**元 智 大 學**

資 訊 工 程 學 系

碩 士 論 文

**Using Candlestick Chart Representation to Predict Taiwan and Indonesia Stock Market**

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指導教授：歐昱言 博士

中華民國 107 年 7 月

**Using Candlestick Chart Representation to Predict Taiwan and Indonesia Stock Market**

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中華民國 107 年 7 月

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# ABSTRACT

This thesis explores predictability in the stock market using Deep Convolutional Network and candlestick charts. The outcome is to design a decision support framework that can be used by traders to provide suggested indications of future stock price direction. Residual network method will be our machine learning algorithm to build deeper convolutional network. From stock market historical data, we converted to candlestick chart for the model analyzing the pattern. Using Taiwan and Indonesian stock market historical time series data we can achieve xx % for 5 days sliding windows period, xx % for 10 days sliding windows period and xx % for 20 days of binary classification accuracy.

This thesis also addresses problems specific to learning with stock market historical time series data, model performance due to sliding windows period days.

Keywords: *Stock Market Prediction, Neural Network, Residual Network*

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# Chapter 1 Introduction

## 1.1. Background

Stock market is something that cannot be separated from modern human life. Investment in stock market is a natural thing done by people around the world. They set aside their income to try their luck by investing in stock market to generate more profit. Traders are more likely to buy a stock whose value is expected to increase in the future. On the other hand, traders are likely to refrain from buying a stock whose value is expected to fall in the future. So, there is a need for accurately predicting the trends in stock market prices in order to maximize capital gain and minimize loss. This is also one of our reasons for doing research and try to make predictions into the field of stock market. Besides, research on stock market is still classified as a difficult thing to do considering the price changes in the stock market can happen suddenly. With the current technological advances, machine learning is a breakthrough in aspects of human life today. In this case we use machine learning to make predictions on the stock market. We choose several learning algorithms in machine learning to enhance our performance result using convolutional neural network, residual network, virtual geometry group network, k-nearest neighborhood and random forest.

Dataset format in machine learning can be various. Many kind of dataset format such as text sequence, image, audio, video, from 1D (one dimension) to 3D (three dimension) can be applicable for machine learning. Taken as an example for the use of images as inputs from machine learning, not only as inputs to classify an animal, items or the other thing, but also as an input to predict a condition, we take the example of Google DeepMind in their research in Alpha Go. Recently, they are successfully get a lot of attention in the research field. By using the image as their input, where the image represents a Go game board, which later this image dataset is used to predict the next step of the opponent in the Go game(Silver, Huang et al. 2016).

On the other occasion, from historical data of stock market converted into audio wavelength using deep convolutional wavenet architecture can be applied to forecast the stock market movement(Borovykh, Bohte et al.).

Our proposed method in this thesis is using a candlestick chart from Taiwan and Indonesia stock market to predict the price movement. We are using three trading period time to analyze the correlation between those period time with the result. Our proposed candlestick chart will represent the sequence of time series with and without the daily volume stock data. Our experiments conduct two kind of image size for candlestick chart, 50 and 20 dimension to analyze the correlation of hidden pattern in various image size. Which later our dataset will be input for several learning algorithms, random forest and k-nearest neighborhood as traditional machine learning and CNN, residual network, VGG network as our modern machine learning. the goal is to analyze the correlation of some parameter such as period time, image size, feature set with the movement of stock market will be going up or going down in the next day.

## 1.2. Related work

Basically, there are many researchers who already done doing the research on the stock market predictions. (Schöneburg 1990) conducted a study using data from a randomly selected German stock market, then using the back-propagation method for their machine learning architecture(!!! INVALID CITATION !!! {}). To our knowledge, stock market data consist of open price data, close price data, high price data, low price data and also volume of the daily movement activity. In addition to using historical time series data from the stock market, some researchers in this field of stock market predictions began to penetrate the method of sentiment analysis to predict and analyze movements in the stock market.

(Bollen, Mao et al. 2011) used their sentiment analysis method by taking data from one of the famous microblogging site Twitter to predict the Dow Jones Industrial Average (DJIA) movements. There are more studies on stock market predictions, they use the input data not only by using elements of historical time series data, but also processing the data into other different forms. (Borovykh, Bohte et al.) tried to use the deep convolutional wave net architecture method to perform analysis and prediction using data from S & P500 and CBOE.

We also found some related work using candlestick charts in their research. (Hu, Hu et al. 2017) in their research using candlestick chart to build a decision-making system in stock market investment. They use the convolutional encoder to learn the patterns contained in the candlestick chart. While (Tsai and Quan 2014) using candlestick chart in his research to be combined with seven different wavelet-based texture to analyze candlestick chart. Next, (do Prado, Ferneda et al. 2013) using candlestick chart to learn the pattern contained in Brazilian stock market by using sixteen candlestick pattern.

Traditional machine learning like Random Forest has been applied to predict the stock market with a good result. (Khaidem, Saha et al. 2016) using Random Forest combine with technical indicator such as Relative Strength Index (RSI) shown a good performance.

# Chapter 2 Data Collection

## 2.1. Data Collection using Yahoo! Finance

We choose two different stock market country, Taiwan and Indonesia. We collected 50 companies stock market data for Taiwan and 10 for Indonesia. Listed on table 1 is Taiwan 50 and table 2 is Indonesia 10.

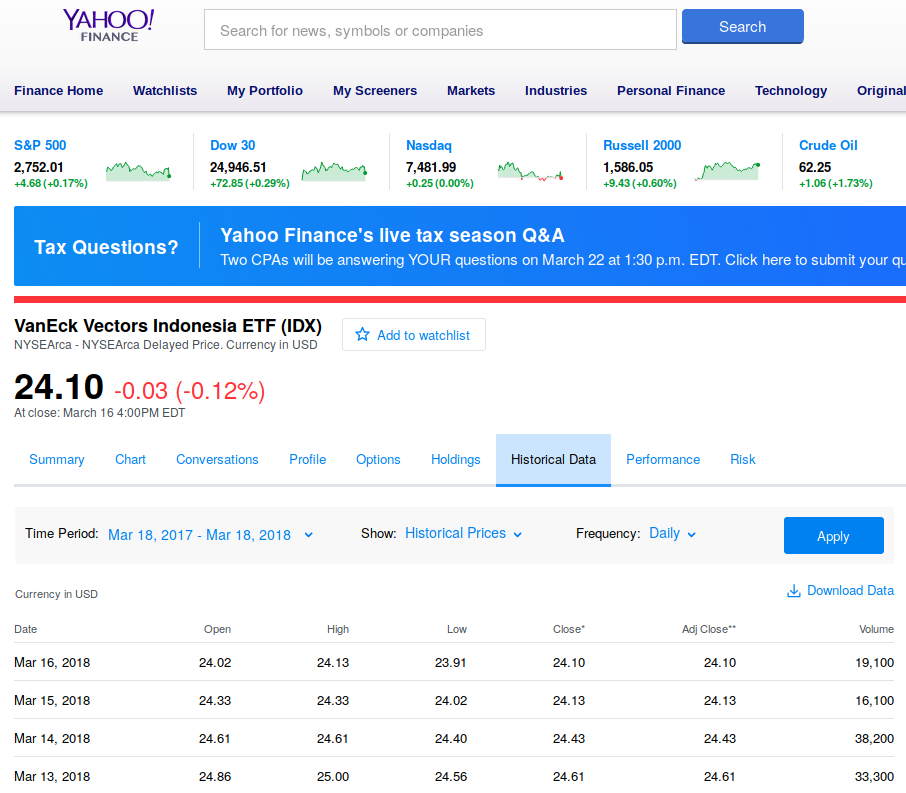
**Table 1** – List of 50 companies from Taiwan stock market, this group of companies called TW50.

|  |  |  |
| --- | --- | --- |
| No | Name | Ticker |
| 1 | Advanced Semiconductor Engineering | 2311.TW |
| 2 | Advantech | 2395.TW |
| 3 | Asia Cement | 1102.TW |
| 4 | Asustek Computer Inc | 2357.TW |
| 5 | AU Optronics | 2409.TW |
| 6 | Catcher Technology | 2474.TW |
| 7 | Cathay Financial Holding | 2882.TW |
| 8 | Chang Hwa Commercial Bank | 2801.TW |
| 9 | Cheng Shin Rubber Industry | 2105.TW |
| 10 | China Development Financial Holdings | 2883.TW |
| 11 | China Life Insurance | 2628.HK |
| 12 | China Steel | 2002.TW |
| 13 | Chunghwa Telecom | 2412.TW |
| 14 | Compal Electronics | 2324.TW |
| 15 | CTBC Financial Holding | 2891.TW |
| 16 | Delta Electronics | 2308.TW |
| 17 | E.Sun Financial Holding | 2884.TW |
| 18 | Far Eastern New Century Corporation | 1402.TW |
| 19 | Far EasTone Telecommunications | 4904.TW |
| 20 | First Financial Holding | 2892.TW |
| 21 | Formosa Chemicals & Fibre | 1326.TW |
| 22 | Formosa Petrochemical | 1301.TW |
| 23 | Formosa Plastics Corp | 1301.TW |
| 24 | Foxconn Technology | 2354.TW |
| 25 | Fubon Financial Holdings | 2881.TW |
| 26 | Hon Hai Precision Industry | 2317.TW |
| 27 | Hotai Motor | 2207.TW |
| 28 | Hua Nan Financial Holdings | 2880.TW |
| 29 | Innolux | 3481.TW |
| 30 | Largan Precision | 3008.TW |
| 31 | Lite-On Technology | 2301.TW |
| 32 | MediaTek | 2454.TW |
| 33 | Mega Financial Holding | 2886.TW |
| 34 | Nan Ya Plastics | 1303.TW |
| 35 | Nanya Technology | 2408.TW |
| 36 | Pegatron | 4938.TW |
| 37 | Pou Chen | 9904.TW |
| 38 | President Chain Store | 2912.TW |
| 39 | Quanta Computer | 2382.TW |
| 40 | Siliconware Precision Industries | 2325.TW |
| 41 | SinoPac Financial Holdings Co. Ltd. | 2890.TW |
| 42 | Taishin Financial Holdings | 2887.TW |
| 43 | Taiwan Cement | 1101.TW |
| 44 | Taiwan Cooperative Financial Holding | 5880.TW |
| 45 | Taiwan High Speed Rail | 2633.TW |
| 46 | Taiwan Mobile | 3045.TW |
| 47 | Taiwan Semiconductor Manufacturing | 2330.TW |
| 48 | Uni-president Enterprises | 1216.TW |
| 49 | United Microelectronics | 2303.TW |
| 50 | Yuanta Financial Holding | 2885.TW |

**Table 2** – List of 10 companies of Indonesia stock market

|  |  |  |
| --- | --- | --- |
| No | Name | Ticker |
| 1 | Perusahaan Perseroan (Persero) PT Telekomunikasi Indonesia Tbk | TLKM.JK |
| 2 | PT Bank Central Asia Tbk | BBCA.JK |
| 3 | PT Bank Central Asia Tbk | HMSP.JK |
| 4 | PT Bank Rakyat Indonesia (Persero) Tbk | BBRI.JK |
| 5 | PT Bank Rakyat Indonesia (Persero) Tbk | ASII.JK |
| 6 | PT Bank Mandiri (Persero) Tbk | BMRI.JK |
| 7 | PT Unilever Indonesia Tbk | UNVR.JK |
| 8 | PT Gudang Garam Tbk | GGRM.JK |
| 9 | PT Bank Negara Indonesia (Persero) Tbk | BBNI.JK |
| 10 | PT United Tractors Tbk | UNTR.JK |

In this data collection we are using application program interface (API) service from Yahoo! Finance to get historical time series data for each stock market that we are using for the dataset (Figure 1). From the time period that we have been set in the following table 3, we certainly get some trading days data, starting from Monday until Friday is the trading days period.



**Figure 1**- Yahoo! Finance website, provide an API to download historical time series data

**Table 3 -** The period time of our dataset, separated between the training and testing

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| STOCK DATA | TRAINING DATA | | TESTING DATA | |
| TW 50 | 2000/01/01 | 2016/12/31 | 2017/01/01 | 2018/06/14 |
| ID 10 | 2000/01/01 | 2016/12/31 | 2017/01/01 | 2018/06/14 |

Segregation of data based on predetermined time for data training and data testing is important, where some studies make mistakes by scrambling data, this is certainly fatal because the data we use is time-series.

## 2.2. Feature Investigation

The data we get from the data collection is in the form of time-series data. This time series of data contains several elements in daily stock market activity. Some of these elements are open price, close price, high price, low price and volume. The element can be said as feature set, where we will describe one by one feature set.

### 2.2.1. Opening Price

Opening price is the first price in daily activity of the stock market that is noted when the stock market is open in the specified time period. In this case for example Taiwan stock market and Indonesian stock market will open at 09:00.

The price of the first trade for any listed stock is its daily opening price. There are several day-trading strategies based on the opening of a market. Gap Fade and Fill. "Traders attempt to profit from the price correction that usually takes place subsequent to a sizable price gap at the opening. Another popular strategy is to fade a stock at the open that is showing strong pre-market indication contrary to the rest of the market, or to similar stocks in a common sector or index.

### 2.2.2. Closing Price

The closing price is the final price at which a security is traded on a given trading day. The closing price represent the most up-to-date valuation of a security until trading commences on the next trading day. Taiwan stock market close precisely at 3:00 p.m. while Indonesian stock market will be close precisely at 4:00 p.m.

Closing prices do not reflect corporate actions, which may skew returns significantly. For example, on June 9, 2014, Apple Inc. (NASDAQ: AAPL) issued a seven-for-one stock split. Therefore, Apple's shares outstanding was increased by a multiple of seven, while its closing share price was divided by seven. On June 6, 2014, prior to Apple's stock split, it had a closing price of $ 645.57 per share. After Apple's seven-for-one stock split, the stock had a closing price of $ 93.70 per share on June 9, 2014. Since the closing price does not include adjustments for corporate actions, the calculation of Apple's returns based on closing prices would have indicated a return of -85.49%, or ($ 93.70 - $ 645.56) / $ 645.57, in just one trading day.

### 2.2.3. Highest Price

High price or today’s high is the highest price at which a stock traded during the course of the day. Today’s high is typically higher than the closing or opening price. More often than not this is higher than the closing price.

When you look at a stock quote, you can find today's high by looking at the second number listed next to "Range." One way that day traders and technical analysts use today's high, along with today's low, is to help them identify gaps or sudden jumps up or down in a stock's price with no trading in between those two prices. For example, if today's low is $25 and the previous day's high is $20, there is gap. The identification of a gap, along with other market signals such as changes in trading volume and overall bullish or bearish sentiment, helps market analysts generate buy and sell signals for particular stocks.

### 2.2.4. Lowest Price

Today’s low or low price is the lowest price at which a stock trades over the course of a trading day. Today’s low is typically lower than the opening or closing price.

When you look at a stock quote, you can find today's low by looking at the first number listed next to "Range." Today's low and today's high are important to day traders and technical analysts, who seek to earn profits from a security's short-term price movements and identify and track trends. One way that day traders use today's low along with today's high is to identify gaps, or sudden jumps up or down in a stock's price with no trading in between. Gaps are used in technical analysis to identify directional movement, average true range/price volatility, candlestick patterns and more. Traders then analyze these patterns to determine profitable entry and exit points.

### 2.2.5. Volume

Volume is the number of shares or contracts traded in a security or an entire market during a given period of time.

For every buyer, there is a seller, and each transaction contributes to the count of total volume. That is, when buyers and sellers agree to make a transaction at a certain price, it is considered one transaction. If only five transactions occur in a day, the volume for the day is five.

Volume is an important indicator in technical analysis as it is used to measure the relative worth of a market move. If the markets make a strong price movement, then the strength of that movement depends on the volume for that period. The higher the volume during the price move, the more significant the move.

## 2.3. Data Preprocessing

We are processing our time series data using library matplotlib in python programming to convert from the historical data that we have prepared into a candlestick chart. We divide the time period which used to create candlestick chart based on 5 days trading data, 10 days trading data and also 20 days trading data.

The amount of data that can be different because we will only make a candlestick chart that qualifies based on the time period that we have set in the following table 4.

**Table 4** – Number of dataset following their period of trading days

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 5 PERIOD | | 10 PERIOD | | 20 PERIOD | |
| sTOCK dATA | TRAINING | TESTING | TRAINING | TESTING | TRAINING | TESTING |
| tw 50 | 198569 | 17164 | 198151 | 16950 | 197819 | 16414 |
| id 10 | 34350 | 3611 | 34232 | 3582 | 34233 | 3482 |

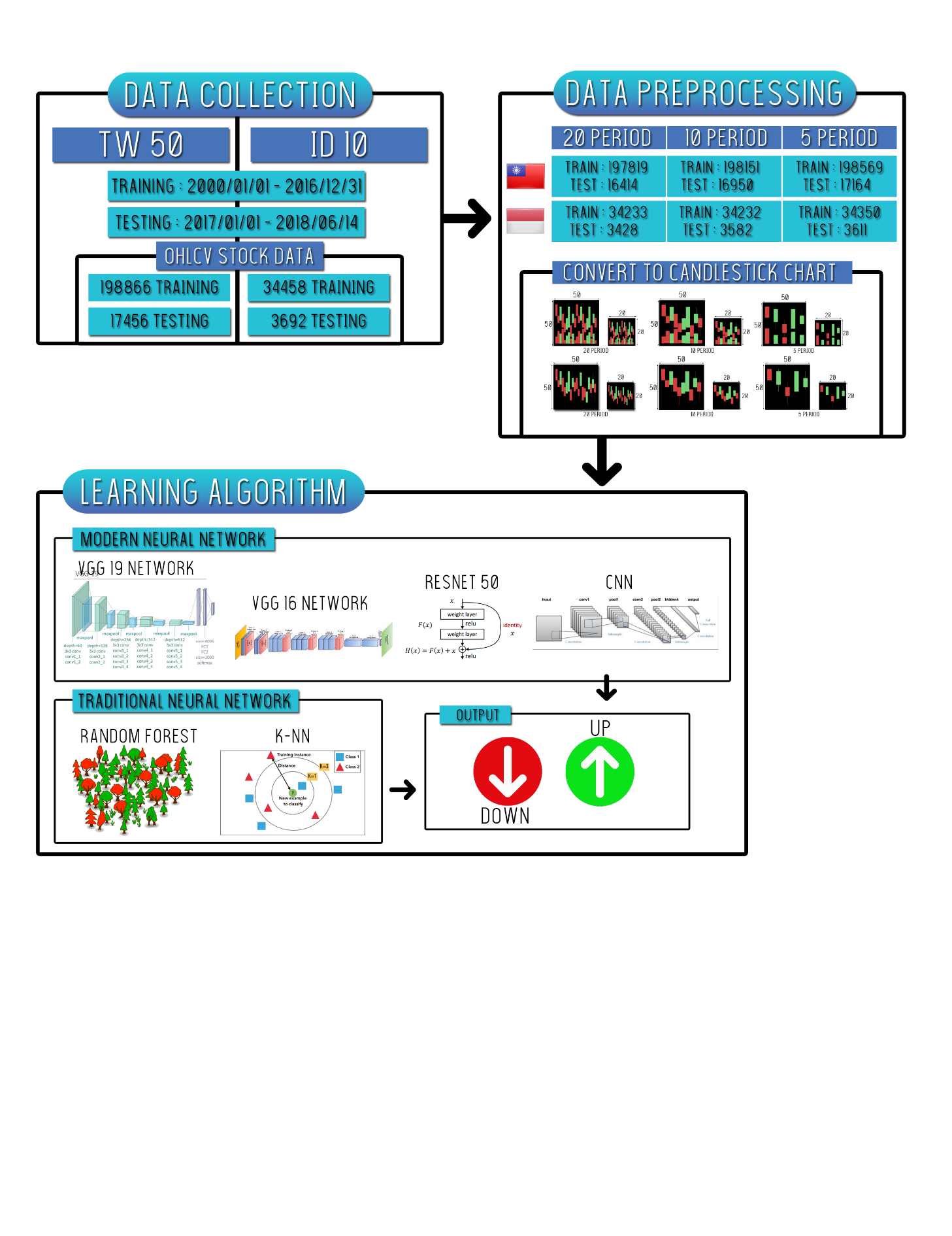
Besides the period time, we also divided our candlestick chart with and without volume indicator. The general candlestick chart usually only consists of time series data such as open price, close price, low price and high price (figure.2). Adding a volume indicator into candlestick chart is one of our parameter to find out correlation between enrich candlestick chart information and prediction result.



**Figure 2** - General way to visualizing the candlestick chart

The proposition of positive and negative dataset on training and testing can be good s

# Chapter 3 Methodology



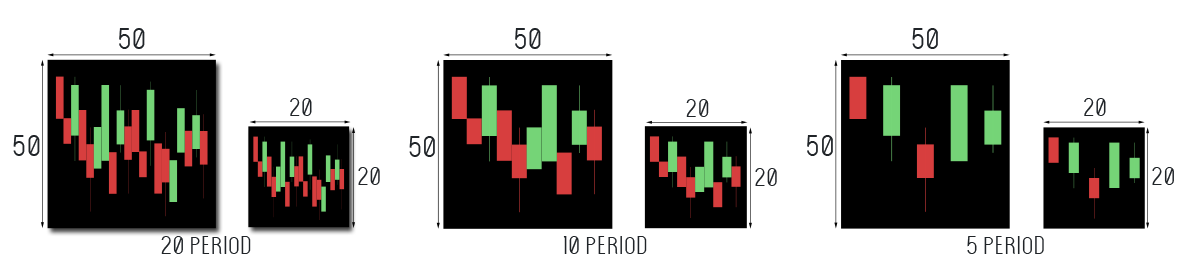
**Figure 3** – Our methodology design

Those figure below (Figure 3), shows about the design architecture of our proposed stock market prediction. The process is started with collecting data using Yahoo! Finance API and then using sliding window to generate the period data before using computer graphic technique to create candlestick chart images.

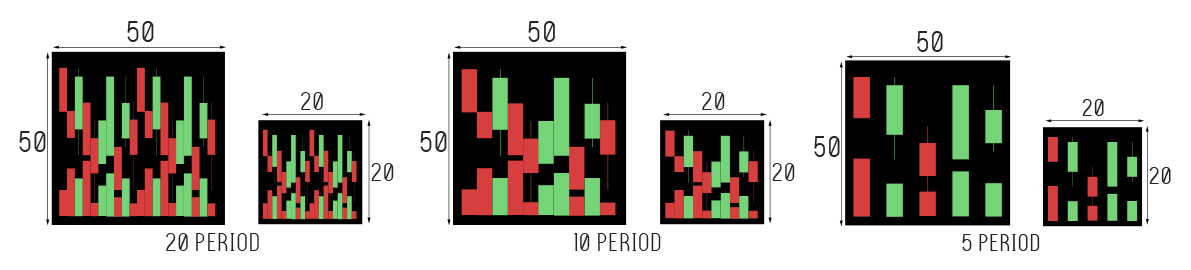
## 3.1. Chart Encoding

Candlestick chart show that emotion by visually representing the size of price moves with different colors. Traders use the candlestick chart to make trading decision based on regularly occurring patterns that help forecast the short-term direction of the price. Just like a bar chart, a candlestick chart shows the stock market’s open price, high, low, and close price during those period time. The candlestick chart has a wide part, which is called body, the body represents the price range between the open and close of that day’s trading. When the body is filled in red, it means the close was lower than the open price. If the body is filled in green, it means the close was higher than the open price.

We use computer graphics techniques with the help of a python library called Matplotlib(Hunter 2007) to convert this time series data into a candlestick image 50x50 and 20x20 dimension with RGB.

****Figure 4 describe our candlestick chart representation with volume whether figure 5 describe our candlestick chart without volume.

**Figure 4** – Proposed candlestick chart without volume indicator with different period time and size.

**Figure 5** - Proposed candlestick chart with volume indicator with different period time and size.

We are using black color as our candlestick chart background, and then for each candlestick chart we are using green color for indicator if its closing price is higher than open price, and red color if its closing price is lower than opening price.

## 3.2. Binary Classification

Our goal here is to perform binary classification of stock market movements using candlestick chart. Where we will use the value of "1" as an indicator that there is an increase or closing price will rise in the future with t = n + 1, while "0" is the opposite, if the closing price will decrease in the future. The diagram for making this label is available in figure 5.



**Figure 6** - Logic statement of our binary classification

## 3.3. Convolutional Neural Network

Convolutional Neural Networks are very similar to ordinary Neural Networks from the previous chapter: they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity.

The whole network still expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other. And they still have a loss function (e.g. SVM/Softmax) on the last (fully-connected) layer and all the tips/tricks we developed for learning regular Neural Networks still apply.

### 3.3.1. CNN Architecture Overview

In figure 6, Neural Networks receive an input (a single vector), and transform it through a series of hidden layers. Each hidden layer is made up of a set of neurons, where each neuron is fully connected to all neurons in the previous layer, and where neurons in a single layer function completely independently and do not share any connections. The last fully-connected layer is called the “output layer” and in classification settings it represents the class scores.



**Figure 7** - A regular 3-layer Neural Network

### 3.3.2. Residual Network

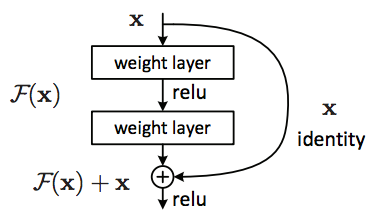
Developed by Kaiming He et al. was the winner of ILSVRC 2015. It features special skip connections and a heavy use of batch normalization. The architecture is also missing fully connected layers at the end of the network.



**Figure 8** – ResNet Architecture shows many layers for different configuration

As per what we have seen so far, increasing the depth should increase the accuracy of the network, as long as overfitting is taken care of. But the problem with increased depth is that the signal required to change the weights, which arises from the end of the network by comparing ground-truth and prediction becomes very small at the earlier layers, because of increased depth. It essentially means that earlier layers are almost negligible learned. This is called vanishing gradient.

The second problem with training the deeper networks is, performing the optimization on huge parameter space and therefore naively adding the layers leading to higher training error. Residual networks allow training of such deep networks by constructing the network through modules called residual models as shown in the figure 8. This is called degradation problem.



**Figure 9** - Residual learning: a building block

By comparing with other CNNs architecture, residual network have been prove with the most minimum error rate according to table 3.

**Table 5** - Residual Network proved that this network have the most minimum error-rate

|  |  |  |  |
| --- | --- | --- | --- |
| Year | CNN | Developed by | Top-5-error-rate |
| 2012 | AlexNet | Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever | 15.3 % |
| 2013 | ZFNet | Matthew Zeller, Rob Fergus | 14.8 % |
| 2014 | GoogLeNet | Google | 6.67 % |
| 2014 | VGG Net | Simonyan, Zisserman | 7.3 % |
| 2015 | ResNet | Kaiming He | 3.57 % |

### 3.3.3 VGG Network

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

### 3.3.4 Random Forest

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

## 3.4. Performance Evaluation

There are some statistical measure of the performance evaluation to evaluate the result of all the classifiers (binary classification test) by measuring the sensitivity (true positive rate or recall), specificity (true negative rate), accuracy and Matthew's correlation coefficient (MCC) for each class of efflux protein families. In general, TP is true positive or correctly identified, FP is false positive or incorrectly identified, TN is true negative or correctly rejected and FN is false negative or incorrectly rejected. Formulated as follows:

Sensitivity is called true positive rate or recall measures the performance of positives data are correctly identified.

Otherwise, to measure the proposition of negative rate the specificity formula is used during the prediction result and performance all classifiers.

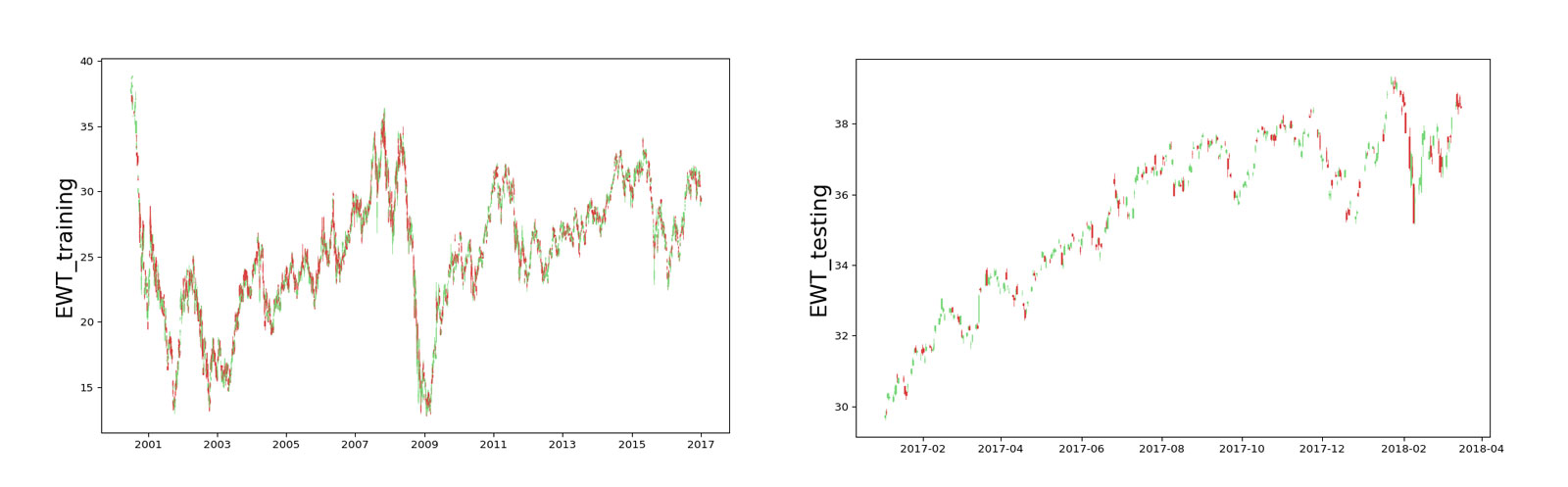
The accuracy formula measures the quality all classifiers with based on the true value or maximum predicted values compared with measurement results.

Then, Matthews’s correlation coefficient or MCC is used to predict binary (two class) classifications and focus on the quality of predicted binary. During the prediction results MCC returns a value between -1 and +1. If the correlation value closer to +1 indicates perfect prediction, and otherwise if the correlation value closer to -1 indicates total disagreement between prediction and observation.

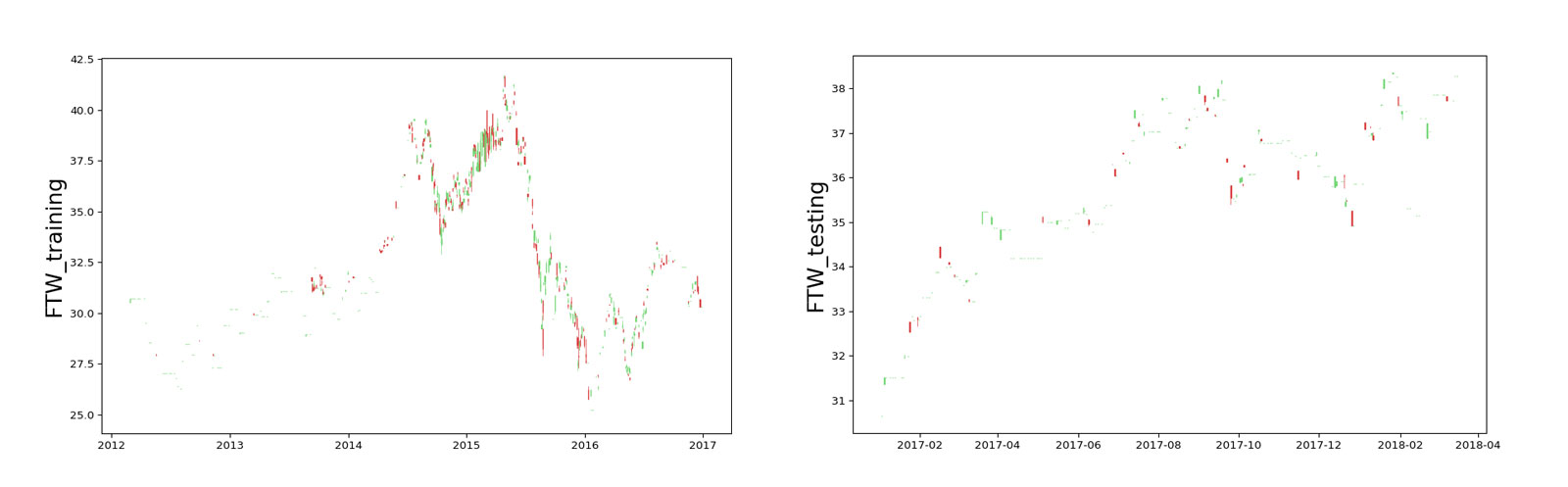
# Chapter 4 Experimental Results

## 4.1. Analysis Data

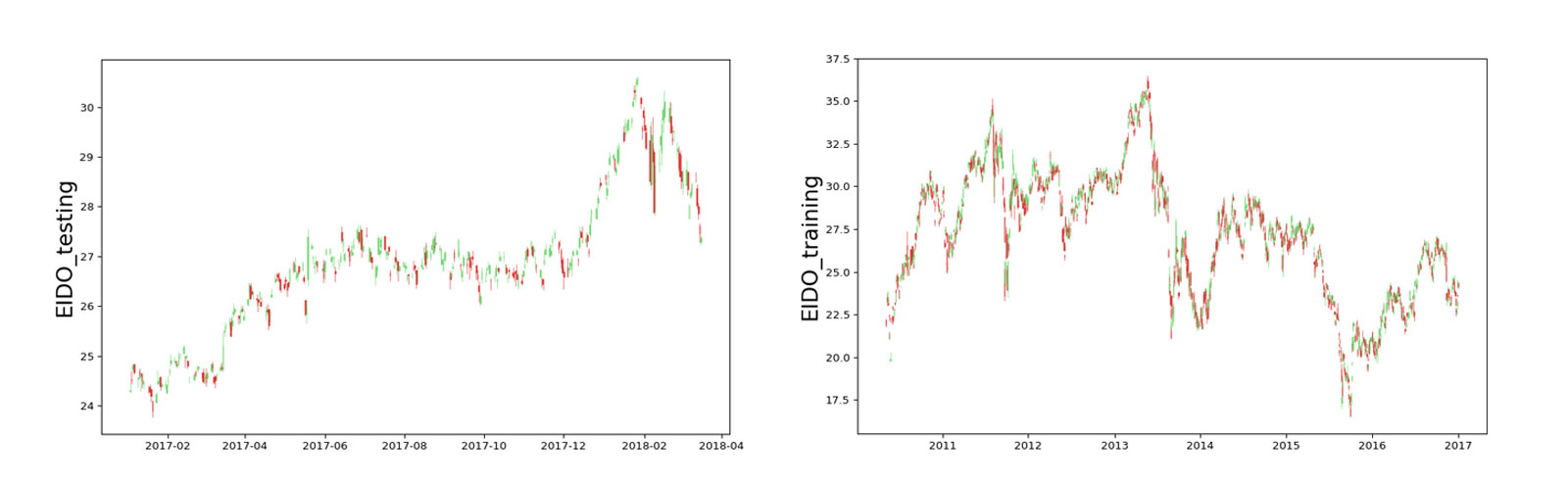
Since we have a different stock market time series data sources, we would like to visualizing the fully candlestick chart with all of the time span duration. This a whole candlestick chart should help us to understand our time series data behavior.



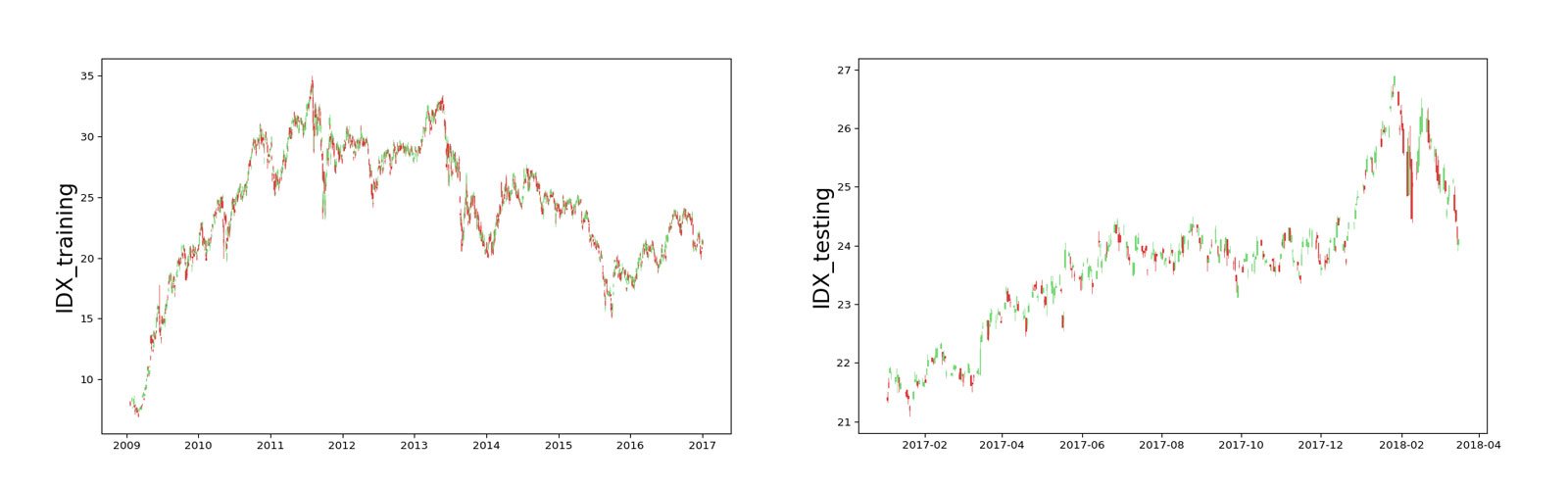
**Figure 10** – EWT from Taiwan stock market, candlestick chart for training and testing data



**Figure 11** – FTW from Taiwan stock market, candlestick chart for training and testing data



**Figure 12** – EIDO a stock market from Indonesia, candlestick chart for training and testing data



**Figure 13** – IDX a stock market from Indonesia, candlestick chart for training and testing data

In the data which we visualized, it can be seen that there are some parts that may affect the quality of the prediction. Recalling that a successful prediction with reliable results is one of the major factors of the dataset.

## 4.2. Classification for Each Stock Market

In this study we try to make stock market predictions by using binary classification. Where the value 1 on the label means there is a price increase on the next day, while the value 0 is the reverse of it.

We try to apply this binary classification to each stock market data we have prepared. There are four sources of stock market data we use. We also divide the retrieval period based on the duration of the five days, ten days and also twenty days of trading days to create a sequence of sliding windows that will be converted to candlestick chart. Here is a table of results from binary classification predictions that we do with CNN architecture more precisely residual network.

**Table 6** – Result from ResNet 50 for all stock market period days

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | | 5 PERIOD | | | | 10 PERIOD | | | | 20 PERIOD | | | |
|  | EWT | FTW | EIDO | | IDX | EWT | FTW | | EIDO | IDX | EWT | | FTW | EIDO | IDX |
| Acc | 92.90% | 84.80% | 78.80% | | 82.00% | 90.80% | 87.40% | | 81.90% | 84.00% | 82.20% | | 86.20% | 81.90% | 81.50% |
| Spec | 90.60% | 78.30% | 73.50% | | 77.70% | 86.50% | 88.50% | | 77.80% | 80.20% | 80.50% | | 86.80% | 81.90% | 78.60% |
| Sens | 93.90% | 88.70% | 81.60% | | 84.10% | 93.40% | 86.50% | | 85.00% | 86.60% | 83.40% | | 85.70% | 81.90% | 84.30% |
| MCC | 83.50% | 67.40% | 54.20% | | 60.50% | 80.30% | 74.40% | | 63.00% | 66.90% | 63.60% | | 72.50% | 63.70% | 63.10% |

**Table 7** – Result from ResNet 101 for all stock market period days

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | | 5 PERIOD | | | | 10 PERIOD | | | | 20 PERIOD | | | |
|  | EWT | FTW | EIDO | | IDX | EWT | FTW | | EIDO | IDX | EWT | | FTW | EIDO | IDX |
| Acc | 92.90% | 84.80% | 78.80% | | 82.00% | 90.80% | 87.40% | | 81.90% | 84.00% | 82.20% | | 86.20% | 81.90% | 81.50% |
| Spec | 90.60% | 78.30% | 73.50% | | 77.70% | 86.50% | 88.50% | | 77.80% | 80.20% | 80.50% | | 86.80% | 81.90% | 78.60% |
| Sens | 93.90% | 88.70% | 81.60% | | 84.10% | 93.40% | 86.50% | | 85.00% | 86.60% | 83.40% | | 85.70% | 81.90% | 84.30% |
| MCC | 83.50% | 67.40% | 54.20% | | 60.50% | 80.30% | 74.40% | | 63.00% | 66.90% | 63.60% | | 72.50% | 63.70% | 63.10% |

**Table 8** – Result from ResNet 152 for all stock market period days

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | | 5 PERIOD | | | | 10 PERIOD | | | | 20 PERIOD | | | |
|  | EWT | FTW | EIDO | | IDX | EWT | FTW | | EIDO | IDX | EWT | | FTW | EIDO | IDX |
| Acc | 92.90% | 84.80% | 78.80% | | 82.00% | 90.80% | 87.40% | | 81.90% | 84.00% | 82.20% | | 86.20% | 81.90% | 81.50% |
| Spec | 90.60% | 78.30% | 73.50% | | 77.70% | 86.50% | 88.50% | | 77.80% | 80.20% | 80.50% | | 86.80% | 81.90% | 78.60% |
| Sens | 93.90% | 88.70% | 81.60% | | 84.10% | 93.40% | 86.50% | | 85.00% | 86.60% | 83.40% | | 85.70% | 81.90% | 84.30% |
| MCC | 83.50% | 67.40% | 54.20% | | 60.50% | 80.30% | 74.40% | | 63.00% | 66.90% | 63.60% | | 72.50% | 63.70% | 63.10% |

# Chapter 5 Conclusion and Future Works

After doing some experiments to do the stock market prediction, among other experiments it is using several different data periods. The data period is five days trading data, ten days trading data, and also twenty days trading data. In addition we also use some kind of residual network that is distinguished by the number of layers in our architecture. Among other is the residual network with the number 50 layers, one 101 layers, and also 152 layers. With some experiments, the conclusion with the best result is X. It shows that experiment with X can produce X.

Given that the results may not be satisfactory enough, for the future we want to try to improve those results and also add features to this research. Using candlestick chart image on input data is new, the possibility of doing more research on image processing handling will further improve prediction results. To make it easier for readers other than the source code available in github, the possibility of building a web server would be great.

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