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資 訊 工 程 學 系

碩 士 論 文

Using Deep Learning Neural Networks and Candlestick Chart Representation to Predict Stock Market

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ABSTRACT

Stock market prediction is still a challenging problem because there are many factors effect to the stock market price such as company news and performance, industry performance, investor sentiment, social media sentiment and economic factors. This work explores the predictability in the stock market using Deep Convolutional Network and candlestick charts. The outcome is utilized to design a decision support framework that can be used by traders to provide suggested indications of future stock price direction. We perform this work using various types of neural networks like convolutional neural network, residual network and visual geometry group network. From stock market historical data, we converted it to candlestick charts. After that, these candlestick charts will be feed as input for training a Convolution neural network model. This Convolution neural network model will help us to analyze the patterns inside the candlestick chart and predict the future movements of stock market. Using Taiwan 50 and Indonesian 10 stock market historical time series data we can achieve a promising results- 92.2 % and 92.1 % accuracy for Taiwan and Indonesia stock market respectively. Our performance results significantly outperform the existing methods.

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

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Chapter 1
Introduction

1.1. Background

The stock market is something that cannot be separated from modern human life. The 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. Therefore, an accurate prediction for the trends in the stock market prices in order to maximize capital gain and minimize loss is urgent demand. Besides, stock market prediction is still a challenging problem because there are many factors effect to the stock market price such as company news and performance, industry performance, investor sentiment, social media sentiment and economic factors. According to Fama's efficient market hypothesis, argued that stocks always trade at their fair value, making it impossible for investors to either purchase undervalued stocks or sell stocks for inflated prices[1]. As such, it should be impossible to outperform the overall market through expert stock selection or market timing, and that the only way an investor can possibly obtain higher returns is by chance or by purchasing riskier investments. With the current technological advances, machine learning is a breakthrough in aspects of human life today and deep neural network has shown potential in many research fields. In this research, we apply different types of machine learning algorithms to enhance our performance result for stock market prediction using convolutional neural network, residual network, virtual geometry group network, k-nearest neighborhood and random forest.

Dataset format in machine learning can be different. 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, the image is used not only as input for image classification, but also as an input to predict a condition. We take the example of Google DeepMind in their research in Alpha Go[2]. 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.

On the other occasion, from historical data of stock market converted into audio wavelength using deep convolutional wave net architecture can be applied to forecast the stock market movement[3].

Our proposed method in this work is using a candlestick chart from Taiwan and Indonesia stock market to predict the price movement. We utilized three trading period times to analyze the correlation between those period times 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 sizes (i.e. 50 and 20 dimension) for candlestick chart to analyze the correlation of hidden pattern in various image size. Thereafter our dataset will be feed as input for several learning algorithms of random forest and k-nearest neighborhood as traditional machine learning, CNN, residual network and VGG network as our modern machine learning. The goal is to analyze the correlation of some parameters such as period time, image size, feature set with the movement of stock market to check whether it will be going up or going down in the next day.

1.1.1 Candlestick Chart

Candlestick chart is a style of financial chart used to describe the price movements for a given period of time. Candlestick chart is also called a Japanese candlestick chart because it has been developed in the 18th century by Munehisa Hooma, a Japanese rice trader of financial instruments [4]. Each candlestick typically shows one day of trading data, thus a month chart may show the 20 trading days as 20 candlestick charts. Candlestick chart is like a combination of line-chart and a bar-chart, while each bar represents all four important pieces of information for that trading day. It consists of the open, the close, the high and low price.

Candlesticks are usually composed of the real body, an upper and a lower shadow. If the opening price is higher than the closing price, then the real body will filled by red or black color. Otherwise, the real body will be drawn with green or white color. The upper and a lower shadow represent the high and low price ranges within a specified time period. However, not all candlesticks have a shadow. The Figure 1 given clear explanation about real body and the shadows in candlestick.

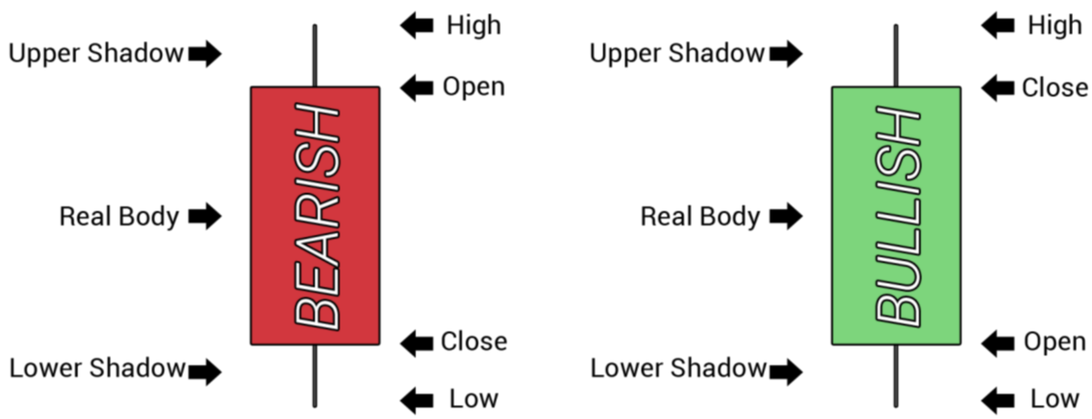


Figure 1 – Candlestick formation of bearish and bullish.

Candlestick chart are a visual aid for decision making in stock exchange. Each candlestick provides an easy-to-decipher picture of price action. Immediately a trader can compare the relationship between the open and close as well as the high and low. The relationship between the open and close is considered vital information and forms the essence of candlesticks. Bullish candlesticks, where the close is greater than the open, indicate buying pressure. Bearish candlesticks, where the close is less than the open, indicate selling pressure. It serves as a cornerstone of technical analysis. The main usage of a candlestick patterns is to identify trends. Looking at a candlestick, one can identify an asset's opening and closing prices, highs and lows, and overall range for a specific time frame[5].

1.1.2 Candlestick Pattern

In technical analysis, a candlestick pattern is a movement in prices shown graphically on a candlestick chart that some believe can predict a particular market movement. The recognition of the pattern is subjective and programs that are used for charting have to rely on predefined rules to match the pattern. Forty-one recognized patterns categorized into simple and complex patterns shown in Table 1 and Table 2 respectively.

Table 1 – Simple candlestick patterns

No	Name	Description
1	Big Black Candle	It has an unusually long black/red body with a wide range between high and low. Prices open near the high and close near the low. Considered as **bearish** pattern
2	Big White Candle	It has an unusually long white/green body with a wide range between high and low of the day. Prices open near the low and close near the high. Considered a **bullish** pattern.
3	Black Body	Formed when the opening price is higher than the closing price. Considered to be a **bearish** signal.
4	Doji	Formed when opening and closing prices are virtually the same. The lengths of shadows can vary.
5	Dragonfly Doji	Formed when the opening and the closing prices are at the highest of the day. If it has a longer lower shadow it signals a more **bullish** trend. When appearing at market bottoms it is considered to be a reversal signal.
6	Gravestone Doji	Formed when the opening and closing prices are at the lowest of the day. If it has a longer upper shadow it signals a **bearish** trend. When it appears at market top it is considered a reversal signal.
7	Long-Legged Doji	It consists of a Doji with very long upper and lower shadows. Indicates strong forces balanced in opposition.
8	Hanging Man	It consists of a small body near the high with a little or no upper shadow and a long lower tail. The lower tail should be two or three times the height of the body. Considered a **bearish** pattern during an uptrend.
9	Hammer	It consists of a small body near the high with a little or no upper shadow and a long lower tail. Considered a **bullish** pattern during a downtrend.
10	Inverted Black Hammer	A black/red body in an upside-down hammer position. Usually considered a bottom reversal signal.
11	Inverted Hammer	Candlestick in an upside-down hammer position.
12	Long Lower Shadow	Candlestick is formed with a lower tail that has a length of 2/3 or more of the total range of the candlestick. Normally considered a **bullish** signal when it appears around price support levels.
13	Long Upper Shadow	Candlestick with an upper shadow that has a length of 2/3 or more of the total range of the candlestick. Normally considered a **bearish** signal when it appears around price resistance levels.
14	Marubozu	A long or a normal candlestick with no shadow or tail. The high and the lows represent the opening and the closing prices. Considered a continuation pattern.
15	Shooting Star	Candlestick that has a small body, a long upper shadow and a little or no lower tail. Considered a **bearish** pattern in an uptrend.

16	Spinning Top	Candlestick with a small body. The size of shadows can vary. Interpreted as a neutral pattern but gains importance when it is part of other formations.
17	White Body	It formed when the closing price is higher than the opening price and considered a **bullish** signal.
18	Shaven Bottom	Candlestick with no lower tail. [Compare with Inverted Hammer.]
19	Shaven Head	Candlestick with no upper shadow. [Compared with hammer.]

Table 2 – Complex candlestick patterns

No	Name	Description
1	Bearish Harami	It consists of an unusually large white body followed by a small black body (contained within large white body). It is considered as a **bearish** pattern when preceded by an uptrend.
2	Bearish Harami Cross	A large white body followed by a Doji. Considered as a reversal signal when it appears at the top.
3	Bearish 3-Method Formation	A long black body followed by three small bodies (normally white) and a long black body. The three white bodies are contained within the range of first black body. This is considered as a **bearish** continuation pattern.
4	Bullish 3-Method Formation	Consists of a long white body followed by three small bodies (normally black) and a long white body. The three black bodies are contained within the range of first white body. This is considered as a **bullish** continuation pattern.
5	Bullish Harami	Consists of an unusually large black body followed by a small white body (contained within large black body). It is considered as a **bullish** pattern when preceded by a downtrend.
6	Bullish Harami Cross	A large black body followed by a Doji. It is considered as a reversal signal when it appears at the bottom.
7	Dark Cloud Cover	Consists of a long white candlestick followed by a black candlestick that opens above the high of the white candlestick and closes well into the body of the white candlestick. It is considered as a **bearish** reversal signal during an uptrend.
8	Engulfing Bearish Line	Consists of a small white body that is contained within the followed large black candlestick. When it appears at top it is considered as a major reversal signal.
9	Engulfing Bullish	Consists of a small black body that is contained within the followed large white candlestick. When it appears at bottom it is interpreted as a major reversal signal.
10	Evening Doji Star	Consists of three candlesticks. The first candlestick is a large white body candlestick followed by a Doji that gap above the white body. The third candlestick is a black body that closes well into the white body. When it appears at the top it is considered as a reversal signal. It signals

		more bearish trend than the evening star pattern because of the doji that has appeared between the two bodies.
11	Evening Star	Consists of a large white body candlestick followed by a small body candlestick (black or white) that gaps above the previous. The third is a black body candlestick that closes well within the large white body. It is considered as a reversal signal when it appears at top level.
12	Falling Window	A window (gap) is created when the high of the second candlestick is below the low of the preceding candlestick. It is considered that the window should be filled with a probable resistance.
13	Morning Doji Star	Consists of a large black body candlestick followed by a Doji that occurred below the preceding candlestick. On the following day, a third white body candlestick is formed that closed well into the black body candlestick which appeared before the Doji. It is considered as a major reversal signal that is more bullish than the regular morning star pattern because of the existence of the Doji.
14	Morning Star	Consists of a large black body candlestick followed by a small body (black or white) that occurred below the large black body candlestick. On the following day, a third white body candlestick is formed that closed well into the black body candlestick. It is considered as a major reversal signal when it appears at bottom.
15	On Neckline	In a downtrend, consists of a black candlestick followed by a small body white candlestick with its close near the low of the preceding black candlestick. It is considered as a bearish pattern when the low of the white candlestick is penetrated.
16	Three Black Crows	Consists of three long black candlesticks with consecutively lower closes. The closing prices are near to or at their lows. When it appears at top it is considered as a top reversal signal.
17	Three White Soldiers	Consists of three long white candlesticks with consecutively higher closes. The closing prices are near to or at their highs. When it appears at bottom it is interpreted as a bottom reversal signal.
18	Tweezer Bottoms	Consists of two or more candlesticks with matching bottoms. The candlesticks may or may not be consecutive and the sizes or the colors can vary. It is considered as a minor reversal signal that becomes more important when the candlesticks form another pattern.
19	Tweezer Tops	Consists of two or more candlesticks with matching tops. The candlesticks may or may not be consecutive and the sizes or the colors can vary. It is considered as a minor reversal signal that becomes more important when the candlesticks form another pattern.
20	Doji Star	Consists of a black or a white candlestick followed by a Doji that gap above or below these. It is considered as a reversal signal with confirmation during the next trading day.
21	Piercing Line	Consists of a black candlestick followed by a white candlestick that opens lower than the low of preceding but closes more than halfway into black body candlestick. It is considered as reversal signal when it appears at bottom.

22	Rising Window	A window (gap) is created when the low of the second candlestick is above the high of the preceding candlestick. It is considered that the window should provide support to the selling pressure.

1.2. Related work

There are many researchers have been started to develop the computational tool for the stock market prediction. Schöneburg conducted a study using data from a randomly selected German stock market, then using the back-propagation method for their machine learning architecture[6]. To our knowledge, stock market data consist of open price data, close price data, high price data, low price data and volume of the daily movement activity. In addition, to use the 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. used their sentiment analysis method by taking data from one of the famous microblogging site Twitter to predict the Dow Jones Industrial Average (DJIA) stock market movements[7]. There are more studies on stock market predictions; they not only using input data format from elements of historical time series data, but also processing the input 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[3].

We also found some related works using candlestick charts in their research. Do Prado, Ferneda et al. used the candlestick chart to learn the pattern contained in Brazilian stock market by using sixteen candlestick patterns[8]. Tsai and Quan utilized the candlestick chart to combine with seven different wavelet-based textures to analyze the candlestick chart[9]. While, Hu, Hu et al.used the candlestick chart to build a decision-making system in stock market investment. They used the convolutional encoder to learn the patterns contained in the candlestick chart[10].

Patel, Shah et al. used ten technical parameters from stock trading data for their input data and compare four prediction models, Artificial Neural Network (ANN), Support Vector Machine (SVM), random forest and naïve-Bayes[11]. Traditional machine learning like Random Forest has been applied to predict the stock market with a good result. Khaidem, Saha et al. combine the Random Forest with technical indicator such as Relative Strength Index (RSI) shown a good performance[12]. Adding more feature set can be one of the way to enrich your dataset and enhance the result of classification. According to Zhang, Zhang et al. input data not only from historical stock trading data, a financial news and users' sentiments from social media can be correlated to predict the movement in stock market[13].

Different from most of existing studies that only consider stock trading data, news events or sentiments in their models, our proposed method utilized a representation of candlestick chart images to analyze and predict the movement of stock market with a novel to compare modern and traditional neural network.

Chapter 2
Data Collection

2.1. Data Collection using Yahoo! Finance

Getting the right data in the right format is very important in machine learning because it will help our learning system go to the right way and achieve a good result. Getting the right data means gathering or identifying the data that correlates with the outcomes you want to predict; i.e. data that contains a signal about events which you care about. The data needs to be aligned with the problem you are trying to solve. Example, the Kitten pictures are not very useful when you are building a facial identification system. A data scientist must do verifying that the data is aligned with the problem you are seeking to solve. If you do not have the right data, then your efforts to build an AI solution must return to the data collection stage.

Deep learning and machine learning more generally, needs a good training set to work properly. Collecting and constructing the training set – a sizable body of known data – takes time and domain-specific knowledge of where and how to gather relevant information. The training set acts as the benchmark against which deep-learning nets are trained. That is what they learn to reconstruct before they are unleashed on data which they have not seen before.

We trained and evaluated our model on two different stock markets, i.e. Taiwan and Indonesia. We collected 50 company stock markets for Taiwan and 10 company stock markets for Indonesia based on their growth in technical analysis as a top stock market. The data statistics of two above datasets of 50 Taiwan company stock markets and 20 Indonesia company stock markets are shown in Table 3 and Table 4 respectively.

Table 3 – List of 50 companies from Taiwan stock market taken on March 17th 2018, this group of companies called TW50. Currency value using Taiwan dollar.

No	Name	Ticker	Volume	52 Week Range
1	Advanced Semiconductor Engineering	2311.TW	86,190,484	44.15 - 46.10
2	Advantech	2395.TW	1,174,771	187.00 - 239.00
3	Asia Cement	1102.TW	6,401,159	26.10 - 36.15
4	Asustek Computer Inc	2357.TW	736,167	241.00 - 301.50

5	AU Optronics	2409.TW	43,954,252	11.60 - 14.45
6	Catcher Technology	2474.TW	5,926,206	276.50 - 399.00
7	Cathay Financial Holding	2882.TW	11,747,984	47.60 - 56.80
8	Chang Hwa Commercial Bank	2801.TW	3,636,570	16.10 - 18.10
9	Cheng Shin Rubber Industry	2105.TW	5,879,979	43.95 - 65.50
10	China Development Financial Holdings	2883.TW	35,958,075	8.71 - 11.70
11	China Life Insurance	2823.TW	4,618,403	28.10 - 33.30
12	China Steel	2002.TW	7,224,897	23.20 - 25.95
13	Chunghwa Telecom	2412.TW	5,586,401	101.50 - 115.00
14	Compal Electronics	2324.TW	11,083,265	18.75 - 22.90
15	CTBC Financial Holding	2891.TW	15,959	60.40 - 62.00
16	Delta Electronics	2308.TW	4,494,421	98.30 - 165.50
17	E.Sun Financial Holding	2884.TW	20,970,56	17.70 - 21.9
18	Far Eastern New Century Corporation	1402.TW	10,601,923	23.85 - 32.95
19	Far EasTone Telecommunications	4904.TW	5,178,396	70.20 - 79.40
20	First Financial Holding	2892.TW	5,878,114	18.65 - 21.10
21	Formosa Chemicals & Fibre	1326.TW	4,412,919	89.10 - 124.00
22	Formosa Petrochemical	6505.TW	1,704,984	101.50 - 131.00
23	Formosa Plastics Corp	1301.TW	8,386,377	88.70 - 113.50
24	Foxconn Technology	2354.TW	2,351,570	71.60 - 102.00
25	Fubon Financial Holdings	2881.TW	7,478,484	45.10 - 55.10
26	Hon Hai Precision Industry	2317.TW	36,224,415	79.50 - 122.50
27	Hotai Motor	2207.TW	488,891	260.00 - 388.00
28	Hua Nan Financial Holdings	2880.TW	4,124,287	16.40 - 18.10
29	Innolux	3481.TW	27,146,129	10.80 - 16.30
30	Largan Precision	3008.TW	1,092,062	3,000.00 - 6,075.00
31	Lite-On Technology	2301.TW	6,226,617	35.80 - 53.00
32	MediaTek	2454.TW	3,278,038	248.50 - 374.50
33	Mega Financial Holding	2886.TW	7,585,128	23.35 - 27.50
34	Nan Ya Plastics	1303.TW	4,607,884	73.10 - 88.40
35	Nanya Technology	2408.TW	16,327,613	57.30 - 107.50
36	Pegatron	4938.TW	4,244,411	60.60 - 100.00
37	Pou Chen	9904.TW	5,325,496	33.70 - 43.65
38	President Chain Store	2912.TW	885,870	247.00 - 361.50
39	Quanta Computer	2382.TW	4,050,033	51.10 - 80.00

40	Siliconware Precision Industries	2325.TW	28,090,566	50.90 - 51.10
41	SinoPac Financial Holdings Co. Ltd.	2890.TW	10,121,911	8.97 - 11.45
42	Taishin Financial Holdings	2887.TW	6,485,948	12.85 - 15.05
43	Taiwan Cement	1101.TW	19,271,854	33.35 - 47.30
44	Taiwan Cooperative Financial Holding	5880.TW	6,415,733	15.30 - 18.20
45	Taiwan High Speed Rail	2633.TW	4,977,816	21.40 - 26.85
46	Taiwan Mobile	3045.TW	2,293,834	105.00 - 112.00
47	Taiwan Semiconductor Manufacturing	2330.TW	29,716,311	210.00 - 270.50
48	Uni-president Enterprises	1216.TW	6,725,605	56.40 - 80.00
49	United Microelectronics	2303.TW	20,428,290	13.40 - 18.65
50	Yuanta Financial Holding	2885.TW	10,191,720	12.75 - 14.65

Table 4 – List of 10 companies of Indonesia stock market taken on March 17th 2018. This list named ID 10. Currency value using Indonesian Rupiah.

No	Name	Ticker	Volume	52 Week Range
1	Perusahaan Perseroan (Persero) PT Telekomunikasi Indonesia Tbk	TLKM.JK	120,850,800	3,250.00 - 4,840.00
2	PT Bank Central Asia Tbk	BBCA.JK	14,787,200	18,100.00 - 24,700.00
3	PT Bank Central Asia Tbk	HMSP.JK	12,466,700	3,230.00 - 5,550.00
4	PT Bank Rakyat Indonesia (Persero) Tbk	BBRI.JK	101,906,100	2,720.00 - 3,920.00
5	PT Bank Rakyat Indonesia (Persero) Tbk	ASII.JK	27,647,800	6,250.00 - 8,850.00
6	PT Bank Mandiri (Persero) Tbk	BMRI.JK	35,536,800	6,250.00 - 9,050.00
7	PT Unilever Indonesia Tbk	UNVR.JK	1,317,800	43,875.00 - 58,100.00
8	PT Gudang Garam Tbk	GGRM.JK	413,900	61,925.00 - 86,400.00
9	PT Bank Negara Indonesia (Persero) Tbk	BBNI.JK	25,450,600	6,750.00 - 10,175.00
10	PT United Tractors Tbk	UNTR.JK	4,970,000	27,625.00 - 40,500.00

In this data collection, we use the application program interface (API) service from Yahoo! Finance to get historical time series data for each stock market shown in Figure 2. From the period that we have been set in the following Table 5, we certainly get some periods of trading day, starting from Monday until Friday is the period of trading day.

Table 5 - 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

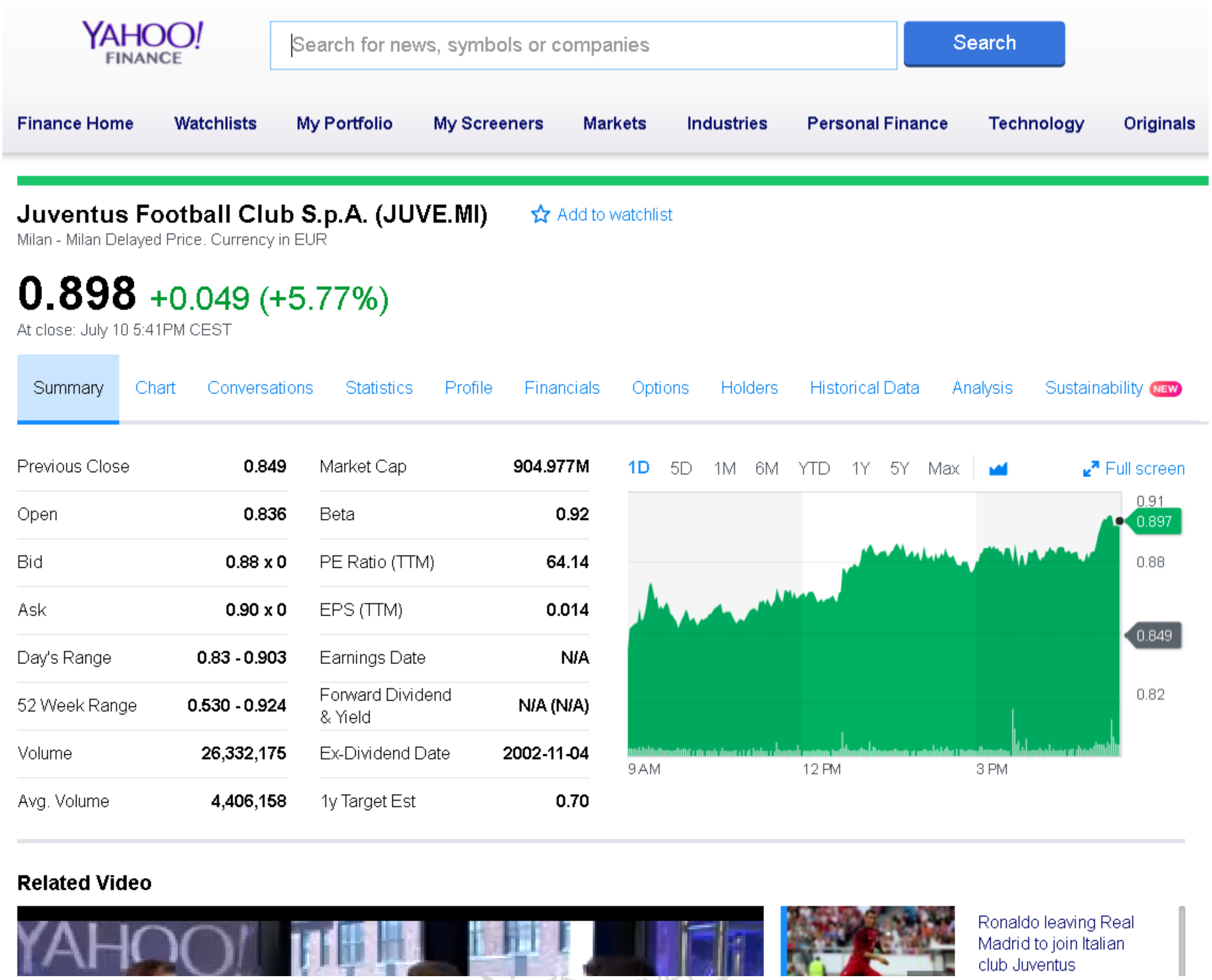


Figure 2 – Yahoo! Finance website, provide an API to download historical time series data

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

2.2. Time Series Data Feature Set

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. These elements are considered as feature sets which we will describe one by one in next section.

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 opens in the specified period. In this work, Taiwan stock market and Indonesian stock market will open at 09:00 a.m.

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. 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 used to fade a stock at the opening price that shows the strong pre-market indication contrary to the rest of the market or 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 close precisely at 4:00 p.m.

Closing prices do not reflect corporate actions, which may return significantly. For example, on June 9, 2014, Apple Inc. (NASDAQ: AAPL) issued a seven-for-one stock split. Therefore, Apple's shares were 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.

Traders and technical analysts use today's high, along with today's low 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.

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, 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.

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[14]. We divide the period used to create candlestick chart based on 5 trading days' data, 10 trading days' data and 20 trading days' data.

The amount of data is shown in Table 6 can be different number because we will only generate a candlestick chart that is qualified based on the period set in the following Table 3.

Table 6 – 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 shown in Figure 3. Adding a volume indicator into candlestick chart is one of our approaches to find out correlation between enrich candlestick chart information and prediction result.

Figure 3 - General way to visualizing the candlestick chart

Chapter 3
Methodology

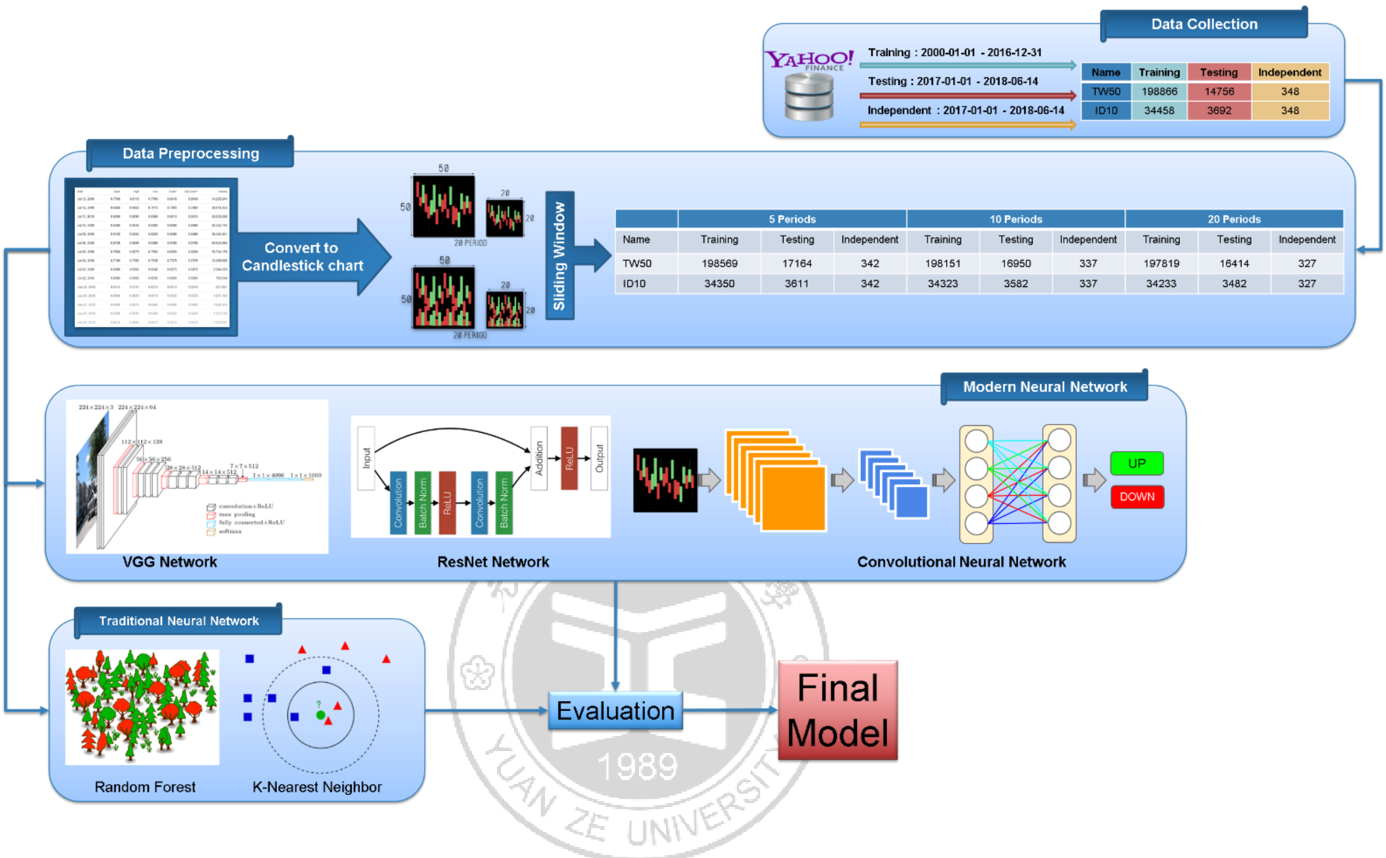


Figure 4 – Our methodology design

The architecture of our proposed stock market prediction is shown in Figure 4. The first, we collect the data from stock market historical data using Yahoo! Finance API. After that, we utilized the computer graphic technique to generate the candlestick chart images before using sliding window technique to generate the period data. Finally, our candlestick charts are feed as input into some deep learning neural networks models for stock market prediction, and the outputs will be binary class to indicate the price will going up or down in the near future.

3.1. Chart Encoding

Candlesticks 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 implemented in python library called Matplotlib[14] to convert this time series data into a candlestick image size as 50x50 and 20x20 dimension with RGB(Red Green Blue) channel.

Figure 5 and Figure 6 describe our candlestick chart representation in different period time and size with volume and without volume respectively.

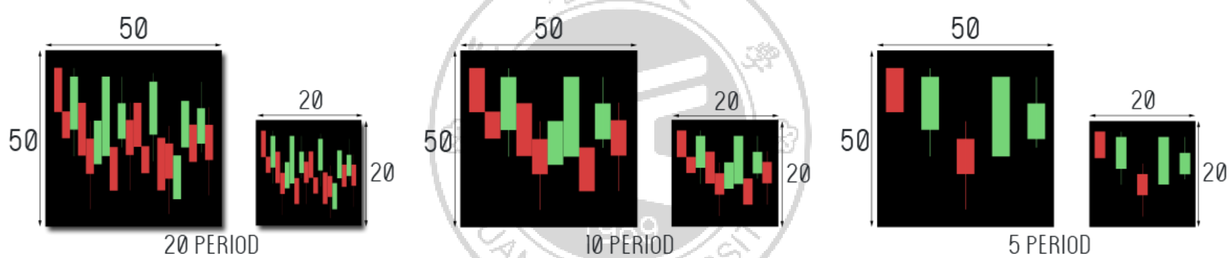


Figure 5 – Proposed candlestick chart without volume indicator in different period time and size.

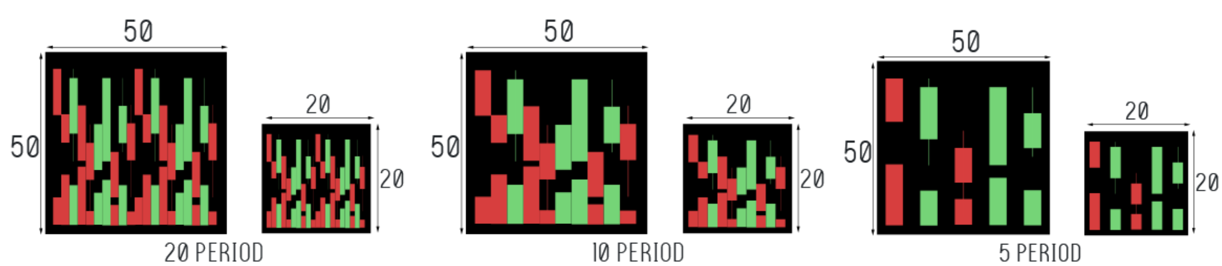


Figure 6 - Proposed candlestick chart with volume indicator in different period time and size.

We utilized the black color as our candlestick chart background. For each candlestick chart, we configure the volume indicator to show a red bar if the closing price for the stock is lower than the opening price meaning negative volume, and green for days where the closing price is higher than opening price meaning positive volume.

3.2. Binary Classification

Our goal here is to perform binary classification of stock market movements by analyzing and find the hidden pattern inside candlestick chart. As shown in Figure 7, the indicator is labeled as 1 if our model predict the closing price will rise in the next day and labeled as 0 if our model predict the closing price will decrease in the next day.

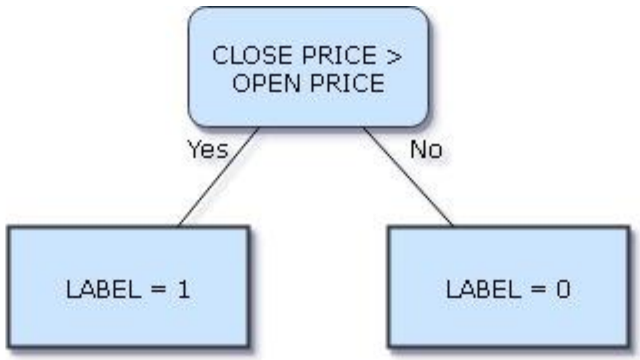


Figure 7 - Logic statement of our binary classification

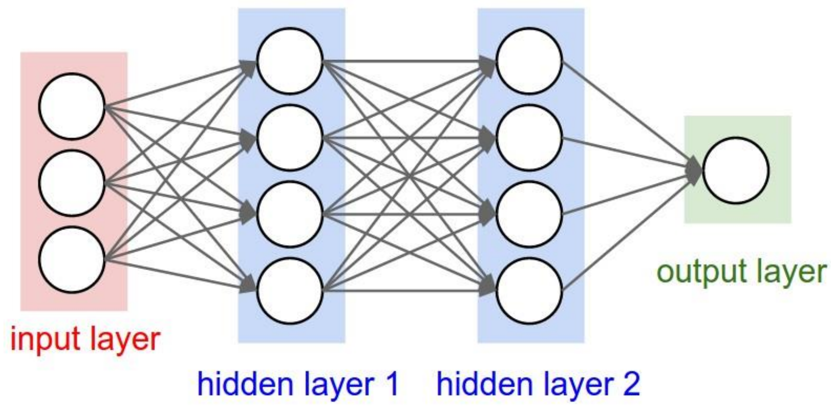
3.3. Learning Algorithm

There is a lot of excitement surrounding the fields of Neural Networks (NN) and Deep learning (DL), due to numerous well-publicized successes that these systems have achieved in the last few years. We will use some Deep Learning Networks (DLN) based on Convolutional Neural Network to perform our classification on stock market prediction. Besides the DLN, we also apply some traditional Machine Learning (ML) algorithms to compare with DLN. Those traditional Machine Learning algorithms are Random Forest and K-Nearest Neighbors algorithms.

3.3.1. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are very similar to ordinary Neural Networks (NN). They are made up of neurons with 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. Moreover, 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.

As shown in Figure 8, 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.



https://www.pyimagesearch.com/wp-content/uploads/2016/08/simple_neural_network_header-768x377.jpg

Figure 8 - A regular 3-layer Neural Network

Our CNN model architecture consist of 4 layers of convolutional 2d, 4 layers of max pooling 2d, and 3 dropouts. The detail of CNN model architecture is shown in Table 7. The Conv layer is the core building block of a Convolutional Network that does most of the computational heavy lifting. The pool layers are in charge of down sampling the spatial dimensions of the input. The most common setting is to use max pooling with 2x2 receptive fields (i.e. F=2), and with a stride of two (i.e. S=2). Note that this discards exactly 75% of the activations in an input volume (due to down sampling by 2 in both width and height). Another slightly less common setting is to use 3x3 receptive fields with a stride of two, but this makes. It is very uncommon to see receptive field sizes for max pooling that are larger than three because the pooling is then too lossy and aggressive. This usually leads to worse performance.

Table 7 – CNN architecture of our proposed method.

CNN Configuration
Input
Conv2D-32 ReLU
max-pooling
Conv2D-48 ReLU
max-pooling
Dropout
Conv2D-64 ReLU
max-pooling
Conv2D-96 ReLU
max-pooling
Dropout
Flatten
Dense-256
Dropout
Dense-2

3.3.2. Residual Network

Developed by He, Zhang et al. was the winner of ILSVRC 2015[15]. 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. ResNets are currently by far state of the art Convolutional Neural Network models

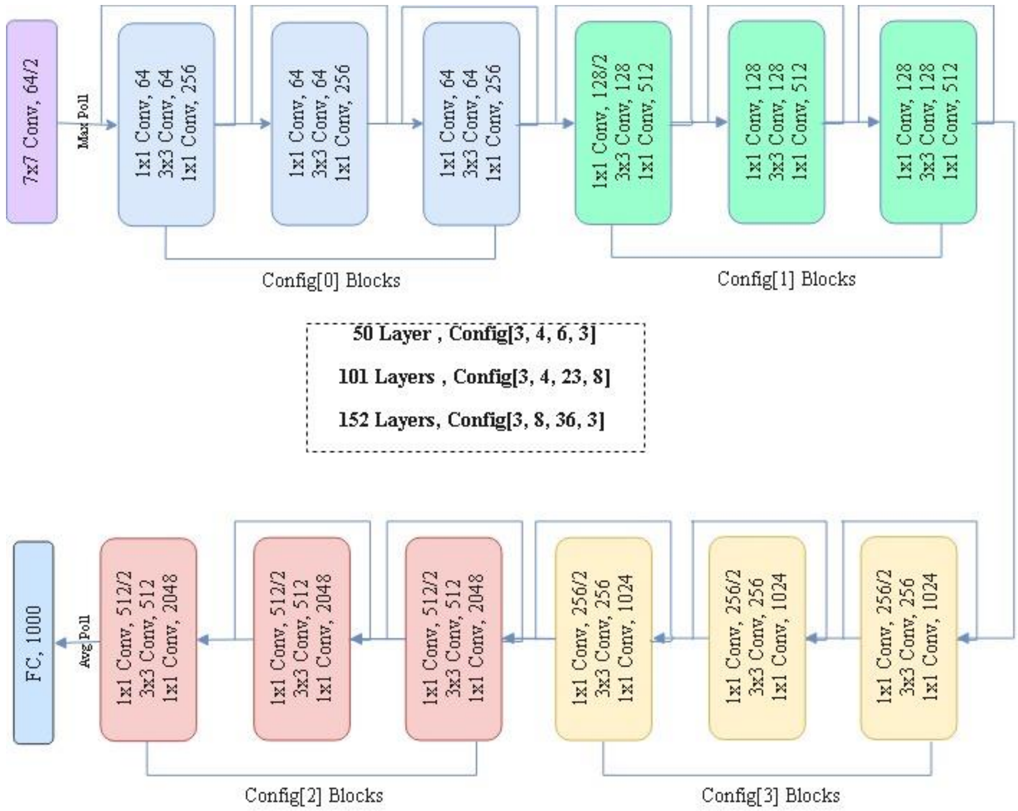


Figure 9 – ResNet Architecture shows many layers for different configuration

As we have seen so far, increasing the depth should increase the accuracy of the network, as long as overfitting is taken care of. Nevertheless, 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 shown in Figure 10. This is called degradation problem.

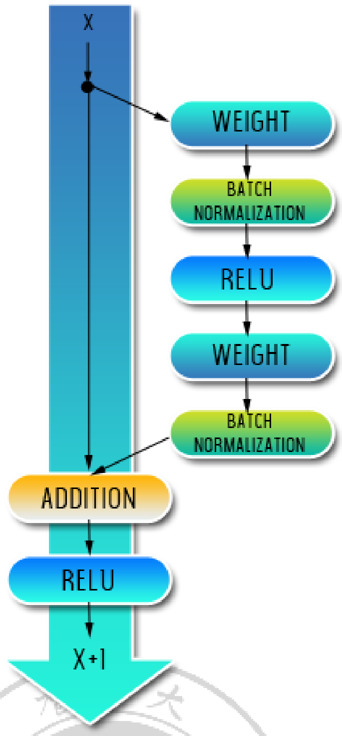


Figure 10 – The residual module in ResNet as originally proposed by He, Zhang et al.

By comparing with other CNNs architecture, residual network has been proving with the most minimum error rate according to Table 8.

Table 8 - Residual Network proved that this network have the most minimum error-rate

Year	CNN	Developed by	Top-5-error-rate
2012	AlexNet	Krizhevsky, Sutskever et al[16]	15.3 %
2013	ZFNet	Zeiler and Fergus[17]	14.8 %
2014	GoogLeNet	Szegedy, Ioffe et al.[18]	6.67 %
2014	VGG Net	Simonyan and Zisserman[19]	7.3 %
2015	ResNet	He, Zhang et al.[15]	3.57 %

3.3.3 VGG Network

The VGG network architecture was introduced by Simonyan and Zisserman[19]. It is named VGG because this architecture is from VGG group, Oxford. This network is characterized by its simplicity, using only 3x3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by max pooling. Two fully connected layers, each with

4096 nodes are then followed by a softmax classifier shown in Table 9. The “16” and “19” stand for the number of weight layers in the network. Unfortunately, there are two major drawbacks with VGGNet. First, it is painfully slow to train and the second the network architecture weights themselves are quite large.

Table 9 – VGG network configuration

ConvNet Configuration	
16 weight layers	19 weight layers
Input (RGB Image)	
Conv3-64 Conv3-64	Conv3-64 Conv3-64
max-pooling	
Conv3-128 Conv3-128	Conv3-128 Conv3-128
max-pooling	
Conv3-256 Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256 Conv3-256
max-pooling	
Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
max-pooling	
Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
max-pooling	
FC-4096	
FC-4096	
Soft-max	

3.3.4 Random Forest

Random Forest classifier is a classifier with Consist of many decision trees and adopted the technique of random decision forest prioritizes predictive performance by using multiple learning algorithms (ensemble learning). In general, Decision trees are a learning methods used in data search technique. The method used by the idea of combining the "bagging" idea or called

"Bootstrap Aggregating" (reduce variance) and the random selection of features in the training sets (classification and regression tree).

Next we will bring more detail how we can use the various options in Random Forest usefully. Most of the options depend on two data objects generated by random forests. When the training set for the current tree is drawn by sampling with replacement, about one-third of the cases are left out of the sample. This OOB (out-of-bag) data is used to get a running unbiased estimate of the classification error as trees are added to the forest. It is also used to get estimates of variable importance. After each tree is built, all of the data are run down the tree, and proximities are computed for each pair of cases. If two cases occupy the same terminal node, their proximity is increased by one. At the end of the run, the proximities are normalized by dividing by the number of trees. Proximities are used in replacing missing data, locating outliers, and producing illuminating low-dimensional views of the data.

The difference between Random Forest algorithm and the decision tree algorithm is that in Random Forest, the processes of finding the root node and splitting the feature nodes will run randomly. We applied our random forest algorithm from a machine learning python library called skicit-learn[20].

3.3.5 K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a classifier with based on the Lazy learning and Instance-based (IBk) learning algorithms (selection K based value based on model evaluation method or cross validation). Further, Lazy learning is a learning method with the purposed to store training data and enables the training data is used when there is a query request is made (waits until it is given a test) by the system. Similarity measure applied to the KNN with the aim to compare every new case with available cases (training data) that has been previously saved. Conversely different with eager learning, eager learning is a learning method with the intention of preparing training process data earlier, then wait for the query request (a test). KNN implemented lazy learning method which has the distinct advantage that it can solve the problem by comparing the problem with similar past problem (case-based reasoning). KNN adopted a supervised learning approach by utilizing the data in this case must have class/label and this learning model of the algorithm can be used for classification and regression predictive problems.

We also using skicit-learn python library for our KNN classifier. Furthermore, we used a K-D Tree algorithm in our KNN to perform prediction with default parameter from scikit-learn library.

3.4. Performance Evaluation

There are some statistics measures of the performance evaluation to evaluate the result of all the classifiers by measuring the sensitivity (true positive rate or recall), specificity (true negative rate), accuracy and Matthew's correlation coefficient (MCC)**.** 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:

$$Sensitivity = \frac{TP}{TP + FN}$$

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

$$Specitivity = \frac{TN}{TN + FP}$$

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

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

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

$$MCC = \frac{TP\ x\ TN - FP\ x\ FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

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 and Discussion

4.1. 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 price increasing on the next day, while the value 0 is the reverse of it.

We trained and evaluated our binary classification model on two challenging datasets, i.e. Taiwan 50 and Indonesia 10 stock market. Taiwan 50 dataset includes 50 company stock markets from Taiwan and Indonesia 10 dataset includes 10 company stock markets from Indonesia which most of them are the top stock market in both countries. We also divide the retrieval period based on the duration of the 5 days, 10 days and 20 days of trading days to create a sequence of sliding windows that will be converted to candlestick chart. Another hands, we also generate the candlestick chart with and without volume indicator for 2 different image sizes, 50 and 20 dimension.

4.1.1 Classification for Taiwan 50 dataset

Our first experiment is to compare several classifiers using Taiwan 50 dataset with different trading days and image dimension. Tables 10, 11, and 12 show our result of Taiwan 50 in different trading days' period by 50 dimension of candlestick chart with combination of volume price indicator. Table 11 shows that CNN aim get better result than the other classifiers with 91.5 % accuracy in 10 trading days' period by 50 dimension of candlestick chart with combination of volume price indicator.

Table 10 – Result of 5 period with volume indicator in 50-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	7090	1763	6927	1384	79.7	83.7	81.7	0.634
Resnet50	6792	1792	6898	1682	79.4	80.2	79.8	0.595
VGG16	6841	1625	7065	1633	81.3	80.7	81.0	0.62
VGG19	6718	1742	6948	1756	80.0	79.3	79.6	0.592
CNN	7100	1458	7232	1374	83.2	83.8	83.5	0.67

Table 11 – Result of 10 period with volume indicator in 50-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6678	1428	7801	1043	84.5	86.5	85.4	0.708
Resnet50	6299	837	8524	790	91.1	88.9	90.1	0.799
VGG16	6298	887	8474	791	90.5	88.8	89.8	0.792
VGG19	6345	874	8487	744	90.7	89.5	90.2	0.8
CNN	6469	785	8576	620	**91.6**	**91.3**	**91.5**	**0.827**

Table 12 – Result of 20 period with volume indicator in 50-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6354	1013	8348	735	89.2	89.6	89.4	0.785
Resnet50	6792	1792	6898	1682	79.4	80.2	79.8	0.595
VGG16	6841	1625	7065	1633	81.3	80.7	81.0	0.62
VGG19	6718	1742	6948	1756	80.0	79.3	79.6	0.592
CNN	7100	1458	7232	1374	83.2	83.8	83.5	0.67

Tables 13, 14, and 15 show our result for Taiwan 50 with 20-dimension image. Table 15 concludes that CNN method with volume indicator in 20-dimension image significantly outperforms the others with 90.6% accuracy.

Table 13 – Result of 5 period with volume indicator in 20-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	7160	1692	6998	1314	80.5	84.5	82.5	0.651
KNN	6095	2251	6439	2379	74.1	71.9	73.0	0.46
Resnet50	6792	1603	7087	1682	81.6	80.2	80.9	0.617
VGG16	6755	1561	7129	1719	82.0	79.7	80.9	0.618
VGG19	6750	1611	7079	1724	81.5	79.7	80.6	0.611
CNN	7005	1396	7294	1469	83.9	82.7	83.3	0.666

Table 14 – Result of 10 period with volume indicator in 20-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6810	1200	8004	900	87.0	88.3	87.6	0.751
KNN	5902	2123	7106	1819	77.0	76.4	76.7	0.533
Resnet50	6638	1192	8012	1072	87.0	86.1	80.6	0.731

VGG16	6657	1275	7929	1053	86.1	86.3	86.2	0.723
VGG19	6440	1025	8179	1270	88.9	83.5	86.4	0.726
CNN	6781	1242	7987	940	86.5	87.8	87.1	0.742

Table 15 – Result of 20 period with volume indicator in 20-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6390	870	8471	683	90.7	90.3	90.5	0.808
KNN	5199	1849	7512	1890	80.2	73.3	73.3	0.536
Resnet50	6232	757	8584	841	91.9	88.1	90.3	0.801
VGG16	6315	806	8535	758	91.4	89.3	90.5	0.806
VGG19	6280	813	8528	793	91.3	88.8	90.2	0.801
CNN	6397	860	8501	692	90.8	90.2	**90.6**	0.808

As we mentioned in our experiments method about finding the correlation between with or without volume indicator to enhance our result. Next we check our prediction result without combination of volume price indicator. Similar to using combination of volume price indicator, we also evaluate our method in 5, 10 and 20 trading day period. Tables 16, 17 and 18 show our prediction result for Taiwan 50 in 5, 10 and 20 trading days' period by 50-dimension image respectively. Table 18 shows that using 20 periods can achieve better result than the others with 92.2% accuracy.

Table 16 – Result of 5 period without volume indicator in 50-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	7217	1650	7040	1257	81.0	85.2	83.1	0.662
Resnet50	6643	1612	7078	1831	81.4	78.4	79.9	0.599
VGG16	6772	1585	7105	1702	81.8	79.9	80.8	0.617
VGG19	6737	1577	7113	1737	81.9	79.5	80.7	0.614
CNN	7213	1423	7267	1261	83.6	85.1	84.4	0.687

Table 17 – Result of 10 period without volume indicator in 50-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6828	1198	8006	882	87.0	88.6	88.6	0.753
Resnet50	6535	1132	8072	1175	87.7	84.8	86.4	0.725
VGG16	6660	1197	8007	1050	87.0	86.4	86.7	0.733
VGG19	6311	1002	8202	1399	89.1	81.9	85.8	0.713

CNN	6794	994	8210	916	89.2	88.1	88.7	0.773

Table 18 – Result of 20 periods without volume indicator in 50-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6403	897	8444	670	90.4	90.5	90.5	0.806
Resnet50	6348	908	8433	725	90.3	80.7	90.1	0.798
VGG16	6361	799	8542	712	91.4	89.9	90.8	0.813
VGG19	6316	798	8543	757	91.5	89.3	90.5	0.807
CNN	6415	629	8712	658	**93.3**	**90.7**	**92.2**	**0.84**

Tables 19, 20, and 21 show the result of Taiwan 50 in 5, 10, and 20 trading days' period without volume indicator in 20-dimension image. Both of VGG19 and CNN in Table 21 show good performance with 91% accuracy.

Table 19 – Result of 5 periods without volume indicator in 20-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	7227	1649	7041	1247	81.0	85.3	83.1	0.663
KNN	6793	1502	7188	1681	82.7	80.2	81.5	0.629
Resnet50	7116	1685	7005	1358	80.6	84.0	82.3	0.646
VGG16	6937	1719	6971	1537	80.2	81.9	81.0	0.621
VGG19	6733	1727	6963	1741	80.1	79.5	79.8	0.596
CNN	7032	1321	7369	1442	84.8	83.0	83.9	0.678

Table 20 – Result of 10 periods without volume indicator in 20-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	6825	1227	7977	885	86.7	88.5	87.5	0.75
KNN	6449	1182	8022	1261	87.2	83.6	85.6	0.709
Resnet50	6557	1179	8025	1153	87.2	85.0	86.2	0.722
VGG16	6711	1277	7927	999	86.1	87.0	86.5	0.73
VGG19	6484	1142	8062	1226	87.6	84.1	86.0	0.718
CNN	6801	1105	8099	909	88.0	88.2	88.1	0.761

Table 21 – Result of 20 periods without volume indicator in 20-dimension image for Taiwan 50.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC

Random Forest	6377	871	8470	696	90.7	90.2	90.5	0.806
KNN	6060	905	8436	1013	90.3	85.7	88.3	0.761
Resnet50	6181	771	8570	892	91.7	87.4	89.9	0.793
VGG16	6212	754	8587	861	91.9	87.8	90.2	0.799
VGG19	6366	772	8569	707	91.7	90.0	**91.0**	0.817
CNN	6402	805	8536	671	81.7	91.4	**91.0**	0.817

From all experiments about Taiwan 50, we conclude a summary result with and without volume indicator for different trading days' period and image dimension result. Table 22 shows that CNN in 20 trading days' period with 50-dimension image and volume indicator is better than the others with 91.5% accuracy. In addition, without volume indicator for Taiwan 50, CNN in 20 trading days' period with 50 dimension performs better than the others with 92.2% accuracy. From the result of both of those experiments, it indicates that the method using CNN model with longer trading day's period without volume indicator can achieve the best result for Taiwan 50 dataset.

Table 22 – Summary result of Taiwan 50 with their best classifier for each trading days and image dimension with volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
CNN	5	50	83.2	83.8	83.5	0.67
CNN	10	50	88.6	87.3	88.0	0.758
CNN	20	50	**91.6**	**91.3**	**91.5**	**0.827**
CNN	5	20	83.9	82.7	83.3	0.666
Random Forest	10	20	87.0	88.3	87.6	0.751
CNN	20	20	90.8	90.2	90.6	0.808

Table 23 – Summary result of Taiwan 50 with their best classifier for each trading days and image dimension without volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
CNN	5	50	83.6	85.1	84.4	0.687
CNN	10	50	89.2	88.1	88.7	0.773
CNN	20	50	**93.3**	90.7	**92.2**	**0.84**
CNN	5	20	84.8	83.0	83.9	0.678
CNN	10	20	88.0	88.2	88.1	0.761
CNN	20	20	81.7	91.4	91.0	0.817

4.1.2 Classification for Indonesia 10 dataset

Our next experiment is performing our proposed method in Indonesia stock market dataset. Indonesia is a promising country with good growth for their gross domestic product[21]. Tables 24, 25 and 26 show our prediction result for Indonesia 10 dataset with volume indicator by 50-dimension image. CNN with 20 trading days' period get better result than the others with 90.0% accuracy.

Table 24 – Result of 5 periods with volume indicator in 50-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1554	445	1334	278	75.0	84.8	80.0	0.602
KNN	1290	370	1306	301	77.9	81.1	77.9	0.59
Resnet50	1564	344	1435	268	80.7	85.4	83.1	0.661
VGG16	1447	307	1472	385	82.7	79.0	80.8	0.617
VGG19	1477	366	1413	355	79.4	80.6	80.0	0.601
CNN	1575	389	2390	257	78.1	86.0	82.1	0.643

Table 25 – Result of 10 periods with volume indicator in 50-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1450	394	1511	227	79.3	86.5	82.7	0.657
KNN	1158	362	1543	519	81.0	69.1	75.4	0.505
Resnet50	1483	217	1688	194	88.6	88.4	88.5	0.77
VGG16	1404	268	1637	273	85.9	83.7	84.9	0.697
VGG19	1424	271	1634	253	85.8	84.9	85.4	0.706
CNN	1423	245	1660	254	87.1	84.9	86.1	0.72

Table 26 – Result of 20 periods with volume indicator in 50-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1370	289	1652	171	85.1	88.9	86.8	0.736
KNN	1061	213	1728	480	89.0	68.9	80.1	0.597
Resnet50	1364	212	1729	177	89.1	88.5	88.8	0.774
VGG16	1346	194	1747	195	90.0	87.3	88.8	0.774
VGG19	1335	194	17147	206	90.0	86.6	88.5	0.767
CNN	1388	195	1746	153	90.0	**90.1**	**90.0**	**0.798**

Tables 27, 28 and 29 show our result for Indonesia 10 dataset with volume indicator in 20-dimension image. From those Table results, we see that the method using CNN with 20 trading days' period outperforms the other methods with 87.1% accuracy.

Table 27 – Result of 5 periods with volume indicator in 20-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1541	471	1308	291	73.5	84.1	78.9	0.58
KNN	1297	368	1308	294	78.0	81.5	79.7	0.596
Resnet50	1508	377	1402	324	78.8	82.3	80.6	0.612
VGG16	1403	361	1418	429	79.7	76.6	78.1	0.563
VGG19	1416	382	1397	416	78.5	77.3	77.9	0.558
CNN	1563	455	1324	269	74.4	85.3	80.0	0.602

Table 28 – Result of 10 periods with volume indicator in 20-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1445	404	1501	232	78.8	86.2	82.2	0.649
KNN	1139	363	1542	538	80.9	67.9	74.8	0.494
Resnet50	1330	335	1570	347	82.4	79.3	81.0	0.618
VGG16	1357	298	1607	320	84.4	80.9	82.7	0.653
VGG19	1336	291	1614	341	84.7	79.7	82.4	0.645
CNN	1432	318	1587	245	83.3	85.4	84.3	0.686

Table 29 – Result of 20 periods with volume indicator in 20-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1341	287	1654	200	85.2	87.0	86.0	0.719
KNN	1014	232	1709	527	88.0	65.8	78.2	0.558
Resnet50	1328	318	1623	213	83.6	86.2	84.8	0.694
VGG16	1360	285	1656	181	85.3	88.3	86.6	0.732
VGG19	1315	291	1650	226	85.0	85.3	85.2	0.701
CNN	1303	211	1730	238	89.1	84.6	**87.1**	0.738

The prediction result without using the volume indicator for Indonesia 10 with 50-dimension image of 5, 10 and 20 periods shown in Tables 30, 31 and 32 respectively. The best performance result achieved using CNN in 20 trading days' period with 92.1% accuracy.

Table 30 – Result of 5 periods without volume indicator in 50-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1358	426	1250	233	74.6	85.4	79.8	0.602
KNN	1290	370	1306	301	77.9	81.1	79.5	0.59
Resnet50	1398	351	1325	193	79.1	87.9	83.3	0.671
VGG16	1278	320	1356	313	80.9	80.3	80.6	0.612
VGG19	1274	338	1338	317	79.8	80.1	80.0	0.599
CNN	1362	342	1334	229	79.6	85.6	82.5	0.625

Table 31 – Result of 10 periods without volume indicator in 50-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1248	345	1456	173	80.8	87.8	83.9	0.682
KNN	1153	270	1531	268	85.0	81.1	83.3	0.661
Resnet50	1241	344	1457	180	80.9	87.3	83.7	0.678
VGG16	1183	205	1596	238	88.6	83.3	86.3	0.721
VGG19	1191	241	1560	230	86.6	83.8	85.4	0.704
CNN	1231	225	1576	190	87.5	86.6	87.1	0.74

Table 32 – Result of 20 periods without volume indicator in 50-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1245	256	1839	140	87.8	89.9	88.6	0.768
KNN	1165	220	1875	220	89.5	84.1	87.4	0.736
Resnet50	1206	144	1951	179	93.1	87.1	90.7	0.806
VGG16	1267	184	1911	118	91.2	91.5	91.3	0.821
VGG19	1255	169	1926	130	91.9	90.6	91.4	0.822
CNN	1276	165	1930	109	**92.1**	**92.1**	**92.1**	**0.837**

Tables 33, 34 and 35 show our prediction result for 20-dimension image without using the volume indicator in Indonesia 10. Table 35 shows that VGG16 with 90.7% accuracy is better with the other results.

Table 33 – Result of 5 periods without volume indicator in 20-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1365	402	1274	226	76.0	85.8	80.8	0.62
KNN	1297	368	1308	294	78.0	81.5	79.7	0.596
Resnet50	1234	338	1338	348	79.8	78.1	79.0	0.58
VGG16	1328	410	1266	263	75.5	83.5	79.4	0.591
VGG19	1280	335	1341	311	80.0	80.5	80.2	0.604
CNN	1311	279	1397	380	83.4	82.4	82.9	0.658

Table 34 – Result of 10 periods without volume indicator in 20-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1228	334	1467	193	81.5	86.4	83.6	0.674
KNN	1171	265	1536	250	85.3	82.4	84.0	0.676
Resnet50	1201	275	1526	220	84.7	84.5	84.6	0.69
VGG16	1196	278	1523	225	84.6	84.2	84.4	0.685
VGG19	1242	326	1475	179	81.9	87.4	84.3	0.688
CNN	1217	263	1538	204	85.4	85.6	85.5	0.708

Table 35 – Result of 20 periods without volume indicator in 20-dimension image for Indonesia 10.

Classifier	TN	FN	TP	FP	Sensitivity	Specificity	Accuracy	MCC
Random Forest	1230	259	1836	155	87.6	88.8	88.1	0.756
KNN	1297	368	1308	294	68.0	81.5	79.7	0.596
Resnet50	1223	203	1892	162	90.3	88.3	89.5	0.782
VGG16	1242	179	1916	143	91.5	89.7	**90.7**	0.808
VGG19	1268	212	1883	117	89.9	91.6	90.5	0.806
CNN	1234	178	1917	151	91.5	89.1	90.5	0.803

From all experiment results with Indonesia 10 dataset, we conclude a summary result with and without volume indicator in Tables 36 and 37 respectively. It shows that the CNN method with 20 trading days' period in 50 dimension using volume indicator show the best result with 90.0% accuracy in Table 37. While the CNN method in 20 trading days' period with 20-dimension image without using the volume indicator performs better result with 92.1% accuracy. It indicates that the method using CNN model with longer trading day's period without volume indicator can achieve the best result for Indonesia 10 dataset.

Table 36 – Summary result of Indonesia 10 with their best classifier for each trading days and image dimension with volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
Resnet50	5	50	80.7	85.4	83.1	0.661
Resnet50	10	50	88.6	88.4	88.5	0.77
CNN	20	50	90.0	90.1	90.0	0.798
Resnet50	5	20	78.8	82.3	80.6	0.612
CNN	10	20	83.3	85.4	84.3	0.686
CNN	20	20	89.1	84.6	87.1	0.738

Table 37 – Summary result of Indonesia 10 with their best classifier for each trading days and image dimension without volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
Resnet50	5	50	79.1	87.9	83.3	0.671
CNN	10	50	87.5	86.6	87.1	0.74
CNN	20	50	**92.1**	**92.1**	**92.1**	**0.837**
CNN	5	20	83.4	82.4	82.9	0.658
CNN	10	20	85.4	85.6	85.5	0.708
VGG16	20	20	91.5	89.7	90.7	0.808

4.2. Independent testing result

Measuring our model result not only used performance evaluation. We also performed an independent test to see that our proposed method is reasonable. During this independent test, we used two index stock exchange data from each country. Yuanta/P-shares Taiwan Top 50 ETF represented independent data test for our Taiwan50, whereas Jakarta Composite Index is our independent data set test for Indonesia10. Both of the stock exchange data are taken from 1st January, 2017 until 14th June 2018.

Tables 38 and 39 show our independent test result for Taiwan50 using volume indicator and without using volume indicator respectively. The independent test result for Indonesia10 using and without using volume indicator are shown in Tables 40 and 41 respectively. As shown in Tables 38, 39, 40 and 41, our CNN with 20 trading days' period and 50-dimension image get best result for both independent test. It indicated again that our proposed method outperforms the others.

Table 38 – Independent test result for Taiwan50 using 0050.tw with volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
CNN	5	50	82.1	77.1	79.9	0.593
CNN	10	50	85.7	81.5	84.0	0.669
CNN	20	50	95.8	87.1	92.7	0.839
CNN	5	20	82.6	83.0	82.8	0.654
RF	10	20	44.8	84.4	60.7	0.305
CNN	20	20	92.9	89.7	91.8	0.821

Table 39 – Independent test result for Taiwan50 using 0050.tw without volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
CNN	5	50	82.1	81.0	81.6	0.63
CNN	10	50	89.7	83.7	87.3	0.735
CNN	20	50	94.3	91.4	**93.3**	0.854
CNN	5	20	81.1	82.4	81.6	0.631
CNN	10	20	89.7	86.7	88.5	0.761
CNN	20	20	92.0	93.1	92.4	0.838

Table 40 – Independent test result for Indonesia10 using JKSE with volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
RESNET50	5	50	80.0	88.8	83.9	0.681
RESNET50	10	50	90.9	84.7	89.3	0.733
CNN	20	50	87.2	83.5	86.2	0.67
RESNET50	5	20	75.0	82.1	77.8	0.558
CNN	10	20	83.9	75.3	81.7	0.559
CNN	20	20	83.9	82.4	83.5	0.616

Table 41 – Independent test result for Indonesia10 using JKSE without volume indicator.

Classifier	Period	Dimension	Sensitivity	Specificity	Accuracy	MCC
RESNET50	5	50	79.3	86.6	82.2	0.645
CNN	10	50	90.6	87.1	89.3	0.772
CNN	20	50	90.6	88.7	**89.9**	0.786
CNN	5	20	81.7	78.4	80.4	0.595
CNN	10	20	86.9	88.7	87.5	0.741

VGG16	20	20	91.3	81.2	88.7	0.712

4.3. Comparison

To further evaluate the effectiveness of our predictive model, we also compare our result with the other related works. The first comparison is between our proposed method with [12], they used three different stock market datasets with different trading period time. Samsung, General Electric and Apple are their stock market data with one, two and three months of trading period respectively. We applied our proposed model in their datasets to compare our prediction performance with their result shown in [12]. The comparison result for Samsung, Apple, and GE stock market shown in Table 42, 43, and 44 respectively. Based on these comparison results, it revealed that our performance results outperformed the prediction results from [12].

Table 42 – Comparison result with Khaidem, Saha et al. 2016 for Samsung stock market.

Khaidem, Saha et al. – Samsung					
Name	Trading Period	ACC	Precision	Recall	Specificity
Khaidem, Saha et al. 2016	1 month	86.8	88.1	87.0	0.865
Our	1 month	**87.5**	88.0	**87.0**	**0.891**
Khaidem, Saha et al. 2016	2 month	90.6	91.0	92.5	0.88
Our	2 month	**94.2**	**94.0**	**94.0**	0.862
Khaidem, Saha et al. 2016	3 month	93.9	92.4	**95.0**	0.926
Our	3 month	**94.5**	**94.0**	**95.0**	0.882

Table 43 – Comparison result with Khaidem, Saha et al. 2016 for Apple stock market.

Khaidem, Saha et al. – Apple					
Name	Trading Period	ACC	Precision	Recall	Specificity
Khaidem, Saha et al. 2016	1 month	88.2	89.2	90.7	84.8
Our	1 month	**89.6**	**90.0**	90.0	**86.3**
Khaidem, Saha et al. 2016	2 month	93.0	94.1	93.8	91.9
Our	2 month	**93.6**	94.0	**94.0**	87.7
Khaidem, Saha et al. 2016	3 month	94.5	94.5	96.1	0.923
Our	3 month	**95.6**	**96.0**	96.1	0.885

Table 44 – Comparison result with Khaidem, Saha et al. 2016 for GE stock market.

Khaidem, Saha et al. – GE					
Name	Trading Period	ACC	Precision	Recall	Specificity
Khaidem, Saha et al. 2016	1 month	84.7	85.5	87.6	0.809
Our	1 month	**90.2**	**90.0**	**90.0**	0.86
Khaidem, Saha et al. 2016	2 month	90.8	91.3	93.0	0.876
Our	2 month	**97.8**	**98.0**	**98.0**	**0.993**
Khaidem, Saha et al. 2016	3 month	92.5	93.1	94.5	0.895
Our	3 month	**97.4**	**98.0**	**98.0**	**0.983**

Second comparison is between our proposed method with [11]. They utilized four different stock market datasets from India stock exchange. In this comparison, we followed their dataset using Nifty50, S7P BSE Sensex, Reliance Industry and Infosys stock market datasets. Accuracy and F-measure were used for their performance evaluation. As comparison results shown in Table 45, Our proposed model yielded 97.2 %, 93.9 %, 93.4 % and 93.9% for accuracy with S7P BSE Sensex, Reliance Industry, Nifty50 and Infosys stock market datasets respectively. It indicated that our proposed method is superior to Patel work [11].

Table 45 – Comparison result with Patel, Shah et al. 2015

[11] –S&P BSE SENSEX			**[11] – NIFTY 50**		
	ACC	F-measure		ACC	F-measure
Patel, Shah et al. 2015	89.84	0.9026	Patel, Shah et al. 2015	89.52	0.8935
Our	**97.2**	**0.97**	Our	**93.4**	**0.93**
[11] – Reliance Industry			**[11] - Infosys**		
Patel, Shah et al. 2015	92.22	0.9234	Patel, Shah et al. 2015	90.01	0.9017
Our	**93.9**	**0.94**	Our	**93.9**	**0.94**

Last comparison is between our proposed method with [13]. Their dataset composition is similar with us. They are using thirteen Hong Kong stock market, whereas we used fifty Taiwan stock market datasets and ten Indonesia stock market datasets. Their methodology is combine sentiment analysis on social media and finance news. As shown in Table 46, Our proposed method achieved 92 % significantly outperforms Zhang method [13].

Table 46 – Comparison result with Zhang, Zhang et al. 2018

[13] – Hong Kong 13		
	Accuracy	MCC
Zhang, Zhang et al. 2018	61.7	0.331
Our	**92.6**	**0.846**

Chapter 5
Conclusion and Future Works

In this study, we present a new method for stock market prediction using 2 stock market datasets including 50 company stock markets for Taiwan50 datasets and 10 company stock markets for Indonesian datasets. The first, to find out the correlation between enrich candlestick chart information and stock market prediction performance, we utilized the computer graphic technique to generate the candlestick chart images for stock market data. After that, we employ the sliding window technique to generate the period data. Finally, a CNN learning algorithm is employed to build our model for stock market prediction.

We found that the model using long-term trading days' period with CNN learning algorithm achieved the highest performance of sensitivity, specificity, accuracy, and MCC. It proved that Convolutional neural network could find the hidden pattern inside the candlestick chart images to forecast the movement of specific stock market in the future. Adding the indicator such as volume in candlestick chart not really help the algorithms increase finding the hidden pattern.

The comparison experiments indicated that our proposed method provide highly accurate forecast compare to the other existing methods. Patel, Shah et al.[11] used trading data from Reliance Industries, Infosys Ltd., CNX Nifty and S&P Bombay Stock Exchange (BSE) Sensex during 10 years with accuracy in the range of 89 – 92 % while we achieved accuracy in the range of 93 – 97 %. Khaidem, Saha et al.[12] method achieved the accuracy in the range of 86 – 94 % using three trading datasets from Samsung, GE and Apple while we achieved in the range of 87 – 97 %. Zhang, Zhang et al.[13] utilized 13 different companies in Hong Kong stock exchange with accuracy 61 %. Meanwhile, our method achieved 92 % for accuracy.

For the future works we want to extend our work being able to predict the percentage change on the price movements. For the convenience of experimental scientists, we developed a user-friendly webserver for predicting stock market using our final model. Available at http://140.138.155.216/deepcandle, DeepCandle is a system through which users can easily predicting stock market in the near future. Users only need to input the date target, and our models will process them and return a summary. The provided web interface is constructed such that users can easily access its functions and comfortably use it without a deep understanding of computing.

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