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DEVELOPMENT OF FINANCIAL DISTRESS PREDICTION MODEL FOR NON-MANUFACTURING FIRMS IN INDONESIA USING SUPPORT VECTOR MACHINE, K-NEAREST NEIGHBOUR AND LOGISTIC REGRESSION

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ABSTRACT

Identifying firm's financial health performance when in distress condition is important before the bankruptcy. One of the tools is to use financial distress prediction model to provide early warning of corporate failure. In Indonesia, the development of financial distress model mainly focuses on manufacturing firms. While there are rarely models developed specifically to non-manufacturing companies. This study applies three method, namely Support Vector Machine and K-Nearest Neighbour as the machine learning algorithms, and Logistic Regression as the statistical causal model to build financial prediction model Indonesian non-manufacturing firms. These methods are chosen since they less vulnerable to statistical assumptions and can construct FDP models for more complex data context. The data which used to construct the models are consist of 136 healthy firms and 42 distress firms. The combination of feature set from accounting and market perspective are used to build financial distress prediction model. The empirical result shows the best performance would be achieved by all of the algorithm when using the feature set of combination between market and accounting variable. Majority of the developed models would improve the performance from previous existing model. The prediction of Indonesian non-manufacturing firms in the period of 2019 shows the all of the model which developed in this research statistically significant to outperform Altman Z-Score and Support Vector Machine can reach the highest F1-Score. On the other hand, although the models and Distance to Default shows that there is not statistically difference for the overall performance, all of the developed model produced higher accuracy, precision, recall and F1-Score. Since there is no significant difference except for LR model 3, it is strongly recommended to use all of well perform algorithm if possible, to compare the result between one model to the other, and decide the firm's financial condition based on the majority of the model's prediction result.

Keyword : *Financial Distress Prediction, Bankruptcy, Support Vector Machine, K-Nearest Neighbour, Logistic Regression, Altman Z-Score, Distance to Default*

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Surabaya, 21st July 2020

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CHAPTER 1
PRELIMINARY

This chapter will explain about the background and the purpose of this study. The construction of this chapter consists of background, formulation of the problem, research purpose, benefit, scope and writing system of this research.

1.1 Background

Corporate failure or bankruptcy considered the most significant challenge that faced by businesses in various industries, as there is an enormous economic consequence. Bankruptcy will heavily cost to its stakeholder as the company cannot generate income anymore or the losses of investment that has put in the company. Therefore, identifying firms’ financial health condition when in poor condition is very important since it could lead the bankruptcy. The declining condition of a firm’s performance is called financial distress (Ninh, et al., 2018). These conditions can influence by many factors, namely competition, economic crisis, government policy, firm decision-making, and social factor. The situation forced the company to survive through this situation with the right strategic planning and correct decision making.

One of the tools is to use the financial distress prediction model. This tool provides an assessment of a firm's financial condition to provide early warning of corporate failure. The study in early warning of corporate failure and bankruptcy has been observed widely among researchers and academics in different countries. The study's core is on the Financial Distress Prediction (FDP) to find the right and most accurate method in evaluating firms' financial performance.

FDP measure the current financial data through various approaches, such as mathematical, statistical, or intelligence model. Sun, et al. (2014) has made a review on state-of-the-art from previous FDP modeling method development in the recent year. The development of FDP can be divide into several categories as follow: the pure single classifier method; hybrid technique that is integrating two methods of artificial intelligence with other technique; ensemble method that combines the classification of multiple classifiers to produce FDP; and dynamic FDP modeling which focus on updating mechanism of the model and can gradually emerge new sample data with time going on. The standard approaches used in FDP is accounting-based and market-based models. In this regard, both models are used to predict financial distress and provide information for risk management and assessing the creditworthiness of a firm as the model classifies firms into several categories.

In general accounting-based model divided into four common methods for FDP, namely linear probability model, logit model, probit model and discriminant analysis (Elliott, et al., 2014). The first accounting-based model was developed by Beaver (1966) for assessing company's risk of bankruptcy through financial ratio based on balance sheet data. The model utilized a univariate approach, where it analyzes one variable at a time in determination of bankruptcy. Beaver model then criticized because univariate model only emphasis on individual signal which can be susceptible to faulty interpretation and is potentially confusing (Altman, 1968). Then Altman (1968) build other models of FDP with accounting-based using multiple discriminant analysis (MDA).

Among all existing FDP method, Altman Z-score gain the popularity compare to other method to evaluate financial performance of firms by analyst in the past few decades. Altman is famous since he can determine the best ratio in predicting financial distress through his model, which can represent the standard financial metric. Altman (1968) mentioned there five standard categories in the evaluation of the firms financial condition which are liquidity, profitability, leverage, solvency and activity ratio. The consideration to choose the ratio is the popularity in literature and relenvancies to the study. This technique completes the shortcoming of the univariate model by considering all influential factor since MDA classify an observation into one several a priori grouping dependent upon the observation's individual characteristic with multivariate analysis (Altman, 1968).

The other indicative approach to do Financial Distress Prediction is using the perspective from the capital market. Companies that go public utilize the existence of the capital market to obtain sources of funding or alternative financing (Hariyani & Sujianto, 2017). The existence of the capital market can reflect the performance and financial condition of a firm. The market will respond positively through an increase in the company's stock price if the company's financial condition and performance are good. Before investing their funds in a company, investors and creditors will always see the company's financial condition first. This because it will be hazardous when the shares owned from the specific company are suspended or delisted from the market, which will cause the plummeted share price and result because of the loss of investment. This delisting process of the company categorizes as a corporate failure (Altman & Narayanan, 1997).

There are several possibilities that can caused the delisting. It can be merger, new owner's will or other reason. However, it can also become dangerous as the delisted one is a troubled company whose business is going concerned, no clarity for the business's continuation, or even bankruptcy since it will harm the stock investors. The stock price for delisted company usually plummeted in the negotiation market or have no worth anymore when the company eventually fallen into the bankruptcy. The data showed that between 2013 and 2020 in Indonesia, 32 companies have delisted from the Indonesia Stock Exchange. Almost 45% of delisted companies engage in the non-manufacturing field. This implies that there are still high chances of a firm being delisted or bankrupt, and it becomes an indication of the risk in investing in a non-manufacturing company.

One useful data available and publicly available with easy access is utilizing the data based on the market condition as the other perspective in doing FDP. The market condition can be analyzed using stock market data information, and one of the approaches is using the model from Merton (1974). The Merton model utilized the stock market data to compare a firm's liabilities against the firm's assets. This produced an advantage since it can provide instant updates base on the firm's leverage ratio and volatilities from quoted stock. The Merton model has become the basis of the Distance to Default (DD) model. The asset value and the asset volatility then combine into a risk measure called Distance to Default, which is directly related to the creditworthiness of the equity issuing firm (Byström, 2006). he model can capture the business risk through the standard deviation of the firm's asset's annual percentage change in the market value. The default point terms refer to the value of the firm's asset falling below the value of the debt. The likelihood of a company defaulting on its debt obligation over time horizon will measure as a distance to corporate failure. This achieves by measure the expected default frequency using the cumulative normal distribution from distance to default value.

The accounting-based model and the market-based model are both indeed useful in measuring the risk of bankruptcy. Altman Z-Score Gain popularity on its predictive power at a year before bankruptcy by determining best feature inside of the model according standard financial metric to assess the company financial performance. Distance to Default also can provide a good financial health assessment through the equity volatility based on stock price and the leverage ratio in generating the probability of default. But there is a major drawback on both method since it was built using statistical method.

The discriminant analysis, as the base model to build Altman Z-Score, has to fulfill several statistical assumptions. The assumptions are the model need to have a multivariate normality; equal covariance matrices; and linear relation relations among the independent variables. These assumptions are hard to be fulfilled when using the data of financial ratio, especially normality and linearity assumption. Beside of that, there are also a statistical restriction which apply in Distance to Default. The model will assume the distribution of expected default frequency is in normal distribution. All of these assumptions will require to be fulfilled to gain an optimal prediction result or either wise when the assumptions have not fulfilled the result of prediction can be suspicious and it makes the model less accurate. Early study has proven the violation on these assumption for independent variables frequently occur within financial data (Deakin, 1972) and it will contain limitation in terms effectiveness and validity (Lin, et al., 2011). And recent study shows the popular technique to build the model of financial distres prediction is using the artificial intelligence method since the method are less vulnerable to statistical assumptions and can construct FDP models for more complex data context (Sun, et al., 2014).

Previous study in Indonesia mainly focus on development of prediction model for manufacturing firms, namely the development of financial distress using machine learning (Nisa, et al., 2017) and financial distress prediction using statistical analysis of Logistic Regression (Hidayat & Meiranto, 2014). While for non-manufacturing, the previous studies not much focus on the development of models but more on research that applies statistical models that have been made previously, such as namely prediction of financial distress for bank using Altman, Grover and Springate model (Kurniawati & Kholis, 2016) and similar other research.The development of the financial distress prediction model in Indonesia are rarely focus on non-manufacturing firms and using machine learning. Altman (2000) revised the Z-Score model for non-manufacture firms since there is a potential industry effect which is more likely to take place when such an industry-sensitive variable as asset turnover is included. Therefore, the last variable is excluded from the model when it is applied to non-manufacturing firm. Although this revised model is satisfying, Altman still advocate building and testing models derived from the country's own data (Altman, 2005). In addition, direct application of statistical model such as Altman original model still preferable, but according to Boďa & Úradníček (2016), the re-estimation of Altman Z-Score which developed by using local data is advisable to achieve the best accuracy in prediction of distress firms. This also support by Singh & Mishra (2016) which found that re-estimation of the Z-score for Indian manufacturing firms using Indian sample gives improvement on the overall predictive accuracy.

Based on this condition there is a need to develop an accurate financial distress prediction model for non-manufacturing firms in Indonesia, which is less restricted to the statistical assumption. The performance's evaluation of the previous existing model, namely Altman Z-Score and Distance to Default also required to see how well it will perform when applies to Indonesian non-manufacturing firms as the empirical evidence whether it is necessary to develop a new model and comparison for the developed model. The development of financial distress prediction model will focus on experiment of combination between market and accounting perspective as the model's feature by using algorithms which less restricted to the statistical assumption to create more accurate model. There are 3 algorithm or method which is used in the study, namely Support Vector Machine, K-Nearest Neighbor and Logistic Regression. Support Vector Machine and K-Nearest Neighbor are chosen since both of algorithm categorized as artificial intelligence method. Artificial intelligence method become appealing to be used since it is not restricted to statistical assumption and has some additional advantage. Support Vector Machine has the capability to do classification work and advantage which this model is not easy to run into over-fitting even for relatively small sample (Sun, et al., 2014). Shin, et al. (2005), has done the study of bankruptcy prediction modeling for South Korean companies using support vector machine, and drew the conclusion that this method outperformed MDA, Logit and NN. To provide comparison, K-Nearest Neighbor is chosen since it can provide more simple algorithm to be applied and able to do binary classification work. On the other hand, Logistic Regression is chosen since it is able to do a comprehensive financial distress prediction although it is a statistical method (Ninh, et al., 2018). In addition, it is less restricted to statiscal assumption, such as normality; a constant variance of residuals; no linear relationship between the dependent; and independent variables (Josephat & Ame, 2018).

1.2 Formulation of Problem

The problem that will be solved from this study is the development financial distress prediction model for Indonesian non-manufacturing companies using Support Vector Machine, K-Nearest Neighbour and Logistic Regression method with combination of feature set between market and accounting perspective.

1.3 Objective

The comprehensive objective of this research is listed below.

1. Evaluate the performance of Altman Z-Score and Distance to Default when applied to Indonesian non-manufacturing firm’s data.
2. Develop models to predict the financial condition of Indonesian non-manufacturing firms.
3. Identify the influence of market, accounting and the combination of both perspective to the model performance
4. Identify the recommended financial prediction models to apply for Indonesian non-manufacturing firms.

1.4 Benefit of Research

The benefit of this research is listed below.

1. Establish models of financial distress prediction which more accurate, robust and applicable for Indonesian non-manufacturing firms.
2. Provide insight for firm's stakeholder in identifying the threat of bankruptcy.

1.5 The Scope of the Research

The scope of this research consists of limitation and assumption that used in this study.

1.5.1 Limitation

The limitation used in this study are as follow :

1. The output produce by K-Nearest Neighbour and Support Vector Machine is in the form of binary prediction, in either safe or distress zone.
2. This study only focus on the model development of financial distress prediction with Support Vector Machine, K-Nearest Neighbor and Logistic Regression.
3. The data set used in the experiment consist of 136 healthy firms from 2016-2018 and 42 distress firms from 2009-2019.
4. The variable which used as the feature in development of the model only consider variable from Altman Z-Score and Distance to Default, namely working capital to total asset ratio; retained earnings to total asset ratio; earnings before and tax to total asset ratio; book value of equity to total liabilities ratio; market volatility; and leverage ratio.

1.5.2 Assumption

The assumptions used in this study are as follow :

1. The firms which labeled in the grey zone between the rating of BB+ until B- by Pefindo are classified as the distress firms.

1.6 Writing System

The writing system will show the writing construction to show the result of the study. This study writing system is consist of six chapter, and the description of content for each chapter will be shown below.

CHAPTER I	PRELIMINARY This chapter are construct based on the things which will underlie, determine the direction and the scope of this study. The study is conducted based on the background and formulation of the problem, then it will go toward the direction according to the Research Purpose, Benefit of the Research and limited by The Scope of the Research.
CHAPTER II	LITERATURE REVIEW This chapter is contained theoretical concepts which will support this study.
CHAPTER III	RESEARCH METHODOLOGY This chapter consist of the description of stages which will be conduct by the author to answer the purpose of the research. The stages are consisting of identification, data gathering, data processing, analysis of the result and conclusion
CHAPTER IV	DATA COLLECTION AND PROCESSING This chapter consist the stages to gathered data and the step to process the data to gain the insight and conclusion that is required according to the research purposes.
CHAPTER V	DATA ANALYSIS AND INTEPRETATION This chapter will explain the process that needs to analyze and the discussion based on the result of data gathering and processing.
CHAPTER VI	CONCLUSION AND SUGGESTION This chapter consist of the conclusion which is the summary for the whole discussion to answer the research purpose that

this study wants to reach and also the related suggestion and recommendation for the next study and the study’s object.

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CHAPTER 2
LITERATURE REVIEW

This chapter consist of theories that used in the study. The theories become the basis to construct the study as will be done for data gathering and analysis to reach the conclusion. Literature review of this study is consist theory of classification of industrial sector according Indonesia Stock Exchange, corporate failure concept, Altman Z-Score model, Financial Ratio, Distance to Default and Support Vector Machine.

2.1 Classification of Industrial Sector

The stock that trade in Indonesia Stock Exchange (IDX) can be classified in 9 sectors, which are: Agriculture; Mining; Basic Industries and Chemicals; Miscellaneous Industry; Consumer Goods Industry; Property, Real Estate and Building Construction; Infrastructure, Utility and Transportation; Finance; and Trade, Service and Investment.

1. Agriculture: businesses sector in the fields of food crops, plantations, animal husbandry, fisheries, forestry, and services that are directly related to these fields. The subsector is:
    - Crops
    - Plantation
    - Animal Husbandary
    - Fishery
2. Mining: Businesses sector in mining and quarrying, such as coal, oil and gas mining, metal ore, rock quarrying, clay, sand, salt mining and quarrying, mineral mining, chemicals, and fertilizer materials, as well as mining of casts, asphalt and limestone. The subsector is:
    - Coal Mining
    - Crude Petroleum & Natural Gas Production
    - Metal and Mineral Mining
    - Land / Stone Quarrying

3. Basic industry & chemicals: sector industry that consist of basic and chemical industry. Basic industries include the business of converting basic materials into semi-finished goods; or finished goods that will still be processed in the next economic sector. The chemical industry includes the business of processing basic chemical-related materials that will be used in subsequent production processes and the pharmaceutical industry. The subsector is:
    - Cement
    - Ceramics, Glass, Porcelain
    - Metal And Allied Products
    - Chemicals
    - Plastics and Packaging
    - Animal Feed
    - Wood Industries
    - Pulp and Paper
    - Others
4. Miscellaneous industry: sector industry which make heavy and light machinery; including its supporting components. The subsector is:
    - Machinery And Heavy Equipment
    - Automotive and Components
    - Textile, Garment
    - Footwear
    - Cable
    - Electronics
5. Consumer goods industry: sector industry of processing that converts basic / semi-finished materials into finished goods which generally can be consumed by personal /household. The subsector is:
    - Energy
    - Toll Road, Airport, Harbor and Allied Products
    - Telecommunication
    - Transportation

- Non Building Construction

6. Property, real estate, and building construction: Sector industry of construction that includes the business of making, repairing, demolishing houses and various types of buildings. Real estate includes the business of buying, selling, renting and operating various residential and non-residential buildings. The subsector is:
    - Property and Real Estate
    - Building Construction
7. Infrastructure, utility, and transportation: sector industry which include energy supply, transportation and telecommunications facilities, as well as infrastructure buildings and supporting services. Infrastructure buildings include non-building and house. The subsector is:
    - Energy
    - Toll Road, Airport, Harbor and Allied Products
    - Telecommunication
    - Transportation
    - Non Building Construction
8. Finance: sector industry that related to the financial sector, including financial intermediaries, financial institutions, insurance companies, securities companies and investment companies. The subsector is:
    - Bank
    - Financial Institution
    - Securities Company
    - Insurance
    - Others
9. Trade, service, and investment: sector industry that covers the trading business of large and small / retail parties, as well as businesses related to the service sector such as hotels, restaurants, computers and equipment, advertising and media and the printing industry. The subsector is:
    - Wholesale
    - Retail Trade
    - Restaurant, Hotel and Tourism

- Advertising, Printing & Media
- Healthcare
- Computer And Services
- Investment Company
- Others

2.2 Corporate Failure

Corporate failure is the situation where the company has to stop doing its commercial activity due inability to fulfill its obligation to lenders, preferred stock shareholders, suppliers or where a firm is bankrupt according to law (Abdulkareem, 2015). Firm's failure can be classified as economic and legal failure (Meeks & Meeks, 2009). Economic failure happens when the firms fail achieving the return on the capital that invested on it, with the criterion of economic failure is present discounted value of net future cash flows generated by the company's assets if they are retained is lower than net realizable value of the assets. The economic criterion for company failure is written as follow:

$$A_{pv} < A_{nrv}$$

where A_{pv} represent the discounted value of net future cash that produced by the company asset if they are retained in the existing use and A_{nrv} represent the net realizable value of the asset, if it used for the alternative use. While for legal financial failure is happen when the company faces the financial insolvency, with the criterion of firm's asset is lower than value of the firm liabilities. The legal criterion for company failure is written as follow:

$$A < L$$

where A represent asset and L represent liabilities. This failure will leads firms to be liquidated and eventually firms will declared as bankrupt. The concept of corporate failure is also defined as the bankruptcy that filled by a company, bond defaults, bank loan defaults, insolvency, the delisting of a firm, liquidation and government interference through special financing (Altman & Narayanan, 1997).

The definition above match with the bankruptcy concept in Indonesia. The bankruptcy in Indonesia regulated in *Undang-Undang* No. 37 *tahun* 2007. The Indonesian Bankruptcy Law consist of regulation in bankruptcy and suspension of debt payment obligations. From this law it can be known based on the Article No. 2 stated if the company will decide as bankrupt, when the company cannot pay off the debt that is due and can be billed by its creditor, and declared as bankrupt by the court.

2.2.1 Implication of Corporate Failure

Corporate failure has several implications. Abdulkareem (2015) describe bankruptcy has damage to shareholder and cost. The significant implication for shareholders and the reputation of the company representative as the firm’s fall into failure, especially for the owner, they will be experiencing significant losses when company is moving toward failure. Beside of that company’s failure cause a considerable damages and enormous costs to the whole economy and society (Ahn, et al., 2000).

Before reach its total failures of commercial activity, firms will be undergone several stages. In terms of failure phases, there are three different failure processes experienced by the company which begins with successful processes and ends with a case of insolvency. The first indication is a defect that include skills shortages or personal mistakes, for example administrative weakness, such as an authoritarian executive director, and failures in accounting skills, such as budgetary monitors. The second is indicated by the mistake which become the trajectory of corporate failure. Mistake happen as the consequence of the defect that happen in the first place, for instance high leverage, the company's inability to continue or failure in large projects, and over-trading. Mistake and other dysfunction symptom is considered as the last indication of symptom that eventually leads to failure, such as creative accounting or deteriorating ratios (Abdulkareem, 2015). Based on the argument above it can be seen that failure does not occur suddenly.

There are importance to identify firm’s financial condition. This due to financial and non-financial symptoms can be the lead to identify the firm’s financial deteriorating condition (Ropega, 2011). Such condition will further result firms into: a decreasing of sales, profit and liquidity (Ooghe & Prijcker., 2008); the shrinking size of market share (Crutzen & Caillie, 2008); the significant increasing level of debt (Argenti, 1976); and excessive energy that exceeds the company's capacities (Ooghe & Prijcker., 2008). Beside of that, there are positive relationship between financial condition and firms performance during economic downturn, and more highly leveraged firms tend to lose market share and experience lower operating profits than their competitors as there cost that occurs during that condition (Šarlija & Jeger, 2011). The three main cost that occurs as the result of financial distress' firms: financially distressed firm may lose customers, valuable suppliers, and key employees resulting financially distress' firms will lose significant market share to their healthy counterparts in industry downturns and weakens the competitive position of a firm; there are a high possibility for a financially distressed firm is more likely to violate its debt covenants which will caused further dead weight losses in the form of financial penalties, accelerated debt repayment, operational inflexibility, and managerial time and resources spent on negotiations with the lenders; and there are costly external financing that caused the financial distressed firm may have to forgot positive NPV projects.

2.2.2 Financial Distress

Financial distress is a term in the financial studies available which is often used describe the condition of the firms prior to corporate bankruptcy as a sign before it reach the failure phase. Financial distress indicates a state where the company's cash flow at that time was very low and the company was suffering losses without being insolvent (Purnanandam, 2007). The financial distress also defined by Levratto (2013) as the condition where firm's liabilities exceed its book value of assets, which often lead to failure. Many literatures refer financial distress as the financial difficulties of the firm that include inability to pay debts or preferred dividend and the corresponding consequences such as overdraft of bank deposits, liquidation for interests of creditors, and even entering the statutory bankruptcy proceeding. Such definition is originated from Beaver (1966) which analogize an enterprise as a reservoir formed by the cash flow, composed of cash inflows and outflows. An enterprise in financial distress is just like a reservoir whose water is drained. (Sun, et al., 2014).

Financial distress terms are closely related to the bankruptcy terms. Ninh, et al. (2018) describe corporate bankruptcy will undergone four stages. The first stage is the incubation of firm's financial situation. Then it will continue to the second stage that called financial embarrassment where the firm's management aware of its financial distress condition. The third stage is the firm's experiencing financial insolvency in which the firms cannot fulfill its financial obligation due to lack of fund. And the final stage is where the firm's financial insolvency is confirmed. The firm's will describe then as bankrupt by the court decision as the official determination, and should be sold its asset to pay the creditor (Poston, et al., 1994). This imply financial distress terms is different from bankruptcy. Financial distress is a condition when the firm cannot fulfill its financial obligations to banks, supplier, tax authorities and employee because of a decrease in the firm's business operations, illiquid assets and high fixed costs. By contrast, bankruptcy is the terms of final state in which financial failure where the firms will stop doing commercial activity after financial distress condition. In some cases, financial distress can be detected before the company falls into insolvency. Therefore, financial distress does not always progress to bankruptcy (Ninh, et al., 2018).

2.3 Altman Z-Score

The Altman Z-score is model that has been widely applied to predict bankruptcies of firms. The model works based on a weighted linear combination of four or five common accounting ratios as the variable in the model to gain the Z-score. The weights, or coefficients, of the Z-score formula are estimated using a sample of distressed firms and a matched sample of survived firms, where the matching is based on industrial sectors and market capitalization. The accounting ratios to be included in the Z-score formula may vary for different industrial sectors. The Z-score is useful to assessing financial health of a company and predicting bankruptcy based on the information from corporate balance sheets (Elliott, et al., 2014).

Altman Z-Score model has been revised and updated several times. This model was originally developed by Altman (1968) using a multivariate statistical model to distinguish failed firms from non-failed firms. The study examined 22 financial ratio that categorize into profitability, activity, liquidity, solvency and leverage with the sample of sixty-six manufacturing firms which divided equally between the existing firms during the study and the manufacturing firms that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act during the period of 1946-1965. In the update of Altman et al. (1977), a new financial distress model (ZETA) focusing on specific sectors. Altman (2000) improved his models from 1968 and 1977 with the introduction of the Z'-score model, which includes four financial ratios. In revised Z-score model (Z'-score), the variable of X4 is subtituted into market value and the coefficient for several variable has been changed. With the new model, the distribution of the score is tighter with larger group overlap (Altman, 2000). The further development of this model (Z-score) is dedicated for the adaptation model for non-manufacturing firms. The model is useful for the industry with the type of financing of asset which high variation between the companies and important adjustment are not made. The Z-score model is modified the initial model from five variable into four variable. The Z-score model also known as the final version of the Z-score model was the emerging market score (EMS) model, which includes typical characteristics of emerging markets and seems appropriate for estimating the default probability in developing countries and ranking firms with a specific score. The accuracy of this last model was demonstrated by the 95% and 73% accuracy at year one and year two prior to failure, respectively. This model have applied this model in emerging market corporate for Mexican firms with the issues of Eurobonds denominated in U.S. dollar before the 1994 crisis (Altman, 2005). The Z-score formula used for the emerging market and non-manufacturer is written as follow:

$$\mathrm{Z} = 6.56\,\mathrm{X}_1 + 3.26\,\mathrm{X}_2 + 6.72\,\mathrm{X}_3 + 1.05\mathrm{X}_4 + 3.25$$

where X_1= Working capital / Total Assets; X_2= Retained Earning / Total Assets; X_3= Earning before Interest and Taxes / Total Assets; X_4= Book value of Equity / Total Assets.

The results obtained from the model then classified to determine financial condition of the firm. The criteria used to interpret the Z-score model is;

- Safe Zone : Z > 5.85
- Gray Zone 4.15 < Z < 5.85
- Distress Zone : Z < 4.15

Altman (1968) stated that the utilization of comprehensive list of financial ratios can have a high degree correlation with each other when used to assessing a firm's bankruptcy potential. The ratios that used in the model of Altman classified to measure five standard category, which are liquidity, profitability, leverage, solvency and activity ratio (Altman, 1968).

2.3.1 Working Capital to Total Assets Ratio

Ratio of working capital related to total asset used to measure current assets of the firms relative to its total capitalization. According to Altman (1968), this ratio is proved to be the most valuable of financial liquidity ratio and best to describe discontinuance of company, since when a firm experiencing consistent operating losses, the firm's current assets will shrinking to its total assets (Altman, 1968).

2.3.2 Retained Earnings to Total Assets Ratio

This ratio shows the company's leverage or the measurement of firm's profitability from the distribution of retained earnings and total assets. Firms with high retained earnings to total assets ratio means that the higher the firms finance its assets using retention of the earning so it has lower debt and risk capital (Altman, 2000).

2.3.3 Earnings Before Interest and Tax to Total Assets Ratio

EBIT related to total asset ratio will show the productivity of company assets. Atman (1968) describe this ratio appropriate for studies dealing with corporate failure since it can capture firm's earning power ability related to its total asset and insolvency when the total liabilities exceed the firm's asset.

2.3.4 Book Value of Equity to Total Liabilities Ratio

Book value of equity to total liabilities ratio will show firm's ability to cover the debts based on the asset owned (Ninh, et al., 2018). Book value of equity consist of share capital, general reserve, retained earnings and revaluation reserve that recognize in the statement of financial position and used to measure difference between total asset and liabilities. A higher gearing ratio will increase borrower security charges and claim on firm's cash flows and hence increase the likelihood in avoiding bankruptcy (Range, et al., 2018).

2.5 Distance to Default

Distance to Default is the methodology using the basis from model created by Merton (1974). Within the model, Merton used asset value and volatility can that combined into a risk measure called distance to default. Input required for running the model is the information based on the market price of stock. The model can be used to evaluate the creditworthiness of the equity issuing firm. (Byström, 2006). This model has four advantage for prediction of financial failure as it is stated by Ninh, et al. (2018): the exponentially increasing in timeliness of corporate bankruptcy predictions; the enhancement of default risk's power indicator as the volatility of market based variable is included in the model to read the fluctuation which plays a key role in default prediction; the model account information the larger information than accounting based model which can generally reflect price of the market; and the market price more suitable in doing default prediction as it ability to reflects forward-looking information or future expectations of cash flow, rather than the model with basis of accounting which can reveals only backward-looking or past performance (Ninh, et al., 2018).

The model then further developed by Byström (2006) with the modification of the original model into simplified model. As explained by Byström, the model has advantage to highlight the driver of the default, which are equity volatility and firm's leverage ratio. The new simple version employs three components or observable parameters to estimate default probability, such as the book value of firm liability, market value and the volatility of equity. The model has already apply to a sample of 27 United State non-financing firms in various industries, and based on the study it is known that the model produced distance to default very similar with original Merton model (Byström, 2006).

There are several variable to be calculated before determining the probability of default using Distance to Default method. The first is the determine volatility of equity from stock price. The step to determine the volatility will be shown below.

1. Determine the log closing stock price changes. The formula to determine the logprice changes is as follow.

$$\text{Logprice changes}_{\text{t}} = \ln(\text{closing stock price}_{\text{t}}/\text{closing stock price}_{\text{t}-1})$$

2. Calculate the standard deviation of volatility.
3. Divide standard deviation to number of day to gain the annualized volatility

In the mode the leverage ratio defines as follow:

$$\text{Leverage (L)} = \frac{\text{F}}{\text{V}_{\text{E}} + \text{F}}$$

Where, F = book value of debt; and V_{A} = market value of the firm's asset. The simplified Distance of Default (DD) is written in formula as follow:

$$\text{DD} = \frac{\ln(\text{L})}{(\text{L} - 1)} \times \frac{1}{\sigma_{\text{E}}}$$

Where, L = leverage ratio; and σ_{E} = volatility of the firm's equity.

In classifying the firms to the group of safe, grey or distress condition, the cumulative normal distribution is used to measure expected default frequency (EDF) from calculation result of Distance to Default value, since there are a close relationship between Distance to Default and the probability of default (Ninh, et al., 2018). The EDF than need to be map into Lopez (2004) S&P rating. For a particular realization of future asset value A_{it+H}, a "distance to default" measure is calculated and used to determine a firm's "expected default frequency™" (or EDF™) based on KMV's proprietary default database (Lopez, 2004).

Table 2.1 Classification of firm based on corporate rating and EDF value

Zone	Corporate Rating	EDF Value
Safe	AAA	(0.00, 0.02]
	AA+	(0.02, 0.03]
	AA	(0.03, 0.04]
	AA-	(0.04, 0.05]
	A+	(0.05, 0.07]
	A	(0.07, 0.09]
	A-	(0.09, 0.14]
	BBB+	(0.14, 0.21]
	BBB	(0.21, 0.31]
	BBB-	(0.31, 0.52]
Grey	BB+	(0.52, 0.86]
	BB	(0.86, 1.43]
	BB-	(1.43, 2.03]
	B+	(2.03, 2.88]
	B	(2.88, 4.09]
	B-	(4.09, 6.94
Distress	CCC+	(6.94, 11.78]
	CCC	(11.78, 14.00]
	CCC-	(14.00, 16.70]
	CC	(16.70, 17.00]
	C	(17.00, 18.25]
	D	(18.25, 20.00]

(Source: Ninh, et al., 2018)

2.4 Support Vector Machine

Support Vector Machine (SVM) is a technique that used to do prediction in the case of regression and classification (Santosa & Umam, 2018). The SVM technique is also part of supervised algorithm that means it require training data to produces the optimal border line in separating between two kinds of object. The optimal border line is called as plane or hyper planes. SVM constructs linear model to estimate the decision function using non-linear class boundaries based on support vectors. If the data is linearly separated, SVM trains linear machines for an optimal hyper plane that separates the data by maximizing distance between hyper plane and support vector. Support vectors are the two closest training point's data which are originally come from different class or groups. All other training examples are irrelevant for determining the binary class boundaries. In addition, SVM also has the capability to classify non-linear data through mapping the input vector into the higher-dimensional feature space with kernel trick. If the data is not linearly separated, SVM will uses non-linear machines to find a hyper plane that minimize the number of errors for the training set (Shin, et al., 2005).

The decision rule for construction of SVM can divided into two group depends on the case, which are linear and non-linear. For the linearly separable case, the decision rules defined by an optimal hyper plane separating the binary decision classes. The labeled training example is define as$[x_i, y_i]$, an input vector of $x_i \in R^n$, a class value $y_i \in \{-1,1\}$, with i=1,…,l. It can be written in the mathematical formulation as follow:

$$Y = sign\left(\sum_{i=1}^{N} y_i a_i (x \cdot x_i) + b\right)$$

The formula has the element of Y as the outcome, y_i that represent class value of the training example of x_i, and $\cdot$ which stand for the inner product. It also consist of vector $x = (x_1, x_2, \dots, x_n)$ which corresponds to an input and the vector x_i, i=1,…,N, are the support vectors. The formula also has b and a_i which act as parameters in order to determine the hyperplane. On the other hand, for the non-linearly separable case, a high-dimensional formulation can be written as follow:

$$Y = sign\left(\sum_{i=1}^{N} y_i a_i K(x, x_i) + b\right)$$

Inside of the formulation, there are the function K (x, xi). The function is defined as kernel function. It it used to produce the inner products for the construction of machines with different types of non-linear decision surfaces in the input space. There are three common types decision rule to follow within the constructing stage of SVM:

a) A polynomial machine with kernel function

$$K\ (x, x_i) = (x \cdot x_i + 1)^d$$

where d is the degree of the polynomial kernel

b) A radial basis function machine with kernel function

$$K\ (x, x_i) = exp\ (-1/\delta^2 (x - x_i)^2)$$

where δ^2 is the bandwidth of the radial basis function kernel

c) A two-layer NN machine with kernel function

$$K\,(x, x_i) = S\,[(x \cdot x_i)] = 1/[1 + \exp\{v\,(x \cdot x_i) - c\}]$$

where v and c is defined as parameters of a sigmoid function $S\,[(x \cdot x_i)]$ to satisfy the inequality of $c \geq v$.

2.5 K-Nearest Neighbour

K-Nearest Neighbour (K-NN) is one of the supervised classification method. The classification algorithm is done according to the knowledge which gained based on previous past data. The terms of Nearest Neighbor refers to the classification method that classifying unlabeled examples based on closest distance with the class of similar labeled examples (Wiyono & Abidin, 2018). Handayani (2019) define the step to do the K-NN as follow.

a) Determine the parameter K (number of closest neighbour)
b) Calculating the distance (similarity) between all training records and new objects
c) Sorting data based on distance value from the smallest to the largest value
d) Retrieving data from a number of k value
e) Determining the most-frequent labels occuring in the k training records closest to the object

K-NN algorithm have distance metric to determine which class that closest to the test data. Several of distance metric to determine the distance value that can be used on K-NN algorithm are:

a) Euclidean Distance

The formula of Euclidean Distance is:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

b) Manhattan distance

The formula of City Block Distance is:

$$d(x,y) = \sum_{i=1}^{n} |x_i - y_i|$$

c) Chebychev distance

The formula of Chebychev Distance is:

$$d(x,y) = \lim_{p\to\infty} \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p}$$

2.6 Logistic Regression

Logistic Regression actually is not a method to solve regression problem, but classification (Santosa & Umam, 2018). Logistic regression use to solve classification problem with two class (binary classification). This method suitable to be implemented when the dependent variable is dichotomous (Hosmer, et al., 2013). The analysis from this method will include predicted probabilities of retention for combinations of the independent variables (Pyke & Sheridant, 1993).

Logistic regression is more robust than linear and discriminant analysis since the model is not require to follow normality assumption a constant variance of residuals, no linear relationship between the dependent and independent variables but there are several assumption which the data need to follow. Josephat & Ame (2018) mentioned several assumption that should be check when using logistic regression to enhance the power of the model. The assumption are sample size; expected cell frequencies; linearity in the logit; multi-collinearity; outliers and influential cases; as well independence of residuals.

Previous study has found the indication if the use of Logit model improved the discriminate performance of FDP and provided more information to researchers. On one hand, the Logit model is applicable to FDP for its non-continuous dependent variable expressed as financial distress probability. On the other hand, the Logit model is not based on the assumptions that independent variables should follow normal distribution and equal covariance. However, it still requires that the independent variables have no linear functional relationship which proven by multi-collinearity problem (Sun, et al., 2014).

2.7 Performance Measurement on Financial Prediction Models.

The performance measurement is done to assess the outputs of learning algorithms and evaluate different input to each learning algorithm. Each model will produce the outcome in the form of classification of firm's zone. The experimental outcome will be illustrated with the confusion matrix as follow.

Table 2.2 Confusion matrix

		Prediction	
		1	-1
Actual	1	True Negative	False Positive
	-1	False Negative	True Positive

The outcome will become true positive when the model able to classify distress firms in the distress zone. True negative happens when the model correctly predicts the healthy firms into the safe zone. False negative happens when the models miss predict the distress firms into safe zone, while false positive happen when the model miss classified the healthy firms into distress zone.

There are several parameters used to measure model's performance which used in this study, namely accuracy, error rate, precision, recall and F1-Score. Accuracy is ratio of the correctly classified to the total number of samples. The ratio shows the overall effectiveness of the algorithm (Sokolova, et al., 2006). Accuracy is suitable for the balance data set composition between class. The formula to calculate accuracy will be shown below.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total number of observation}}$$

Error rate is measurement of misclassification probability when using the model. The formula to calculate error rate will be shown below

$$\text{Error rate} = 1 - \text{Accuracy}$$

Precision will calculate the ratio of the correct classification of distress firms to the total number of firms which predict as distress. The ratio informs the predictive power of algorithm (Sokolova, et al., 2006).

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall or sensitivity or true positive rate refers to the ratio of number correctly classified firms as distress to the number of total firms which actually in distress condition. This ratio measures the effectiveness of the algorithm on a single class (Sokolova, et al., 2006).

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

F1-Score provides a single score that balances both the concerns of precision and recall in one number (Tharwat, 2018).

$$\text{F1} - \text{Score} = 2\ \text{X}\ \frac{\text{Precision X Recall}}{\text{Precision} + \text{Recall}}$$

2.8 Previous Research and Research Positioning.

This sub chapter will show the algorithm used and the object which become the focus in previous research to show the gap. Based on the gap in the previous research, the positioning of this research can be determined. Although there are many researches that already do the development of the financial prediction model, there is rarely research that focus non-manufacturing firms, especially in Indonesia by using the algorithm which less restricted to the statistical assumption. This research is the continuation to fill the gap that has never been done before in the previous research.

Table 2.3. Previous Research and Research Positioning

Research	Data		Method		Object		Aspect Analysed	
	Indonesia	Non-Indonesia	Artificial Intelligence	Statistical	Manufacture	Non-manufacture	Accounting	Market
Financial Ratios, Discriminant Analysis and the Prediction of Corporate (Altman, 1968)		V		V	V		V	
An Emerging Market Credit Scoring System for Corporate Bonds (Altman, 2005)		V		V		V	V	
Merton Unraveled: A Flexible Way of Modeling Default Risk (Byström, 2006)		V		V	V	V		V
Financial Distress Analysis with Data Mining Approach for Go-Public Manufacturing Industry in Indonesia (Firdausi, et al., 2012)	V			V	V		V	
Analisis Model Prediksi Financial Distress *Pada Perusahaan Perbankan Syariah Di Indonesia* (Kurniawati & Kholis, 2016)	V			V		V	V	
Model Prediksi Financial Distress Pada Perusahaan Manufaktur Go Public *di Indonesia* (Nisa, et al., 2017)	V		V		V		V	V
This research	V		V	V		V	V	V

CHAPTER 3
RESEARCH METHODOLOGY

This chapter explain about the systematic plan of research methodology used for this study. This research is divided into three stages. The first stage is object selection and data collection. The second stage is the development of financial prediction models. The last stage is the analysis and data interpretation. Then based on all the stage before, the finding of this study and further suggested research to complete the study then will show in the section of conclusion and suggestion. The flowchart of the research methodology will be shown in the picture below.

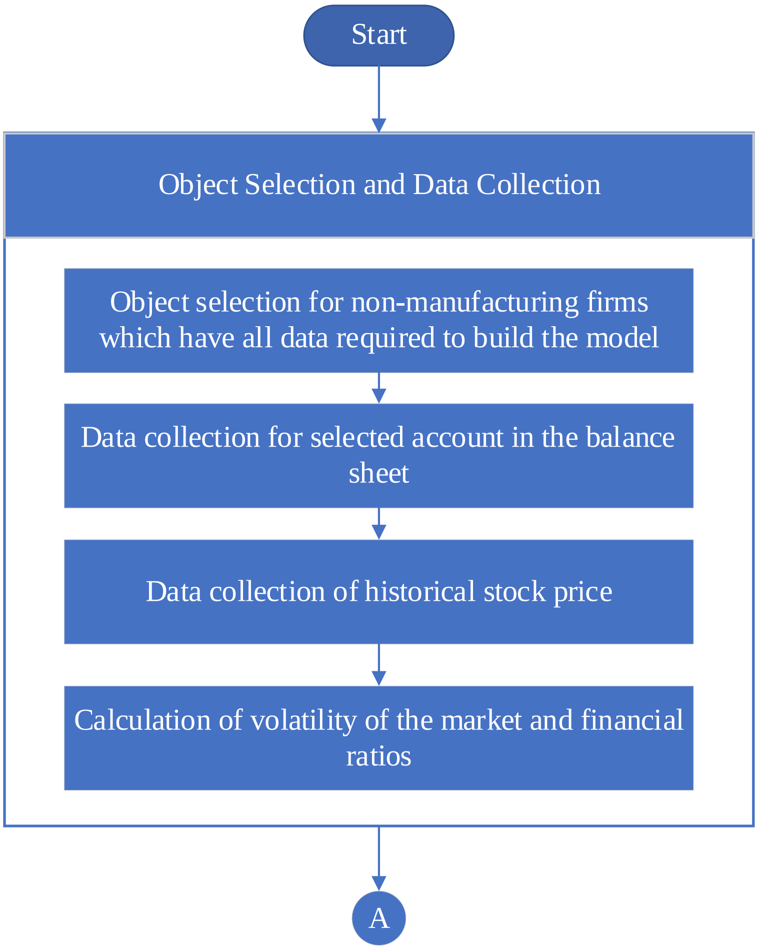

Figure 3.1 Methodology Flowchart

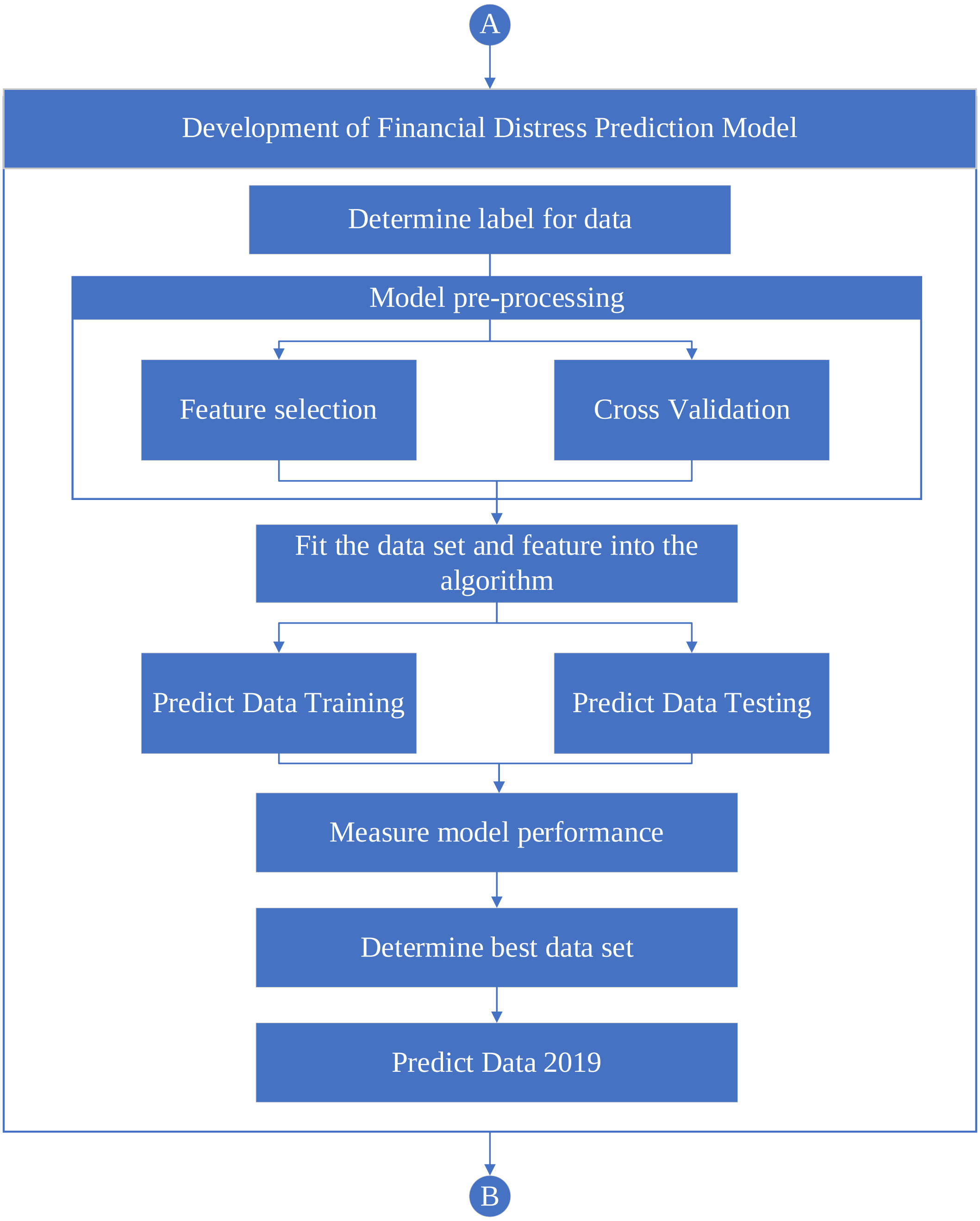

Figure 3. 1. Methodology Flowchart

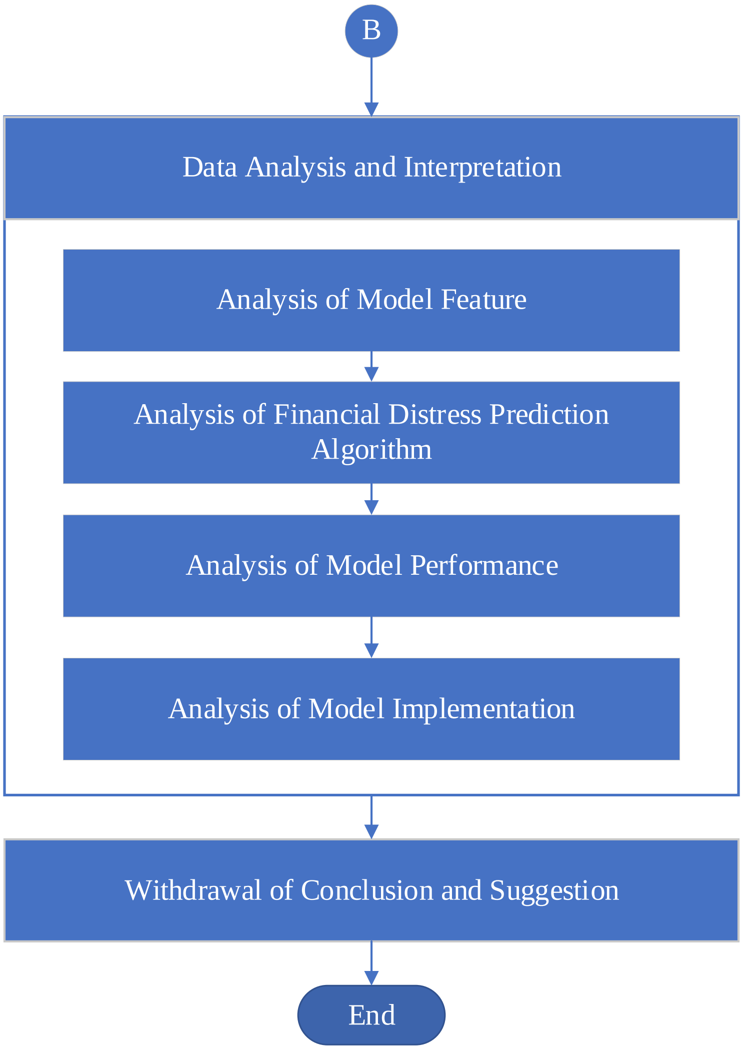

Figure 3. 1. Methodology Flowchart

3.1 Object Selection and Data Collection

The object that will be observed in this study is selected non-manufacturing firms which listed in Indonesia Stock Exchange. In the Indonesia Stock Exchange official website, all of the public firms categorize into 9 sectors. The related sector that will further observed in this study consist of 4 that have business of tertiary sector, which are: Property, real estate, and building construction; Infrastructure, utility, and transportation; Finance; and Trade, service, and investment. There are also additional research data requirement that include the company is listed in Indonesia Stock Exchange and has a credit rating on the Pefindo site. Credit Rating on Pefindo site is used as the label for data training.

There are also data which taken without any credit rating in Pefindo, which is the data of delisted firms which labeled as distress firm. This data are taken one or two years before firms are delisting from the Indonesian Stock Exchange between the period of 2009-2020. The next is the data collecting of accounting variable from balance sheet and market variable from market value equity and historical stock price data. The selected account data in the balance sheet then will use to calculate financial ratio while the historical stock data will use to calculate volatility of market price.

3.2 Development of the Financial Distress Prediction Model

The development of the new model is the main goal of this study. This will achieve in several steps. All of the models that used to construct financial distress prediction are supervised model therefore it needs data training with labels embedded in each data training. Each selected firm then will be labelled according to the condition of each firm. Labelling process consist of 2 stage. At first, firms will be categorized according to its credit rating. In this research, the credit rating of the firms is taken from Pefindo. Pefindo is independent credit rating agency that assess Indonesian firm. The score is calculated to the entities based their debt instruments listed in Indonesia Stock Exchange House. Then, the firms will group based on its rating into safe, grey or distress following the grouping system in Ninh (2018).

The next is model pre-processing stage. It consist of three activity, which are variable selection process as a feature in developing models, multi-collinearity test and K-Fold Cross Validation. The first is variable selection. There are several model which develop with different feature. These features is chosen to predict the dependent variable, which has the purpose to determine the classification of firm's zone in either safe or distress. In order to gain the conclusion, there are six decision variables that taken based on previous model, which are working capital to total asset ratio; retained earnings to total asset ratio; earnings before interest and tax (EBIT) to total assets ratio; book value of equity to total liabilities ratio; book value of debt to market value equity plus book value of debt as the leverage ratio; and volatility of equity. And the second process is cross validation. The method which use is K-Fold Cross Validation. This process will divide the data set into several group of training and testing that use as the input of data experiment process.

When the pre-processing stage is complete, the next is to do experiment. The purpose is to evaluate the estimator performance on various data set, determine features to make an accurate model, and algorithm which suitable for the features used in the model.The experiment will include: the development of models through different algorithms, features and data set. The algorithms which used to build the model are Support Vector Machine, K-Nearest Neighbor and Logistic Regression. This will include fit data set and feature into the model and doing prediction on data set.

After experiment, the performance of each developed model performance will be measured. The measurement used to determine the best model to be used in certain circumtances. The model's performance will also be compared to Altman Z-Score and Distance to Default, to see whether the model will produce better accuracy to the previous existing model. Since this report has the objective to establish a financial prediction model to predict firms' condition and the interest is to get the accurate prediction when the firms are in the distress condition, this study will mainly use F1-Score as the parameter of performance measure. There is two perspective of performance measure, the first is performance measurement for each algorithm and the second is the performance measurement for each model.

Then, the best data set will be determined based on the group of data set which produce the best performance to predict the data testing. Data testing is the data which held from the training process, so there is process to validate the model performance. Therefore, the performance of the model to predict the test data is considered can be used to represent the actual condition when the model do the financial distress prediction.

The last is to do the simulation of the best group data set to predict Data 2019. Different from prediction on data training and data test, this step is done as the simulation for the selected best prediction model in doing financial prediction on newest available data. The training data set, which produce best performance to predict data testing, will be chosen to as the model to do the prediction on Data 2019

3.3 Data Analysis and Interpretation

Data analysis and interpretation will include analysis of model feature, analysis of developed model, analysis of model performance and analysis of model implementation. The explanations are as follow:

- The first part is the discussion about the feature's influence feature that used in the model. There are three models with different combination of feature which developed in this study, namely model with the feature of combination between market and accounting perspective; model with the feature of accounting perspective; and model with feature of market perspective. Each model performance will be examined and compare with others to see the performance when different feature used in the model.
- The second part consist of analysis of algorithm used to develop the model. This analysis will focus on the discussion about each models' performance that develop with different algorithm and feature used to predict data training and data testing.
- The third part is the analysis of comparison models. This analysis will focus on comparison of overall performance between models. The discussion will include discussion about how well the model perform in predicting Data 2019 and how is the model performance compare to the previous existing model, namely the Altman Z-score and Distance to Default and new develop model.
- The last analysis is about the implementation of the models when used to predict Indonesian non-manufacturing data firms base on the previous performance in predict the data training, data testing and data 2019.

3.4 Conclusion and Suggestion

The last stage in the research is to draw conclusions and suggestions from the research that has been done. Conclusions are made based on the research objectives that were set at the beginning. While suggestions are made to accommodate the shortcomings of conducting research and for further research progress.

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CHAPTER 4
DATA COLLECTION AND PROCESSING

This chapter will explain the process of data collection the step in creating the Financial Distress Prediction model including the model assumption check, data processing, the model prediction result using data testing and the comparison between the result with the previous model.

4.1 Dataset for Research Experiment.

The research used initial sample that consist of one hundred seventy-eight (178) Indonesian go public non-manufacturing firms that divided into two groups. Group one consists of 136 the healthy firm which classified by Pefindo.com within the credit rating between AAA to BBB-. Meanwhile group 2 consist of 42 distress firm's data prior to bankrupt, delisted plus the firms which classified by Pefindo.com within the credit rating BB+ to D. The initial sample will be used as one data set to processed and analyzed further using the model in predicting financial distress. The detail for credit rating and the corporate name which used as the data set will be shown in the table below.

Table 4.1 Data Set in Developing the Model of Financial Distress Prediction

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	D	Delisting
Indosat, Tbk. (2016)		Fastfood Indonesia, Tbk. (2016)	Astra International, Tbk. (2016)	Global Mediacom, Tbk. (2016)	Alam Sutera Realty, Tbk. (2016)	Adhi Karya (Persero), Tbk. (2016)	Bali Towerindo Sentra Tbk (2016)	Express Transindo Utama, Tbk. (2016)	Humpuss Intermoda Transportasi, Tbk. (2016)	Express Transindo Utama, Tbk. (2017)	Bakrie Telecom, Tbk. (2016)			Indofarma (Persero), Tbk. (2016)			Bakrieland Development, Tbk. (2016)				Arpeni Pratama Ocean Line, Tbk. (2016)	Amstelco Indonesia (2012)
Indosat, Tbk. (2017)		Fastfood Indonesia, Tbk. (2017)	Astra International, Tbk. (2017)	Global Mediacom, Tbk. (2017)	Alam Sutera Realty, Tbk. (2017)	Adhi Karya (Persero), Tbk. (2017)	Bali Towerindo Sentra Tbk (2017)	Lippo Karawaci, Tbk. (2016)	Humpuss Intermoda Transportasi, Tbk. (2017)		Bakrie Telecom, Tbk. (2017)			Indofarma (Persero), Tbk. (2017)			Bakrieland Development, Tbk. (2017)				Arpeni Pratama Ocean Line, Tbk. (2017)	Asia Natural Resources Tbk (2013)
Indosat, Tbk. (2018)		Fastfood Indonesia, Tbk. (2018)	Astra International, Tbk. (2018)	Global Mediacom, Tbk. (2018)	Alam Sutera Realty, Tbk. (2018)	Adhi Karya (Persero), Tbk. (2018)	Bali Towerindo Sentra Tbk (2018)	Lippo Karawaci, Tbk. (2017)	Humpuss Intermoda Transportasi, Tbk. (2018)		Bakrie Telecom, Tbk. (2018)			Indofarma (Persero), Tbk. (2018)			Bakrieland Development, Tbk. (2018)				Arpeni Pratama Ocean Line, Tbk. (2018)	Bara Jaya Internasional Tbk (2018)
Perusahaan Gas Negara Tbk (2016)		Jasa Marga (Persero), Tbk. (2016)	Bumi Serpong Damai, Tbk. (2016)	Summarecon Agung, Tbk. (2016)	Apexindo Pratama Duta, Tbk. (2016)	Agung Podomoro Land, Tbk. (2016)	Bukaka Teknik Utama Tbk (2016)	Lippo Karawaci, Tbk. (2018)									Trikomsel Oke, Tbk (2016)				Berlian Laju Tanker, Tbk. (2016)	Citra Maharlika Nusantara Corpora Tbk (2016)
Perusahaan Gas Negara Tbk (2017)		Jasa Marga (Persero), Tbk. (2017)	Bumi Serpong Damai, Tbk. (2017)	Summarecon Agung, Tbk. (2017)	Apexindo Pratama Duta, Tbk. (2017)	Agung Podomoro Land, Tbk. (2017)	Bukaka Teknik Utama Tbk (2017)	PP Properti, Tbk. (2017)									Trikomsel Oke, Tbk (2017)				Berlian Laju Tanker, Tbk. (2017)	Davomas abadi (2013)
Perusahaan Gas Negara Tbk (2018)		Jasa Marga (Persero), Tbk. (2018)	Bumi Serpong Damai, Tbk. (2018)	Wijaya Karya (Persero), Tbk. (2017)	Apexindo Pratama Duta, Tbk. (2018)	Agung Podomoro Land, Tbk. (2018)	Bukaka Teknik Utama Tbk (2018)	PP Properti, Tbk. (2018)									Trikomsel Oke, Tbk (2018)				Berlian Laju Tanker, Tbk. (2018)	Dayaindo resource (2011)
Telekomunikasi Indonesia, Tbk. (2016)		Mitra Adiperkasa, Tbk. (2016)	Kimia Farma (Persero), Tbk. (2016)	Wijaya Karya (Persero), Tbk. (2018)	Astra Graphia Tbk. (2016)	Citra Marga Nusaphala Persada, Tbk. (2016)	Bukit Uluwatu Villa, Tbk. (2016)														Express Transindo Utama, Tbk. (2018)	Dwi Aneka Jaya Kemasindo Tbk (2017)
Telekomunikasi Indonesia, Tbk. (2017)		Mitra Adiperkasa, Tbk. (2017)	Kimia Farma (Persero), Tbk. (2017)	Wijaya Karya (Persero), Tbk. (2019)	Astra Graphia Tbk. (2017)	Citra Marga Nusaphala Persada, Tbk. (2017)	Bukit Uluwatu Villa, Tbk. (2017)															Grahamas Citrawisata Tbk (2018)
Telekomunikasi Indonesia, Tbk. (2018)		Mitra Adiperkasa, Tbk. (2018)	Kimia Farma (Persero), Tbk. (2018)		Astra Graphia Tbk. (2018)	Citra Marga Nusaphala Persada, Tbk. (2018)	Bukit Uluwatu Villa, Tbk. (2018)															Indo Citra Finance Tbk (2012)
		XL Axiata, Tbk. (2016)	Matahari Putra Prima, Tbk. (2016)		Media Nusantara Citra, Tbk. (2016)	Humpuss Intermoda Transportasi, Tbk. (2016)	Duta Anggada Realty, Tbk. (2016)															Inovisi Infracom Tbk (2014)
		XL Axiata, Tbk. (2017)	Matahari Putra Prima, Tbk. (2017)		Media Nusantara Citra, Tbk. (2017)	Humpuss Intermoda Transportasi, Tbk. (2017)	Duta Anggada Realty, Tbk. (2017)															Katarina Utama (2011)
		XL Axiata, Tbk. (2018)	Matahari Putra Prima, Tbk. (2018)		Media Nusantara Citra, Tbk. (2018)	Humpuss Intermoda Transportasi, Tbk. (2018)	Duta Anggada Realty, Tbk. (2018)															Leo Investment Tbk (2019)
			Pembangunan Jaya Ancol, Tbk. (2016)		Modernland Realty, Tbk. (2016)	Inti Bangun Sejahtera Tbk (2016)	Duta Pertiwi, Tbk. (2016)															Panca wirasakti (2011)
			Pembangunan Jaya Ancol, Tbk. (2017)		Modernland Realty, Tbk. (2017)	Inti Bangun Sejahtera Tbk (2017)	Duta Pertiwi, Tbk. (2017)															Permata Prima Sakti Tbk (2014)
			Pembangunan Jaya Ancol, Tbk. (2018)		Summarecon Agung, Tbk. (2018)	Inti Bangun Sejahtera Tbk (2018)	Duta Pertiwi, Tbk. (2018)															Jasa Angkasa Semesta (2008)
					Surya Semesta Internusa, Tbk. (2016)	Intiland Development, Tbk. (2016)	FKS Multi Agro, Tbk. (2016)															New Century Development (2010)
					Surya Semesta	Intiland Development, Tbk. (2017)	FKS Multi Agro, Tbk. (2017)															Surya Intrindo Makmur (2011)

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	D	Delisting
					Internusa, Tbk. (2017)																	
					Tiphone Mobile Indonesia, Tbk. (2016)	Intraco Penta, Tbk. (2016)	FKS Multi Agro, Tbk. (2018)															Sekawan Intipratama
					Tiphone Mobile Indonesia, Tbk. (2017)	Intraco Penta, Tbk. (2017)	Garuda Indonesia (Persero), Tbk. (2016)															Sigmagold Inti Perkasa Tbk (2018)
						Intraco Penta, Tbk. (2018)	Garuda Indonesia (Persero), Tbk. (2017)															Surabaya agung Industri (2012)
						Jaya Bersama Indo Tbk (2016)	Garuda Indonesia (Persero), Tbk. (2018)															Surya Inti Permata(2011)
						Jaya Bersama Indo Tbk (2017)	Intiland Development, Tbk. (2018)															Truba Alam Manunggal Engineering Tbk (2017)
						Jaya Bersama Indo Tbk (2018)	Metrodata Electronics, Tbk. (2016)															
						Modernland Realty, Tbk. (2018)	Metrodata Electronics, Tbk. (2017)															
						Nusa Konstruksi Enjiniring, Tbk. (2016)	Metrodata Electronics, Tbk. (2018)															
						Nusa Konstruksi Enjiniring, Tbk. (2017)	Perdana Gapuraprima, Tbk. (2016)															
						Nusa Konstruksi Enjiniring, Tbk. (2018)	Perdana Gapuraprima, Tbk. (2017)															
						Panorama Sentrawisata, Tbk. (2016)	Perdana Gapuraprima, Tbk. (2018)															
						Panorama Sentrawisata, Tbk. (2017)	Tiphone Mobile Indonesia, Tbk. (2018)															
						Panorama Sentrawisata, Tbk. (2018)	Weha Transportasi Indonesia, Tbk. (2016)															
						PP Properti, Tbk. (2016)	Weha Transportasi Indonesia, Tbk. (2017)															
						Surya Semesta Internusa, Tbk. (2018)	Weha Transportasi Indonesia, Tbk. (2018)															
						Tigaraksa Satria, Tbk. (2016)																
						Tigaraksa Satria, Tbk. (2017)																
						Tigaraksa Satria, Tbk. (2018)																

4.2 Application of Previous Existing Model for Indonesian Data.

This subchapter will show the result of the application of the previous existing model in predicting the available test data on each group dataset. The result of prediction on data test using the methods of Altman Z-Score and Distance to Default will be shown below.

Table 4.2 Prediction result on testing data using Distance to Default.

Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
Group 1	0.778	0.222	1.000	0.375	0.545
Group 2	0.933	0.067	0.857	0.750	0.800
Group 3	0.867	0.133	0.857	0.545	0.667
Group 4	0.889	0.111	0.800	0.500	0.615
Average	0.867	0.133	0.879	0.543	0.657

Table 4.3 Prediction result on testing data using Altman Z-Score.

Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
Group 1	0.689	0.311	0.550	0.688	0.611
Group 2	0.622	0.378	0.320	1.000	0.485
Group 3	0.600	0.400	0.360	0.818	0.500
Group 4	0.578	0.422	0.280	0.875	0.424
Average	0.622	0.378	0.378	0.845	0.505

Based on the prediction result, Distance to Default reach higher average performance for all of the parameter than Altman Z-Score except in recall.

4.3 Model Pre-processing

Model processing is consist of the step which is done before training and testing process to form the model. This stage will include the step to prepare the feature used to develop the model, the test of multicollinearity between all variable and determine cross validation data set.

4.3.1. Feature Selection

Feature selection process consists of activity to choose a feature that will be used as independent variable in predicting the dependent variable. This study uses several perspectives as the feature in the model, namely accounting and market perspective. In order to gain insight on how each perspective influence the model performance, there are several models to be developed with different feature. This become the basis of the variable selection process. There are three models to be developed: models with combination of market and accounting perspective; model with accounting perspective; and model with market perspective. This includes six variable which consider in this study. The detail of variables will be show in the table below.

Table 4.4 Details of Variable to construct the model

Variable name	Description
X1	Volatility of equity
X2	Book value of debt / (Market Value of the firms + Book value of debt)
X3	Working Capital / Total Assets Ratio
X4	Retained Earnings / Total Assets Ratio
X5	Earnings Before Interest and Tax (EBIT) / Total Assets Ratio
X6	Book Value of Equity/Total Liabilities Ratio

The development of the model will be divided into three model since the interest of this research is to know how each perspective influence to the model performance, there are three model which will be developed. Model 1 is the model with combination of market and accounting perspective. This model has a total six variables as the feature in the model. This model included four of variables are taken from Altman Z-Score, which represent the accounting perspective, and the other two variables are taken from Distance to Default, which represent the market perspective. While the Model 2 has a total four variables as the feature in the model. The model only uses variables which originally from Altman Z-Score and represent accounting perspective. And for Model 3, it consists of feature that represent market perspective. The detail of variable selection to become feature in the model will be shown in the table below.

Table 4.5 Variable selection for each model.

Variable	Model 1	Model 2	Model 3
Variable 1	X1	X3	X1
Variable 2	X2	X4	X2
Variable 3	X3	X5	
Variable 4	X4	X6	
Variable 5	X5		
Variable 6	X6		

4.3.1 K-Fold Cross Validation

There are a limited number of data that used to build a model in this study. This can cause a mis-guided interpretation of model performance if the model only trained and perform to predict to in-sample data. For instance, a small portion of error, which produce by the model when predicting the data test, will result to very high increase of error measurement and cause to interpretation of a poor model performance. In the absence of a very large designated test set that can be used to directly estimate the test error rate, a number of technique of cross validation on can be used to estimate a better model measurement (James, et al., 2017). Cross validation will provide check on the performance on a new unseen data or test data; and assesment on how good the model will perform outside the determined data set.

K-Fold Cross Validation is used as the method in this study since the desire is to gain insight on the generalization ability of the model on the random dataset within certain number of group. The parameter of K is determined as 4 because there are unbalanced data between the healthy firms with the distress firms. The portion of distress firms is smaller than healthy firms, therfore the bigger the K will cause to smaller portion of distress firms in the data set that can also result to misguided interpretation of the model performance. The dataset will be randomized first and then divided into 4-fold or section, 3 section will be included in training data and 1 section will become the data test. The process is repeated K times and each time different fold or a different group of data points are used for validation. In this cross validation, the K is determined as 4 because there are unbalanced data between the healthy firms with the distress firms. The dataset will be randomed first and then divided into 4 section, 3 section is training data that consist of 133 data and 1 section is testing data that consist of 45 data. The composition of each group is shown below.

Table 4.6 Data set composition used for experiment

Group	Training		Testing	
	Healthy	Distress	Healthy	Distress
1	107	26	29	16
2	99	34	37	8
3	102	31	34	11
4	99	34	37	8

4.4 Fit the Data Set and Feature into the Model.

This research will use three algorithms in developing the financial prediction model. By this way, there are option to choose algorithm to be applied in predicting the financial condition of the firms based on performance result with different feature used in the models. The method used as the algorithm to develop the model are Support Vector Machine, K-Nearest Neighbor and Logistic Regression.

4.4.1 Support Vector Machine

Support vector machine is a supervised machine learning. So, it requires training data to build the model and use it to predict the data test. The training and test will follow group set which determine in the cross-validation process. The development of FDP using Support Vector Machine for each group of data set for each model is done by using software MATLAB 8.5 R2015a with certain code to enter training data into the algorithm.The output or decision function of the model is in the binary form, to classify firm's financial condition in either safe or distress. The prediction result for data training will be shown in the table below.

Table 4.7 Prediction result on training data using Support Vector Machine.

Model	Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
Model 1	Group 1	0.940	0.060	1.000	0.692	0.818

Model	Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
	Group 2	0.940	0.060	1.000	0.765	0.867
	Group 3	**0.985**	**0.015**	**1.000**	**0.935**	**0.967**
	Group 4	0.925	0.075	1.000	0.706	0.828
	Average	0.947	0.053	1.000	0.775	0.870
Model 2	Group 1	0.932	0.068	1.000	0.654	0.791
	Group 2	0.932	0.068	1.000	0.735	0.847
	Group 3	**0.940**	**0.060**	**1.000**	**0.742**	**0.852**
	Group 4	0.925	0.075	1.000	0.706	0.828
	Average	0.932	0.068	1.000	0.709	0.829
Model 3	Group 1	0.962	0.038	0.889	0.923	0.906
	Group 2	**0.977**	**0.023**	**0.970**	**0.941**	**0.955**
	Group 3	0.955	0.045	0.931	0.871	0.900
	Group 4	0.917	0.083	0.926	0.735	0.820
	Average	0.953	0.047	0.929	0.868	0.895

The result show the highest performance can be achieve when Model 1 use data set from Group 3, Model 2 use data set from Group 3 and Model 3 use data set from Group 2. The highest average is achieve by Model 3 with the value of F1-score is 0.895.

4.4.2 K-Nearest Neighbour

The development of FDP using K-Nearest Neighbour is done by using software MATLAB 8.5 R2015a. The composition of data training and testing follow follow group set which determine in the cross-validation process. The distance metric which used in the algorithm is euclidean distance to emphesize the distance between data.

There are several steps to develop models by using K-Nearest Neighbour. The first is to determine the parameter of K. The parameter will determine using experiment on a data set with different parameter of K. The K which produce the best performance will be chosen as the parameter to build the model. The experiment of number of K that used for building the model will be shown in the table below. The parameter and the training data set then will input into the software.

Table 4.8 Recapitulation on experiment with different parameter of K

K	Accuracy	Precision	Recall	F1 Score
1	**0.956**	**1.000**	**0.750**	**0.857**
2	**0.956**	**1.000**	**0.750**	**0.857**
3	**0.956**	**1.000**	**0.750**	**0.857**
4	0.933	1.000	0.625	0.769
5	0.933	1.000	0.625	0.769
6	0.933	1.000	0.625	0.769

For the K parameter between 1, 2 and 3 have the highest accuracy, precision, recall and F1 score. The author determine k parameter to be 3 because, since it is the parameter with the highest number of K that produce best F1 score since the lower the K can be cause higher possibility to be overfitting of the model. The prediction result for data training will be shown in the table below.

Table 4.9 Prediction result on training data using K-Nearest Neighbour

Model	Data	Accuration	Error Rate	Precision	Recall	F1 score
Model 1	Group 1	0.940	0.060	1.000	0.692	0.818
	Group 2	0.940	0.060	0.964	0.794	0.871
	Group 3	0.947	0.053	1.000	0.774	0.873
	Group 4	**0.955**	**0.045**	**1.000**	**0.824**	**0.903**
	Average	0.945	0.055	0.991	0.771	0.866
Model 2	Group 1	0.947	0.053	0.913	0.808	0.857
	Group 2	**0.940**	**0.060**	**1.000**	**0.765**	**0.867**
	Group 3	0.925	0.075	0.957	0.710	0.815
	Group 4	0.932	0.068	0.931	0.794	0.857
	Average	0.936	0.064	0.950	0.769	0.849
Model 3	Group 1	0.940	0.060	0.875	0.808	0.840
	Group 2	**0.955**	**0.045**	**0.912**	**0.912**	**0.912**
	Group 3	0.955	0.045	0.903	0.903	0.903
	Group 4	0.932	0.068	0.903	0.824	0.862
	Average	0.945	0.055	0.898	0.862	0.879

The result show the highest performance to predict the training data can be achieve when Model 1 use data set from Group 4, Model 2 use data set from Group 2 and

Model 3 use data set from Group 2. The highest average is achieve by Model 3 with the value of F1-score is 0.879.

4.4.3 Logistic Regression

The development of FDP using Logistic Regression is done by using statistical software package SPSS version 16.0 for analysis. Binary logistic regression model was used in order to assess and identify the influence of variables. There are several test to each model to see whether the required assumption have been met and to check the model performance. There are multi-collinearity test, goodness of fit test and likelihood ratio test.

Multi-collinearity test in this research consist of two stage the first stage is the test correlation using coefficient result of Pearson C and the second stage is the collinearity statistic test using VIF (variable inflation factor). Multi-collinearity occurs when one independent variable nearly combination of other variables, and it should be avoided as it would impact the parameter estimate (Lin, 2008). This will cause several problems such as the difficulties to find the correct prediction and find out precise effect on each predictor. In addition, multi-collinearity also influences the capability of the model to predict new test data which can lower the prediction result. The correlation test is meant to see if any pairs of predictor variable that highly correlated with each other, since multi-collinearity can arise if any linear combination of independent variables is correlated with any other linear combination. Any pair variable with the correlation coefficient 0.9 will consider as highly correlated with each other (Dohoo, et al., 1996). The result of correlation test will show in the table below.

Table 4.10 Correlation coefficient between variables.

Variable	X1	X2	X3	X4	X5	X6
X1	1	-0.03849	0.10103	0.065197	0.100018	-0.00753
X2	-0.03849	1	-0.21138	0.001494	-0.15728	-0.21932
X3	0.10103	-0.21138	1	0.708357	0.617987	0.334195
X4	0.065197	0.001494	0.708357	1	0.68936	0.261645
X5	0.100018	-0.15728	0.617987	0.68936	1	0.22276
X6	-0.00753	-0.21932	0.334195	0.261645	0.22276	1

Since there is no pair variable with coefficient correlation above 0.9, it indicates that there is no high correlation between any pair variable that used to construct the Financial Distress Prediction model.

The second stage is determining the collinearity between variables using VIF score of independent variables represent ability of variable explained by another independent variable. Multi-collinearity indicated when the VIF score is above 10 (Lin, 2008).

Table 4.11 Multi-collinearity test for each variable

Variable	Collinearity Statistics	
	Tolerance	VIF
X1	0.984177	1.01607
X2	0.860357	1.16230
X3	0.421447	2.37277
X4	0.365812	2.73364
X5	0.477642	2.09362
X6	0.857986	1.16552

Based on the able above, all of the variable that will be used in the Financial Distress Prediction have the VIF score below 10 which indicate there are no collinearity exist.

The next test is goodness of fit test. The goodness of fit test is the model diganostic test to describe how well the model fits into a set of observations (Maydeu-Olivares & Forero, 2010). From all the combination of data set, there are only 2 models which is not fit, namely Model 3 with the data set from Group 3 and Model 3 with the data set grom Group 4 since the P-value is lower than the than the level of significance at 5%. The goodness of fit test result will be shown in the table below.

Table 4.12 Goodness of fit Test

Model	Data	Hosmer and Lemeshow Test		
		Chi-square	df	Sig.
Model 1	Group 1	8.925	8	0.349
	Group 2	2.337	8	0.969
	Group 3	11.938	8	0.154
	Group 4	4.396	8	0.820

Model	Data	Hosmer and Lemeshow Test		
		Chi-square	df	Sig.
Model 2	Group 1	2.594	8	0.957
	Group 2	8.883	8	0.352
	Group 3	7.325	8	0.502
	Group 4	4.298	8	0.829
Model 3	Group 1	9.377	8	0.311
	Group 2	11.020	8	0.201
	Group 3	43.590	0	0.000
	Group 4	92.136	0	0.000

The second test is likelihood ratio. It is the test for overall model fit in Logistic Regression. -2 Loglikelihood is the statistic that shows how poorly the model predicts, the smaller the statistic the better the model (Zewude & Ashine, 2016). The result shows that the smallest likelihood ratio can be achieve by using Model 1 with data set from Group 1 with the ratio value of 35.76. Meanwhile the R Square statistic represent the ability of independent variable to explain the dependent variable, so the greater the value the better the model. The highest R Square statistic can be achieve with Model 1 using data set from Group 2 with the value of Cox & Snell R Square of 0.576 and Nagelkerke R Square of 0.848.

Table 4.13 Likelihood ratio test

Model	Data	Model Summary		
		-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Model 1	Group 1	**35.76**	0.513	0.817
	Group 2	37.20	**0.576**	**0.848**
	Group 3	43.10	0.533	0.805
	Group 4	52.26	0.525	0.773
Model 2	Group 1	37.27	0.507	0.808
	Group 2	37.59	0.574	0.846
	Group 3	44.07	0.530	0.800
	Group 4	52.41	0.524	0.772
Model 3	Group 1	130.68	0.006	0.009
	Group 2	149.94	0.010	0.014
	Group 3	144.18	0.002	0.003
	Group 4	132.22	0.133	0.196

The software then generate the coefficient for variables that use in logistic regression equation to predict the data in every model that was built. The table below is shown the variable's coefficient and also constant in each model.

Table 4.14 Financial distress predictor coefficient for each different input

Model	Data	Cut-off score	Coefficient						
			X1	X2	X3	X4	X5	X6	Constant
Model 1	Group 1	0.500	-0.531	-1.012	1.409	12.273	-2.313	-1.272	3.568
	Group 2	0.017	-0.183	1.018	-4.563	14.655	-0.063	-1.973	2.756
	Group 3	0.848	-0.519	-0.330	-1.357	8.522	0.405	-0.917	2.929
	Group 4	0.343	0.281	-0.372	-1.844	10.622	-0.698	-0.840	2.060
Model 2	Group 1	0.500			0.634	12.932	-1.947	-1.336	2.786
	Group 2	0.500			-2.556	12.862	0.703	-1.753	2.342
	Group 3	0.820			-1.357	9.495	-1.306	-0.985	2.524
	Group 4	0.340			-2.028	10.952	-0.691	-0.807	1.954
Model 3	Group 1	0.840	-0.132	-0.580					1.761
	Group 2	0.684	0.188	-0.625					0.987
	Group 3	0.760	0.213	-0.130					1.175
	Group 4	0.500	4.128	0.081					-0.197

This coefficient will be implemented in logistic regression equation to generate the probability of firm will fall into financial distress zone. The probability will range between 0 to 1. The lower the probability value, means the higher the probability of a firm fall into distress zone. If the probability result is below the cut-off score, then the firms will classify as distress firms. The equation used will follow the formula that will be shown below.

$$P = \frac{\exp(b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 + b_0)}{1 + \exp(b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 + b_0)}$$

Where, P =probability of firms will fall into distress condition; b_i= coefficient of variable i_{th}; x_i= independent variable i_{th}.

The prediction result based on the usage of logistic regression formula for data training will be shown in the table below.

Table 4.15 Prediction result on training data using Logistic Regression

Model	Data	Accuration	Error Rate	Precision	Recall	F1 score
Model 1	Group 1	0.954887	0.090226	0.973451	0.8846154	0.92691
	Group 2	0.947368	0.105263	0.953912	0.9067142	0.929715
	Group 3	**0.954887**	**0.090226**	**0.972222**	**0.9032258**	**0.936455**
	Group 4	0.932331	0.135338	0.958333	0.8676471	0.910738
	Average	0.947368	0.105263	0.96448	0.8905506	0.925954
Model 2	Group 1	0.947368	0.105263	0.949405	0.8799425	0.913355
	Group 2	0.947368	0.105263	0.953912	0.9067142	0.929715
	Group 3	**0.954887**	**0.090226**	**0.972222**	**0.9032258**	**0.936455**
	Group 4	0.932331	0.135338	0.958333	0.8676471	0.910738
	Average	0.945489	0.109023	0.958468	0.8893824	0.922566
Model 3	Group 1	0.255639	0.744361	0.51584	0.5082674	0.512026
	Group 2	0.774436	0.225564	0.763	0.5781343	0.657826
	Group 3	0.75188	0.24812	0.672984	0.7035104	0.687909
	Group 4	**0.932331**	**0.067669**	**0.958333**	**0.8676471**	**0.910738**
	Average	0.678571	0.321429	0.727539	0.6643898	0.692125

The result show the highest performance to predict the training data can be achieve when Model 1 use data set from Group 3, Model 2 use data set from Group 2 and Model 3 use data set from Group 3. The highest average is achieve by Model 1 with the value of F1-score is 0.925954.

4.5 Prediction on Data Testing.

This sub chapter will show the result of prediction for testing using Support Vector Machine, K-Nearest Neighbour and Logistic Regression for each developed model. The purpose of doing prediction on data testing to see the model performance to predict the unseen data from the data set. The overall performance of model to predict a various group of data set then will measure by taking the average value of performance.

4.5.1 Support Vector Machine

The prediction result for data testing with Support Vector Machine model will be shown in the table below.

Table 4.16 Prediction result on training data using Support Vector Machine.

Model	Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
Model 1	Group 1	0.889	0.111	1.000	0.688	0.815
	Group 2	0.889	0.111	0.636	0.875	0.737
	Group 3	0.933	0.067	0.900	0.818	0.857
	Group 4	**0.978**	**0.022**	**1.000**	**0.875**	**0.933**
	Average	0.922	0.078	0.884	0.814	0.836
Model 2	Group 1	0.867	0.133	0.917	0.688	0.786
	Group 2	0.800	0.200	0.455	0.625	0.526
	Group 3	0.889	0.111	1.000	0.545	0.706
	Group 4	**0.933**	**0.067**	**0.857**	**0.750**	**0.800**
	Average	0.872	0.128	0.807	0.652	0.704
Model 3	Group 1	0.889	0.111	1.000	0.688	0.815
	Group 2	0.867	0.133	0.600	0.750	0.667
	Group 3	**0.956**	**0.044**	**1.000**	**0.818**	**0.900**
	Group 4	0.911	0.089	0.833	0.625	0.714
	Average	0.906	0.094	0.858	0.720	0.774

The result show the highest performance to predict the data test can be achieve when Model 1 use data set from Group 4, Model 2 use data set from Group 4 and Model 3 use data set from Group 3. The highest average is achieve by Model 1 with the value of F1-score is 0.836.

4.5.2 K- Nearest Neighbour

The prediction result for data testing with K-Nearest Neighbour model will be shown in the table below.

Table 4.17 Prediction result on training data using K-Nearest Neighbour

Model	Data	Accuracy	Error rate	Precision	Recall	F1 Score
Model 1	Group 1	0.8889	0.1111	1.0000	0.6875	0.8148
	Group 2	**0.9556**	**0.0444**	**1.0000**	**0.7500**	**0.8571**
	Group 3	0.8667	0.1333	0.8571	0.5455	0.6667

Model	Data	Accuracy	Error rate	Precision	Recall	F1 Score
	Group 4	**0.9556**	**0.0444**	**1.0000**	**0.7500**	**0.8571**
	Average	0.9167	0.0833	0.9643	0.6832	0.7989
Model 2	Group 1	0.8667	0.1333	0.9167	0.6875	0.7857
	Group 2	0.9111	0.0889	0.8333	0.6250	0.7143
	Group 3	0.8667	0.1333	0.8571	0.5455	0.6667
	Group 4	**0.9333**	**0.0667**	**0.8571**	**0.7500**	**0.8000**
	Average	0.8944	0.1056	0.8661	0.6520	0.7417
Model 3	Group 1	0.9556	0.0444	1.0000	0.8750	0.9333
	Group 2	0.8444	0.1556	0.5455	0.7500	0.6316
	Group 3	0.8889	0.1111	0.7500	0.8182	0.7826
	Group 4	**0.9778**	**0.0222**	**1.0000**	**0.8750**	**0.9333**
	Average	0.9167	0.0833	0.8239	0.8295	0.8202

The result show the highest performance to predict the data test can be achieve when Model 1 use data set from Group 2 and Group 4, Model 2 use data set from Group 4 and Model 3 use data set from Group 3. The highest average is achieve by Model 3 with the value of F1-score is 0.8202.

4.5.3 Logistic Regression

The prediction result for data testing with Logistic Regression model will be shown in the table below.

Table 4.18 Prediction result on training data using Logistic Regression.

Model	Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
Model 1	Group 1	0.933	0.067	1.000	0.813	0.897
	Group 2	0.933	0.067	1.000	0.625	0.769
	Group 3	0.933	0.067	0.900	0.818	0.857
	Group 4	**0.978**	**0.022**	**1.000**	**0.875**	**0.933**
	Average	0.944	0.056	0.975	0.783	0.864
Model 2	Group 1	0.933	0.067	1.000	0.813	0.897
	Group 2	0.933	0.067	0.857	0.750	0.800
	Group 3	0.933	0.067	0.833	0.909	0.870
	Group 4	**0.978**	**0.022**	**0.889**	**1.000**	**0.941**
	Average	0.944	0.056	0.895	0.868	0.877
Model 3	Group 1	0.356	0.644	0.356	1.000	0.525

Model	Data	Accuration	Error Rate	Average Precision	Average Recall	F1 score
	Group 2	0.644	0.356	0.318	0.875	0.467
	Group 3	0.267	0.733	0.250	1.000	0.400
	Group 4	**0.933**	**0.067**	**1.000**	**0.625**	**0.769**
	Average	0.550	0.450	0.481	0.875	0.540

The result show the highest performance to predict the data test can be achieve when Model 1 use data set from Group 4, Model 2 use data set from Group 4 and Model 3 use data set from Group 4. The highest average is achieve by Model 2 with the value of F1-score is 0.877.

4.6 Summary of the prediction model.

This subchapter will show the summary of the best group set that have highest performance in prediction of data testing; and the average performance of the developed model with different data set on predicting the training and testing data in two perspective, method and model side.

The summary of group data which produce the best performance in predicting the data testing will be shown below. This group set will be the basis of the training data set to be used for simulation of model performance in predicting the Data 2019 and do the future prediction job.

Table 4.19 Recapitulation of the best group set based on the performance in predict the data testing.

Model		Data Set	Accuracy	Error Rate	Precision	Recall	F1 Score
SVM	Model 1	Group 4	0.978	0.022	1.000	0.875	0.933
	Model 2	Group 4	0.933	0.067	0.857	0.750	0.800
	Model 3	Group 3	0.956	0.044	1.000	0.818	0.900
KNN	Model 1	Group 4	0.9556	0.0444	1.0000	0.7500	0.8571
	Model 2	Group 4	0.9333	0.0667	0.8571	0.7500	0.8000
	Model 3	Group 4	0.9778	0.0222	1.0000	0.8750	0.9333
LR	Model 1	Group 4	0.978	0.022	1.000	0.875	0.933
	Model 2	Group 4	0.978	0.022	0.889	1.000	0.941
	Model 3	Group 4	0.933	0.067	1.000	0.625	0.769

From the method side, the summary of average performance for each method in predicting data training and testing will be shown in the table below.

Table 4.20 Summary of the average model's performance in predicting data training base on algorithm perspective.

Model		Avg. Accuracy	Avg. Error Rate	Avg. Precision	Avg. Recall	Avg. F1 Score
SVM	Model 1	0.947	0.053	1.000	0.775	0.870
	Model 2	0.932	0.068	1.000	0.709	0.829
	Model 3	0.953	0.047	0.929	0.868	0.895
KNN	Model 1	0.945	0.055	0.991	0.771	0.866
	Model 2	0.936	0.064	0.950	0.769	0.849
	Model 3	0.945	0.055	0.898	0.862	0.879
LR	**Model 1**	**0.947**	**0.105**	**0.964**	**0.891**	**0.926**
	Model 2	0.945	0.109	0.958	0.889	0.923
	Model 3	0.678	0.321	0.727	0.664	0.692

Table 4.21 Summary of the average model's performance in predicting data testing base on algorithm perspective.

Model		Avg. Accuracy	Avg. Error Rate	Avg. Precision	Avg. Recall	Avg. F1 Score
SVM	Model 1	0.922	0.078	0.884	0.814	0.836
	Model 2	0.872	0.128	0.807	0.652	0.704
	Model 3	0.906	0.094	0.858	0.720	0.774
KNN	Model 1	0.917	0.083	0.964	0.683	0.799
	Model 2	0.894	0.106	0.866	0.652	0.742
	Model 3	0.894	0.106	0.813	0.783	0.783
LR	Model 1	0.944	0.056	0.975	0.783	0.864
	Model 2	**0.944**	**0.056**	**0.895**	**0.868**	**0.877**
	Model 3	0.550	0.450	0.481	0.875	0.540
Distance to Default		0.867	0.133	0.879	0.543	0.657
Z-Score		0.622	0.378	0.378	0.845	0.505

Based on the table summary of prediction on data training, it can be known or Support Vector Machine, the highest average performance to predict the data test can be achieve with the Model 3 with the average F1-Score of 0.895 and it apply the same for K-Nearest Neighbour method with the F1-Score of 0.879. While for Logistic Regression, Model 1 is showing the greatest performance among others model. From the table, it is known that the Model 1 of Logistic Regression show the highest result on predicting the data training. On the other hand, summary of the prediction model table shows the best average performance of model using Support Vector Machine can be achieved when using Model 1; K-Nearest Neighbour when using Model 1 and Logistic Regression when using Model 2. The highest average performance can be achieve by Model 2 Logistic Regression, with the F1-score of 0.877.

From the perspective of model, the summary of average performance of each model in predicting data training and testing will be shown in the table below.

Table 4.22 Summary of the average model's performance in predicting data training base on model feature set perspective.

Model		Avg. Accuracy	Avg. Error Rate	Avg. Precision	Avg. Recall	Avg. F1 Score
Model 1	SVM	0.947	0.053	1	0.775	0.87
	KNN	0.945	0.055	0.991	0.771	0.866
	LR	0.947	0.105	0.964	0.891	0.926
	Average	**0.947**	**0.071**	**0.985**	**0.812**	**0.887**
Model 2	SVM	0.932	0.068	1	0.709	0.829
	KNN	0.936	0.064	0.95	0.769	0.849
	LR	0.945	0.109	0.958	0.889	0.923
	Average	0.938	0.08	0.97	0.789	0.867
Model 3	SVM	0.953	0.047	0.929	0.868	0.895
	KNN	0.945	0.055	0.898	0.862	0.879
	LR	0.678	0.321	0.727	0.664	0.692
	Average	0.859	0.141	0.851	0.798	0.822

Table 4.23 Summary of the average model's performance in predicting data training base on model feature set perspective

Model		Avg. Accuracy	Avg. Error Rate	Avg. Precision	Avg. Recall	Avg. F1 Score
Model 1	SVM	0.922	0.078	0.884	0.814	0.836
	KNN	0.917	0.083	0.964	0.683	0.799
	LR	0.944	0.056	0.975	0.783	0.864
	Average	**0.928**	**0.072**	**0.941**	**0.76**	**0.833**
Model 2	SVM	0.872	0.128	0.807	0.652	0.704
	KNN	0.894	0.106	0.866	0.652	0.742
	LR	0.944	0.056	0.895	0.868	0.877
	Average	0.904	0.096	0.856	0.724	0.774
Model 3	SVM	0.906	0.094	0.858	0.72	0.774
	KNN	0.894	0.106	0.813	0.783	0.783
	LR	0.55	0.45	0.481	0.875	0.54
	Average	0.783	0.217	0.717	0.793	0.699
Distance to Default		0.867	0.133	0.879	0.543	0.657
Z-Score		0.622	0.378	0.378	0.845	0.505

The summary of prediction result with data training shows that: Model 1 that develop with Logistic Regression can reach the highest average prediction performance among other; It is similar For Model 2, which shows that the highest average prediction can reach when using Logistic Regression; And for Model 3, it is best to use K-Nearest Neighbor. Almost similar, the summary of prediction result of data testing shows that the highest average performance to predict the data testing with Model 1 can be reach when using Logistic Regression. It also applies to Model 2 which show that Logistic Regression have the highest performance compare to algorithm. While on the Model 3, the highest performance can be reach when using Support Vector Machine.

4.7 Prediction on Data 2019.

This sub chapter will show the performance result on financial distress prediction on Data 2019 for each develop model. Although it has the similar purpose with prediction on data testing, the prediction on Data 2019 will provide the insight on how well if the model used the best data set as the training, to predict new data. In addition, this step is done as the last test on the model in doing financial prediction on newest available data. The training data set, which produce best performance to predict data testing, will be chosen to as the model to do the prediction on Data 2019.

The composition for Data 2019 is include total 52 firm's data, where it is divided into two class. The first class is the healthy firm, which has 45 data and the second class is the distress firms, which has 7 data. The data training that use for predicting the Data 2019 is the data set that generate the highest prediction performance on data testing. The result of prediction will be shown below.

Table 4.24 The prediction result of Data 2019.

Company	Actual Condition	Prediction Result										
		SVM			KNN			LR			Z-Score	DtD
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3		
Panorama Sentrawisata, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Garuda Indonesia (Persero), Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Astra Graphia Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
FKS Multi Agro, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Intraco Penta, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Tigaraksa Satria, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Citra Marga Nusaphala Persada, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Jasa Marga (Persero), Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Bakrie Telecom, Tbk.	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Healthy
Bali Towerindo Sentra Tbk	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Indosat, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Inti Bangun Sejahtera Tbk	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Telekomunikasi Indonesia, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Tiphone Mobile Indonesia, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Trikomsel Oke, Tbk	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Distress	Healthy	Distress	Healthy
XL Axiata, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Arpeni Pratama Ocean Line, Tbk.	Distress	Distress	Distress	Healthy	Distress	Distress	Healthy	Distress	Distress	Healthy	Distress	Healthy
Berlian Laju Tanker, Tbk.	Distress	Distress	Distress	Healthy	Distress	Distress	Distress	Distress	Distress	Healthy	Distress	Distress
Humpuss Intermoda Transportasi, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Matahari Putra Prima, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy	Distress	Distress
Mitra Adiperkasa, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Fastfood Indonesia, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Jaya Bersama Indo Tbk	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy

Company	Actual Condition	Prediction Result										
		SVM			KNN			LR			Z-Score	DtD
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3		
Pembangunan Jaya Ancol, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Agung Podomoro Land, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Alam Sutera Realty, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Bakrieland Development, Tbk.	Distress	Distress	Healthy	Distress	Healthy	Healthy	Distress	Healthy	Healthy	Distress	Healthy	Healthy
Bukit Uluwatu Villa, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Bumi Serpong Damai, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Duta Anggada Realty, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Duta Pertiwi, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Intiland Development, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Lippo Karawaci, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Modernland Realty, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Nusa Konstruksi Enjiniring, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Perdana Gapuraprima, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
PP Properti, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Summarecon Agung, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Surya Semesta Internusa, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Apexindo Pratama Duta, Tbk.	Healthy	Distress	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy	Distress	Healthy
Perusahaan Gas Negara Tbk	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Global Mediacom, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Media Nusantara Citra, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Metrodata Electronics, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Adhi Karya (Persero), Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Bukaka Teknik Utama Tbk	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Wijaya Karya (Persero), Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Express Transindo Utama, Tbk.	Distress	Distress	Distress	Healthy	Distress	Distress	Healthy	Distress	Distress	Healthy	Distress	Healthy

Company	Actual Condition	Prediction Result										
		SVM			KNN			LR			Z-Score	DtD
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3		
Weha Transportasi Indonesia, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Healthy
Astra International, Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
Indofarma (Persero), Tbk.	Distress	Distress	Healthy	Distress	Distress	Distress	Distress	Healthy	Healthy	Healthy	Distress	Healthy
Kimia Farma (Persero), Tbk.	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Distress	Distress

The summary of performance for each model will be shown in the table below.

Table 4.25 The result of Prediction on Data 2019 with the best group set.

Model		Accuracy	Error Rate	Precision	Recall	F1Score
SVM	**Model 1**	**0.981**	**0.019**	**0.875**	**1.000**	**0.933**
	Model 2	0.962	0.038	1.000	0.714	0.833
	Model 3	0.942	0.058	1.000	0.571	0.727
KNN	Model 1	0.981	0.019	1.000	0.857	0.923
	Model 2	0.942	0.058	0.750	0.857	0.800
	Model 3	0.962	0.038	1.000	0.714	0.833
LR	Model 1	0.962	0.038	1.000	0.714	0.833
	Model 2	0.923	0.077	0.714	0.714	0.714
	Model 3	0.904	0.096	1.000	0.286	0.444
Distance to Default		0.846	0.154	0.333	0.143	0.2
Z-score		0.519	0.481	0.2	0.857	0.324

Based on table it can be known that the highest performance can be achieve when using the Model 1 of Support Vector Machine with the F1-score of 0.93333. In order to see whether any models have the accuracy or overall performance that significantly different with other, this research use McNemar test. The test is a non-parametric test for two related samples that particularly useful for before-after measurement of the same subjects (Kim, 2003).

Table 4.26 shows the result of McNemar test which used to statistically compare prediction accuracy for Data 2019 among the developed Model. Based on the table, it can be known that the models of Support Vector Machine which is developed using the feature set of Model 1 performance is statistically significant at 5% to outperform the models of Logistic Regression which developed using feature set of Model 3. The model of K-Nearest Neighbour with feature set in Model 2 is statistically significant at 10% to outperform models of Logistic Regression with the feature set of Model 3. All of the models are also statistically significant to outperform Altman Z-Score, but it is not applied to Distance to Default, since the statistic shows all of the models are not significant. The difference for the rest of developed model is appear to be not statistically significant difference between each other.

Table 4.26 McNemar values (p-values) for the pairwise performance's comparison.

Model	SVM Model 2	SVM Model 3	KNN Model 1	KNN Model 2	KNN Model 3	LR Model 1	LR Model 2	LR Model 3	Altman Z-Score	DtD
SVM Model 1	0.25	0.13	0.50	1.00	0.25	0.25	1.00	**0.03***	**0.00***	0.18
SVM Model 2		1.00	1.00	0.25	1.00	1.00	0.50	0.38	**0.00***	0.69
SVM Model 3			0.63	0.22	1.00	1.00	0.45	0.50	**0.00***	1.00
KNN Model 1				0.50	1.00	1.00	1.00	0.22	**0.00***	0.45
KNN Model 2					0.38	0.25	1.00	**0.07****	**0.00***	0.18
KNN Model 3						1.00	0.69	0.25	**0.00***	0.69
LR Model 1							0.50	0.38	**0.00***	0.69
LR Model 2								0.13	**0.00***	0.22
LR Model 3									**0.00***	1.00

*P<0.1, **P<0.05.

CHAPTER 5
DATA ANALYSIS AND INTERPRETATION

5.1 Analysis of Application Previous Existing Model for Indonesian Data.

This sub chapter will explain the application of the previous existing model in predicting the Indonesian data, namely Altman Z-Score and Distance to Default. The performance of each model measured to evaluate how well the model performed when it applied in prediction of financial distress for Indonesian non-manufacturing firms.

5.1.1 Application of Altman Z-Score

The application of Altman Z-Score has relatively poor performance. In almost all of the parameter, Altman Z-Score has lower score than Distance to Default in prediction of data test. This also similar in the prediction of Data 2019, which shows if the model cannot produce higher score in all of the parameter except the recall. In addition, all of the developed model statistically outperforms Altman Z-Score. This indicate that this model is not applicable to Indonesian data, since the model built based on U.S firms' data. The model will generate inaccurate prediction when it is applied to Indonesian non-manufacturing firms. Based on this finding, it implies that the model needs to be improved. From his journal, Altman (2005) himself has advocate building and testing the model derived from the country's own data. This result also in accordance to the research Singh & Mishra (2016), which found that if the performance of the financial distress model will be better when it developed with local firms data rather than using the original model.

5.1.2 Application of Distance to Default

Distance to Default has better result in the data testing prediction for almost all parameter, except for recall when it compared to the Altman Z-Score. This happen the same in the Data 2019 prediction. This model produced a relatively good accuracy when it is compared to the developed model, since the difference of accuracy is not differed too much. Based on the McNemar's test, all of the developed model is not statistically outperformed Distance to Default. This indicate the overall performance of Distance to Default model is relatively good. However, the average F1-Score of the Distance to Default when predicting the data test and Data 2019 is outperform by all of the developed model. This is because the recall score is low, which indicate that the proportion of the positive sample were correctly classified is low. In this case, the positive sample is the distress firms. And since the interest of this study also include to establish the model that has an accurate prediction of financial distress firms, the model should also have a good F1-Score. The result shows that the application of Distance to Default will produce inaccurate result in determining the Indonesian non-manufacturing distress firms.

5.2 Analysis of Model Feature

There are three models with different feature which developed in this study. Each model represents different perspective with different set of variables when developing the model. Model 1 represent the combination of market and accounting perspective with 6 variables, which originally from Altman Z-Score and Distance to Default. Model 2 represent the accounting perspective with 4 variables, which originally from Altman Z-Score. Model 3 represent the market perspective with 2 variables, which originally from Distance to Default. All of the model was developed using different algorithm in several data set. This analysis will focus on the discussion about the algorithm which suitable to develop specific feature set.

5.2.1 Analysis of Model with Feature of Combination between Market and Accounting Perspective

All of the algorithm shows a good performance when using this set of features. Support Vector Machine can fit the data set with this feature well, since the average accuracy of prediction of data training and data testing is not differed too far. In addition, the test on data 2019 shows, with using model through SVM algorithm, the model can reach higher F1-Score which indicate the model is good to be implemented using SVM.

K-Nearest Neighbor also shows a good performance since accuracy is relatively stable. The performance of F1-Score has decrease when prediction result on training data is compare to testing data, meanwhile it climbed back up when the model is used to predict data 2019. This indicate if Model 1 implemented by using K-NN will still suitable and produce a good result.

Logistic Regression has the highest average performance when predict the data training and data testing using the feature set in Model 1. Although the performance of F1-Score is slightly drop when predict Data 2019, the model accuracy is relatively stable. Base on this performance, it implies that if Logistic Regression is suitable to develop with this feature.

The summary of the model's performance with perspective model also shows if the model, which use combination of market and accounting perspective as the features, has the highest of average performance both in prediction data training and data testing among other set feature. This indicate the model of financial distress prediction will have higher performance if it contains both perspective from market and financial

5.2.2 Analysis of Model with Feature of Accounting Perspective

The prediction using the feature set in Model 2 shows a good result for all algorithm. The development of Model 2 using Support Vector Machine algorithm shows a slight fluctuation of average performance in F1-Score but relatively stable accuracy. The result of F1-Score data testing prediction is lower compared to result of training. But in Data 2019 prediction, the F1-Score performance is rising again compare to the prediction of data testing. This imply that the model is suitable with this feature to do the prediction of financial condition since the accuracy is relatively stable, and it would produce to best prediction result when the best data set is applied in the model.

Similar with SVM, K-Nearest Neighbor shows relatively stable in accuracy and slight of fluctuation in F1-score performance. The F1-Score result on predicting the data training is slightly dropped when it is compared to the performance to predict the data test. However, it shows a better result when predict the Data 2019. From this it can imply that if feature set in the Model 2 is suitable to use in K-NN since overall accuracy is relatively stable. Applying best data set also would improve the performance of the model in the prediction.

Logistic Regression shows a stable result and has highest average performance in accuracy and F1-Score between the other algorithm in the both prediction, data training and data testing. The result of prediction on Data 2019 show if there is a decreasing performance in F1-Score and followed with the accuracy is relatively similar with the result on prediction on data training and data testing. This imply that the model may slightly overfit, and it failed to predict some of data correctly. And since the Data 2019 consist only seven data of distress firms, the failure to predict will impact much to the F1-Score performance. Base on this result, although the model has very high performance in data training and data testing prediction, there should be a further observation regarding the performance of this model with more sample of distress firms in data set to get bigger picture about the model performance.

5.2.3 Analysis of Model with Feature of Market Perspective

Base on the summary table, the highest average prediction performance for all parameter in predicting data training can be achieved when using Support Vector Machine. While for predict the test data and Data 2019, the highest average performance of F1-Score, precision and recall are achieved when using K-Nearest Neighbor.

The models which develop use the feature set of market perspective show a good and poor performance. The good performance is achieved when the model develops using K-Nearest Neighbor and Support Vector Machine. While poor performance display when the model is developed using Logistic Regression.

In developing the feature set with Support Vector Machine, the model can reach the highest average performance of F1-Score in predicting data training compare to the other algorithm. But it slightly drops when use to test the data testing. The performance of F1-Score continues to be decreased, although it is not much, when the performance to predict data test is compared to the performance to predict the Data 2019. Although there is a difference in the F1-Score, the accuracy is remained stable. The data of distress firms is unbalance with the healthy firms, which cause a failure to do right classification of distress firms can result to the decrease in performance. Based on this result, it implies that the feature set in Model 3 would still suitable with SVM algorithm since the overall performance is stable.

The K-Nearest Neighbor show more stability in to develop the feature set of Model 3. Although it has not reached the highest F1-Score in predict the data training, the model is well performed to predict the data test and Data 2019. This prove by the highest F1-Score performance can be reach when using the feature set which develop with K-NN to do the prediction. This imply that the model is suitable to do the financial distress prediction using the feature set in the Model 3.

Logistic Regression did not produce a good prediction performance with the model 3. The average model performance is far below when compare to another model which develop with another algorithm. Even it did not improve the model if the model is compared to the previous existing model. The model only slightly has a better performance than Altman Z-Score and Distance to Default. The reason is because the Logistic Regression algorithm did not fit to the feature use to build the model. From the Goodness of Fit test, shows there are two models that are not a good fit, namely the models which are developed with data set from Group 3 and Group 4. As it explains by Josephat & Ame (2018) research which prove that the not-a-good-fit model would have lower classification accuracy rate. In addition, the likelihood ratio test shows a result of high value of -2 Log likelihood when it compares to other feature set in the model which build with Logistic Regression, which describe that this model would have worse results than other models. Therefore, the development of feature set of Model 3 using Logistic Algorithm will likely produce a poor performance of prediction result.

5.3 Analysis of Financial Distress Prediction Algorithm

This research use 3 different algorithm in developing financial distress model, namely Support Vector Machine and K-Nearest Neighbor as the artificial intelligence method and Logistic Regression as statistical method. The analysis will focus on the discussion of best feature to use when using an algorithm, that include comparison with previous existing model and the examination on each algorithm performance in developing the model

5.3.1 Support Vector Machine Financial Distress Prediction Model

The development of financial prediction model with Support Vector Machine has improve the performance compare to previous existing models, which are Altman Z-Score and Distance to Default. This prove by when predicting the data test, the developed model has higher average F1-Score, accuracy, precision and recall. It indicates that the model can predict financial distress firms more accurate.

Based on the comparison of performance between prediction of data training and testing, the overall performance in predicting the training data is higher than when the model is used to predict the testing data. It indicates that the model is slightly overfit, and the performance will slightly decrease when predicting the data test. Even so, the result is still considered as good since the developed model shows a better accuracy than the previous study. Model 1, Model 2 and Model 3 has accuracy respectively of 92%, 87% and 90% and it is higher compare to the previous study of Min & Lee (2005) which has 83% accuracy. In addition, previous study also shows if there is a decrease in performance when after comparing the performance to predict the data training to data testing (Min & Lee, 2005).

The stability of performance in the prediction job is reflect from the Model 1 performance. In addition, Model 1 have the greater performance compare to another model in prediction of data testing and Data 2019. While for the feature set in Model 2 and Model 3, although it can also produce a good prediction since the accuracy produces from each model is higher than the previous model, but the performance display in F1-Score slightly less stable. By this result, it indicates that the complete feature of financial and market perspective is best feature to be implement in Support Vector Machine that will support the model to produce better accuracy to predict the unseen data from the model and more robust.

5.3.2 K-Nearest Neighbour Financial Distress Prediction Model

The model which is built from K-Nearest Neighbor algorithm provide more better result from the previous existing model. The result shows that the performance of the Model 1, Model 2 and Model 3 have higher average performance than Altman Z-Score and Distance to Default. This indicate the model have greater power in determine the financial condition of the firms and predict the distress firms in the future compare to the previous existing model.

Similar with Support Vector Machine, the overall average performance for K-Nearest Neighbor is higher when predicting the data training than data testing. This indicate a slight overfitting, since when the model is used to predict the data test, the performance is decreasing. But the results obtained when the model is used to predict Data 2019 are beyond expectations since the performance of F1-Score and accuracy goes up and it can higher than the performance to predict the training data. This indicate that the algorithm can produce good prediction result for the data test with the training data set, but with little caution since because the model is slightly less stable.

There is not much different power between the three of feature set that used within the K-NN algorithm. The ability to produce the correct prediction is relatively similar between one model to another. In addition, there K-NN can shows the best performance compare to another algorithm when developing the model with the feature set in Model 3, which indicate Model 3 would be best to develop using K-NN. But based on the performance, Model 1 can produce the best performance of accuracy and F1-score in prediction of data testing and Data 2019. This indicate that the combination of accounting and market perspective is the best feature set to be used in the K-NN algorithm although the feature set in Model 2 and Model 3 can also produce the good result of prediction.

5.3.3 Logistic Regression Financial Distress Prediction Model

Logistic Regression is categorized as the statistical method, similar with Altman Z-Score and Distance to Default since there is assumptions assumption that must be fulfilled and several test to check whether the model is good or not. In the Goodness of Fit test, the majority of the model is statistically fit to the model and there is 2 model which is not fit at the significance of 0.05, namely the Model 3 with data set from Group 3 and Model 3 with the data set Group 4. And from the likelihood ratio test, it is known that the model which is statistically fit will produce smaller likelihood test which means it have better prediction result means; and higher R-Square, which indicate if independent variable in the model have greater to explain the dependent variable.

The result shows that the use Logistic Regression, the developed model can achieve better result from the previous existing model when it fulfill the statistical assumption. The average performance from Model 1 and Model 2 and reach higher F1-Score and accuracy than the Altman Z-Score and Distance to Default. While for Model 3, it reach lower result of F1-Score compare to Distance to Default and only slightly higher than Altman Z-Score. This indicate the financial distress prediction model can be improve with the development of the new model using the Indonesian non-manufacturing firms data when the statistical assumption is fulfilled. When the model is not fit to predict the data, it will decrease the capability of the model in producing good result of prediction.

The model of Logistic Regression also indicate a slight overfitting and result to decreasing performance in predicting the data test. From the result comparison between prediction on data training and data testing, the model can predict better in training data than on testing data and Data 2019. Base on the previous study, it shows similar result of the decreasing performance when the performance to predict the data training is compared with performance to compare the data testing (Min & Lee, 2005).

The summary that can be made based on the experiment of Logistic Regression model is that model can produce the highest average performance with the feature set in Model 1. The model 1 may not produce the highest average performance in prediction of data testing, but the different is not too far with Model 1 and in addition, Model 1 can produce the highest average in F1-Score to predict the data training and Data 2019. While the performance of Logistic Regression is not stable when using the Model 2 since the performance is drop when it used to predict Data 2019. And for Model 3, it has not produced a good average F1-Score and overall performance since there is a model which is not fulfill the asumption and the high likelihood ratio, which indicate the model will perform a poor job to do the prediction.

5.4 Analysis of Model Performance

This analysis is focus on the comparison between the model's performance, to see if there is any significant difference between the performance of one model to other. This analysis will also include the discussion about the performance of the best group data set performance and best feature to be used for each algorithm to predict Data 2019 since prediction of Data 2019 is consider as simulation of the actual condition in the future and can be used to give a picture of the best selected group data set ability performance when it is implemented. As it explains in the chapter of Design of Experiment, the selection of the best group as the data set to be fit into the algorithm and implemented in real condition is based on the group which produce highest performance of F1-Score in predicting the data test.

In Data 2019 prediction, The result of McNemar test implies if there is only two of models, namely Model of Support Vector Machine with the feature set from Model 1 and Model of K-Nearest Neighbor with feature set from Model 2, statistically significant to outperform the overall performance Model of Logistic Regression with feature set from Model 3. And based on the statistic result, the rest of the models is not significantly different. Although it may not statistically different with each other, the F1-Score can be used to distinguish between the model's performance. The best F1-Score performance in predicting Data 2019 is achieve by Support Vector Machine model with feature set from Model 1. This means SVM can outperform K-NN and Logistic Regression. Beside of that, each algorithm that use the feature of Model 1 can achieve better F1-Score than when using feature set from Model 2 and Model 3.

The performance of the model shows that if the best group set of data testing is use as the training set of the data, the model can produce better performance compare to previous existing model. From the McNemar test shows if all of the model is statistically significant to outperform Altman Z-Score. On the other hand, the result is surprisingly different in Distance to Default, which shows no models that are significant enough to outperform it. This means from overall performance, it may there is no statistical proof which can differ the performance between Distance to Default with the developed model. But in the result of F1-

Score, Distance to Default give very poor performance compare to the developed model. This study interest in creating an accurate to predict the financial distress firms that reflect in F1-Score of model performance, the use of Distance to Default will cause a doubt of prediction result for distress firms. And since, the developed model has the F1-Score greater than Distance to Default, the developed model will perform better job at predicting the distress firms.

5.5 Analysis of Model Implementation

This analysis will focus on appropriate model to be implemented. The analysis will include the discussion of model's application to be used in prediction job; and discussion about the feature set with the algorithm which suitable to be implemented in the model based on the previous analysis.

Support Vector Machine is categorized as an artificial intelligence, supervised machine learning model. This means the model that develop with Support Vector Machine need a data training before doing the predict data test. The process to input the training data will require to use software and coding process so the training data can fit with the algorithm. After that, the model can be used to predict the data test. Similar to SVM, K-Nearest Neighbor is artificial intelligence, supervised machine learning model. It required the same things so the application can be more practical. But since the algorithm is simple, it can also be done manually since it only measures the closest distance between data training and data test to determine the class classification. On the other hand, Logistic Regression will simpler to be use manually. Logistic Regression has the output of equation to measure financial distress probability. Therefore, it is simple enough to do prediction job using this model since the model can directly be use by input the data in the variable. The classification then will be done base on the cut-off value.

The application of Support Vector Machine in different feature set are no statistically significant between one model to the other. So, it means all the model would likely to have a similar performance. Although it is not significant, the model of SVM will best to use feature of combination between market and accounting perspective since the model is proven to have highest performance compare to other feature set and outperform models with different algorithm.

Almost similar with SVM, K-Nearest Neighbor has a good result using all feature. Even though the performance is lower than SVM, but the difference is not far and it is not statistically significance. Feature set in Model 1 produce the best performance when it is developed using K-Nearest Neighbor algorithm. Beside of that, K-Nearest Neighbor also has advantage in making the highest performance among the other algorithm when using the feature set of Model 3. This indicate that the application of KNN will be best to use the feature set of combination of accounting and market variable, but the use of market variable as the only feature in the model is also acceptable because it is not significantly different.

On the other hand, the models which develop using Logistic Regression algorithm experienced an unexpected decline in performance. The F1-Score shows a good result in the prediction of data training and data testing, but it slightly drop when predicting the Data 2019, especially in the model with feature set from Model 2. Similar with SVM and KNN for prediction of Data 2019, model with the feature set from Model 1 reach the highest prediction between the other feature set. This means the Logistic Regression would be best to be applied with the feature set of combination between market and accounting variable. For application with feature set taken from accounting variable require a further research with bigger data set to confirm the capability of this model in doing prediction. In addition, based on the performance which has shown, the models is strongly not recommended to use only feature set from the market perspective only, since the prediction performance that generated by the model would be very low and inaccurate.

In summary, all of the models are capable and well perform to do prediction on distress firms except for Logistic Regression with the feature set with model 3. The application of the model will be returned to the user's ability, because the use of artificial intelligence-based models requires the ability to code to run algorithms in software, while the causal method is carried out based on the established equations. However, it is strongly recommended to use the well perform algorithms to compare the result between one model to the other, and decide the firm’s financial condition based on the majority of the model’s prediction result.

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CHAPTER 6
CONCLUSION AND SUGGESTION

This chapter will explain the conclusions that answer the objectives of this thesis research and will also be given suggestions for improvement in further research.

6.1 Conclusion

The following is the conclusion of the research to the research's objective regarding the development of Financial Prediction Model for Indonesia non-manufacturing firms.

1. The performance's evaluation of previous existing model indicate that both of the model need to be improved to produce an accurate model to predict the financial distress firm since the empirical result show Altman Z-Score has low overall performance and Distance to Default displayed inaccurate result to correctly predict the postive sample as distress firm.
2. This study develop Financial Distress Prediction models with different algorithm and feature set with experiment to establish more accurate models. Algorithm which applied in this study are Support Vector Machine, K-Nearest Neighbor and Logistic Regression. Each algorithms are used to develop models with different feature set which represent combination of accounting and market perspective; accounting perspective; and market perspective. The study also utilize cross validation to see overview of model performance in doing prediction across different data set that fit into the model. The design of experiment was created in the development process to accommodate and evaluate the used of several combination of feature set, algorithm and data set in the development of the model.
3. The result of the model performance based on the experiment which has done in this study shows that majority of feature set will produce a good prediction result and suitable to the algorithm that used in this

study. Based on the average performance of each feature set used in the model, the feature set of combination between accounting and market perspective give the highest F1-Score and accuracy. All of the algorithm are suitable to used this feature set and it will support the model to have a better performance compared. For feature with accounting perspective also produce and fit well to all of the algorithm, but the performance is lower when it is compared to the complete feature. While the lowest average performance came from the model with feature set of market perspective only, since Logistic Regression model did not fit when using it. This feature only can produce a good performance when it is applied on the artificial intelligence model.

4. The performance on prediction Data 2019 give the illustration when the best group set of each developed model is applied to do the actual financial distress prediction job. Compare to the previous existing model, all of the model statistically significant to outperform Altman Z-Score. And even though, it is not statistically significant, the result of prediction show if the developed model have higher F1-Score and accuracy compare to Distance to Default. The result of empirical analysis shows that the model of Support Vector Machine with feature set from Model 1 reach the highest F1-score and outperform the other models. Despite there is a difference on performance parameter, other model actually can also produce a good result of prediction since it is not statistically significant different, except for Logistic Regression with the feature set from Model 3 which have a poor result of prediction. Therefore the application would depend on the user ability, but it is strongly recommended to use all of well perform algorithm if possible, to compare the result between one model to the other, and decide the firm's financial condition based on the majority of the model's prediction result.

6.2 Suggestion

The suggestions that can be given for further research are as follows.

1. Further research needs to involve larger data set to see the consistency of performance of the feature sets and algorithms used in the financial distress prediction model

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APPENDIX

Appendix 1. Matlab Code for Support Vector Machine algorithm.

```
data1=[data(46:178,:)];
data2=[data(1:45,:);data(91:178,:)];
data3=[data(1:90,:);data(136:178,:)];
data4=[data(1:133,:)];
y1=[y(46:178,:)];
y2=[y(1:45,:);y(91:178,:)];
y3=[y(1:90,:);y(136:178,:)];
y4=[y(1:133,:)];
databaru1=[data(1:45,:)];
databaru2=[data(46:90,:)];
databaru3=[data(91:135,:)];
databaru4=[data(134:178,:)];
mdl=fitcsvm(data1,y1,'Standardize',true,'KernelFunction','RBF',...
   'KernelScale','auto');
Testing1=predict(mdl,databaru1);
Training1=predict(mdl,data1);
mdl=fitcsvm(data2,y2,'Standardize',true,'KernelFunction','RBF',...
   'KernelScale','auto');
Testing2=predict(mdl,databaru2);
Training2=predict(mdl,data2);
mdl=fitcsvm(data3,y3,'Standardize',true,'KernelFunction','RBF',...
   'KernelScale','auto');
Testing3=predict(mdl,databaru3);
Training3=predict(mdl,data3);
mdl=fitcsvm(data4,y4,'Standardize',true,'KernelFunction','RBF',...
   'KernelScale','auto');
Testing4=predict(mdl,databaru4);
Training4=predict(mdl,data4);
```

Appendix 2. Matlab Code for K-Nearest Neighbour algorithm.

```
data1=[data(46:178,:)];
data2=[data(1:45,:);data(91:178,:)];
data3=[data(1:90,:);data(136:178,:)];
data4=[data(1:133,:)];
y1=[y(46:178,:)];
y2=[y(1:45,:);y(91:178,:)];
y3=[y(1:90,:);y(136:178,:)];
y4=[y(1:133,:)];
databaru1=[data(1:45,:)];
databaru2=[data(46:90,:)];
databaru3=[data(91:135,:)];
databaru4=[data(134:178,:)];

%defining best k parameter in KNN
mdl6=fitcknn(data4,y4,'NumNeighbors',6,'distance','euclidean');
D6=predict(mdl6,databaru4);
mdl5=fitcknn(data4,y4,'NumNeighbors',5,'distance','euclidean');
D5=predict(mdl5,databaru4);
mdl4=fitcknn(data4,y4,'NumNeighbors',4,'distance','euclidean');
D4=predict(mdl4,databaru4);
mdl3=fitcknn(data4,y4,'NumNeighbors',3,'distance','euclidean');
D3=predict(mdl3,databaru4);
mdl2=fitcknn(data4,y4,'NumNeighbors',2,'distance','euclidean');
D2=predict(mdl2,databaru4);
mdl1=fitcknn(data4,y4,'NumNeighbors',1,'distance','euclidean');
D1=predict(mdl1,databaru4);

%Running KNN Model
mdl1=fitcknn(data1,y1,'NumNeighbors',3,'distance','euclidean');
A1=predict(mdl1,databaru1);
A2=predict(mdl1,data1);
```

```
mdl2=fitcknn(data2,y2,'NumNeighbors',3,'distance','euclidean');
B1=predict(mdl2,databaru2);
B2=predict(mdl2,data2);
mdl3=fitcknn(data3,y3,'NumNeighbors',3,'distance','euclidean');
C1=predict(mdl3,databaru3);
C2=predict(mdl3,data3);
mdl4=fitcknn(data4,y4,'NumNeighbors',3,'distance','euclidean');
D1=predict(mdl4,databaru4);
D2=predict(mdl4,data4);
```

Appendix 3. Recapitulation of firm's number of share outstanding, closing stock price and market value of equity.

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Panorama Sentrawisata, Tbk.	2018	1,200,000,000	Rp 370	Rp 444,000,000,000
Panorama Sentrawisata, Tbk.	2017	1,200,000,000	Rp 550	Rp 660,000,000,000
Panorama Sentrawisata, Tbk.	2016	1,200,000,000	Rp 625	Rp 750,000,000,000
Garuda Indonesia (Persero), Tbk.	2018	25,980,000,000	Rp 298	Rp 7,742,040,000,000
Garuda Indonesia (Persero), Tbk.	2017	25,980,000,000	Rp 300	Rp 7,794,000,000,000
Garuda Indonesia (Persero), Tbk.	2016	25,980,000,000	Rp 338	Rp 8,781,240,000,000
Astra Graphia Tbk.	2018	1,350,000,000	Rp 1,330	Rp 1,795,500,000,000
Astra Graphia Tbk.	2017	1,350,000,000	Rp 1,310	Rp 1,768,500,000,000
Astra Graphia Tbk.	2016	1,350,000,000	Rp 1,900	Rp 2,565,000,000,000
FKS Multi Agro, Tbk.	2018	480,000,000	Rp 4,000	Rp 1,920,000,000,000
FKS Multi Agro, Tbk.	2017	480,000,000	Rp 2,400	Rp 1,152,000,000,000
FKS Multi Agro, Tbk.	2016	480,000,000	Rp 4,060	Rp 1,948,800,000,000
Intraco Penta, Tbk.	2018	3,340,000,000	Rp 488	Rp 1,629,920,000,000
Intraco Penta, Tbk.	2017	3,340,000,000	Rp 428	Rp 1,429,520,000,000

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Intraco Penta, Tbk.	2016	3,340,000,000	Rp 295	Rp 985,300,000,000
Tigaraksa Satria, Tbk.	2018	918,490,000	Rp 3,350	Rp 3,076,941,500,000
Tigaraksa Satria, Tbk.	2017	918,490,000	Rp 2,600	Rp 2,388,074,000,000
Tigaraksa Satria, Tbk.	2016	918,490,000	Rp 3,280	Rp 3,012,647,200,000
Citra Marga Nusaphala Persada, Tbk.	2018	3,620,000,000	Rp 1,280	Rp 4,633,600,000,000
Citra Marga Nusaphala Persada, Tbk.	2017	3,620,000,000	Rp 1,540	Rp 5,574,800,000,000
Citra Marga Nusaphala Persada, Tbk.	2016	3,620,000,000	Rp 1,465	Rp 5,303,300,000,000
Jasa Marga (Persero), Tbk.	2018	7,260,000,000	Rp 4,280	Rp 31,072,800,000,000
Jasa Marga (Persero), Tbk.	2017	7,260,000,000	Rp 6,400	Rp 46,464,000,000,000
Jasa Marga (Persero), Tbk.	2016	7,260,000,000	Rp 4,320	Rp 31,363,200,000,000
Bali Towerindo Sentra Tbk	2018	3,666,671,900	Rp 1,560	Rp 5,720,008,164,000
Bali Towerindo Sentra Tbk	2017	3,666,671,900	Rp 1,530	Rp 5,610,008,007,000
Bali Towerindo Sentra Tbk	2016	3,666,671,900	Rp 1,050	Rp 3,850,005,495,000
Indosat, Tbk.	2018	5,433,933,500	Rp 1,685	Rp 9,156,177,947,500
Indosat, Tbk.	2017	5,433,933,500	Rp 4,800	Rp 26,082,880,800,000
Indosat, Tbk.	2016	5,433,933,500	Rp 6,450	Rp 35,048,871,075,000
Inti Bangun Sejahtera Tbk	2018	1,350,904,927	Rp 8,300	Rp 11,212,510,894,100
Inti Bangun Sejahtera Tbk	2017	1,350,904,927	Rp 8,100	Rp 10,942,329,908,700
Inti Bangun Sejahtera Tbk	2016	1,350,904,927	Rp 1,850	Rp 2,499,174,114,950
Telekomunikasi Indonesia, Tbk.	2018	99,062,216,600	Rp 3,750	Rp 371,483,312,250,000
Telekomunikasi Indonesia, Tbk.	2017	99,062,216,600	Rp 4,440	Rp 439,836,241,704,000
Telekomunikasi Indonesia, Tbk.	2016	99,062,216,600	Rp 3,980	Rp 394,267,622,068,000

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Tiphone Mobile Indonesia, Tbk.	2018	7,302,194,889	Rp 940	Rp 6,864,063,195,660
Tiphone Mobile Indonesia, Tbk.	2017	7,302,194,889	Rp 100	Rp 730,219,488,900
Tiphone Mobile Indonesia, Tbk.	2016	7,302,194,889	Rp 855	Rp 6,243,376,630,095
XL Axiata, Tbk.	2018	10,687,960,423	Rp 1,980	Rp 21,162,161,637,540
XL Axiata, Tbk.	2017	10,687,960,423	Rp 2,960	Rp 31,636,362,852,080
XL Axiata, Tbk.	2016	10,687,960,423	Rp 2,310	Rp 24,689,188,577,130
Humpuss Intermoda Transportasi, Tbk.	2018	7,101,084,801	Rp 700	Rp 4,970,759,360,700
Humpuss Intermoda Transportasi, Tbk.	2017	7,101,084,801	Rp 730	Rp 5,183,791,904,730
Humpuss Intermoda Transportasi, Tbk.	2016	7,101,084,801	Rp 770	Rp 5,467,835,296,770
Matahari Putra Prima, Tbk.	2018	7,529,147,920	Rp 152	Rp 1,144,430,483,840
Matahari Putra Prima, Tbk.	2017	7,529,147,920	Rp 452	Rp 3,403,174,859,840
Matahari Putra Prima, Tbk.	2016	7,529,147,920	Rp 1,480	Rp 11,143,138,921,600
Mitra Adiperkasa, Tbk.	2018	16,600,000,000	Rp 805	Rp 13,363,000,000,000
Mitra Adiperkasa, Tbk.	2017	16,600,000,000	Rp 620	Rp 10,292,000,000,000
Mitra Adiperkasa, Tbk.	2016	16,600,000,000	Rp 540	Rp 8,964,000,000,000
Fastfood Indonesia, Tbk.	2018	1,995,138,579	Rp 1,670	Rp 3,331,881,426,930
Fastfood Indonesia, Tbk.	2017	1,995,138,579	Rp 1,440	Rp 2,872,999,553,760
Fastfood Indonesia, Tbk.	2016	1,995,138,579	Rp 1,500	Rp 2,992,707,868,500
Jaya Bersama Indo Tbk	2018	1,283,330,000	Rp 1,560	Rp 2,001,994,800,000
Jaya Bersama Indo Tbk	2017	1,283,330,000	Rp 1,220	Rp 1,565,662,600,000
Jaya Bersama Indo Tbk	2016	1,283,330,000	Rp 1,220	Rp 1,565,662,600,000
Pembangunan Jaya Ancol, Tbk.	2018	1,599,999,996	Rp 1,260	Rp 2,015,999,994,960
Pembangunan Jaya Ancol, Tbk.	2017	1,599,999,996	Rp 1,320	Rp 2,111,999,994,720

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Pembangunan Jaya Ancol, Tbk.	2016	1,599,999,996	Rp 2,020	Rp 3,231,999,991,920
Agung Podomoro Land, Tbk.	2018	19,364,561,700	Rp 152	Rp 2,943,413,378,400
Agung Podomoro Land, Tbk.	2017	19,364,561,700	Rp 210	Rp 4,066,557,957,000
Agung Podomoro Land, Tbk.	2016	19,364,561,700	Rp 210	Rp 4,066,557,957,000
Alam Sutera Realty, Tbk.	2018	19,649,411,888	Rp 312	Rp 6,130,616,509,056
Alam Sutera Realty, Tbk.	2017	19,649,411,888	Rp 356	Rp 6,995,190,632,128
Alam Sutera Realty, Tbk.	2016	19,649,411,888	Rp 352	Rp 6,916,592,984,576
Bukit Uluwatu Villa, Tbk.	2018	6,811,269,200	Rp 206	Rp 1,403,121,455,200
Bukit Uluwatu Villa, Tbk.	2017	6,811,269,200	Rp 260	Rp 1,770,929,992,000
Bukit Uluwatu Villa, Tbk.	2016	6,811,269,200	Rp 285	Rp 1,941,211,722,000
Bumi Serpong Damai, Tbk.	2018	19,246,696,192	Rp 1,255	Rp 24,154,603,720,960
Bumi Serpong Damai, Tbk.	2017	19,246,696,192	Rp 1,700	Rp 32,719,383,526,400
Bumi Serpong Damai, Tbk.	2016	19,246,696,192	Rp 1,755	Rp 33,777,951,816,960
Duta Anggada Realty, Tbk.	2018	3,141,390,962	Rp 242	Rp 760,216,612,804
Duta Anggada Realty, Tbk.	2017	3,141,390,962	Rp 306	Rp 961,265,634,372
Duta Anggada Realty, Tbk.	2016	3,141,390,962	Rp 360	Rp 1,130,900,746,320
Duta Pertiwi, Tbk.	2018	331,129,952	Rp 316	Rp 104,637,064,832
Duta Pertiwi, Tbk.	2017	331,129,952	Rp 350	Rp 115,895,483,200
Duta Pertiwi, Tbk.	2016	331,129,952	Rp 400	Rp 132,451,980,800
Intiland Development, Tbk.	2018	10,365,854,185	Rp 308	Rp 3,192,683,088,980
Intiland Development, Tbk.	2017	10,365,854,185	Rp 350	Rp 3,628,048,964,750
Intiland Development, Tbk.	2016	10,365,854,185	Rp 500	Rp 5,182,927,092,500
Lippo Karawaci, Tbk.	2018	23,077,689,619	Rp 254	Rp 5,861,733,163,226

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Lippo Karawaci, Tbk.	2017	23,077,689,619	Rp 488	Rp 11,261,912,534,072
Lippo Karawaci, Tbk.	2016	23,077,689,619	Rp 720	Rp 16,615,936,525,680
Modernland Realty, Tbk.	2018	12,533,067,322	Rp 226	Rp 2,832,473,214,772
Modernland Realty, Tbk.	2017	12,533,067,322	Rp 294	Rp 3,684,721,792,668
Modernland Realty, Tbk.	2016	12,533,067,322	Rp 342	Rp 4,286,309,024,124
Nusa Konstruksi Enjiniring, Tbk.	2018	5,541,165,000	Rp 50	Rp 277,058,250,000
Nusa Konstruksi Enjiniring, Tbk.	2017	5,541,165,000	Rp 58	Rp 321,387,570,000
Nusa Konstruksi Enjiniring, Tbk.	2016	5,541,165,000	Rp 55	Rp 304,764,075,000
Perdana Gapuraprima, Tbk.	2018	4,276,655,336	Rp 110	Rp 470,432,086,960
Perdana Gapuraprima, Tbk.	2017	4,276,655,336	Rp 103	Rp 440,495,499,608
Perdana Gapuraprima, Tbk.	2016	4,276,655,336	Rp 183	Rp 782,627,926,488
PP Properti, Tbk.	2018	61,675,671,883	Rp 117	Rp 7,216,053,610,311
PP Properti, Tbk.	2017	61,675,671,883	Rp 189	Rp 11,656,701,985,887
PP Properti, Tbk.	2016	61,675,671,883	Rp 340	Rp 20,969,728,440,220
Summarecon Agung, Tbk.	2018	14,426,781,680	Rp 805	Rp 11,613,559,252,400
Summarecon Agung, Tbk.	2017	14,426,781,680	Rp 945	Rp 13,633,308,687,600
Summarecon Agung, Tbk.	2016	14,426,781,680	Rp 1,325	Rp 19,115,485,726,000
Bakrie Telecom, Tbk.	2018	36,600,000,000	Rp 50	Rp 1,830,000,000,000
Bakrie Telecom, Tbk.	2017	36,600,000,000	Rp 50	Rp 1,830,000,000,000
Bakrie Telecom, Tbk.	2016	36,600,000,000	Rp 50	Rp 1,830,000,000,000
Indofarma (Persero), Tbk.	2018	3,099,267,500	Rp 6,500	Rp 20,145,238,750,000
Indofarma (Persero), Tbk.	2017	3,099,267,500	Rp 5,900	Rp 18,285,678,250,000
Indofarma (Persero), Tbk.	2016	3,099,267,500	Rp 4,680	Rp 14,504,571,900,000

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Bakrieland Development, Tbk.	2018	43,521,913,019	Rp 50	Rp 2,176,095,650,950
Bakrieland Development, Tbk.	2017	43,521,913,019	Rp 50	Rp 2,176,095,650,950
Bakrieland Development, Tbk.	2016	43,521,913,019	Rp 50	Rp 2,176,095,650,950
Arpeni Pratama Ocean Line, Tbk.	2018	13,710,166,667	Rp 58	Rp 822,610,000,000
Arpeni Pratama Ocean Line, Tbk.	2017	13,710,166,667	Rp 58	Rp 795,189,666,667
Arpeni Pratama Ocean Line, Tbk.	2016	13,710,166,667	Rp 58	Rp 795,189,666,667
Berlian Laju Tanker, Tbk.	2018	23,483,317,538	Rp 196	Rp 4,602,730,237,448
Berlian Laju Tanker, Tbk.	2017	23,483,317,538	Rp 196	Rp 4,602,730,237,448
Berlian Laju Tanker, Tbk.	2016	23,483,317,538	Rp 196	Rp 4,602,730,237,448
Trikomsel Oke, Tbk	2018	26,007,494,645	Rp 236	Rp 6,137,768,736,220
Trikomsel Oke, Tbk	2017	26,007,494,645	Rp 2,000	Rp 52,014,989,290,000
Trikomsel Oke, Tbk	2016	26,007,494,645	Rp 2,000	Rp 52,014,989,290,000
Express Transindo Utama, Tbk.	2018	2,145,600,000	Rp 90	Rp 193,104,000,000
Express Transindo Utama, Tbk.	2017	2,145,600,000	Rp 50	Rp 107,280,000,000
Express Transindo Utama, Tbk.	2016	2,145,600,000	Rp 170	Rp 364,752,000,000
Asia Natural Resources Tbk	2013	2,275,000,000	Rp 50	Rp 113,750,000,000
Bara Jaya Internasional Tbk	2018	5,760,245,414	Rp 194	Rp 1,117,487,610,316
Citra Maharlika Nusantara Corpora Tbk	2016	3,972,222,100	Rp 50	Rp 198,611,105,000
Dwi Aneka Jaya Kemasindo Tbk	2017	2,500,000,000	Rp 50	Rp 125,000,000,000
Leo Investment Tbk	2019	1,379,000,000	Rp 82	Rp 113,078,000,000
PT SURYA INTRINDO MAKMUR TBK	2011	1,743,240,000	Rp 148	Rp 257,999,520,000
pt jasa angkasa semesta	2008	442,144,722	Rp 50	Rp 22,107,236,100

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
pt new century development	2010	5,888,867,668	Rp 50	Rp 294,443,383,400
Davomas abadi	2013	19,053,011,320	Rp 50	Rp 952,650,566,000
Katarina Utama	2010	570,000,000	Rp 180	Rp 102,600,000,000
Amstelco Indonesia	2011	810,000,000	Rp 64	Rp 51,840,000,000
Dayaindo resource	2012	48,000,000	Rp 50	Rp 2,400,000,000
Panca wirasakti	2011	30,675,512,125	Rp 50	Rp 1,533,775,606,250
Surabaya agung Industri	2011	82,500,000	Rp 61	Rp 5,032,500,000
SURYA INTI PERMATA	2012	5,509,574,061	Rp 2,145	Rp 11,818,036,360,845
SEKAWAN INTIPRATAMA	2011	4,206,964,252	Rp 89	Rp 374,419,818,428
Surya Semesta Internusa, Tbk.	2018	4,705,249,440	Rp 500	Rp 2,352,624,720,000
Surya Semesta Internusa, Tbk.	2017	4,705,249,440	Rp 515	Rp 2,423,203,461,600
Surya Semesta Internusa, Tbk.	2016	4,705,249,440	Rp 434	Rp 2,042,078,256,960
Apexindo Pratama Duta, Tbk.	2018	2,659,850,000	Rp 1,680	Rp 4,468,548,000,000
Apexindo Pratama Duta, Tbk.	2017	2,659,850,000	Rp 1,780	Rp 4,734,533,000,000
Apexindo Pratama Duta, Tbk.	2016	2,659,850,000	Rp 1,780	Rp 4,734,533,000,000
Perusahaan Gas Negara Tbk	2018	24,241,508,196	Rp 2,120	Rp 51,391,997,375,520
Perusahaan Gas Negara Tbk	2017	24,241,508,196	Rp 1,750	Rp 42,422,639,343,000
Perusahaan Gas Negara Tbk	2016	24,241,508,196	Rp 2,700	Rp 65,452,072,129,200
Global Mediacom, Tbk.	2018	15,009,889,177	Rp 242	Rp 3,632,393,180,834
Global Mediacom, Tbk.	2017	15,009,889,177	Rp 590	Rp 8,855,834,614,430
Global Mediacom, Tbk.	2016	15,009,889,177	Rp 615	Rp 9,231,081,843,855
Media Nusantara Citra, Tbk.	2018	14,276,103,500	Rp 690	Rp 9,850,511,415,000
Media Nusantara Citra, Tbk.	2017	14,276,103,500	Rp 1,285	Rp 18,344,792,997,500

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Media Nusantara Citra, Tbk.	2016	14,276,103,500	Rp 1,755	Rp 25,054,561,642,500
Metrodata Electronics, Tbk.	2018	2,455,376,917	Rp 865	Rp 2,123,901,033,205
Metrodata Electronics, Tbk.	2017	2,455,376,917	Rp 650	Rp 1,595,994,996,050
Metrodata Electronics, Tbk.	2016	2,455,376,917	Rp 629	Rp 1,544,432,080,793
Adhi Karya (Persero), Tbk.	2018	3,560,849,376	Rp 1,585	Rp 5,643,946,260,960
Adhi Karya (Persero), Tbk.	2017	3,560,849,376	Rp 1,885	Rp 6,712,201,073,760
Adhi Karya (Persero), Tbk.	2016	3,560,849,376	Rp 2,080	Rp 7,406,566,702,080
Bukaka Teknik Utama Tbk	2018	2,640,452,000	Rp 1,900	Rp 5,016,858,800,000
Bukaka Teknik Utama Tbk	2017	2,640,452,000	Rp 1,550	Rp 4,092,700,600,000
Bukaka Teknik Utama Tbk	2016	2,640,452,000	Rp 750	Rp 1,980,339,000,000
Wijaya Karya (Persero), Tbk.	2019	9,572,000,000	Rp 296	Rp 2,833,312,000,000
Wijaya Karya (Persero), Tbk.	2018	9,572,000,000	Rp 240	Rp 2,297,280,000,000
Wijaya Karya (Persero), Tbk.	2017	9,572,000,000	Rp 272	Rp 2,603,584,000,000
Weha Transportasi Indonesia, Tbk.	2018	886,411,265	Rp 152	Rp 134,734,512,280
Weha Transportasi Indonesia, Tbk.	2017	886,411,265	Rp 202	Rp 179,055,075,530
Weha Transportasi Indonesia, Tbk.	2016	886,411,265	Rp 152	Rp 134,734,512,280
Astra International, Tbk.	2018	40,483,553,140	Rp 8,225	Rp 332,977,224,576,500
Astra International, Tbk.	2017	40,483,553,140	Rp 8,300	Rp 336,013,491,062,000
Astra International, Tbk.	2016	40,483,553,140	Rp 8,275	Rp 335,001,402,233,500
Kimia Farma (Persero), Tbk.	2018	5,554,000,000	Rp 2,750	Rp 15,273,500,000,000
Kimia Farma (Persero), Tbk.	2017	5,554,000,000	Rp 2,700	Rp 14,995,800,000,000
Kimia Farma (Persero), Tbk.	2016	5,554,000,000	Rp 2,600	Rp 14,440,400,000,000
Grahamas Citrawisata Tbk	2018	58,839,958	Rp 860	Rp 50,602,363,880

Company	Year	No. Share Outstanding	Closing Stock Price	Market Value of Equity
Indo Citra Finance Tbk	2012	1,438,370,465	Rp 3,150	Rp 4,530,866,964,750
Inovisi Infracom Tbk	2014	9,990,273,135	Rp 117	Rp 1,168,861,956,795
Permata Prima Sakti Tbk	2014	1,012,000,000	Rp 1,800	Rp 1,821,600,000,000
Sigmagold Inti Perkasa Tbk	2018	5,502,083,747	Rp 50	Rp 275,104,187,350
Truba Alam Manunggal Engineering Tbk	2017	15,799,456,267	Rp 50	Rp 789,972,813,350

Appendix 4. Recapitulation of firm's working capital, retained earnings and EBIT

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Panorama Sentrawisata, Tbk.	2018	Rp 104,363,790,000	Rp 1,813,302,510,000	Rp 247,051,270,000	Rp 9,583,670,000
Panorama Sentrawisata, Tbk.	2017	Rp 439,086,970,000	Rp 2,649,578,530,000	Rp 160,733,810,000	Rp 44,045,730,000
Panorama Sentrawisata, Tbk.	2016	Rp 156,888,120,000	Rp 2,279,403,850,000	Rp 158,308,300,000	Rp 5,675,970,000
Garuda Indonesia (Persero), Tbk.	2018	Rp (1,981,450,000)	Rp 4,155,470,000	Rp (674,780,000)	Rp (199,110,000)
Garuda Indonesia (Persero), Tbk.	2017	Rp (935,110,000)	Rp 3,763,290,000	Rp (443,400,000)	Rp (76,180,000)
Garuda Indonesia (Persero), Tbk.	2016	Rp (398,450,000)	Rp 3,737,570,000	Rp (212,220,000)	Rp 99,100,000
Astra Graphia Tbk.	2018	Rp 1,039,495,000,000	Rp 2,271,344,000,000	Rp 1,292,036,000,000	Rp 366,341,000,000
Astra Graphia Tbk.	2017	Rp 873,174,000,000	Rp 2,411,872,000,000	Rp 1,128,989,000,000	Rp 344,183,000,000
Astra Graphia Tbk.	2016	Rp 735,507,000,000	Rp 1,723,468,000,000	Rp 968,857,000,000	Rp 333,546,000,000
FKS Multi Agro, Tbk.	2018	Rp 77,770,000	Rp 431,540,000	Rp 97,680,000	Rp 19,850,000
FKS Multi Agro, Tbk.	2017	Rp 54,140,000	Rp 338,380,000	Rp 86,270,000	Rp 22,850,000
FKS Multi Agro, Tbk.	2016	Rp 54,870,000	Rp 258,980,000	Rp 72,860,000	Rp 30,190,000
Intraco Penta, Tbk.	2018	Rp 407,871,000,000	Rp 4,999,532,000,000	Rp (1,058,058,000,000)	Rp 25,790,000,000
Intraco Penta, Tbk.	2017	Rp (710,469,000,000)	Rp 5,248,164,000,000	Rp (706,030,000,000)	Rp (127,316,000,000)

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Intraco Penta, Tbk.	2016	Rp (295,186,000,000)	Rp 5,191,586,000,000	Rp (485,459,000,000)	Rp (30,814,000,000)
Tigaraksa Satria, Tbk.	2018	Rp 1,364,740,060,000	Rp 3,485,510,410,000	Rp 1,140,071,950,000	Rp 26,291,440,000
Tigaraksa Satria, Tbk.	2017	Rp 1,202,580,250,000	Rp 2,924,962,980,000	Rp 970,332,260,000	Rp 325,696,480,000
Tigaraksa Satria, Tbk.	2016	Rp 1,042,902,500,000	Rp 2,686,030,340,000	Rp 835,690,840,000	Rp 247,273,470,000
Citra Marga Nusaphala Persada, Tbk.	2018	Rp 3,399,860,590,000	Rp 13,098,505,590,000	Rp 2,222,293,350,000	Rp 904,432,460,000
Citra Marga Nusaphala Persada, Tbk.	2017	Rp 2,480,695,880,000	Rp 10,736,908,060,000	Rp 1,465,407,170,000	Rp 705,926,410,000
Citra Marga Nusaphala Persada, Tbk.	2016	Rp 1,709,807,100,000	Rp 7,937,919,620,000	Rp 1,739,704,650,000	Rp 695,369,780,000
Jasa Marga (Persero), Tbk.	2018	Rp(19,267,618,670,000)	Rp 82,418,600,790,000	Rp 9,896,196,700,000	Rp 5,415,226,370,000
Jasa Marga (Persero), Tbk.	2017	Rp (6,010,875,240,000)	Rp 79,192,772,790,000	Rp 8,124,829,240,000	Rp 4,648,080,260,000
Jasa Marga (Persero), Tbk.	2016	Rp (5,661,104,510,000)	Rp 53,500,322,660,000	Rp 6,491,366,750,000	Rp 4,327,629,990,000
Bali Towerindo Sentra Tbk	2018	Rp (217,153,140,000)	Rp 3,437,653,340,000	Rp 232,431,090,000	Rp 216,023,340,000
Bali Towerindo Sentra Tbk	2017	Rp (207,909,240,000)	Rp 2,421,703,650,000	Rp 149,691,800,000	Rp 158,236,390,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Bali Towerindo Sentra Tbk	2016	Rp (186,545,070,000)	Rp 1,707,249,310,000	Rp 567,059,810,000	Rp 115,147,270,000
Indosat, Tbk.	2018	Rp(13,133,840,000,000)	Rp 53,139,587,000,000	Rp 8,680,020,000,000	Rp 724,353,000,000
Indosat, Tbk.	2017	Rp (6,721,186,000,000)	Rp 50,661,040,000,000	Rp 11,502,892,000,000	Rp 559,479,000,000
Indosat, Tbk.	2016	Rp(11,013,111,000,000)	Rp 50,838,704,000,000	Rp 10,835,606,000,000	Rp 237,508,000,000
Inti Bangun Sejahtera Tbk	2018	Rp 193,464,660,000	Rp 7,725,601,130,000	Rp 1,494,226,870,000	Rp 332,185,150,000
Inti Bangun Sejahtera Tbk	2017	Rp 352,720,640,000	Rp 6,355,270,880,000	Rp 1,252,255,930,000	Rp 277,184,680,000
Inti Bangun Sejahtera Tbk	2016	Rp 559,835,210,000	Rp 5,449,356,090,000	Rp 2,151,960,820,000	Rp 668,993,960,000
Telekomunikasi Indonesia, Tbk.	2018	Rp (2,993,000,000,000)	Rp 206,196,000,000,000	Rp 90,995,000,000,000	Rp 38,845,000,000,000
Telekomunikasi Indonesia, Tbk.	2017	Rp 2,185,000,000,000	Rp 198,484,000,000,000	Rp 84,896,000,000,000	Rp 43,933,000,000,000
Telekomunikasi Indonesia, Tbk.	2016	Rp 7,939,000,000,000	Rp 179,611,000,000,000	Rp 76,615,000,000,000	Rp 39,195,000,000,000
Tiphone Mobile Indonesia, Tbk.	2018	Rp 6,143,121,000,000	Rp 8,339,085,000,000	Rp 2,230,633,000,000	Rp 1,000,943,000,000
Tiphone Mobile Indonesia, Tbk.	2017	Rp 5,965,781,000,000	Rp 8,749,797,000,000	Rp 1,816,713,000,000	Rp 1,031,398,000,000
Tiphone Mobile Indonesia, Tbk.	2016	Rp 6,224,911,000,000	Rp 8,215,481,000,000	Rp 1,519,517,000,000	Rp 1,014,371,000,000
XL Axiata, Tbk.	2018	Rp (8,674,642,000,000)	Rp 57,613,954,000,000	Rp 5,124,931,000,000	Rp (2,771,379,000,000)
XL Axiata, Tbk.	2017	Rp (8,045,774,000,000)	Rp 56,321,441,000,000	Rp 8,405,044,000,000	Rp 1,658,261,000,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
XL Axiata, Tbk.	2016	Rp (7,670,175,000,000)	Rp 54,896,286,000,000	Rp 8,001,601,000,000	Rp 1,686,874,000,000
Humpuss Intermoda Transportasi, Tbk.	2018	Rp (6,770,000)	Rp 197,360,000	Rp 18,910,000	Rp 19,120,000
Humpuss Intermoda Transportasi, Tbk.	2017	Rp (640,000)	Rp 175,560,000	Rp 8,330,000	Rp 17,040,000
Humpuss Intermoda Transportasi, Tbk.	2016	Rp 3,720,000	Rp 165,090,000	Rp 2,620,000	Rp 13,900,000
Matahari Putra Prima, Tbk.	2018	Rp (414,667,000,000)	Rp 4,808,545,000,000	Rp (695,341,000,000)	Rp (929,388,000,000)
Matahari Putra Prima, Tbk.	2017	Rp (1,390,361,000,000)	Rp 5,427,059,000,000	Rp 130,665,000,000	Rp (1,555,177,000,000)
Matahari Putra Prima, Tbk.	2016	Rp 768,578,000,000	Rp 6,701,734,000,000	Rp 1,386,226,000,000	Rp 177,037,000,000
Mitra Adiperkasa, Tbk.	2018	Rp 1,893,914,000,000	Rp 12,632,671,000,000	Rp 2,872,624,000,000	Rp 1,431,203,000,000
Mitra Adiperkasa, Tbk.	2017	Rp 2,233,827,680,000	Rp 11,425,390,080,000	Rp 2,198,886,870,000	Rp 1,075,831,090,000
Mitra Adiperkasa, Tbk.	2016	Rp 2,434,951,650,000	Rp 10,683,437,790,000	Rp 1,905,577,860,000	Rp 929,007,420,000
Fastfood Indonesia, Tbk.	2018	Rp 646,580,180,000	Rp 2,989,693,220,000	Rp 1,340,035,320,000	Rp 266,226,200,000
Fastfood Indonesia, Tbk.	2017	Rp 592,239,490,000	Rp 2,749,422,390,000	Rp 1,093,112,490,000	Rp 154,966,340,000
Fastfood Indonesia, Tbk.	2016	Rp 535,604,930,000	Rp 2,577,819,570,000	Rp 1,022,752,660,000	Rp 218,051,890,000
Jaya Bersama Indo Tbk	2018	Rp 647,850,940,000	Rp 1,047,678,120,000	Rp 163,855,840,000	Rp 140,393,020,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Jaya Bersama Indo Tbk	2017	Rp 220,603,180,000	Rp 528,942,660,000	Rp 48,166,030,000	Rp 118,880,110,000
Jaya Bersama Indo Tbk	2016	Rp 157,198,870,000	Rp 447,013,910,000	Rp 212,040,910,000	Rp 44,687,520,000
Pembangunan Jaya Ancol, Tbk.	2018	Rp (241,628,630,000)	Rp 4,361,394,290,000	Rp 1,549,905,730,000	Rp 424,279,640,000
Pembangunan Jaya Ancol, Tbk.	2017	Rp 28,520,230,000	Rp 3,748,269,800,000	Rp 1,413,484,940,000	Rp 394,040,050,000
Pembangunan Jaya Ancol, Tbk.	2016	Rp (113,052,800,000)	Rp 3,768,551,040,000	Rp 1,261,778,500,000	Rp 240,269,500,000
Agung Podomoro Land, Tbk.	2018	Rp 436,717,450,000	Rp 29,583,829,900,000	Rp 5,814,015,580,000	Rp 1,140,799,320,000
Agung Podomoro Land, Tbk.	2017	Rp 2,212,750,920,000	Rp 28,790,116,010,000	Rp 5,784,458,540,000	Rp 2,038,684,590,000
Agung Podomoro Land, Tbk.	2016	Rp 519,206,170,000	Rp 25,711,953,380,000	Rp 4,451,549,110,000	Rp 1,700,683,470,000
Alam Sutera Realty, Tbk.	2018	Rp (774,686,810,000)	Rp 20,890,925,560,000	Rp 11,447,422,100,000	Rp 1,858,316,590,000
Alam Sutera Realty, Tbk.	2017	Rp (825,520,840,000)	Rp 20,728,430,490,000	Rp 12,263,015,830,000	Rp 1,854,586,470,000
Alam Sutera Realty, Tbk.	2016	Rp (351,912,850,000)	Rp 20,186,130,680,000	Rp 13,103,460,340,000	Rp 964,307,530,000
Bukit Uluwatu Villa, Tbk.	2018	Rp (705,817,880,000)	Rp 4,106,726,920,000	Rp 197,950,420,000	Rp 90,017,700,000
Bukit Uluwatu Villa, Tbk.	2017	Rp (561,990,350,000)	Rp 3,284,333,370,000	Rp 165,483,510,000	Rp 1,840,830,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Bukit Uluwatu Villa, Tbk.	2016	Rp 72,016,240,000	Rp 2,972,885,480,000	Rp 201,989,080,000	Rp 60,225,130,000
Bumi Serpong Damai, Tbk.	2018	Rp 14,717,445,090,000	Rp 52,101,492,200,000	Rp 18,380,056,210,000	Rp 2,149,857,060,000
Bumi Serpong Damai, Tbk.	2017	Rp 10,395,707,000,000	Rp 45,951,188,480,000	Rp 17,168,223,690,000	Rp 5,059,906,870,000
Bumi Serpong Damai, Tbk.	2016	Rp 10,872,912,190,000	Rp 38,536,825,180,000	Rp 12,412,443,100,000	Rp 2,302,165,270,000
Duta Anggada Realty, Tbk.	2018	Rp (493,796,260,000)	Rp 6,905,286,390,000	Rp 1,551,279,420,000	Rp 88,388,480,000
Duta Anggada Realty, Tbk.	2017	Rp (308,931,340,000)	Rp 6,360,845,610,000	Rp 1,534,828,110,000	Rp 123,145,920,000
Duta Anggada Realty, Tbk.	2016	Rp (215,229,390,000)	Rp 6,066,257,600,000	Rp 1,598,007,870,000	Rp 313,514,000,000
Duta Pertiwi, Tbk.	2018	Rp 4,093,351,020,000	Rp 12,642,895,740,000	Rp 6,207,065,000,000	Rp 973,352,540,000
Duta Pertiwi, Tbk.	2017	Rp 3,276,419,510,000	Rp 10,575,681,690,000	Rp 5,282,713,670,000	Rp 627,009,100,000
Duta Pertiwi, Tbk.	2016	Rp 3,068,739,850,000	Rp 9,692,217,790,000	Rp 4,759,245,570,000	Rp 756,702,690,000
Intiland Development, Tbk.	2018	Rp 48,064,050,000	Rp 14,215,535,190,000	Rp 1,851,558,870,000	Rp 326,818,370,000
Intiland Development, Tbk.	2017	Rp (496,263,900,000)	Rp 13,097,184,980,000	Rp 1,631,629,930,000	Rp 344,909,760,000
Intiland Development, Tbk.	2016	Rp (258,400,290,000)	Rp 11,840,059,940,000	Rp 1,385,153,340,000	Rp 404,256,990,000
Lippo Karawaci, Tbk.	2018	Rp 24,841,585,000,000	Rp 49,083,460,000,000	Rp 7,562,706,000,000	Rp 1,941,201,000,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Lippo Karawaci, Tbk.	2017	Rp 27,717,951,000,000	Rp 51,279,026,000,000	Rp 4,361,716,000,000	Rp (338,280,000,000)
Lippo Karawaci, Tbk.	2016	Rp 30,587,100,000,000	Rp 45,603,683,000,000	Rp 7,945,093,000,000	Rp 1,814,373,000,000
Modernland Realty, Tbk.	2018	Rp 1,839,447,830,000	Rp 15,227,479,980,000	Rp 4,621,228,730,000	Rp 508,849,620,000
Modernland Realty, Tbk.	2017	Rp 783,919,610,000	Rp 14,599,669,340,000	Rp 4,740,091,330,000	Rp 1,220,599,650,000
Modernland Realty, Tbk.	2016	Rp 1,004,787,260,000	Rp 14,540,108,290,000	Rp 4,228,365,950,000	Rp 1,047,218,650,000
Nusa Konstruksi Enjiniring, Tbk.	2018	Rp 157,851,390,000	Rp 1,727,826,030,000	Rp (174,355,890,000)	Rp (64,580,890,000)
Nusa Konstruksi Enjiniring, Tbk.	2017	Rp 70,651,710,000	Rp 1,820,798,800,000	Rp (28,047,860,000)	Rp (8,169,120,000)
Nusa Konstruksi Enjiniring, Tbk.	2016	Rp 132,870,570,000	Rp 1,555,022,620,000	Rp (46,299,860,000)	Rp (38,841,560,000)
Perdana Gapuraprima, Tbk.	2018	Rp 1,110,073,790,000	Rp 1,536,453,590,000	Rp 496,102,260,000	Rp 78,977,300,000
Perdana Gapuraprima, Tbk.	2017	Rp 978,895,310,000	Rp 1,499,462,030,000	Rp 461,077,720,000	Rp 48,687,990,000
Perdana Gapuraprima, Tbk.	2016	Rp 1,065,898,890,000	Rp 1,569,319,030,000	Rp 443,793,360,000	Rp 65,216,490,000
PP Properti, Tbk.	2018	Rp 4,728,063,740,000	Rp 16,475,720,490,000	Rp 1,478,458,630,000	Rp 514,620,040,000
PP Properti, Tbk.	2017	Rp 3,711,149,380,000	Rp 12,559,932,320,000	Rp 1,096,081,980,000	Rp 563,695,270,000
PP Properti, Tbk.	2016	Rp 2,760,403,800,000	Rp 8,849,833,870,000	Rp 724,493,030,000	Rp 508,000,290,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Summarecon Agung, Tbk.	2018	Rp 3,268,878,490,000	Rp 23,299,242,070,000	Rp 5,436,359,250,000	Rp 6,903,591,130,000
Summarecon Agung, Tbk.	2017	Rp 2,912,032,090,000	Rp 21,662,950,720,000	Rp 5,042,669,600,000	Rp 6,509,901,480,000
Summarecon Agung, Tbk.	2016	Rp 4,481,445,560,000	Rp 20,810,319,660,000	Rp 4,775,726,360,000	Rp 6,242,958,240,000
Bakrie Telecom, Tbk.	2018	Rp(10,094,849,000,000)	Rp 713,505,000,000	Rp (22,819,050,000,000)	Rp (37,050,000,000)
Bakrie Telecom, Tbk.	2017	Rp (8,928,345,000,000)	Rp 718,022,000,000	Rp (21,555,170,000,000)	Rp (856,616,000,000)
Bakrie Telecom, Tbk.	2016	Rp (8,147,513,000,000)	Rp 1,569,775,000,000	Rp (20,058,573,000,000)	Rp (958,070,000,000)
Indofarma (Persero), Tbk.	2018	Rp 40,255,280,000	Rp 1,442,350,610,000	Rp 105,548,770,000	Rp (4,451,120,000)
Indofarma (Persero), Tbk.	2017	Rp 37,693,190,000	Rp 1,529,874,780,000	Rp 135,311,240,000	Rp 8,079,230,000
Indofarma (Persero), Tbk.	2016	Rp 148,576,740,000	Rp 1,381,633,320,000	Rp 184,656,600,000	Rp (16,499,160,000)
Bakrieland Development, Tbk.	2018	Rp 2,530,627,250,000	Rp 13,606,180,010,000	Rp (1,233,149,540,000)	Rp 2,737,063,580,000
Bakrieland Development, Tbk.	2017	Rp (306,502,530,000)	Rp 14,082,517,540,000	Rp (1,521,785,230,000)	Rp (310,411,780,000)
Bakrieland Development, Tbk.	2016	Rp 309,246,660,000	Rp 14,176,697,750,000	Rp (1,250,250,690,000)	Rp (520,866,150,000)
Arpeni Pratama Ocean Line, Tbk.	2018	Rp (6,522,949,260,000)	Rp 896,202,510,000	Rp (6,894,663,090,000)	Rp 19,726,810,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Arpeni Pratama Ocean Line, Tbk.	2017	Rp (6,327,364,790,000)	Rp 1,167,650,490,000	Rp (6,644,676,790,000)	Rp 26,696,410,000
Arpeni Pratama Ocean Line, Tbk.	2016	Rp (6,136,971,960,000)	Rp 1,214,104,460,000	Rp (6,382,956,050,000)	Rp (121,198,550,000)
Berlian Laju Tanker, Tbk.	2018	Rp (4,923,479)	Rp 71,348,533	Rp (1,228,287,325)	Rp 6,622,675
Berlian Laju Tanker, Tbk.	2017	Rp (4,093,726)	Rp 79,101,200	Rp (1,288,937,229)	Rp (6,983,323)
Berlian Laju Tanker, Tbk.	2016	Rp 1,941,907	Rp 93,774,925	Rp (1,284,394,229)	Rp (13,749,981)
Trikomsel Oke, Tbk	2018	Rp (700,924,290,000)	Rp 193,663,110,000	Rp (7,767,975,210,000)	Rp (53,190,150,000)
Trikomsel Oke, Tbk	2017	Rp (496,208,850,000)	Rp 266,119,940,000	Rp (7,732,516,820,000)	Rp (75,927,530,000)
Trikomsel Oke, Tbk	2016	Rp (3,975,123,750,000)	Rp 430,032,190,000	Rp (7,544,893,660,000)	Rp (392,637,680,000)
Express Transindo Utama, Tbk.	2018	Rp (1,103,991,300,000)	Rp 1,269,024,960,000	Rp (1,118,642,080,000)	Rp (715,073,750,000)
Express Transindo Utama, Tbk.	2017	Rp (82,235,630,000)	Rp 2,010,013,010,000	Rp (288,768,580,000)	Rp (412,431,140,000)
Express Transindo Utama, Tbk.	2016	Rp 537,695,350,000	Rp 2,557,262,840,000	Rp 197,880,450,000	Rp (223,364,580,000)
Asia Natural Resources Tbk	2013	Rp 16,648,006,410	Rp 51,660,943,355	Rp (356,305,546,347)	Rp (1,015,721,757)
Bara Jaya Internasional Tbk	2018	Rp (162,346,582)	Rp 885,506,109	Rp (1,055,237,520)	Rp (135,062,520)
Citra Maharlika Nusantara Corpora Tbk	2016	Rp (329,648,120,000)	Rp 228,789,230,000	Rp (574,794,390,000)	Rp (13,991,080,000)

Company	Year	Working Capital (WC)		Total Assets (TA)		Retained Earnings		EBIT	
Dwi Aneka Jaya Kemasindo Tbk	2017	Rp	292,938,778	Rp	1,308,867,012	Rp	(600,588,960)	Rp	(59,588,988)
Leo Investment Tbk	2019	Rp	48,168,180,161	Rp	154,915,744,913	Rp	(89,148,910,944)	Rp	20,602,328,484
Intrindo Makmur, Tbk.	2011	Rp	(92,901,465,002)	Rp	42,729,100,722	Rp	(154,070,953,470)	Rp	(6,352,742,570)
pt jasa angkasa semesta	2008	Rp	67,919,556,570	Rp	230,816,599,095	Rp	36,906,881,296	Rp	51,955,373,774
pt new century development	2010	Rp	(77,513,910,000)	Rp	170,891,934,000	Rp	(141,285,104,265)	Rp	(36,694,696,000)
Davomas abadi	2013	Rp	441,036,140,000	Rp	2,534,324,880,000	Rp	(2,387,918,505,157)	Rp	(259,701,650,000)
Katarina Utama	2010	Rp	128,506,012,889	Rp	358,908,436,153	Rp	68,657,731,091	Rp	14,970,408,377
Amstelco Indonesia	2011	Rp	22,011,470,219	Rp	26,830,608,276	Rp	(73,180,990,911)	Rp	(21,795,402)
Dayaindo resource	2012	Rp	(6,573,444,343)	Rp	1,310,531,125	Rp	(57,913,443,343)	Rp	(1,802,132,741)
Panca wirasakti	2011	Rp	1,438,739,216,448	Rp	2,860,607,736,087	Rp	145,132,773,833	Rp	85,389,445,683
Surabaya agung Industri	2011	Rp	(327,675,692,420)	Rp	274,314,022,514	Rp	(421,687,099,018)	Rp	(441,884,833)
Surya Inti Permata	2012	Rp	(30,814,659,050)	Rp	1,975,958,750,400	Rp	(2,323,513,113,207)	Rp	(123,394,838,206)
Sekawan Intipratama	2011	Rp	1,331,999,981,079	Rp	1,738,562,323,096	Rp	369,285,230,851	Rp	(40,412,290,596)
Surya Semesta Internusa, Tbk.	2018	Rp	1,425,532,400,000	Rp	7,404,167,100,000	Rp	2,955,594,040,000	Rp	353,908,790,000
Surya Semesta Internusa, Tbk.	2017	Rp	2,445,306,950,000	Rp	8,851,436,970,000	Rp	3,023,495,480,000	Rp	2,028,564,360,000
Surya Semesta Internusa, Tbk.	2016	Rp	1,484,325,500,000	Rp	7,195,448,330,000	Rp	1,918,007,390,000	Rp	440,978,330,000

Company	Year	Working Capital (WC)		Total Assets (TA)		Retained Earnings		EBIT	
Apexindo Pratama Duta, Tbk.	2018	Rp	(348,880,000)	Rp	514,680,000	Rp	(130,040,000)	Rp	(109,850,000)
Apexindo Pratama Duta, Tbk.	2017	Rp	(291,910,000)	Rp	577,630,000	Rp	(26,240,000)	Rp	(107,330,000)
Apexindo Pratama Duta, Tbk.	2016	Rp	55,890,000	Rp	682,370,000	Rp	76,290,000	Rp	(25,480,000)
Perusahaan Gas Negara Tbk	2018	Rp	869,090,000	Rp	7,939,270,000	Rp	2,758,600,000	Rp	638,130,000
Perusahaan Gas Negara Tbk	2017	Rp	1,393,560,000	Rp	8,183,180,000	Rp	2,571,000,000	Rp	514,900,000
Perusahaan Gas Negara Tbk	2016	Rp	1,309,300,000	Rp	6,834,150,000	Rp	2,564,570,000	Rp	444,240,000
Global Mediacom, Tbk.	2018	Rp	2,425,207,000,000	Rp	28,968,162,000,000	Rp	7,343,159,000,000	Rp	1,782,744,000,000
Global Mediacom, Tbk.	2017	Rp	5,091,632,000,000	Rp	27,694,734,000,000	Rp	6,596,599,000,000	Rp	2,026,069,000,000
Global Mediacom, Tbk.	2016	Rp	1,349,234,000,000	Rp	24,624,431,000,000	Rp	6,180,269,000,000	Rp	1,412,175,000,000
Media Nusantara Citra, Tbk.	2018	Rp	5,183,129,000,000	Rp	16,339,552,000,000	Rp	8,691,853,000,000	Rp	2,739,763,000,000
Media Nusantara Citra, Tbk.	2017	Rp	5,259,147,000,000	Rp	15,057,291,000,000	Rp	7,340,787,000,000	Rp	2,665,753,000,000
Media Nusantara Citra, Tbk.	2016	Rp	2,439,271,000,000	Rp	14,239,867,000,000	Rp	6,482,998,000,000	Rp	2,331,933,000,000
Metrodata Electronics, Tbk.	2018	Rp	2,199,019,000,000	Rp	4,852,776,000,000	Rp	1,328,810,000,000	Rp	575,828,000,000

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Metrodata Electronics, Tbk.	2017	Rp 1,846,256,000,000	Rp 4,271,127,000,000	Rp 1,065,320,000,000	Rp 464,767,000,000
Metrodata Electronics, Tbk.	2016	Rp 1,546,333,000,000	Rp 3,876,021,000,000	Rp 880,084,000,000	Rp 442,624,000,000
Adhi Karya (Persero), Tbk.	2018	Rp 6,465,239,980,000	Rp 30,118,614,770,000	Rp 2,995,955,500,000	Rp 1,798,931,180,000
Adhi Karya (Persero), Tbk.	2017	Rp 7,184,381,960,000	Rp 28,332,948,010,000	Rp 2,445,826,250,000	Rp 1,707,671,550,000
Adhi Karya (Persero), Tbk.	2016	Rp 3,791,038,530,000	Rp 20,095,435,960,000	Rp 1,997,136,970,000	Rp 801,157,300,000
Bukaka Teknik Utama Tbk	2018	Rp (112,053,120,000)	Rp 4,414,296,410,000	Rp 1,087,000,990,000	Rp 627,562,690,000
Bukaka Teknik Utama Tbk	2017	Rp 110,300,920,000	Rp 3,507,297,850,000	Rp 525,293,090,000	Rp 217,581,100,000
Bukaka Teknik Utama Tbk	2016	Rp 403,665,620,000	Rp 2,260,452,740,000	Rp 344,721,310,000	Rp 108,022,090,000
Wijaya Karya (Persero), Tbk.	2019	Rp 17,479,988,250,000	Rp 59,230,001,240,000	Rp 5,479,925,960,000	Rp 4,367,728,780,000
Wijaya Karya (Persero), Tbk.	2018	Rp 8,934,490,970,000	Rp 45,683,774,300,000	Rp 4,003,197,890,000	Rp 2,804,568,570,000
Wijaya Karya (Persero), Tbk.	2017	Rp 8,742,818,290,000	Rp 31,355,204,690,000	Rp 3,104,677,060,000	Rp 2,095,421,440,000
Weha Transportasi Indonesia, Tbk.	2018	Rp (33,702,170,000)	Rp 331,404,130,000	Rp 7,189,940,000	Rp 20,750,200,000
Weha Transportasi Indonesia, Tbk.	2017	Rp (30,486,900,000)	Rp 300,003,470,000	Rp 8,859,890,000	Rp (689,950,000)

Company	Year	Working Capital (WC)	Total Assets (TA)	Retained Earnings	EBIT
Weha Transportasi Indonesia, Tbk.	2016	Rp (91,658,360,000)	Rp 304,957,260,000	Rp (38,509,690,000)	Rp (7,805,590,000)
Astra International, Tbk.	2018	Rp 17,142,000,000,000	Rp 344,711,000,000,000	Rp 127,732,000,000,000	Rp 26,868,000,000,000
Astra International, Tbk.	2017	Rp 22,806,000,000,000	Rp 295,830,000,000,000	Rp 113,563,000,000,000	Rp 20,326,000,000,000
Astra International, Tbk.	2016	Rp 21,324,000,000,000	Rp 261,855,000,000,000	Rp 101,642,000,000,000	Rp 17,567,000,000,000
Kimia Farma (Persero), Tbk.	2018	Rp 1,632,165,800,000	Rp 11,329,090,860,000	Rp 2,263,680,030,000	Rp 944,681,980,000
Kimia Farma (Persero), Tbk.	2017	Rp 1,873,363,080,000	Rp 7,272,084,560,000	Rp 1,945,867,890,000	Rp 535,661,370,000
Kimia Farma (Persero), Tbk.	2016	Rp 1,210,528,590,000	Rp 4,612,562,540,000	Rp 1,672,566,670,000	Rp 442,824,100,000
Grahamas Citrawisata Tbk	2018	Rp (4,488,878,325)	Rp 37,582,059,845	Rp (39,904,525,176)	Rp 541,996,673
Indo Citra Finance Tbk	2012	Rp (7,000,580,210)	Rp 951,173,695	Rp (7,165,577,084)	Rp (2,522,733,058)
Inovisi Infracom Tbk	2014	Rp 1,140,838,000,000	Rp 5,077,572,000,000	Rp (527,839,000,000)	Rp 3,828,111,000,000
Permata Prima Sakti Tbk	2014	Rp (3,568,774,000,000)	Rp 6,024,271,000,000	Rp (333,013,000,000)	Rp (345,992,000,000)
Sigmagold Inti Perkasa Tbk	2018	Rp 50,067,581,996	Rp 1,155,079,741,073	Rp (93,128,730,663)	Rp (11,418,998,300)
Truba Alam Manunggal Engineering Tbk	2017	Rp 331,601,604	Rp 638,828,037	Rp (1,350,117,829)	Rp (15,623,872)

Appendix 5. Recapitulation of firms total equity, book value of total liabilities, total current asset and total current liabilities

Company	Year	Total Equity		Book Value of Total Liabilities		Total current asset		Total current liabilities	
Panorama Sentrawisata, Tbk.	2018	Rp	652,098,750,000	Rp	1,161,203,760,000	Rp	563,314,710,000	Rp	458,950,920,000
Panorama Sentrawisata, Tbk.	2017	Rp	668,910,710,000	Rp	1,980,667,820,000	Rp	1,248,544,330,000	Rp	809,457,360,000
Panorama Sentrawisata, Tbk.	2016	Rp	470,751,020,000	Rp	1,808,652,820,000	Rp	868,598,470,000	Rp	711,710,350,000
Garuda Indonesia (Persero), Tbk.	2018	Rp	598,620,000	Rp	3,556,860,000	Rp	1,079,950,000	Rp	3,061,400,000
Garuda Indonesia (Persero), Tbk.	2017	Rp	894,780,000	Rp	2,868,510,000	Rp	986,740,000	Rp	1,921,850,000
Garuda Indonesia (Persero), Tbk.	2016	Rp	992,810,000	Rp	2,744,760,000	Rp	1,165,130,000	Rp	1,563,580,000
Astra Graphia Tbk.	2018	Rp	1,484,227,000,000	Rp	787,117,000,000	Rp	1,764,349,000,000	Rp	724,854,000,000
Astra Graphia Tbk.	2017	Rp	1,321,180,000,000	Rp	1,090,692,000,000	Rp	1,902,849,000,000	Rp	1,029,675,000,000
Astra Graphia Tbk.	2016	Rp	1,166,306,000,000	Rp	557,162,000,000	Rp	1,241,982,000,000	Rp	506,475,000,000
Fks Multi Agro, Tbk.	2018	Rp	101,610,000	Rp	329,930,000	Rp	343,050,000	Rp	265,280,000
Fks Multi Agro, Tbk.	2017	Rp	92,120,000	Rp	246,260,000	Rp	261,530,000	Rp	207,390,000
Fks Multi Agro, Tbk.	2016	Rp	79,090,000	Rp	179,890,000	Rp	193,620,000	Rp	138,750,000
Intraco Penta, Tbk.	2018	Rp	132,068,000,000	Rp	4,867,464,000,000	Rp	2,291,606,000,000	Rp	1,883,735,000,000
Intraco Penta, Tbk.	2017	Rp	464,129,000,000	Rp	4,784,035,000,000	Rp	2,186,005,000,000	Rp	2,896,474,000,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Intraco Penta, Tbk.	2016	Rp 476,473,000,000	Rp 4,715,113,000,000	Rp 2,071,684,000,000	Rp 2,366,870,000,000
Tigaraksa Satria, Tbk.	2018	Rp 1,237,953,780,000	Rp 2,247,556,630,000	Rp 3,293,438,980,000	Rp 1,928,698,920,000
Tigaraksa Satria, Tbk.	2017	Rp 1,068,214,080,000	Rp 1,856,748,900,000	Rp 2,736,455,320,000	Rp 1,533,875,070,000
Tigaraksa Satria, Tbk.	2016	Rp 933,572,670,000	Rp 1,752,457,670,000	Rp 2,489,451,010,000	Rp 1,446,548,510,000
Citra Marga Nusaphala Persada, Tbk.	2018	Rp 6,369,208,640,000	Rp 6,729,296,950,000	Rp 5,102,306,830,000	Rp 1,702,446,240,000
Citra Marga Nusaphala Persada, Tbk.	2017	Rp 5,186,072,460,000	Rp 5,550,835,600,000	Rp 3,929,272,650,000	Rp 1,448,576,770,000
Citra Marga Nusaphala Persada, Tbk.	2016	Rp 4,513,274,980,000	Rp 3,424,644,630,000	Rp 2,619,187,510,000	Rp 909,380,410,000
Jasa Marga (Persero), Tbk.	2018	Rp 16,908,505,290,000	Rp 65,510,095,500,000	Rp 11,813,856,470,000	Rp 31,081,475,140,000
Jasa Marga (Persero), Tbk.	2017	Rp 15,097,652,950,000	Rp 64,095,119,840,000	Rp 18,987,065,060,000	Rp 24,997,940,300,000
Jasa Marga (Persero), Tbk.	2016	Rp 13,679,125,140,000	Rp 39,821,197,520,000	Rp 12,965,884,490,000	Rp 18,626,989,000,000
Bali Towerindo Sentra Tbk	2018	Rp 1,693,916,890,000	Rp 1,743,736,450,000	Rp 299,165,400,000	Rp 516,318,540,000
Bali Towerindo Sentra Tbk	2017	Rp 1,137,803,240,000	Rp 1,283,900,400,000	Rp 287,439,980,000	Rp 495,349,220,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Bali Towerindo Sentra Tbk	2016	Rp 701,574,490,000	Rp 1,005,674,820,000	Rp 136,280,010,000	Rp 322,825,080,000
Indosat, Tbk.	2018	Rp 11,174,104,000,000	Rp 41,965,483,000,000	Rp 7,906,525,000,000	Rp 21,040,365,000,000
Indosat, Tbk.	2017	Rp 13,996,976,000,000	Rp 36,664,064,000,000	Rp 9,479,271,000,000	Rp 16,200,457,000,000
Indosat, Tbk.	2016	Rp 13,350,203,000,000	Rp 37,488,501,000,000	Rp 8,073,481,000,000	Rp 19,086,592,000,000
Inti Bangun Sejahtera Tbk	2018	Rp 5,221,380,250,000	Rp 2,504,220,880,000	Rp 1,149,973,620,000	Rp 956,508,960,000
Inti Bangun Sejahtera Tbk	2017	Rp 4,317,467,150,000	Rp 2,037,803,730,000	Rp 1,199,164,020,000	Rp 846,443,380,000
Inti Bangun Sejahtera Tbk	2016	Rp 3,433,435,910,000	Rp 2,015,920,170,000	Rp 922,990,240,000	Rp 363,155,030,000
Telekomunikasi Indonesia, Tbk.	2018	Rp 98,910,000,000,000	Rp 107,286,000,000,000	Rp 43,268,000,000,000	Rp 46,261,000,000,000
Telekomunikasi Indonesia, Tbk.	2017	Rp 92,713,000,000,000	Rp 105,771,000,000,000	Rp 47,561,000,000,000	Rp 45,376,000,000,000
Telekomunikasi Indonesia, Tbk.	2016	Rp 84,384,000,000,000	Rp 95,227,000,000,000	Rp 47,701,000,000,000	Rp 39,762,000,000,000
Tiphone Mobile Indonesia, Tbk.	2018	Rp 3,885,127,000,000	Rp 4,453,958,000,000	Rp 7,609,754,000,000	Rp 1,466,633,000,000
Tiphone Mobile Indonesia, Tbk.	2017	Rp 3,540,495,000,000	Rp 5,209,302,000,000	Rp 8,034,490,000,000	Rp 2,068,709,000,000
Tiphone Mobile Indonesia, Tbk.	2016	Rp 3,203,132,000,000	Rp 5,012,349,000,000	Rp 7,472,601,000,000	Rp 1,247,690,000,000
Xl Axiata, Tbk.	2018	Rp 18,343,098,000,000	Rp 39,270,856,000,000	Rp 7,058,652,000,000	Rp 15,733,294,000,000
Xl Axiata, Tbk.	2017	Rp 21,630,850,000,000	Rp 34,690,591,000,000	Rp 7,180,742,000,000	Rp 15,226,516,000,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Xl Axiata, Tbk.	2016	Rp 21,209,145,000,000	Rp 33,687,141,000,000	Rp 6,806,863,000,000	Rp 14,477,038,000,000
Humpuss Intermoda Transportasi, Tbk.	2018	Rp 38,250,000	Rp 159,110,000	Rp 37,920,000	Rp 44,690,000
Humpuss Intermoda Transportasi, Tbk.	2017	Rp 26,640,000	Rp 148,920,000	Rp 29,960,000	Rp 30,600,000
Humpuss Intermoda Transportasi, Tbk.	2016	Rp 20,790,000	Rp 144,290,000	Rp 34,730,000	Rp 31,010,000
Matahari Putra Prima, Tbk.	2018	Rp 1,149,211,000,000	Rp 3,659,334,000,000	Rp 2,472,849,000,000	Rp 2,887,516,000,000
Matahari Putra Prima, Tbk.	2017	Rp 1,174,141,000,000	Rp 4,252,918,000,000	Rp 2,485,833,000,000	Rp 3,876,194,000,000
Matahari Putra Prima, Tbk.	2016	Rp 2,429,702,000,000	Rp 4,272,032,000,000	Rp 4,102,458,000,000	Rp 3,333,880,000,000
Mitra Adiperkasa, Tbk.	2018	Rp 5,452,442,000,000	Rp 7,180,229,000,000	Rp 7,312,798,000,000	Rp 5,418,884,000,000
Mitra Adiperkasa, Tbk.	2017	Rp 4,037,833,020,000	Rp 7,387,557,050,000	Rp 6,798,522,370,000	Rp 4,564,694,690,000
Mitra Adiperkasa, Tbk.	2016	Rp 3,203,495,230,000	Rp 7,479,942,560,000	Rp 6,616,255,900,000	Rp 4,181,304,250,000
Fastfood Indonesia, Tbk.	2018	Rp 1,540,493,640,000	Rp 1,449,199,580,000	Rp 1,361,078,180,000	Rp 714,498,000,000
Fastfood Indonesia, Tbk.	2017	Rp 1,293,570,810,000	Rp 1,455,851,580,000	Rp 1,256,248,190,000	Rp 664,008,700,000
Fastfood Indonesia, Tbk.	2016	Rp 1,223,210,990,000	Rp 1,354,608,590,000	Rp 1,210,852,250,000	Rp 675,247,320,000
Jaya Bersama Indo Tbk	2018	Rp 743,778,060,000	Rp 303,900,060,000	Rp 922,029,630,000	Rp 274,178,690,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Jaya Bersama Indo Tbk	2017	Rp 315,667,710,000	Rp 213,274,950,000	Rp 403,940,490,000	Rp 183,337,310,000
Jaya Bersama Indo Tbk	2016	Rp 221,101,890,000	Rp 225,912,020,000	Rp 332,385,830,000	Rp 175,186,960,000
Pembangunan Jaya Ancol, Tbk.	2018	Rp 1,992,662,050,000	Rp 2,368,732,240,000	Rp 989,040,940,000	Rp 1,230,669,570,000
Pembangunan Jaya Ancol, Tbk.	2017	Rp 1,856,241,260,000	Rp 1,892,028,540,000	Rp 687,623,850,000	Rp 659,103,620,000
Pembangunan Jaya Ancol, Tbk.	2016	Rp 1,698,487,730,000	Rp 2,070,063,300,000	Rp 915,674,260,000	Rp 1,028,727,060,000
Agung Podomoro Land, Tbk.	2018	Rp 8,862,837,320,000	Rp 20,720,992,580,000	Rp 8,275,422,730,000	Rp 7,838,705,280,000
Agung Podomoro Land, Tbk.	2017	Rp 8,783,242,410,000	Rp 20,006,873,600,000	Rp 9,432,973,700,000	Rp 7,220,222,780,000
Agung Podomoro Land, Tbk.	2016	Rp 7,508,605,920,000	Rp 18,203,347,460,000	Rp 8,173,958,870,000	Rp 7,654,752,700,000
Alam Sutera Realty, Tbk.	2018	Rp 9,443,503,470,000	Rp 11,447,422,100,000	Rp 1,449,848,160,000	Rp 2,224,534,970,000
Alam Sutera Realty, Tbk.	2017	Rp 8,465,414,660,000	Rp 12,263,015,830,000	Rp 2,317,958,280,000	Rp 3,143,479,120,000
Alam Sutera Realty, Tbk.	2016	Rp 7,082,670,340,000	Rp 13,103,460,340,000	Rp 3,082,309,250,000	Rp 3,434,222,100,000
Bukit Uluwatu Villa, Tbk.	2018	Rp 1,802,195,890,000	Rp 2,304,531,030,000	Rp 388,218,980,000	Rp 1,094,036,860,000
Bukit Uluwatu Villa, Tbk.	2017	Rp 1,474,196,490,000	Rp 1,810,136,880,000	Rp 523,717,100,000	Rp 1,085,707,450,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Bukit Uluwatu Villa, Tbk.	2016	Rp 1,498,281,480,000	Rp 1,474,604,000,000	Rp 558,899,230,000	Rp 486,882,990,000
Bumi Serpong Damai, Tbk.	2018	Rp 26,109,732,970,000	Rp 25,991,759,230,000	Rp 20,948,678,470,000	Rp 6,231,233,380,000
Bumi Serpong Damai, Tbk.	2017	Rp 25,341,472,820,000	Rp 20,609,715,650,000	Rp 17,964,523,960,000	Rp 7,568,816,960,000
Bumi Serpong Damai, Tbk.	2016	Rp 20,640,982,780,000	Rp 17,895,842,400,000	Rp 16,563,751,090,000	Rp 5,690,838,900,000
Duta Anggada Realty, Tbk.	2018	Rp 3,575,908,960,000	Rp 3,329,377,440,000	Rp 320,389,810,000	Rp 814,186,070,000
Duta Anggada Realty, Tbk.	2017	Rp 3,559,457,650,000	Rp 2,801,387,960,000	Rp 357,528,620,000	Rp 666,459,960,000
Duta Anggada Realty, Tbk.	2016	Rp 3,622,836,890,000	Rp 2,443,420,710,000	Rp 389,911,950,000	Rp 605,141,340,000
Duta Pertiwi, Tbk.	2018	Rp 7,606,169,950,000	Rp 5,036,725,790,000	Rp 5,665,261,050,000	Rp 1,571,910,030,000
Duta Pertiwi, Tbk.	2017	Rp 6,661,927,190,000	Rp 3,913,754,490,000	Rp 4,449,119,470,000	Rp 1,172,699,960,000
Duta Pertiwi, Tbk.	2016	Rp 6,136,457,060,000	Rp 3,555,760,730,000	Rp 4,131,536,310,000	Rp 1,062,796,460,000
Intiland Development, Tbk.	2018	Rp 5,841,843,980,000	Rp 8,373,691,210,000	Rp 4,815,971,560,000	Rp 4,767,907,510,000
Intiland Development, Tbk.	2017	Rp 5,623,128,180,000	Rp 7,474,056,800,000	Rp 3,606,927,660,000	Rp 4,103,191,560,000
Intiland Development, Tbk.	2016	Rp 4,980,122,310,000	Rp 6,859,937,630,000	Rp 3,034,100,320,000	Rp 3,292,500,610,000
Lippo Karawaci, Tbk.	2018	Rp 17,737,909,000,000	Rp 31,345,551,000,000	Rp 33,046,506,000,000	Rp 8,204,921,000,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Lippo Karawaci, Tbk.	2017	Rp 17,878,450,000,000	Rp 33,400,576,000,000	Rp 36,463,137,000,000	Rp 8,745,186,000,000
Lippo Karawaci, Tbk.	2016	Rp 18,572,384,000,000	Rp 27,031,299,000,000	Rp 37,453,409,000,000	Rp 6,866,309,000,000
Modernland Realty, Tbk.	2018	Rp 6,829,798,420,000	Rp 8,397,681,560,000	Rp 3,379,233,820,000	Rp 1,539,785,990,000
Modernland Realty, Tbk.	2017	Rp 7,077,456,730,000	Rp 7,522,212,610,000	Rp 3,158,284,470,000	Rp 2,374,364,860,000
Modernland Realty, Tbk.	2016	Rp 6,595,333,000,000	Rp 7,944,775,280,000	Rp 3,921,828,260,000	Rp 2,917,041,000,000
Nusa Konstruksi Enjiniring, Tbk.	2018	Rp 663,911,540,000	Rp 1,063,914,490,000	Rp 1,106,143,700,000	Rp 948,292,310,000
Nusa Konstruksi Enjiniring, Tbk.	2017	Rp 785,920,970,000	Rp 1,034,877,830,000	Rp 969,613,540,000	Rp 898,961,830,000
Nusa Konstruksi Enjiniring, Tbk.	2016	Rp 758,203,490,000	Rp 796,819,130,000	Rp 814,107,490,000	Rp 681,236,920,000
Perdana Gapuraprima, Tbk.	2018	Rp 992,769,890,000	Rp 543,683,710,000	Rp 1,346,121,490,000	Rp 236,047,700,000
Perdana Gapuraprima, Tbk.	2017	Rp 957,745,340,000	Rp 541,716,690,000	Rp 1,251,300,690,000	Rp 272,405,380,000
Perdana Gapuraprima, Tbk.	2016	Rp 940,210,980,000	Rp 629,108,050,000	Rp 1,397,068,990,000	Rp 331,170,100,000
Pp Properti, Tbk.	2018	Rp 5,272,337,610,000	Rp 11,203,382,880,000	Rp 10,413,442,230,000	Rp 5,685,378,490,000
Pp Properti, Tbk.	2017	Rp 4,781,925,340,000	Rp 7,778,006,980,000	Rp 7,106,225,520,000	Rp 3,395,076,140,000
Pp Properti, Tbk.	2016	Rp 2,844,730,040,000	Rp 6,005,103,820,000	Rp 5,538,915,570,000	Rp 2,778,511,770,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Summarecon Agung, Tbk.	2018	Rp 6,903,591,130,000	Rp 16,395,650,940,000	Rp 10,498,095,320,000	Rp 7,229,216,830,000
Summarecon Agung, Tbk.	2017	Rp 6,509,901,480,000	Rp 15,153,049,240,000	Rp 9,187,859,760,000	Rp 6,275,827,670,000
Summarecon Agung, Tbk.	2016	Rp 6,242,958,240,000	Rp 14,567,361,410,000	Rp 8,698,817,090,000	Rp 4,217,371,530,000
Bakrie Telecom, Tbk.	2018	Rp (15,419,083,000,000)	Rp 16,132,588,000,000	Rp 1,616,000,000	Rp 10,096,465,000,000
Bakrie Telecom, Tbk.	2017	Rp (14,155,203,000,000)	Rp 14,873,225,000,000	Rp 5,266,000,000	Rp 8,933,611,000,000
Bakrie Telecom, Tbk.	2016	Rp (13,897,327,000,000)	Rp 15,467,102,000,000	Rp 43,516,000,000	Rp 8,191,029,000,000
Indofarma (Persero), Tbk.	2018	Rp 496,646,170,000	Rp 945,704,440,000	Rp 867,493,110,000	Rp 827,237,830,000
Indofarma (Persero), Tbk.	2017	Rp 526,408,630,000	Rp 1,003,466,150,000	Rp 930,982,220,000	Rp 893,289,030,000
Indofarma (Persero), Tbk.	2016	Rp 575,753,990,000	Rp 805,879,330,000	Rp 853,506,460,000	Rp 704,929,720,000
Bakrieland Development, Tbk.	2018	Rp 8,233,541,750,000	Rp 5,372,638,260,000	Rp 5,073,114,950,000	Rp 2,542,487,700,000
Bakrieland Development, Tbk.	2017	Rp 5,728,030,740,000	Rp 8,354,486,800,000	Rp 6,244,406,520,000	Rp 6,550,909,050,000
Bakrieland Development, Tbk.	2016	Rp 6,066,762,180,000	Rp 8,109,935,570,000	Rp 6,356,260,640,000	Rp 6,047,013,980,000
Arpeni Pratama Ocean Line, Tbk.	2018	Rp (5,931,996,580,000)	Rp 6,828,199,080,000	Rp 296,159,250,000	Rp 6,819,108,510,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Arpeni Pratama Ocean Line, Tbk.	2017	Rp (5,510,275,800,000)	Rp 6,677,926,290,000	Rp 343,714,020,000	Rp 6,671,078,810,000
Arpeni Pratama Ocean Line, Tbk.	2016	Rp (5,238,556,190,000)	Rp 6,452,660,650,000	Rp 222,301,640,000	Rp 6,359,273,600,000
Berlian Laju Tanker, Tbk.	2018	Rp 28,967,836	Rp 42,380,697	Rp 7,910,239	Rp 12,833,718
Berlian Laju Tanker, Tbk.	2017	Rp 29,557,039	Rp 49,544,161	Rp 10,349,688	Rp 14,443,414
Berlian Laju Tanker, Tbk.	2016	Rp 40,355,787	Rp 53,419,138	Rp 18,650,230	Rp 16,708,323
Trikomsel Oke, Tbk	2018	Rp (3,512,026,090,000)	Rp 3,705,689,200,000	Rp 128,387,540,000	Rp 829,311,830,000
Trikomsel Oke, Tbk	2017	Rp (3,497,570,220,000)	Rp 3,763,690,160,000	Rp 174,277,930,000	Rp 670,486,780,000
Trikomsel Oke, Tbk	2016	Rp (6,749,322,060,000)	Rp 7,179,354,240,000	Rp 228,937,340,000	Rp 4,204,061,090,000
Express Transindo Utama, Tbk.	2018	Rp (584,143,220,000)	Rp 1,853,168,180,000	Rp 499,247,070,000	Rp 1,603,238,370,000
Express Transindo Utama, Tbk.	2017	Rp 246,522,880,000	Rp 1,763,490,130,000	Rp 452,880,580,000	Rp 535,116,210,000
Express Transindo Utama, Tbk.	2016	Rp 735,998,960,000	Rp 1,821,263,880,000	Rp 712,446,730,000	Rp 174,751,380,000
Asia Natural Resources Tbk	2013	Rp 35,048,222,346	Rp 16,612,721,009	Rp 19,178,463,379	Rp 2,530,456,969
Bara Jaya Internasional Tbk	2018	Rp 848,700,573	Rp 615,043,862	Rp 54,790,180	Rp 217,136,762
Citra Maharlika Nusantara Corpora Tbk	2016	Rp (153,441,660,000)	Rp 382,230,890,000	Rp 32,339,030,000	Rp 361,987,150,000

Company	Year	Total Equity		Book Value of Total Liabilities		Total current asset		Total current liabilities	
Dwi Aneka Jaya Kemasindo Tbk	2017	Rp	333,315,834	Rp	975,551,178	Rp	355,172,327	Rp	62,233,549
Leo Investment Tbk	2019	Rp	102,773,513,976	Rp	52,142,230,937	Rp	92,956,116,296	Rp	44,787,936,135
Pt Surya Intrindo Makmur Tbk	2011	Rp	(52,932,306,251)	Rp	95,661,406,973	Rp	2,759,941,971	Rp	95,661,406,973
Pt Jasa Angkasa Semesta	2008	Rp	126,331,560,848	Rp	104,485,038,247	Rp	143,882,036,649	Rp	75,962,480,079
Pt New Century Development	2010	Rp	(88,924,917,000)	Rp	257,851,292,000	Rp	88,716,254,000	Rp	166,230,164,000
Davomas Abadi	2013	Rp	2,369,156,930,000	Rp	165,167,950,000	Rp	441,477,650,000	Rp	441,510,000
Katarina Utama	2010	Rp	134,601,772,390	Rp	224,306,663,763	Rp	321,077,746,647	Rp	192,571,733,758
Amstelco Indonesia	2011	Rp	20,419,009,089	Rp	6,411,599,187	Rp	26,036,085,557	Rp	4,024,615,338
Dayaindo Resource	2012	Rp	(5,363,444,343)	Rp	6,673,975,468	Rp	100,531,125	Rp	6,673,975,468
Panca Wirasakti	2011	Rp	2,442,407,853,702	Rp	418,199,882,385	Rp	1,521,157,993,916	Rp	82,418,777,468
Surabaya Agung Industri	2011	Rp	(340,387,099,018)	Rp	614,701,121,531	Rp	265,121,007,003	Rp	592,796,699,423
Surya Inti Permata	2012	Rp	1,279,134,192,649	Rp	696,824,557,751	Rp	174,304,356,538	Rp	205,119,015,588
Sekawan Intipratama	2011	Rp	789,486,494,063	Rp	941,102,531,404	Rp	1,665,233,823,096	Rp	333,233,842,017
Surya Semesta Internusa, Tbk.	2018	Rp	3,943,972,060,000	Rp	3,460,195,040,000	Rp	3,458,662,370,000	Rp	2,033,129,970,000
Surya Semesta Internusa, Tbk.	2017	Rp	4,008,583,150,000	Rp	4,842,853,820,000	Rp	5,085,335,030,000	Rp	2,640,028,080,000
Surya Semesta Internusa, Tbk.	2016	Rp	2,911,919,900,000	Rp	4,283,528,430,000	Rp	3,380,678,960,000	Rp	1,896,353,460,000

Company	Year	Total Equity		Book Value of Total Liabilities		Total current asset		Total current liabilities	
Apexindo Pratama Duta, Tbk.	2018	Rp	(150,270,000)	Rp	664,940,000	Rp	73,340,000	Rp	422,220,000
Apexindo Pratama Duta, Tbk.	2017	Rp	(47,000,000)	Rp	624,630,000	Rp	84,440,000	Rp	376,350,000
Apexindo Pratama Duta, Tbk.	2016	Rp	26,970,000	Rp	655,400,000	Rp	98,580,000	Rp	42,690,000
Perusahaan Gas Negara Tbk	2018	Rp	2,574,540,000	Rp	5,364,740,000	Rp	2,473,610,000	Rp	1,604,520,000
Perusahaan Gas Negara Tbk	2017	Rp	3,740,910,000	Rp	4,442,270,000	Rp	2,235,510,000	Rp	841,950,000
Perusahaan Gas Negara Tbk	2016	Rp	3,163,170,000	Rp	3,670,980,000	Rp	2,124,670,000	Rp	815,370,000
Global Mediacom, Tbk.	2018	Rp	9,497,785,000,000	Rp	19,470,377,000,000	Rp	9,380,777,000,000	Rp	6,955,570,000,000
Global Mediacom, Tbk.	2017	Rp	9,246,259,000,000	Rp	18,448,475,000,000	Rp	9,385,823,000,000	Rp	4,294,191,000,000
Global Mediacom, Tbk.	2016	Rp	9,234,399,000,000	Rp	15,390,032,000,000	Rp	8,687,868,000,000	Rp	7,338,634,000,000
Media Nusantara Citra, Tbk.	2018	Rp	9,865,754,000,000	Rp	6,473,798,000,000	Rp	7,336,848,000,000	Rp	2,153,719,000,000
Media Nusantara Citra, Tbk.	2017	Rp	9,024,688,000,000	Rp	6,032,603,000,000	Rp	6,718,435,000,000	Rp	1,459,288,000,000
Media Nusantara Citra, Tbk.	2016	Rp	8,818,137,000,000	Rp	5,421,730,000,000	Rp	6,638,010,000,000	Rp	4,198,739,000,000
Metrodata Electronics, Tbk.	2018	Rp	1,804,546,000,000	Rp	3,048,230,000,000	Rp	4,294,397,000,000	Rp	2,095,378,000,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Metrodata Electronics, Tbk.	2017	Rp 1,527,149,000,000	Rp 2,743,978,000,000	Rp 3,697,416,000,000	Rp 1,851,160,000,000
Metrodata Electronics, Tbk.	2016	Rp 1,300,558,000,000	Rp 2,575,463,000,000	Rp 3,358,766,000,000	Rp 1,812,433,000,000
Adhi Karya (Persero), Tbk.	2018	Rp 6,274,484,930,000	Rp 23,844,129,840,000	Rp 25,429,544,170,000	Rp 18,964,304,190,000
Adhi Karya (Persero), Tbk.	2017	Rp 5,859,245,550,000	Rp 22,473,702,460,000	Rp 24,817,671,200,000	Rp 17,633,289,240,000
Adhi Karya (Persero), Tbk.	2016	Rp 5,433,255,960,000	Rp 14,662,179,990,000	Rp 16,835,408,080,000	Rp 13,044,369,550,000
Bukaka Teknik Utama Tbk	2018	Rp 1,957,620,400,000	Rp 2,456,676,010,000	Rp 2,184,123,680,000	Rp 2,296,176,800,000
Bukaka Teknik Utama Tbk	2017	Rp 1,547,481,990,000	Rp 1,959,815,850,000	Rp 1,744,873,620,000	Rp 1,634,572,700,000
Bukaka Teknik Utama Tbk	2016	Rp 1,218,982,960,000	Rp 1,041,469,780,000	Rp 1,287,667,680,000	Rp 884,002,060,000
Wijaya Karya (Persero), Tbk.	2019	Rp 14,803,614,300,000	Rp 44,426,386,940,000	Rp 45,731,939,640,000	Rp 28,251,951,390,000
Wijaya Karya (Persero), Tbk.	2018	Rp 12,633,516,350,000	Rp 33,050,257,950,000	Rp 34,910,108,270,000	Rp 25,975,617,300,000
Wijaya Karya (Persero), Tbk.	2017	Rp 11,444,865,000,000	Rp 19,910,339,690,000	Rp 23,651,834,990,000	Rp 14,909,016,700,000
Weha Transportasi Indonesia, Tbk.	2018	Rp 143,004,800,000	Rp 188,399,330,000	Rp 22,696,770,000	Rp 56,398,940,000
Weha Transportasi Indonesia, Tbk.	2017	Rp 144,674,750,000	Rp 155,328,720,000	Rp 22,665,390,000	Rp 53,152,290,000

Company	Year	Total Equity	Book Value of Total Liabilities	Total current asset	Total current liabilities
Weha Transportasi Indonesia, Tbk.	2016	Rp 97,305,170,000	Rp 207,652,090,000	Rp 46,623,260,000	Rp 138,281,620,000
Astra International, Tbk.	2018	Rp 136,947,000,000,000	Rp 207,764,000,000,000	Rp 133,609,000,000,000	Rp 116,467,000,000,000
Astra International, Tbk.	2017	Rp 123,780,000,000,000	Rp 172,050,000,000,000	Rp 121,528,000,000,000	Rp 98,722,000,000,000
Astra International, Tbk.	2016	Rp 111,951,000,000,000	Rp 149,904,000,000,000	Rp 110,403,000,000,000	Rp 89,079,000,000,000
Kimia Farma (Persero), Tbk.	2018	Rp 3,991,792,680,000	Rp 7,337,298,180,000	Rp 6,378,008,240,000	Rp 4,745,842,440,000
Kimia Farma (Persero), Tbk.	2017	Rp 3,211,663,260,000	Rp 4,060,421,300,000	Rp 4,427,595,230,000	Rp 2,554,232,150,000
Kimia Farma (Persero), Tbk.	2016	Rp 2,220,956,230,000	Rp 2,391,606,310,000	Rp 2,906,737,460,000	Rp 1,696,208,870,000
Grahamas Citrawisata Tbk	2018	Rp 7,887,706,824	Rp 29,694,353,021	Rp 9,664,667,292	Rp 14,153,545,617
Indo Citra Finance Tbk	2012	Rp (7,165,577,084)	Rp 8,116,750,779	Rp 951,173,695	Rp 7,951,753,905
Inovisi Infracom Tbk	2014	Rp 1,472,019,000,000	Rp 1,199,654,000,000	Rp 2,340,492,000,000	Rp 1,199,654,000,000
Permata Prima Sakti Tbk	2014	Rp 445,392,000,000	Rp 5,578,879,000,000	Rp 1,139,296,000,000	Rp 4,708,070,000,000
Sigmagold Inti Perkasa Tbk	2018	Rp 954,662,177,554	Rp 200,417,563,519	Rp 206,389,405,141	Rp 156,321,823,145
Truba Alam Manunggal Engineering Tbk	2017	Rp 354,302,421	Rp 284,525,616	Rp 615,657,815	Rp 284,056,211

Appendix 6. Recapitulation of calculation of variables for all firms

Company	Year	X1	X2	X3	X4	X5	X6
Panorama Sentrawisata, Tbk.	2018	0.27582	0.72340	0.05755	0.13624	0.00529	0.56157
Panorama Sentrawisata, Tbk.	2017	0.35400	0.75006	0.16572	0.06066	0.01662	0.33772
Panorama Sentrawisata, Tbk.	2016	0.26733	0.70688	0.06883	0.06945	0.00249	0.26028
Garuda Indonesia (Persero), Tbk.	2018	0.34949	0.00046	-0.47683	-0.16238	-0.04792	0.16830
Garuda Indonesia (Persero), Tbk.	2017	0.25952	0.00037	-0.24848	-0.11782	-0.02024	0.31193
Garuda Indonesia (Persero), Tbk.	2016	0.38557	0.00031	-0.10661	-0.05678	0.02651	0.36171
Astra Graphia Tbk.	2018	0.31359	0.30477	0.45766	0.56884	0.16129	1.88565
Astra Graphia Tbk.	2017	0.26684	0.38147	0.36203	0.46810	0.14270	1.21132
Astra Graphia Tbk.	2016	0.22685	0.17845	0.42676	0.56216	0.19353	2.09330
Fks Multi Agro, Tbk.	2018	0.76983	0.00017	0.18022	0.22635	0.04600	0.30797
Fks Multi Agro, Tbk.	2017	0.78763	0.00021	0.16000	0.25495	0.06753	0.37408
Fks Multi Agro, Tbk.	2016	0.62234	0.00009	0.21187	0.28133	0.11657	0.43966
Intraco Penta, Tbk.	2018	0.28904	0.74914	0.08158	-0.21163	0.00516	0.02713
Intraco Penta, Tbk.	2017	0.54895	0.76994	-0.13537	-0.13453	-0.02426	0.09702
Intraco Penta, Tbk.	2016	0.40059	0.82715	-0.05686	-0.09351	-0.00594	0.10105
Tigaraksa Satria, Tbk.	2018	0.30613	0.42212	0.39155	0.32709	0.00754	0.55080
Tigaraksa Satria, Tbk.	2017	0.71608	0.43741	0.41114	0.33174	0.11135	0.57531
Tigaraksa Satria, Tbk.	2016	0.72631	0.36777	0.38827	0.31112	0.09206	0.53272

Company	Year	X1	X2	X3	X4	X5	X6
Citra Marga Nusaphala Persada, Tbk.	2018	0.35125	0.59222	0.25956	0.16966	0.06905	0.94649
Citra Marga Nusaphala Persada, Tbk.	2017	0.19814	0.49892	0.23104	0.13648	0.06575	0.93429
Citra Marga Nusaphala Persada, Tbk.	2016	0.38942	0.39238	0.21540	0.21916	0.08760	1.31788
Jasa Marga (Persero), Tbk.	2018	0.31044	0.67828	-0.23378	0.12007	0.06570	0.25811
Jasa Marga (Persero), Tbk.	2017	0.25106	0.57974	-0.07590	0.10260	0.05869	0.23555
Jasa Marga (Persero), Tbk.	2016	0.28982	0.55941	-0.10581	0.12133	0.08089	0.34351
Bali Towerindo Sentra Tbk	2018	0.16418	0.23363	-0.06317	0.06761	0.06284	0.97143
Bali Towerindo Sentra Tbk	2017	0.25645	0.18624	-0.08585	0.06181	0.06534	0.88621
Bali Towerindo Sentra Tbk	2016	0.36517	0.20711	-0.10927	0.33215	0.06745	0.69762
Indosat, Tbk.	2018	0.38745	0.82089	-0.24716	0.16334	0.01363	0.26627
Indosat, Tbk.	2017	0.24193	0.58432	-0.13267	0.22706	0.01104	0.38176
Indosat, Tbk.	2016	0.29186	0.51682	-0.21663	0.21314	0.00467	0.35611
Inti Bangun Sejahtera Tbk	2018	0.59412	0.18257	0.02504	0.19341	0.04300	2.08503
Inti Bangun Sejahtera Tbk	2017	0.88750	0.15699	0.05550	0.19704	0.04361	2.11869
Inti Bangun Sejahtera Tbk	2016	0.70676	0.44648	0.10273	0.39490	0.12277	1.70316
Telekomunikasi Indonesia, Tbk.	2018	0.30757	0.22409	-0.01452	0.44130	0.18839	0.92193
Telekomunikasi Indonesia, Tbk.	2017	0.19620	0.19386	0.01101	0.42772	0.22134	0.87654

Company	Year	X1	X2	X3	X4	X5	X6
Telekomunikasi Indonesia, Tbk.	2016	0.27552	0.19454	0.04420	0.42656	0.21822	0.88614
Tiphone Mobile Indonesia, Tbk.	2018	0.49345	0.39353	0.73667	0.26749	0.12003	0.87229
Tiphone Mobile Indonesia, Tbk.	2017	0.29493	0.87706	0.68182	0.20763	0.11788	0.67965
Tiphone Mobile Indonesia, Tbk.	2016	0.35537	0.44532	0.75770	0.18496	0.12347	0.63905
Xl Axiata, Tbk.	2018	0.53549	0.64982	-0.15056	0.08895	-0.04810	0.46709
Xl Axiata, Tbk.	2017	0.38497	0.52302	-0.14285	0.14923	0.02944	0.62354
Xl Axiata, Tbk.	2016	0.41335	0.57707	-0.13972	0.14576	0.03073	0.62959
Humpuss Intermoda Transportasi, Tbk.	2018	0.32764	0.00003	-0.03430	0.09581	0.09688	0.24040
Humpuss Intermoda Transportasi, Tbk.	2017	0.43812	0.00003	-0.00365	0.04745	0.09706	0.17889
Humpuss Intermoda Transportasi, Tbk.	2016	0.17892	0.00003	0.02253	0.01587	0.08420	0.14408
Matahari Putra Prima, Tbk.	2018	0.56830	0.76176	-0.08624	-0.14461	-0.19328	0.31405
Matahari Putra Prima, Tbk.	2017	0.43877	0.55549	-0.25619	0.02408	-0.28656	0.27608
Matahari Putra Prima, Tbk.	2016	0.41254	0.27713	0.11468	0.20685	0.02642	0.56875
Mitra Adiperkasa, Tbk.	2018	5.56863	0.34952	0.14992	0.22740	0.11329	0.75937
Mitra Adiperkasa, Tbk.	2017	0.36764	0.41786	0.19551	0.19246	0.09416	0.54657
Mitra Adiperkasa, Tbk.	2016	0.38107	0.45488	0.22792	0.17837	0.08696	0.42828
Fastfood Indonesia, Tbk.	2018	0.41754	0.30311	0.21627	0.44822	0.08905	1.06300

Company	Year	X1	X2	X3	X4	X5	X6
Fastfood Indonesia, Tbk.	2017	0.29920	0.33631	0.21541	0.39758	0.05636	0.88853
Fastfood Indonesia, Tbk.	2016	0.45333	0.31160	0.20777	0.39675	0.08459	0.90300
Jaya Bersama Indo Tbk	2018	0.00000	0.13179	0.61837	0.15640	0.13400	2.44744
Jaya Bersama Indo Tbk	2017	0.00000	0.11989	0.41706	0.09106	0.22475	1.48010
Jaya Bersama Indo Tbk	2016	0.00000	0.12610	0.35166	0.47435	0.09997	0.97871
Pembangunan Jaya Ancol, Tbk.	2018	0.67086	0.54022	-0.05540	0.35537	0.09728	0.84124
Pembangunan Jaya Ancol, Tbk.	2017	0.26793	0.47253	0.00761	0.37710	0.10513	0.98109
Pembangunan Jaya Ancol, Tbk.	2016	0.40517	0.39043	-0.03000	0.33482	0.06376	0.82050
Agung Podomoro Land, Tbk.	2018	0.36838	0.87562	0.01476	0.19653	0.03856	0.42772
Agung Podomoro Land, Tbk.	2017	0.36280	0.83108	0.07686	0.20092	0.07081	0.43901
Agung Podomoro Land, Tbk.	2016	0.30808	0.81740	0.02019	0.17313	0.06614	0.41248
Alam Sutera Realty, Tbk.	2018	0.31928	0.65123	-0.03708	0.54796	0.08895	0.82495
Alam Sutera Realty, Tbk.	2017	0.28658	0.63677	-0.03983	0.59160	0.08947	0.69032
Alam Sutera Realty, Tbk.	2016	0.37935	0.65452	-0.01743	0.64913	0.04777	0.54052
Bukit Uluwatu Villa, Tbk.	2018	0.95862	0.62156	-0.17187	0.04820	0.02192	0.78202
Bukit Uluwatu Villa, Tbk.	2017	0.37556	0.50547	-0.17111	0.05039	0.00056	0.81441
Bukit Uluwatu Villa, Tbk.	2016	0.40307	0.43170	0.02422	0.06794	0.02026	1.01606
Bumi Serpong Damai, Tbk.	2018	0.37423	0.51832	0.28248	0.35277	0.04126	1.00454
Bumi Serpong Damai, Tbk.	2017	0.23680	0.38646	0.22623	0.37362	0.11011	1.22959

Company	Year	X1	X2	X3	X4	X5	X6
Bumi Serpong Damai, Tbk.	2016	0.33801	0.34632	0.28214	0.32209	0.05974	1.15340
Duta Anggada Realty, Tbk.	2018	0.43274	0.81411	-0.07151	0.22465	0.01280	1.07405
Duta Anggada Realty, Tbk.	2017	0.66602	0.74452	-0.04857	0.24129	0.01936	1.27061
Duta Anggada Realty, Tbk.	2016	0.64841	0.68360	-0.03548	0.26343	0.05168	1.48269
Duta Pertiwi, Tbk.	2018	0.54315	0.97965	0.32377	0.49095	0.07699	1.51014
Duta Pertiwi, Tbk.	2017	0.14642	0.97124	0.30981	0.49952	0.05929	1.70218
Duta Pertiwi, Tbk.	2016	0.15659	0.96409	0.31662	0.49104	0.07807	1.72578
Intiland Development, Tbk.	2018	0.40536	0.72397	0.00338	0.13025	0.02299	0.69764
Intiland Development, Tbk.	2017	0.21816	0.67321	-0.03789	0.12458	0.02633	0.75235
Intiland Development, Tbk.	2016	0.30011	0.56963	-0.02182	0.11699	0.03414	0.72597
Lippo Karawaci, Tbk.	2018	0.33629	0.84246	0.50611	0.15408	0.03955	0.56588
Lippo Karawaci, Tbk.	2017	0.30463	0.74784	0.54053	0.08506	-0.00660	0.53527
Lippo Karawaci, Tbk.	2016	0.30053	0.61931	0.67072	0.17422	0.03979	0.68707
Modernland Realty, Tbk.	2018	0.32889	0.74778	0.12080	0.30348	0.03342	0.81330
Modernland Realty, Tbk.	2017	0.35524	0.67121	0.05369	0.32467	0.08360	0.94087
Modernland Realty, Tbk.	2016	0.37999	0.64956	0.06910	0.29081	0.07202	0.83015
Nusa Konstruksi Enjiniring, Tbk.	2018	0.37423	0.79339	0.09136	-0.10091	-0.03738	0.62403
Nusa Konstruksi Enjiniring, Tbk.	2017	0.23680	0.76303	0.03880	-0.01540	-0.00449	0.75943
Nusa Konstruksi Enjiniring, Tbk.	2016	0.33801	0.72334	0.08545	-0.02977	-0.02498	0.95154
Perdana Gapuraprima, Tbk.	2018	0.41621	0.53612	0.72249	0.32289	0.05140	1.82601

Company	Year	X1	X2	X3	X4	X5	X6
Perdana Gapuraprima, Tbk.	2017	0.73872	0.55153	0.65283	0.30750	0.03247	1.76798
Perdana Gapuraprima, Tbk.	2016	0.61313	0.44563	0.67921	0.28279	0.04156	1.49451
Pp Properti, Tbk.	2018	0.38964	0.60824	0.28697	0.08974	0.03124	0.47060
Pp Properti, Tbk.	2017	0.38781	0.40021	0.29548	0.08727	0.04488	0.61480
Pp Properti, Tbk.	2016	0.59697	0.22262	0.31192	0.08187	0.05740	0.47372
Summarecon Agung, Tbk.	2018	0.44812	0.58537	0.14030	0.23333	0.29630	0.42106
Summarecon Agung, Tbk.	2017	0.35244	0.52640	0.13442	0.23278	0.30051	0.42961
Summarecon Agung, Tbk.	2016	0.41376	0.43249	0.21535	0.22949	0.29999	0.42856
Bakrie Telecom, Tbk.	2018	0.00000	0.89812	-14.14825	-31.98163	-0.05193	-0.95577
Bakrie Telecom, Tbk.	2017	0.00000	0.89044	-12.43464	-30.02021	-1.19302	-0.95172
Bakrie Telecom, Tbk.	2016	0.00000	0.89420	-5.19024	-12.77799	-0.61032	-0.89851
Indofarma (Persero), Tbk.	2018	0.86023	0.04484	0.02791	0.07318	-0.00309	0.52516
Indofarma (Persero), Tbk.	2017	0.83348	0.05202	0.02464	0.08845	0.00528	0.52459
Indofarma (Persero), Tbk.	2016	0.77724	0.05264	0.10754	0.13365	-0.01194	0.71444
Bakrieland Development, Tbk.	2018	5.99597	0.71173	0.18599	-0.09063	0.20116	1.53250
Bakrieland Development, Tbk.	2017	0.60932	0.79335	-0.02176	-0.10806	-0.02204	0.68562
Bakrieland Development, Tbk.	2016	0.00000	0.78844	0.02181	-0.08819	-0.03674	0.74807
Arpeni Pratama Ocean Line, Tbk.	2018	0.00000	0.89248	-7.27843	-7.69320	0.02201	-0.86875

Company	Year	X1	X2	X3	X4	X5	X6
Arpeni Pratama Ocean Line, Tbk.	2017	0.00000	0.89359	-5.41889	-5.69064	0.02286	-0.82515
Arpeni Pratama Ocean Line, Tbk.	2016	0.00000	0.89029	-5.05473	-5.25734	-0.09983	-0.81184
Berlian Laju Tanker, Tbk.	2018	0.00000	0.00001	-0.06901	-17.21531	0.09282	0.68351
Berlian Laju Tanker, Tbk.	2017	0.00000	0.00001	-0.05175	-16.29479	-0.08828	0.59658
Berlian Laju Tanker, Tbk.	2016	0.00000	0.00001	0.02071	-13.69656	-0.14663	0.75546
Trikomsel Oke, Tbk	2018	0.99165	0.37646	-3.61930	-40.11076	-0.27465	-0.94774
Trikomsel Oke, Tbk	2017	1.05119	0.06748	-1.86461	-29.05651	-0.28531	-0.92929
Trikomsel Oke, Tbk	2016	0.79166	0.12128	-9.24378	-17.54495	-0.91304	-0.94010
Express Transindo Utama, Tbk.	2018	0.96408	0.90563	-0.86995	-0.88150	-0.56348	-0.31521
Express Transindo Utama, Tbk.	2017	0.52167	0.94265	-0.04091	-0.14367	-0.20519	0.13979
Express Transindo Utama, Tbk.	2016	0.85031	0.83314	0.21026	0.07738	-0.08735	0.40411
Asia Natural Resources Tbk	2013	0.00000	0.12743	0.32226	-6.89700	-0.01966	2.10972
Bara Jaya Internasional Tbk	2018	0.00000	0.35500	-0.18334	-1.19168	-0.15253	1.37990
Citra Maharlika Nusantara Corpora Tbk	2016	0.00000	0.65806	-1.44084	-2.51233	-0.06115	-0.40144
Dwi Aneka Jaya Kemasindo Tbk	2017	0.30946	0.88642	0.22381	-0.45886	-0.04553	0.34167
Leo Investment Tbk	2019	0.00000	0.31559	0.31093	-0.57547	0.13299	1.97102
Pt Surya Intrindo Makmur Tbk	2011	0.00000	0.27049	-2.17420	-3.60576	-0.14867	-0.55333

Company	Year	X1	X2	X3	X4	X5	X6
Pt Jasa Angkasa Semesta	2008	0.00000	0.82537	0.29426	0.15990	0.22509	1.20909
Pt New Century Development	2010	0.00000	0.46687	-0.45358	-0.82675	-0.21472	-0.34487
Davomas Abadi	2013	0.00000	0.14776	0.17403	-0.94223	-0.10247	14.34393
Katarina Utama	2010	0.53597	0.68615	0.35805	0.19130	0.04171	0.60008
Amstelco Indonesia	2011	0.00000	0.11007	0.82039	-2.72752	-0.00081	3.18470
Dayaindo Resource	2012	0.00000	0.73551	-5.01586	-44.19082	-1.37512	-0.80364
Panca Wirasakti	2011	0.00000	0.21424	0.50295	0.05073	0.02985	5.84029
Surabaya Agung Industri	2011	0.00000	0.99188	-1.19453	-1.53724	-0.00161	-0.55374
Surya Inti Permata	2012	0.68932	0.05568	-0.01559	-1.17589	-0.06245	1.83566
Sekawan Intipratama	2011	0.00000	0.71538	0.76615	0.21241	-0.02324	0.83890
Surya Semesta Internusa, Tbk.	2018	0.34384	0.59527	0.19253	0.39918	0.04780	1.13981
Surya Semesta Internusa, Tbk.	2017	0.38126	0.66650	0.27626	0.34158	0.22918	0.82773
Surya Semesta Internusa, Tbk.	2016	0.35980	0.67717	0.20629	0.26656	0.06129	0.67979
Apexindo Pratama Duta, Tbk.	2018	0.37613	0.00015	-0.67786	-0.25266	-0.21343	-0.22599
Apexindo Pratama Duta, Tbk.	2017	0.11582	0.00013	-0.50536	-0.04543	-0.18581	-0.07524
Apexindo Pratama Duta, Tbk.	2016	0.11229	0.00014	0.08191	0.11180	-0.03734	0.04115
Perusahaan Gas Negara Tbk	2018	0.58956	0.00010	0.10947	0.34746	0.08038	0.47990
Perusahaan Gas Negara Tbk	2017	0.36959	0.00010	0.17030	0.31418	0.06292	0.84212
Perusahaan Gas Negara Tbk	2016	0.41471	0.00006	0.19158	0.37526	0.06500	0.86167
Global Mediacom, Tbk.	2018	0.40455	0.84277	0.08372	0.25349	0.06154	0.48781
Global Mediacom, Tbk.	2017	0.42731	0.67566	0.18385	0.23819	0.07316	0.50119

Company	Year	X1	X2	X3	X4	X5	X6
Global Mediacom, Tbk.	2016	0.46727	0.62507	0.05479	0.25098	0.05735	0.60002
Media Nusantara Citra, Tbk.	2018	0.38745	0.39657	0.31721	0.53195	0.16768	1.52395
Media Nusantara Citra, Tbk.	2017	0.24193	0.24747	0.34928	0.48752	0.17704	1.49599
Media Nusantara Citra, Tbk.	2016	0.29186	0.17790	0.17130	0.45527	0.16376	1.62644
Metrodata Electronics, Tbk.	2018	0.41476	0.58936	0.45315	0.27382	0.11866	0.59200
Metrodata Electronics, Tbk.	2017	0.19086	0.63226	0.43226	0.24942	0.10882	0.55655
Metrodata Electronics, Tbk.	2016	0.20721	0.62513	0.39895	0.22706	0.11420	0.50498
Adhi Karya (Persero), Tbk.	2018	0.35435	0.80860	0.21466	0.09947	0.05973	0.26315
Adhi Karya (Persero), Tbk.	2017	0.34647	0.77002	0.25357	0.08632	0.06027	0.26072
Adhi Karya (Persero), Tbk.	2016	0.34620	0.66439	0.18865	0.09938	0.03987	0.37056
Bukaka Teknik Utama Tbk	2018	0.52327	0.32872	-0.02538	0.24625	0.14217	0.79686
Bukaka Teknik Utama Tbk	2017	0.42623	0.32380	0.03145	0.14977	0.06204	0.78961
Bukaka Teknik Utama Tbk	2016	0.62787	0.34465	0.17858	0.15250	0.04779	1.17044
Wijaya Karya (Persero), Tbk.	2019	0.39974	0.94005	0.29512	0.09252	0.07374	0.33322
Wijaya Karya (Persero), Tbk.	2018	0.43257	0.93501	0.19557	0.08763	0.06139	0.38225
Wijaya Karya (Persero), Tbk.	2017	0.32108	0.88436	0.27883	0.09902	0.06683	0.57482
Weha Transportasi Indonesia, Tbk.	2018	0.21824	0.58304	-0.10170	0.02170	0.06261	0.75905
Weha Transportasi Indonesia, Tbk.	2017	0.24173	0.46452	-0.10162	0.02953	-0.00230	0.93141
Weha Transportasi Indonesia, Tbk.	2016	0.19551	0.60648	-0.30056	-0.12628	-0.02560	0.46860
Astra International, Tbk.	2018	0.29329	0.38422	0.04973	0.37055	0.07794	0.65915

Company	Year	X1	X2	X3	X4	X5	X6
Astra International, Tbk.	2017	0.21278	0.33864	0.07709	0.38388	0.06871	0.71944
Astra International, Tbk.	2016	0.32837	0.30914	0.08143	0.38816	0.06709	0.74682
Kimia Farma (Persero), Tbk.	2018	0.58919	0.32450	0.14407	0.19981	0.08339	0.54404
Kimia Farma (Persero), Tbk.	2017	0.39221	0.21308	0.25761	0.26758	0.07366	0.79097
Kimia Farma (Persero), Tbk.	2016	0.48399	0.14209	0.26244	0.36261	0.09600	0.92865
Grahamas Citrawisata Tbk	2018	0.00000	0.36981	-0.11944	-1.06180	0.01442	0.26563
Indo Citra Finance Tbk	2012	0.00000	0.64176	-7.35994	-7.53341	-2.65223	-0.88281
Inovisi Infracom Tbk	2014	0.00000	0.50650	0.22468	-0.10396	0.75393	1.22704
Permata Prima Sakti Tbk	2014	0.00000	0.75385	-0.59240	-0.05528	-0.05743	0.07984
Sigmagold Inti Perkasa Tbk	2018	0.00000	0.42147	0.04335	-0.08063	-0.00989	4.76337
Truba Alam Manunggal Engineering Tbk	2017	0.00000	0.26480	0.51908	-2.11343	-0.02446	1.24524