the Indonesia Stock Exchange are starting to experience difficulties due to the impact of the Covid-19 pandemic. According to [7] this condition will lead to an economic crisis due to the impact of the pandemic.

Of the many sectors affected by Covid-19, the property and real estate sector is one sector that has a large multiplier impact on the economy. The property and real estate sector have a great influence on other industries such as the material industry, logistics, services, financial industry, and banking [8]. That is why authorities in many countries pay great attention to any developments in the property and real estate sector. However, during the Covid-19 pandemic, this sector can be said to be completely paralyzed [9].

One example of a case that has shocked the world economy due to financial distress from the property and real estate sector is the case of the giant company of a Chinese property, Evergrande, at the end of 2021. The main reason was that Evergrande, like other property sector companies, run its business mostly from debt [10] [11]. Reporting from [12] Indonesian Minister of Finance Sri Mulyani admitted that she was worried about the financial crisis in Evergrande. According to her, the financial crisis due to company's dependence on debt is a new risk to the world. This reinforces that modeling financial distress predictions for companies in the property and real estate sectors is an important thing to do.

Various methods have been developed to predict the company's financial distress. Reference [13] started the financial distress prediction model using the company's financial ratios, [14] developed the Altman Z-Score, [15] developed logistic regression to determine the possibility of

XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE

A. Azizah and E. D. Ariyani (Eds.): iCAST-SS 2022, ASSEHR 719, pp. 397–402, 2022.
https://doi.org/10.2991/978-2-494069-83-1_72

the company experiencing financial distress. In addition, [16] also developed a financial distress forecast using the Factor Analysis method.

To reduce the weaknesses of the previous statistical methods, statistical methods began to be combined with Machine Learning [2], [17], [18]. Machine learning is a computational and statistical approach to extracting patterns and trends from data. Machine learning can be defined as computer applications and statistical mathematical algorithms that are adopted by means of learning that comes from data and produces accurate predictions [19]. The learning process in machine learning is an attempt to acquire intelligence through two stages, including training and testing [20]. Some famous combination methods of statistics and machine learning are decision trees using k-nearest neighborhood, genetic algorithm (GA), artificial neural network (ANN) and support vector machine (SVM).

Among the various models, the Support Vector Machine (SVM) model developed by [21] is claimed to be the most successful model in prediction and classification. The same thing was also concluded by [22]. In their research that applied 16 classifiers to 21 data sets showed that SVM is the most powerful method in machine learning. According to [23] and [24] SVM is a supervised learning technique to make predictions, both in the case of classification and regression. Furthermore, [25] stated that SVM is a machine learning method that works on the principle of Structural Risk Minimization (SRM) with the aim of finding the best hyperplane that separates two classes (categories) in the input space. Two classes in SVM are denoted by class -1 and class +1. The best hyperplane is a hyperplane that is located in the middle between two sets of objects from two classes (categories). The best dividing hyperplane between the two classes (category) can be found by measuring the margin of the hyperplane and finding its maximum point. Margin is the distance between the hyperplane and the closest pattern of each class. This closest pattern is called a support vector.

SVM has the basic principle of a linear classifier and was developed to work on non-linear problems by including kernel tricks in high-dimensional workspaces. The Kernel in SVM can be linear or non-linear, namely Radial Basis Function (RBF), polynomial, or sigmoid [26]. SVM has advantages including in determining the distance using a support vector so that the computational process becomes fast [21]. According to [27] SVM is a classifier that has the advantage of being able to process high-dimensional data, without experiencing a significant decrease in performance. In several studies, it was shown that SVM is an efficient method [28] [29].

Several previous studies have applied the SVM prediction model in the field of financial distress such as [30] who applied SVM to predict bankruptcy using the Fuzzy function, [31] who proposed the SVM ensemble method with several feature selections, [32] who applied SVM to Prediction of Financial distress and bankruptcy for Japanese Corporations, [33] in their research about predicting Financial Distress and bankruptcy in industrial companies operating in the Czech Republic Using the SVM Method, [2] applying machine learning methods including SVM in predicting bankruptcy of companies in China, as well as [34] who applied SVM to the prediction of financial distress of companies in the consumer goods industry.

This study applies SVM in predicting financial distress in property and real estate sector companies using linear and nonlinear kernels (Radial Basis Function and Polynomial) and pre-processing feature selection using Principal Component Analysis (PCA). This model was formed in order to produce a high accuracy value and a low level of misclassification so that it can be a reference for stakeholders such as management, investors, and banking institutions in making the right decisions about the companies of the property and real estate sector.

II. Methods

A. Data and Variables

The data used in this study is quantitative data in the form of financial ratios of property and real estate sector companies from 2018-2021 listed on the Indonesia Stock Exchange. The population in this study is the Property and Real Estate Sector Companies listed on the Indonesia Stock Exchange. The sample taken is a saturated sample of 61 companies with 2018-2021 financial statements.

The variables used in this study are divided into two parts, which are:

1. Dependent variable
   The dependent variable is the classification of financial distress of companies that are labeled as -1 for companies experiencing financial distress and labeled +1 for companies that are not experiencing financial distress. The criteria used to determine a company experiencing financial distress is if the company in its financial statements meets one or more of the following criteria [35] [36]
   a. Negative working capital;
   b. Negative operating profit; or
   c. Negative net income.
2. Independent variable
   The independent variables are in the form of financial ratios with the following details:
   - Liquidity Ratio:
     Working Capital to total Asset (X1), Current Ratio (X2), Quick Ratio (X3), Account Receivable Turnover (X4), and Inventory Turnover (X5)
   - Solvability Ratio:
     Debt-to-Equity (X6) and Leverage Ratio (X7)
   - Profitability Ratio:
     Gross Profit Margin (X8), Net Profit Margin (X9), Operating Profit Margin (X10), Return on Equity (X11), and Return on Assets (X12)
   - Asset Utilization Ratio:
     Asset Turnover Rate (X13), Working Capital Turnover Rate (X14), and Fixed Asset Turnover Rate (X15)
   - Investor Ratio:
     Earning Per Share (X16), Price Earning Ratio (X17), and Book Value Per Share (X18)

Because this study aims to predict, the dependent variable used is the n-th year period while the independent variable is the n-1-th period.

B. The Data Analysis Step

There are three steps of data analysis of this study:

1. Pre-processing

   At this stage, cleaning and transformation are carried out on the data and samples used. After cleaning and transformation, dimension reduction is carried out on the independent variable/feature using the Principal Component Analysis (PCA) method. The purpose of dimensional reduction is to form a new variable (called Principal Component/PC) which is a linear combination of independent variables where these new variables do not have multicollinearity with each other. Then the selection of variables/features based on the eigenvectors that meet the criteria (the absolute value of the eigenvectors is more than 0.3) from the Principal Component (PC) that is formed.

2. Modeling

   a. At this stage the data is divided into two groups, namely training data and testing data. Training data is a group of data used to form a model, while testing data is data used to measure the accuracy of the model formed. The distribution of training and testing data is using the K-Fold Cross Validation method. A 10-fold CV is one of the recommended K-fold CVs for selecting the best model because it tends to provide less biased accuracy estimates compared to an ordinary CV, leave-one-out CV, and bootstrap [37]. In a 10-fold CV, the data is divided into 10 folds of approximately equal size, so that 10 subsets of data are obtained to evaluate the performance of the model. For each of the 10 data subsets, CV will use 9 folds for training and 1-fold for testing alternately for up to 10 iterations.

   b. Determine the value of the parameter constant C > 0 which is a tolerance for misclassification errors. A high C value indicates the softer margin used. The risk of using a high C value can lead to overfitting of the model, while if the C value is too low, the model will overgeneralize in the classification [37]. The C values used in this study were 0.0, 0.5, 1.0, and 5.0.

   c. The model is then formed using SVM with RapidMiner software using Linear Kernel, Radial Basis Function Kernel, and Polynomial Kernel.

3. Model Evaluation

   The model is evaluated using the confusion matrix as shown in Table 1. The calculation of accuracy and error rate can be computed using the following formula

TABLE 1. CONFUSION MATRIX.

Category		True Class		Total
		FD	***Not FD***	
Pred. Class	FD	TP	FP	P'
	Not FD	FN	TN	N'
Total		P	N	

$$accuracy = \frac{TP+TN}{P+N} \quad (1)$$

$$error\,rate = \frac{FP+FN}{P+N} \quad (2)$$

Besides that, the measurements that can be used to evaluate the classification are

$$precision = \frac{TP}{TP+FP} \quad (3)$$

$$recall = \frac{TP}{TP+FN} = \frac{TP}{P} \quad (4)$$

TP (True Positive) is the number of financial distress cases in property and real estate sector companies that were successfully predicted by the SVM model. TN (True Negative) is the number of cases in property and real estate companies that do not have financial distress issues and the SVM also predicted it as well. While FP (False Positive) and FN (False Negative) are when the SVM failed to predict the right condition in a case. Results and Discussions

C. Pre-Processing

At the pre-processing stage, cleaning is carried out with the criteria of removing incomplete data subsets of all attributes (variables) used. After cleaning, a transformation is carried out by making the data follow a normal distribution (normalize data, which has a mean of 0 and a variance of 1). After cleaning and transformation, dimension reduction is carried out on the independent variable/feature using the Principal Component Analysis (PCA) method.

The variance of PCs formed by PCA is shown in Table 2. There are 18 Principal Components (PC) formed. However, the PC that was chosen was PC1 because it has the highest proportion of variance compared to other PCs. Then the selection of variables or attributes based on the eigenvectors that meet the criteria (the absolute value of the eigenvectors is more than 0.3) from PC1 is formed.

TABLE 2. VARIANCE OF PRINCIPAL COMPONENT

PC	Std Dev	Proportion of Var	Cumulative Var
PC1	2.034	0.230	0.230
PC2	1.607	0.143	0.373
PC3	1.344	0.100	0.474
PC4	1.171	0.076	0.550
PC5	1.127	0.071	0.620
PC6	1.031	0.059	0.679
PC7	0.981	0.053	0.733
PC8	0.972	0.052	0.785
PC9	0.894	0.044	0.830
PC10	0.849	0.040	0.870
PC11	0.818	0.037	0.907
PC12	0.731	0.030	0.937
PC13	0.708	0.028	0.965
PC14	0.567	0.018	0.983
PC15	0.450	0.011	0.994
PC16	0.221	0.003	0.996
PC17	0.194	0.002	0.999
PC18	0.159	0.001	1.000

TABLE 3. THE EIGEN VECTOR.

Variable	Eigen Vector PC1	Abs Eigen Vector PC1
X12. Return On Asset	0.444	0.444
X11. Return On Equity	0.439	0.439
X9. Net Profit Margin	0.415	0.415
X16. Earnings per share	0.327	0.327
X10. Operating Profit Margin	0.303	0.303
X5. Inventory TO	-0.284	0.284
X18. Book Value Per Share	0.262	0.262
X8. Gross Profit Margin	0.181	0.181
X13. Asset Turnover	0.167	0.167
X7. Leverage Ratio	-0.124	0.124
X6. Debt to Equity	-0.090	0.090
X1 (Working Capital to total Asset)	0.046	0.046
X15. Fix Asset Turnover	0.034	0.034
X2 (Current Ratio)	-0.029	0.029
X14. Working capital Turnover	0.027	0.027
X3. Quick Ratio	-0.025	0.025
X17. Price Earnings Ratio	-0.005	0.005
X4. Account Receivable Turnover (TO)	0.003	0.003

Table 3 shows that there are five variables/attributes that have absolute values of PC1 eigenvectors greater than 0.3, namely X12 (Return on Assets), X11 (Return on Equity), X9 (Net Profit Margin), X16 (Earning Per Share), and X10 (Operating Profit Margin). Thus, for further analysis, only data from these five variables are used.

D. Modelling

Dividing the data into two sets, which are training and testing data sets using 10-fold CV. The next step is forming the SVM model using three types of the kernel, which are Linear, Polynomial, and RBF. For the linear kernel, the parameter used to form the SVM model is C = 0.0, C=0.5, C=1.0, dan C=5.0. While to form the SVM model using a polynomial kernel, the degree of a polynomial and the value of C are needed. The degree of a polynomial that will be tested in this study is 2, 3, and 4 while C=0.0, C= 0.5, C = 1.0, dan C = 5.0. To form an SVM model with a Radial Basis Function (RBF) kernel, first, determine the value of parameters. The value of C were 0.0, 0.5, 1.0, and 5.0 and the value of sigma were 1, 2, 3, and 4.

The SVM models that have been formed are evaluated with a confusion matrix which determines how many prediction classes are right for the original class. The criteria used in this confusion matrix are accuracy (number of cases correctly predicted compared to total cases), error rate (number of cases incorrectly predicted compared to total cases), precision, and recall. A good model is one that has high accuracy, precision, and recall but also has a low error rate. The evaluation results of the best models in each kernel type formed in this study are shown in Table 4.

TABLE 4. MODEL EVALUATION.

Kernel Type	Evaluation (%)			
	Accuracy	*Error rate*	*Precision*	*Recall*
Linier C=5.0	81.06	18.94	89.09	59.04
Polynomial, degree=2, C=5.0	70.15	29.85	76.32	34.94
RBF sigma=1, C=1.0	82.99	17.01	86.15	67.47

TABLE 5. THE CONFUSION MATRIX OF THE BEST SVM.

Category		True Class		Total
		FD	*Not FD*	
Predicton Class	FD	56	9	65
	Not FD	27	119	146
Total		83	128	211

Table 4 shows that the SVM model using RBF kernel type and the value of parameter sigma = 1 and C = 1.0 gave the highest accuracy rate which is 82.99% and the lowest error rate which is 17.01%. This model was also supported by the value of precision of 86.15% and a recall value of 67.47%. While the SVM model using Linear and Polynomial kernel types only gave the best accuracy value of 81.06% and 70.15% respectively which is lower than the accuracy of the RBF kernel type. The RBF Kernel Type model using sigma=1 is as follows:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2(1)^2}\right) = \exp\left(-\frac{\|x_i - x_j\|^2}{2}\right) \qquad (5)$$

The confusion matrix formed from that model is shown in Table 5. It is shown that from 83 cases of financial distress in property and real estate companies, the best SVM can predict 56 cases successfully, while 27 cases of financial distress can not be predicted by the model. Also, that model can predict 119 cases out of 129 cases of non-financial distress accurately, only 9 cases were miss-predicted. This result shows that the SVM model based on the Radial Basis Function kernel gives high accuracy in predicting the financial distress of property and real estate companies. This model can be used to predict another case of financial distress in property and real estate companies listed in the Indonesian Stock Exchange as decision consideration in investments, or any other significant decisions.

III. CONCLUSSIONS

After going through various stages, namely pre-processing, modeling, and evaluation, this research concludes: Pre-processing with cleaning and feature selection using Principal Component Analysis (PCA) produces 5 independent variables used in the model, namely X12 (Return on Assets), X11 (Return on Equity), X9 (Net Profit Margin), X16 (Earning Per Share), and X10 (Operating Profit Margin). The best model formed is the SVM model with the Radial Basis Function (RBF) kernel with the value of parameter sigma = 1 and C = 1.0. This model has an accuracy value of 82.99% and an error rate of 17.01% in predicting the financial distress of property and real estate companies listed on the Indonesian Stock Exchange.

ACKNOWLEDGMENT

Gratitude is expressed to the P3M Politeknik Negeri Bali for funding this research.

REFERENCES

[1] H. Platt and M. Platt, "Predicting corporate financial distress: Reflections on choice-based sample bias," *Journal of Economics and Finance,* vol. 26, no. 2, p. 184–199, 2002.

[2] Y. Li and Y. Wang, "Machine Learning Methods of Bankruptcy Prediction Using Accounting Ratios," *Open Journal of Business and Management,* vol. 6, pp. 1-20, 2018.

[3] Z. Hua, Y. Wang, X. Xu, B. Zhang and L. Liang, "Predicting corporate financial distress based on integration of support vector machine and logistic regression," *Expert Systems with Applications,* vol. 33, p. 434–440, 2007.

[4] J. Jackson, M. Weiss, A. Schwarzenberg, R. Nelson, K. Sutter and M. Shuterland, "Global Economic Effects of COVID-19," Congressional Research Service, 2021.

[5] Muhyiddin and H. Nugroho, "A Year of Covid-19: A Long Road to Recovery and Acceleration of Indonesia's Development," *The Indonesian Journal of Development Planning,* vol. 5, no. 1, pp. 1-19, April 2021.

[6] S. Sidik, "CNBC Indonesia," CNBC , 12 Mei 2020. [Online]. Available: https://www.cnbcindonesia.com/market/20200512080335-17-157760/50-lebih-emiten-sekarat-karena-corona-cuma-kuat-sampai-juni . [Accessed 27 Februari 2022].

[7] K. Safitri, " Mitigating the Impact of the Covid-19 Pandemic on the Capital Market (Meredam Dampak Pandemi Covid-19 di Pasar Modal)," Kompas, 28 Juli 2020. [Online]. Available: https://money.kompas.com/read/202 0/07/28/173724126/meredamdampak-pandemi-covid- 19-dipasar-modal?page=all . [Accessed 27 Februari 2022].

[8] I. Nurfahrudin and R. Rahadi, "Application of Bankruptcy Prediction Models For Real Estate Company on The Indonesia Stock Exchange (IDX)," *Jurnal Ilmiah Indonesia,* vol. 6, no. 10, 2021.

[9] Sunarsip, " Property Outlook 2022 and Growth Prerequisites (Outlook Properti 2022 dan Prasyarat Pertumbuhannya)," CNBC Indonesia, 20 Desember 2021. [Online]. Available: https://www.cnbcindonesia.com/opini/20211220113050-14-300546/outlook-properti-2022-dan-prasyarat-pertumbuhanny. [Accessed 27 Februari 2022].

[10] M. Metzler, M. Ewi and D. Dam, "THE GREAT RESET: Evergrande and the Final Meltdown of the Global Financial System," Deutsche MarktScreening Agentur Gmbh. , 2021.

[11] A. Iswara, " Evergrande Crisis: The Beginning of Disaster, IDR 4 Quadrillion in Debt, and Thousands of Orangtle Losses (Krisis Evergrande: Awal Mula Petaka, Utang Rp 4 Kuadriliun, dan Ruginya Ribuan Orangtle)," Kompas, 20 Desember 2021. [Online]. Available: https://www.kompas.com/global/read/2021/10/ 02/203602470/krisis-evergrande-awal-mulapetaka-utang-rp-4-kuadriliun-danruginya?page=al. [Accessed 26 Februari 2022].

[12] S. Evanda, " Sri Mulyani Reveals the Extraordinary Impact of the China Evergrande Crisis (Sri Mulyani Ungkap Dampak Luar Biasa Krisis China Evergrande)," Okezone, 24 September 2021. [Online]. Available: https://economy.okezone.com/read/2021/09/23/320/2475892/sri-mulyani-ungkap-dampak-luar-biasa-krisis-china-evergrande. [Accessed 26 Februari 2022].

[13] W. Beaver, " Financial Ratios as Predictors of Failure," *Journal of Accounting Research,* vol. 4, pp. 71-111, 1966.

[14] E. I. Altman, "Financial Ratios Discriminant Analysis and The Prediction of Corporate Bankriptcy," *Journal of Finance,* vol. 23, pp. 589-609, 1968.

[15] J. Ohlson, " Financial Ratios and Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research,* vol. 18, pp. 109-131, 1980.

[16] R. West, "A Factor-Analytic Approach to Bank Condition," *Journal of Banking & Finance,,* vol. 9, pp. 253-266, 1985.

[17] R. Wilson and R. Sharda, "Bankruptcy Prediction Using Neural Networks," *Decision Support System,* vol. 11, pp. 545-557, 1994.

[18] C. Tsai, "Financial Decision Support using Neural Networks and Support Vector Machines.," *Expert Systems,* vol. 25, pp. 380-393, 2008.

[19] J. Brand, B. Koch and J. Xu, Machine Learning, London: SAGE Publications Ltd , 2020.

[20] G. B. Huang, Q. Y. Zhu and C. K. Siew, "Extreme Learning Machine: Theory and Applications," *Neurocomputing,* vol. 70, no. 1, p. 489–501, 2006.

[21] V. Vapnik and C. Cortes, " Support Vector Networks," *Machine Learning,* vol. 20, pp. 273-297, 1995..

[22] D. Meyer, F. Leisch and K. Hornik, "The Support Vector Machine Under Test," *Neurocomputing,* vol. 55, no. 1, p. 169–186., 2003.

[23] C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," *Data Mining and Knowledge Discovery,* vol. 2, no. 2, pp. 121-167, 1998.

[24] J. Han, M. Kamber and J. Pei, Data Mining: Concepts and Techniques 3rd Edition, Massachusetts: Elsevier Inc, 2012.

[25] S. Komarudin, D. Anggraeni, A. Riski and A. Hadi, "Classification of genetic expression in prostate cancer using support vector machine method," *Journal of Physics: Conference series,* pp. 1-10, 2020.

[26] A. Nugroho, A. Witarto and D. Handoko, "Application of Support Vector Machine in Bioinformatics," in *Indonesian Scientific Meeting in Central Japan*, Gifu-Japan, 2003.

[27] I. Purnawa, "Support Vector Machin Pada Information Retrieval," *Jurnal Pendidikan dan Teknologi Kejuruan,* vol. 12, no. 2, pp. 173-180, 2015.

[28] H. Brcher, G. Knolmayer and M. Mittermayer, "Document Classification Methods for Organizing Explicit Knowledge," in *the Third European Conference on Organizational Knowledge, Learning, and Capabilities*, 2002.

[29] S. Chakrabarti, S. Roy and M. Soundalgekar, "Fast and Accurate Text Classification Via Multiple Linear Discriminant Projections," *VLDB Journal,* vol. 12, pp. 170-185, 2002.

[30] A. Chaudhuri and K. De, "Fuzzy Support Vector Machine for Bankruptcy Prediction," *Applied Soft Computing Journal,* vol. 11, pp. 2472-2486, 2011.

[31] J. Sun and H. Li, "Financial Distress Prediction using Support Vector Machines: Ensemble vs. Individual," *Applied Soft Computing Journal,* vol. 12, pp. 2254-2265, 2012.

[32] M. Matsumaru and K. Kawanaka, "Bankruptcy Prediction for Japanese Corporations using Support Vector Machine, Artificial Neural Network, and Multivariate Discriminant Analysis," *International Journal of Industrial Engineering and Operations Management (IJIEOM),* pp. 78-96, 2019.

[33] J. Horak, J. Vrbka and P. Suler, "Support Vector Machine Methods and Artificial Neural Networks Used for the Development of Bankruptcy Prediction Models and their Comparison," *Journal of Risk and Financial Management,* pp. 1-15, 2020.

[34] A. Chmielewska, "Bankruptcy prediction of small- and medium-sized enterprises in Poland based on the LDA and SVM methods," *Statistics In Transition,* pp. 179-195, 2021.

[35] R. Whitaker, "The early stage of financial distress," *Journal of Economics and Finance,* pp. 123-133, 1999.

[36] Nurhayati, A. Mufidah and A. Kholidah, "The Determinants of Financial Distress of Basic Industry and Chemical Companies Listed in Indonesia Stock Exchange," *Review Of Management And Entrepreneurship,* pp. 19-26, 2017.

[37] P. Sihombing and O. Hendarsin, "Perbandingan Metode Artificial Neural Network (ANN) dan Support Vector Machine (SVM) untuk Klasifikasi Kinerja Perusahaan Daerah Air Minum (PDAM) di Indonesia," *Jurnal Ilmu Komputer,* vol. XIII, no. 1, pp. 9-20, 2020.