Decision Science Letters 9 (2020) 207–214

Contents lists available at GrowingScience

Decision Science Letters

homepage: www.GrowingScience.com/dsl

Delisting sharia stock prediction model based on financial information: Support Vector Machine

Endri Endri[a*], Kasmir Kasmir[a] and Andam Dewi Syarif[a]

[a]*Masters in Management, Universitas Mercu Buana, Jakarta, Indonesia*

C H R O N I C L E

Article history:
Received September 9, 2019
Received in revised format: October 25, 2019
Accepted November 5, 2019
Available online November 5, 2019

Keywords:
Delisting
Islamic stocks
Financial information
Support vector machines

A B S T R A C T

The purpose of this research is to develop an early warning system model that can anticipate the occurrence of delisting of Islamic stocks (ISSI) using Support Vector Machines (SVM). Financial variables used consist of debt to equity, return on invested capital, asset turn over, quick ratio, current ratio, return on assets, return on equity, leverage, long term debt, and interest coverage. The population of this study is 335 sharia shares registered at ISSI in the period 2012-2017, with a total sample of 102 companies. The results show that the financial variables had a predictive power to the occurrence of delisting of Islamic stocks in the ISSI index. The effect of the independent variable or predictor variable is the financial ratio to the target variable or the dependent variable that is the potential for delisting of Islamic stocks in the ISSI index. With the development of 4 SVM models with different levels of prediction accuracy, SVM Model 1 with an accuracy rate of 71.57%, SVM Model 2 with an accuracy rate of 72.55%, SVM Model 3 with an accuracy rate of 82.35% and SVM Model 4 with an accuracy rate of 100%, it can be concluded that the SVM Model 4 is the best model.

1. Introduction

The capital market is part of the financial market that provides funding for companies for various investment activities of the company. The capital market is also one way for companies to find funds by selling rights company ownership to the community (Saqib, 2013). As an alternative to conventional capital market conditions which in some cases are not in line with sharia principles, since July 3, 1997 Islamic stocks and screening of Islamic stocks in Indonesia produced ISSI (Indonesia Sharia Stock Index) stock indexes. Stocks included in this index are the ones that meet the criteria for sharia shares as determined by the National Sharia Board and the stock exchange. These criteria consist of quantitative and qualitative criteria. In addition to the ISSI index, the Indonesia Stock Exchange also has another sharia index, JII (Jakarta Islamic Index) where 30 of the best performing ISSI shares are included in this index (Firmansyah, 2017). The expectation of the public for the growth of companies incorporated in Islamic stock issuers is quite good and it is shown by the capitalization of Islamic stocks continues to experience growth. Based on OJK statistical data in 2012, the total capitalization of sharia shares by 2.4 trillion increased to 3.5 trillion, or by the end of 2017, an increase of 43% over 5 years. The number of Islamic shares continues to grow from 304 shares in 2012 to 359 shares in 2017 an increase of 18% in just five years (OJK Statistics, 2017). The distribution of Islamic stock issuers is dominated by businesses engaged in the Trade, Services and Investment sectors (25.65%), the Property, Real Estate & Construction sector (16.71%), the Basic Industry and Chemical sectors (14.99%), Infrastructure, Utilities and Transportation sectors (10.09%) and other sectors each under 10% (OJK Road Map, 2016-2019). Over the last five years there has been an increase in the number of stocks of sharia in line with an increase in the number of companies conducting a public offering of stock as well as an increase in issuers whose stock meet the criteria as Islamic stock. Some companies experience delisting from the Indonesian Shariah Stock Index (ISSI). Recorded in the Indonesia Stock Exchange

* Corresponding author. Tel.: +628129204067
E-mail address: endri@mercubuana.ac.id (E. Endri)

doi: 10.5267/j.dsl.2019.11.001

report from 2012 - 2017 there are hundreds of stocks that have been delisted from ISSI where stocks that have been delisted in each semester range between 15-30 firms. Every semester there are new stocks that enter and old ones which are excluded from the Indonesian Islamic stock index. The composition of sharia stock continues to change, in the past five years there have been 249 new stocks accumulated or 74% of total sharia stocks and there are 220 shares that have been delisted from ISSI from total sharia stocks. This number is quite significant and opens up the possibility of an upward trend in the coming semesters that the number of stocks that will be delisted from the Indonesian Islamic stock index will be even higher.

There are some previous studies on stock delisting. In general, companies experience delisting due to failure to meet quantitative criteria set by the exchange such as company size, trading volume, number of shareholders, and meeting qualitative criteria such as corporate governance and protection against bankruptcy threats (Witmer, 2008) (Fungáčová & Hanousek, 2011; Yiannoulis, 2016). There are several previous studies that have tested the accuracy of Zhou (2013) delisting prediction model with Linear Discriminat Analysis (LDA) models achieving an accuracy value of 96.36% and for Neural Network (NN) models with a level of accuracy of 81.13%, Khemais et al. (2016) using the Logistic Regression (LR) model with an accuracy level of 97.70 and Hwang et al. (2014) Logistic Regression with prediction accuracy of 84.44%.

There is a change in the composition of sharia stock on a regular basis in the Indonesian sharia stock index due to the large number of sharia stocks that have been delisted or excluded from the sharia stock index. The occurrence of stock delisting is a risk for stock investors who wish an investment form that is in accordance with sharia. Based on the background that has been explained, this research seeks to find the best model in terms of accuracy in predicting the potential for delisting of Islamic stocks so that it can be known which Islamic stocks are not performing well and have a tendency to experience delisting so that they can be avoided and the indexed is only limited to qualified stocks which are not affected by delisting risk.

2. Literature review

2.1. Early warning system

Early Warning System (EWS) is a series of systems that function to notify the occurrence of an event, which can be a natural or social event. Early warning activities provide information in an easily understood language (Duwipa, 2013). Signal models can be considered as a form of trend analysis, hence EWS is a development of the form of signal theory. The EWS model was originally developed to anticipate economic crises as research conducted by Kaminsky and Reinhart (1999), Kaminsky et al. (1998), Berg and Patillo (1999), and Berg et al. (2004). In general, previous studies used probit and logit models in the development of EWS.

2.2. Signaling theory

Signal Theory was expressed by Ross (1977) and states that company management is benefited from the information they have and given to investors. The information is mainly related to company performance that reflects the prospects in the future to raise the company's stock price. Information is an important tool for investors and information can be known about the current state of the company, past, or even the company's future prospects. The information that is available must be relevant, accurate, timely and complete and must be transferred by investors as an analysis tool in investment decisions in the capital market. Through the publication of information or information that is announced in the media investors may get a bad or good signal for their investment decision efforts (Endri, 2016). The volume of stock trading will reflect the market's reaction. The company has better expectations in the future, if there is a good signal in the information submitted. The impact to attract investors in trading shares. This is reflected in changes in stock trading volume where the market reaction is positive. Market efficiency will show the relationship between published information related to information in the form of financial, political, environmental and social reports on fluctuations in the volume of stock trading (Endri et al., 2019).

2.3. Delisting stocks

Fungáčová & Hanousek (2011) explained delisting in general as the issuance of a stock in an index or list of certain stocks. There are two types of delisting namely voluntary delisting and involuntary delisting. In voluntary delisting of a company intentionally or at their own request, removing the shares from the capital market index or the stock market is executed. In this case the company decides to change the form of a company from a publicly listed company or Go Public to a Limited Company. The decision to withdraw company’s shares from the stock index must be taken in a shareholders' meeting which where a minimum of 75% of the total shareholders must participate in such meeting. While in involuntary delisting or also called compulsory delisting that is the issuance of a stock from the market index capital it is not based on the decision of the issuing company. The decision to exclude a company's shares from the stock index is taken by the capital market authorities based on established regulations (Bakke et al., 2012).

2.4. Support vector machine

Support Vector Networks, also known as SVMs, are supervised learning models that are associated with learning algorithms (Learning Algorithms) used in data analysis by classification and regression (Cortes & Vapnik, 1995). While Olson and Delen (2008) define SVMs as Supervised Learning Methods or supervised learning methods that produce input-output mapping functions (Input-Output Mapping Function) taken from exercise data that has been labeled. Mapping conducted by SVM is divided into two namely 1) a classification function that is useful for making categorization of data, 2) a regression function that is useful for estimating certain data.

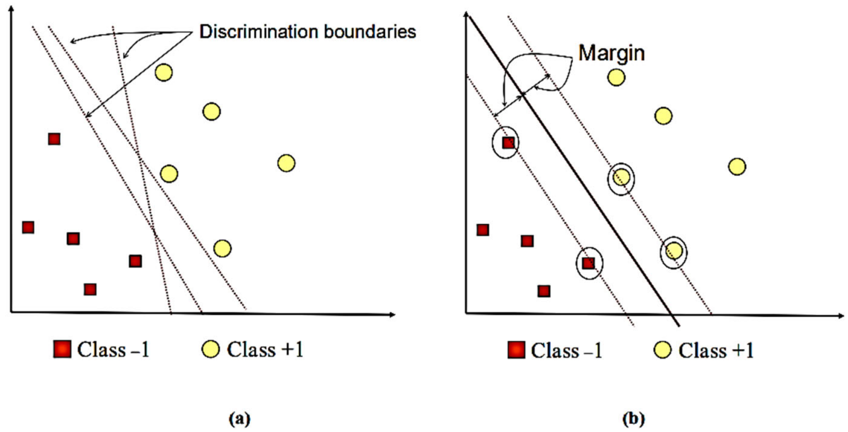


Fig. 1. HyperPlane Function

According to Anwar (2015) SVMs were first developed by Corter and Vapnik in 1995. The SVMs model implements structural risk minimization which seeks to reduce the level of error, and generalization, namely the ability to obtain a small degree of error in the test data. The concept of SVM can be simply explained as an effort to find the best hyperplane where the hyperplane functions as a separator of two classes in the input space. As we can observe from Fig. 1, there are two classes namely +1 and -1. In class -1 the pattern uses the red square symbol and the pattern in class +1 uses the yellow circle symbol. The problem solved in the SVMs algorithm is to resolve class +1 and class -1 by finding the best hyperplane or separator. There are several dividing lines called Discrimination boundaries where the algorithm looks for the best dividing line or hyperplane.

3. Methodology

For this study, the population used includes all companies listed on the Indonesia Stock Exchange (IDX) and the Indonesian Sharia Stock Index (ISSI) and they are entered into Islamic stock issuers from 2012 to 2017. The method of "Purposive Judgment sampling" is a sample selection based on the evaluation of some characteristics of members of the population adjusted to the objectives of the study (Kuncoro, 2003: 119). The sample used is Islamic stock issuers consisting of issuers excluded from the ISSI (Delisted) index. In addition, as a comparison to delisted companies only the information of the companies used that are still registered with ISSI. This study uses secondary data that is data obtained indirectly in the form of Annual Report or annual financial reports taken from the ISSI Indonesia Stock Exchange data over the period 2012 - 2018.

3.1. Dependent variable

The independent variables are used for prediction in research and it is dummy variable which receives the value of one (1) for listing or zero which means the firm is delisted. The following also describe the dependent variables,

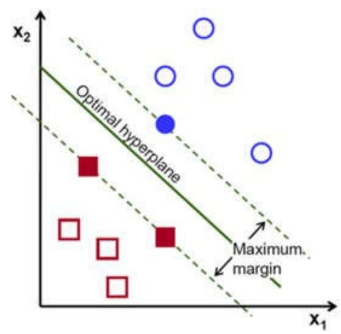
Dependent variable

Liquidity Ratio	
X1 Current Ratio	Current Asset / Current liabilities
X2 Quick Ratio	Current Asset - Inventory / Current liabilities
Solvability Ratio	
X3 Total Debt to Total Assets Ratio	Total Debt / Total Asset
X4 Debt to Equity Eatio	Total Debt / Total Equity
X5 Interest Coverage	EBIT/Interest Expense
X6 Long Term	Long Term Debt/Total Asset
Rentability Ratio	
X7 Return on Asset	EAT / Total Asset
X8 Return on Equity	EAT/ Equity
X9 Rerturn on Invested Capital	EAT/ Invested Capital
Activity Ratio	

X10 Asset Turnover	Sales / Total Asset

3.2. Support Vector Machines (SVMs)

Support vector machine is a data analysis method that can be simply explained as an effort to find the best hyperplane where the hyperplane functions as a separator of two classes in the input space (Byun & Lee, 2003).



According to Tsuda (2000), SVM support can be used to make predictions both using regression and classification. According to Anwar (2015), the ability of SVMs is denoted by the equation:

$$y_i = w_1\phi_1(x) + b$$

where

y_i	Scalar quantity
$\phi_1(x)$	Space feature of x input
w_1	Estimated value of the coefficient with the principle of structural risk minimization

The following are the steps in the analysis of Support Vector Machines (SVMs).

1. Variable Input

These variables include x1 = ROA (Return of Assets) x2 = ROE (Return of Equity), x3 = Leverage, x4 = Debt to Equity, x5 = Growth, x6 = Liquidity Ratio, x7 = Share Liquidity, x8 = Asset Turn Over, x9 = NWCTA, x10 = Firm Size

2. Determination of Variable Type

Determine the type of variable both the input variable and the output variable where the input variable is the ratio data type or continuous data and the output variable is the category data type.

3. Perform analysis and predictions

At this stage the input data will be obtained using the Support Vector Machines algorithm to produce a prediction model that determines the type of Kernel used in SVMs, the number of support vectors used and the support vector class used.

4. Evaluate Model Accuracy

Namely evaluates the accuracy of the SMV model by comparing the actual data and the predicted results generated by the analysis. From the comparison between the predicted value and the actual data, the accuracy level of the model will be obtained in the form of a match between the prediction and the actual data.

The application used for analysis using Support Vector Machine is Statistica Software Version 12 which is classified as a Data Mining method.

5. Findings

In developing the delisting prediction model on ISSI sharia stock using the Support Vector Machine (SVM) model, four models were developed. Each model is grouped based on differences in SVM Type, capacity, kernel Type, Number Support Vector and Support Vector per Class.

Table 1
Type of SVM Model

Model	SVM Type	Kernel Type	Seed
1	Classification Type 2	Linear	2000
2	Classification Type 1	Radial Basis function	1000
3	Classification Type 2	Linear	1500

4	Classification Type 1	Radial Basis function	2000

5.1 Results of SVM Model Development

From the four SVM models developed based on test and training, testing the accuracy of the predictions of each model will be conducted to choose the best SVM model.

5.1.1 SVM-1 Model

This is performed using Classification Type 2, Capacity 10, Linear Type kernel (nu = 0.700) with nu = 0.100, Number Support Vector 59 with 54 bounded and support vector per class = 30 in class (0), 29 in class (1).

Table 2
The results of SVM-1 model

Model SVM 1	Value	Training	Test	Overall
	-1.9890	75.31%	57.14%	71.75%

From Table 2 it is known that the SVM 1 model has a Value of -1.9890, with a level of accuracy or performance in a training session of 75.31% the level of accuracy or performance in a training session is 57.69% and an overall or overall performance of 72.55%.

5.1.2 SVM-2 Model

This is performed using Classification Type 1, Capacity 10, kernel Type Radial Base Function with Gamma = 0.100, Number Support Vector 50 with 46 bounded and support vector per class = 25 in class (0), 25 in class (1).

Table 3
The results of SVM-2 model

Model SVM 2	Value	Training	Test	Overall
	-1.5863	77.63%	57.69%	72.55%

From Table 3 it is known that the SVM 2 model has a Value of -1.5863, with an accuracy or performance level in the training session of 77.63%, an accuracy or performance level in the training session of 57.69% and an overall or overall performance of 72.55%.

5.1.3 SVM-3 Model

This is performed using Classification Type 2, Capacity 10, Linear Type kernel with nu = 0.500, Number Support Vector 42 with 34 bounded and vector support per class = 22 on class (0), 20 on class (1).

Table 4
The results of SVM-3 model

Model SVM 3	Value	Training	Test	Overall
	-7.6058	85.53%	73.08%	82.35%

From Table 4 it is known that the SVM 3 model has a Value of -7.6058, with an accuracy or performance level at a training session of 85.53%, an accuracy or performance level at a training session of 73.08% and an overall or overall performance of 82.35%.

5.1.4 SVM-4 Model

This is performed using Classification Type 1, Capacity 10, kernel Type Radial Base Function with Gamma = 0.100, Number Support Vector 50 with 46 bounded and support vector per class = 25 in class (0), 25 in class (1).

Table 5
The results of SVM-4 model

Model SVM 4	Value	Training	Test	Overall
	-1.5863	77.63%	57.69%	72.55%

From Table 5 it is known that the SVM 4 model has a Value of -1.5863, with an accuracy or performance level at a training session of 77.63%, an accuracy or performance level at a training session of 57.69% and an overall or overall performance of 72.55%.

5.2 Prediction results using the SVM Model

The following will describe the accuracy of the results of each model's predictions by comparing the predicted values with the actual data so that the accuracy level is measured based on the percentage ratio between the number of matches or correct with the total amount of data and likewise the level of error or incorrect.

5.2.1 Level of Accuracy of SVM-1 Model

The following are the results of the calculation of the prediction accuracy using the SVM 1 model.

Table 6
Level of Accuracy of SVM 1 Model

Class name	Total	Correct	Incorrect	Correct (%)	Incorrect(%)
0	50	23	27	46.00	54.00
1	52	50	2	96.15	3.85
ALL	102	73	29	71.57%	28.43%

In our SVM 1 model, based on the results of Table 6, the prediction accuracy of delisting of ISSI sharia stock reached 71.57% with a percentage error rate of 28.43%. Prediction errors occur mostly in Class (0) or in the case of lising, where the prediction error rate in the listing case is 54%, more than half of the predictions are mistaken and the accuracy of the prediction or correct is only 46%, less than half of the class number (0). In addition, for delisting or class (1) prediction accuracy is quite high at 96.15% with an error rate of under five percent at 3.85%.

5.2.2 Level of Accuracy of SVM-2 Model

The following are the results of the calculation of the prediction accuracy using the SVM 2 model.

Table 7
Level of Accuracy of SVM 2 Model

Class name	Total	Correct	Incorrect	Correct (%)	Incorrect(%)
0	50	24	26	48.00	52.00
1	52	50	2	96.15	3.85
ALL	102	74	28	72.55%	27.45%

In the SVM 2 model based on the Table 7 it is known that the accuracy level of the model 72.55% is not much different from the SVM 1 model although the kernel types of the SVM 1 and SVM 2 models are different, where SVM 1 uses the Linear Kernel Type while SVM 2 uses the Radial Basis Function. From the table it is known that the SVM Model 2 also has low accuracy for predicting class (0) because prediction errors reach 52% but for predicting class (1) the accuracy rate is quite high up to 96.15%. In other words the level of accuracy of the SVM 2 model has insignificant differences with the SVM 1 model.

5.2.3 Level of Accuracy of SVM-3 Model

The following are the results of the calculation of the prediction accuracy using the SVM 3 model.

Table 8
Level of Accuracy of SVM 3 Model

Class name	Total	Correct	Incorrect	Correct (%)	Incorrect(%)
0	50	35	15	70.00	30.00
1	52	49	3	94.23	5.77
ALL	102	84	18	82.35%	17.65%

The prediction results in the table above show that the SVM 3 model has a better level of accuracy than the previous models with a correct percentage value of 82.35%. The SVM 3 model uses the same kernel type as the kenel SVM 1 model with a linear type. The difference between the SVM 1 model uses the value of nu = 0.7 while in SVM 3 uses nu = 0.5 and the amount, while the number of Support Vector actually decreases in the SVM 3 model with the number of Support Vector as much as 42 and the SVM 1 model as much as 59. But the reduction in these parameters in fact it brings increased prediction accuracy to SVM models with linear kernel types.

5.2.4 Level of Accuracy of SVM-3 Model

The following are the results of the calculation of the prediction accuracy using the SVM 4 model

Table 9
Level of Accuracy of SVM 4 Model

Class name	Total	Correct	Incorrect	Correct (%)	Incorrect(%)

0	50	50	0	100.00	0.00
1	52	52	0	100.00	0.00
ALL	102	102	0	100.00%	0.00%

In the last model, the SVM 4 model from Table 9, it is obtained data about the level of prediction accuracy with a significantly higher value than the previous models. In the SMV 4 model, the prediction accuracy level reaches 100%, the total value of correct in class (0) and class (1) reaches 100%, and the level of error or incorrect can even be reduced to reach 0%. The SVM 4 model has the same kernel type as the SVM 2 model, which uses the Radial Base Function, but the SVM 4 model has a gamma level of 12, while the SVM 2 gamma is only 0.1. Besides that in the SVM model using Seed 2000 or multiplied more than the SVM model 2 the value of the stop of error parameter is ten times smaller i.e. 0.0001.

5.3 Comparison of the Accuracy Level of the SVM Model

From the results of testing the accuracy of the four SVM models that have been developed, we can compare the accuracy of each model.

Table 10
Comparison of Accuracy of SVM Model

MODEL SVM 1		MODEL SVM 2		MODEL SVM 3		MODEL SVM 4	
	Class All		Class All		Class All		Class All
Total	102	Total	102	Total	102	Total	102
Correct	73	Correct	74	Correct	84	Correct	102
Incorrect	29	Incorrect	28	Incorrect	18	Incorrect	0
Correct (%)	71.57	Correct (%)	72.55	Correct (%)	82.35	Correct (%)	100.00
Incorrect (%)	28.43	Incorrect (%)	27.45	Incorrect (%)	16.56	Incorrect (%)	0.00

From the comparative table of the accuracy of each SVM model, we know that each model has a different level of accuracy where the standard in assessing the high and low accuracy of each model is determined by how much the percentage of conformity between predictions and actual data expressed with the percentage correct and how a small degree of error in prediction is a mistake between prediction and actual data expressed in percentage Incorrect. From the data it is known that the SVM 4 model has the highest level of accuracy compared to other SVM models, reaching 100%. With this it can be concluded that the kernel with the Radial basis function type is more accurate in predicting the delisting of Islamic stocks. From the comparison of SVM 2 and SVM 4 models with the same kernel type, namely Radial basis function, it is known that high gamma values affect the predictive accuracy of SVM models, that the more gamma values are used, the higher the accuracy of the model. In addition, the number of support vectors in each class used influences the accuracy of the model that the models. In the previous SVM models tend to have a lot of errors in the prediction of class (1) or the occurrence of delisting in a stock.

Table 11
Conclusion of the SVM Model

Model	Kernel Type	Number Support Vectors	Support vectors per class	Seed
SVM 1	Linear (nu=0.700)	59 (54 bounded)	30 (0), 29 (1),	2000
SVM 2	Radial Basis function gamma = 0.100	50 (46 bounded)	25 (0), 25 (1),	1000
SVM 3	Linear (nu=0.500)	42 (34 bounded)	22 (0), 20 (1),	1500
SVM 4	Radial Basis function gamma = 12.00	61 (11 bounded)	27 (0), 34 (1)	2000

In the SVM 4 model, Gamma = 12 is greater than the SVM 2 = 0.1 model. While for vector support per class, the model for class (1) SVM 4 model is much higher than other models, which is 34. Because the previous models are quite accurate in predicting class (0), but not accurate enough in predicting class (1).). With the addition of the number of support vectors in class (1) the level of prediction accuracy in class (1) increases to 100%. In addition, the number of Seed also affects the level of prediction accuracy, SVM 4 has a number of Seed 2000 twice that of SVM 2 which only consists of 1000 Seed.

6. Conclusion

Financial variables have predictive power to the occurrence of delisting of Islamic stocks in the ISSI index. The effect of the independent variable or predictor variable is the financial ratio to the target variable or the dependent variable that is the potential for delisting of Islamic stocks in the ISSI index using the Support Vector Machine (SVM) model. The SVM model was developed by 4 SVM models with varying levels of prediction accuracy. SVM Model 1 with an accuracy rate of 71.57%, SVM Model 2 with an accuracy rate of 72.55%, SVM Model 3 with an accuracy rate of 82.35% and SVM Model 4 with an accuracy rate of 100.%, it can be concluded that the SVM Model 4 is the best model. The results of the study provide recommendations for companies to develop predictive models that become automatic information systems and applications with a user-friendly interface. Moreover, they can be an early model in developing an early warning system that is accurate in predicting the delisting of Islamic stocks. For investors to be more careful in choosing sharia stocks and investments and pay attention to the financial aspects of a stock not only in terms of profit but also in terms of financial health that affects the severity of the status of a stock on the Islamic stock index.

References

Anwar, S. (2015). *Handbook Of Research On Islamic Banking And Finance : An Introduction of design Science Research Metodology, An Engineering Approach.* C.V Penebar kata, Ciputat tangerang.

Bakke, T. E., Jens, C. E., & Whited, T. M. (2012). The real effects of delisting: Evidence from a regression discontinuity design. *Finance Research Letters*, *9*(4), 183-193.

Berg, A. & C. Pattillo. (1999). Predicting currency crises: The indicators approach and an alternative. *Journal of International Money and Finance*, *18*(4), 561–86.

Berg, A., E. Borenszstein & C. Pattilo. (2004). Assessing Early Warning Systems: How They Worked in Practice. *IMF Working Paper*, WP/04/52, March.

Byun, H., & Lee, S.W. (2003). A survey on pattern recognition applications of support vector machines. *International Journal of Pattern Recognition and Artificial Intelligence*, *17*(3), 459-486.

Cortes, C., & Vapnik, V.N. (1995). Support vector networks. *Machine Learning*, *20*, 273–297.

Duwipa, F. (2013). *Sistem Peringatan Dini (Early Warning System).* Lembaga Penelitian & Pengembangan Kesejahteraan Sosial LPPK.

Endri. (2016). Dampak Perubahan Satuan Perdagangan dan Fraksi Harga Terhadap Likuiditas Saham, *MIX: Jurnal Ilmiah Manajemen*, *6*(1), 56-69.

Endri, E., Mustafa, B., & Rynandi, O. (2019). Determinants of debt policy of real estate and property companies listed on the Indonesia Stock Exchange. *International Journal of Economics and Financial Issues*, *9*(2), 96-104.

Firmansyah, E. A. (2017). Seleksi Saham Syariah: Perbandingan antara Bursa Efek Indonesia dan Malaysia. *Jurnal Inspirasi Bisnis dan Manajemen*, *1*(1), 1-10.

Fungáčová, Z., & Hanousek, J. (2011). Determinants of firm delisting on the Prague Stock Exchange,“. *Prague Economic Papers*, *20*(4), 348-365.

Hwang, I. T., Kang, S. M., & Jin, S. J. (2014). A delisting prediction model based on nonfinancial information. *Asia-Pacific Journal of Accounting & Economics*, *21*(3), 328-347.

Kaminsky, G., Lizondo, S., & Reinhart, C. M. (1998). Leading indicators of currency crises. *Staff Papers*, *45*(1), 1-48.

Kaminsky, G.& C. Reinhart (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems, *American Economic Review*, *89*(3), 473–500.

Khemais, Z., Nesrine, D., & Mohamed, M. (2016). Credit Scoring and Default Risk Prediction: A Comparative Study between Discriminant Analysis & Logistic Regression. *International Journal of Economics and Finance*, *8*(4), 39.

Kuncoro, M. (2003). *Metode Riset untuk Bisnis & Ekonomi*. Jakarta: Erlangga.

Olson, D. L. & Delen, D. (2008). *Support Vector Machines*. Advanced Data Mining Techniques Berlin: Springer.

Otoritas Jasa Keuangan (2017). *Perkembagan Pasar Modal Syariah: Sinergi Menuju Pasar Modal Syariah yang Lebih Besar dan Berkembang*. Laporan Perkembangan Pasar Modal syariah.

Ross, S.A. (1977). The determination of financial structure: The incentive-signaling approach. *The Bell Journal of Economics*, *8*, 23-40.

Saqib, N. (2013). Impact of development and efficiency of financial sector on economic growth: Empirical evidence from developing countries. *Journal of Knowledge Management, Economics and Information Technology*, *3*(3), 1–15.

Tsuda, K. (2000). Overview of support vector machine. *Journal of IEICE*, *83*(6), 460-466.

Witmer, J. (2008). An examination of Canadian firms delisting from U.S. exchanges. *Bank of Canada Working Paper 2008-11*.

Yiannoulis (2016). Determinants of involuntary delisting inAthens Stock Exchang: 1st MIBES Conference – Heraklion, Crete, Greece, *55*, *22-24*.

Zhou, L. (2013). Predicting the removal of special treatment or delisting risk warning for listed company in China with Adaboost. *Procedia Computer Science, 17*, 633 – 640.