# Short-term Stock Market Price Trend Prediction Using a Customized Deep Learning System

by

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## Abstract

In big data era, deep learning solution for predicting stock market price trend becomes popular. We collected two years of Chinese stock market data according to the financial domain, proposed a fine-tuned stock market price trend prediction system with developing a web application as the use case, meanwhile, conducted a comprehensive evaluation on most frequently used machine learning models and concludes that our proposed solution outperforms leading models. The system achieves an overall trend predicting accuracy of 93%, also achieves significant high scores in other machine learning metrics score in the meantime. Thus, this work provides a solid foundation for further price prediction by classifying the price trend accurately. With the detail-designed evaluation on prediction term lengths, feature engineering and data pre-processing methods, this work also contributes to the stock analysis research community in both financial and technical domain.

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# Chapter 1: Introduction

Stock market is one of the major fields that investors dedicated to, thus stock market price trend prediction is always a hot topic for researchers from both financial and technical domain. While during our literature review, we found merely a limited overlap in previous research from these two domains. In this research project, our objective is to build a state-of-art prediction model for price trend prediction, which focuses on short-term.

As concluded by Fama in (Malkiel & Fama, 1970), financial time series prediction is known as a notoriously difficult task due to the generally accepted, semi-strong form of market efficiency and the high level of noise. Back to the year 2003, Wang et al. in (Wang & Lin, n.d.) already applied Artificial Neural Network on stock market price prediction and focused on volume, a specific feature of the stock market, leveraged research. One of the key findings is that the volume is not effective in improving the forecasting performance on the datasets they used, which was S&P 500 and DJI. Ince and Trafalis in (Ince & Trafalis, 2008) targeted to short-term forecasting and applied their support vector machine (SVM) model on stock price prediction. Their main contribution is performing a comparison between multi-layer perceptron (MLP) and SVM then found that most of the scenarios SVM outperforms MLP, while the result is also affected by different trading strategies. In the meantime, researchers from financial domains were applying conventional statistical methods and signal processing techniques on analyzing stock market data. Lee in (H. S. Lee & Lee, 2006) performed a wavelet analysis focusing on international transmission of stock market movement. The related works in Chapter

2.2 were using the similar conventional statistical methods to analyze the specific phenomena, which narrows down the usage of their proposed solution. Compared with artificial intelligence approaches, the conventional statistical methods seem to be a lack of generalization.

The optimization techniques such as principal component analysis (PCA) were also applied in short-term stock price prediction (Lin, Yang, & Song, 2009). During the years, researchers are not only focusing on stock price-related analysis, but also trying to analyze stock market transactions such as volume burst risks, which expands the stock market analysis research domain broader and indicates this research domain still has high potential (Shih, 2019). As the artificial intelligence technique boosting in recent years, many proposed solutions are trying to collaborate the machine learning and deep learning approaches based on previous approaches, then propose new metrics serve as training features such as (G. Liu & Wang, 2019). This type of previous works belongs to feature engineering domain and can be considered as the inspiration of feature extension idea. Liu et al. in (S. Liu, Zhang, & B, 2017) proposed a convolutional neural network (CNN) and long short-term memory (LSTM) neural network model to analyze the quantitative strategy in stock markets. The CNN serves for the stock selection strategy, automatically extracts features based on quantitative data, then follows an LSTM to preserve the time-series features for improving the profits. The latest work also proposes a similar hybrid neural network architecture, integrates a convolutional neural network with a bidirectional long short-term memory to predict stock market index (Eapen, Automation, & Market, 2019). While the symptom of researchers frequently propose fancy neural

network solution architectures also brings further discussion about the topic: if the high training consumption is worth the result.

In this research project, we used a dataset built and formed by ourselves. The data source is an open-sourced data API called Tushare ("Tushare API," 2018), we illustrate the data collection details in Chapter 2.3.

We obtain price data of 3558 stocks from Chinese stock market; the date range is from Jan 2017 to Mar 2019. We choose the stocks by eliminating the listing date, only choose the stocks whose listing dates are between this date range. The data of year 2017 and year 2018 are for training purpose; then we build the testing dataset by using the first-season price data of 2019.

All the models are used CPU-based training procedure.

Based on an abundant previous works review, we come up with three major research questions and propose a comprehensive solution followed by a thorough evaluation which aims to resolve the research questions. The first objective for this research is to explore how feature engineering benefits model prediction accuracy. By reviewing the related works in both financial and technical domains, we raise the second objective to convert findings from financial domain to the technical procedure that can benefit prediction model design. The third major purpose of this paper is to research how different machine learning algorithms perform on short-term price trend prediction.

In respect of building an efficient model to resolve a specific term length of price trend prediction problems, we make below contributions.

· First, we demonstrate an effective method to convert the findings from the financial domain to a technical procedure consequently contributes to the model

prediction evaluation metric scores. We name this method as feature extension and exploit three means of data pre-processing. The evaluation result has proved that our proposed feature extension is significantly helpful to feature engineering procedures.

· Second, we focus on short-term stock market price trend prediction and customized a state-of-the-art deep learning system using Long Short-term Memory (LSTM). Our approach can accurately select the most effective features by RFE algorithms. By exploiting PCA procedure, it can also achieve a great promotion in model training efficiency without sacrificing too much accuracy. Meanwhile, we involve a state-of-the-art Long Short-term Memory (LSTM) model to retain the features' time dependency and achieves 96%, a significantly high accuracy in predicting price-up trend and a 93.25% overall prediction accuracy.

· Third, by performing a comprehensive evaluation on models used by the most related works and each component of our proposed system, we conclude varies findings which worth leveraging a more in-depth research. It contributes to both technical and financial domain related to stock market analysis by providing new research questions on the perspectives of feature engineering, term lengths, and data pre-processing methods.

Besides, other contributions would be the Chinese stock market dataset we collected and the use case based on our proposed solution.

The novelty of our proposed solution causes our work distinct from previous proposed solution is that we proposed a fine-tuned system instead of an LSTM model only. We observe from previous works and find the gaps between investors and researchers who dedicate in technical domain, and proposed a solution architecture with a comprehensive feature engineering procedure before training the prediction model. With the success of

feature extension method collaborate with recursive feature elimination algorithms, almost all the machine learning algorithms can achieve high accuracy scores (around 90%) of short-term price trend prediction. It proved the effectiveness of our proposed feature extension as a novel method of feature engineering. While after introducing the customized LSTM model, we further improved the prediction scores in all evaluation metrics and outperformed the machine learning models in similar previous works.

The remainder of this paper is organized as follows. Chapter 3 explains the technical keywords that frequently appear in this paper, stresses the strengths and weaknesses of related works, and describes how the previous works related to our research project. We have also concluded a table for quick indexing related works in Chapter 3.2. This chapter also provides the technical background by detailed illustrating the technical indices we exploit in this paper. Chapter 4 is the methodology part; it covers the gap analysis, research problems, and proposed solution. Detailed technical design with algorithms and how the model implemented are also included in this section. At the end of this chapter it also illustrates the use case of our proposed solution, a flexible and easy-to-access web application designed for individual investors. Chapter 5 presents the comprehensive evaluation of our proposed model not only by comparing with the models used in most related works but also in the optimization aspect. Then follows by a subsection, which initials a discussion based on the findings to answer research questions, also other valuable findings that worth bringing about. Chapter 6 lists further research directions that are promising for this paper. Chapter 7 concludes.

# Chapter 2: Dataset of Chinese Stock Market

## 2.1 Introduction of Dataset Preparation

This chapter is a detailed illustration of the dataset contribution.

The second section is the survey part. Stock market-related data are diverse, so we do a comprehensive literature review of financial research works in stock market analysis to specify the data collection directions.

After collecting the data based on the findings from a literature review of previous research works, we define the data structure of the dataset. Section 2.3 described the dataset in detail, it includes the data structure, and data tables in each category of data with the segment definitions.

We also briefly introduce the potential research opportunities of this dataset in the fourth section.

## 2.2 Survey of Existing Works in Financial Domain

In this part, we list the literature review data collection. The primary content for this part is the literature review of previous works in financial domain; they provided the direction of what kind of data we should collect, and how they will benefit the stock market analysis.

We can regard data as raw oil that is being generated with every passing second (Mohammad, Afshar, & Parul, 2018). Before researching the previous works in financial domain for data collection instruction, we first go through the related works of existing public datasets. This step helps us to design the structure of stock market data.

Following section explains two primary reasons of collecting two years Chinese stock market from 2017 to 2018. First reason is that the stock market data of 2017 and 2018 are the most recent data that we had access at the beginning of the research, instead of using historical data, we prefer to use the latest data to keep the evaluation results of our research project more convincing. Alvarez-Ramirez et al. in (Alvarez-Ramirez, Jose, Alvarez, Rodriguez, & Fernandez-Anaya, 2008) used historical data but still analyzed the emergence of anti-correlated behavior in recent two years. Second reason is that two years is a very popular period length among financial data analysis, not only for investors but also for researchers. Paranjape-Voditel and Deshpande in (Paranjape-Voditel, Preeti, & Deshpande, 2013) took the period of investment as two years, and mentioned that two-year is a reasonable period because this period can be easily extended but a lesser period does not reflect the actual impact of policies, corrective factors, market forces generated by intraday trading, etc. on the price of a stock. Moreover, the longest length of analysis period in (Yoshihiro, Yamaguchi, Shingo, Hirasawa, & Hu, 2006) is also two years. (Tripwire, 2019) also mentioned that evaluate the effectiveness of investment plans once a year are necessary, which indicates that the investment environment is changing frequently, naively extending the analysis period might cause side effect.

Yahoo Finance is a popular source of public stock market data. The dataset of two main stock exchanges from India can be obtained from Yahoo via the local IP address (Yahoo, 2018). Besides, S&P 500 stock data can also be obtained from Yahoo Finance (Yahoo, 2019). While the public stock data obtained from Yahoo finance are often sharing a common limitation, the available raw feature only includes four types of price (open, close, high, low) and volume, which leads to an eliminated research scope.

The current situation of public-accessible stock market research datasets inspired us to build a dataset that consists of features collected from diverse domains.

Yao et al. in (Yao, Ma, & He, 2014) leveraged a study based on Chinese stock market, which has similarities with our dataset. They used regression models, the cross-sectional standard deviation (CSSD) of returns, the cross-sectional absolute deviation (CSAD) of returns, also modified the existing model and corrected the multicollinearity and autocorrelation problems presented in the dataset. The dataset was obtained from the Thomson DataStream database, which had two levels of both firm specific and market.

The authors listed detailed descriptions of methodology and background knowledge about data sources. While they did not propose new models but slightly adjusted the existing models and performed the evaluation on Chinese stock market data. One of the findings is significantly important to our work; they found herding behavior in both Shanghai and Shenzhen B-share markets while there was no evidence of herding in the A-share markets. We consider eliminating our research scope according to their findings to control variables.

Rosenstein and Wyatt in (Rosenstein & Wyatt, 1997) did research on how directors, board effectiveness, and shareholder wealth affect the stock prices.

They sampled 170 director announcements drawn from “Who’s News” section of Wall Street Journal (WSJ) between 1981 and 1985. Announcements samples were not included the outside directors. The authors drew a clear conclusion from their examination of inside director appointments. They found 5%, between 5% and 25%, over 25% three ranges of the percentage of inside directors hold the firm’s common stock. For less than 5%, the stock market reaction to the announcement is significantly negative. When the

proportion is between 5% and 25%, the reaction is significantly positive. While for the situation that exceeds 25%, the reaction is not significantly different from zero. While this paper is relatively outdated, the conclusion needs further validation. And the data sample is too small, the result might not have generality. The authors concluded three useful thresholds, and they are a valuable reference for feature selection part when evaluating the proportion of a single stock. They also found that the CEO's age is negatively related to the stock-price effects; it also becomes a potential feature to perform analysis.

Lee and Chen in (M. C. Lee, 2009) focused on the role of firm resources and size and leveraged research about how the new product introductions impact stock price immediately.

They used all announcements pertaining to new products released at the Wall Street Journal Index from 1990 to 1998, exploited ordinary least squares (OLS) regression model and did T-test between pre-announced and announced new products on shareholder value before processing the data as the optimization. The strength of this paper is that they used the traditional statistic method to validate the model, which is a good way to create a baseline for other new data science techniques. While the original dataset is relatively old, we cannot exclude the technology development in recent two decades would impact the evaluation result of regression models. The authors mentioned that the firm size is negatively associated with shareholder value, which is a piece of important evidence for our data collection direction on shareholders. Besides, they studied a specific case of stock price fluctuations, which is heuristic for our research about how to choose a specific use case.

Gui et al. in (Gul, Kim, & Qiu, 2010) analyzed the relationship between stock price and factors as the ownership concentration, audit quality and foreign shareholding based on the stock return and accounting data collected from Chinese stock market. The stock return and accounting data were acquired from the Chinese Stock Market and Accounting Research database. The sample period covered from 1996 to 2003, which was eight years. The authors exploited conventional statistics like R square and SYNCH in their research. With strong financial knowledge background, their research was specified for features that often been omitted or neglected by the researchers from the technical domain. The five main findings are heuristic when selecting features in further study. While the data collection part of auditors and shareholders were done manually. Collecting data manually is time and effort consuming, it might due to the technique limitation since it's a 2010 paper.

From this paper, we recognized a large gap in stock prices research between technical and financial domain. Not alike technical domain, researchers in financial domains are more focus on shareholder and auditor information, which is a significant finding for our research direction. Besides the five main findings they concluded, their research was based on Chinese stock market, the same data source with our research, thus their conclusions are valuable for our research.

Mai et al. conducted research on how social media impact Bitcoin value in (Mai, Shan, Bai, Wang, & Chiang, 2018). The dataset they used was daily market prices (BTC—USD exchange rates) from Bit-Stamp Ltd., the top bitcoin exchange by volume. They built Vector error correction models (VECMs) and used Akaike information criterion (AIC) for choosing the optimal lag length in the model. Their work was the first study to

research if social media will affect the bitcoin price. The limitations located in the data sources and analysis methods. First, the data they were using was secondary data. Second, the bitcoin price is affected by global factors, while the Twitter data they exploited was limited in English. Besides, their work lacks researching of the silent majority and the impact of forum messages. Though this research work is to investigate the relationship between social media and bitcoin value. If we plan to research if a factor would affect the stock price, the research procedure is worth referring to. The primary reference for us is the evaluation part.

Caglayan et al. in (Caglayan, Celiker, & Sonaer, 2018) leveraged a study on comparing hedge fund and non-hedge fund and involved research on how these two kinds of funds affect the related stock price. Stock prices and returns data were obtained from the Center for Research in Security Prices (CRSP) Monthly Stock File. The accounting data were obtained from CRSP/Compustat Merged Database. The quarterly data on institutional holdings were acquired from the CDA/Spectrum database maintained by Thomson Reuters. They conducted samples and pre-processing on the data: Only US common stocks traded on the AMEX, NASDAQ, and NYSE are included. To control the variables, they excluded stocks with negative book equity values. Besides, to alleviate the bid-ask bounce effect, they also eliminated stock with very low share prices. Then applied descriptive statistics to illustrate their findings. The strengths of their work are that they applied the statistical methods on a large data combination of both accounting data and stock price data. Another strength of this paper is their clear and useful conclusions of funding behaviors. The only drawback of this work is that they didn't explain the methodology and model structure clearly. Based on the trading behaviors, the authors

compared hedge funds and other institutions. They concluded that compared to other institutions, hedge funds are better able to identify overpriced growth stocks. Another important finding is that when the book-to-market values of stocks become public information, the hedge funds preference from growth stocks will immediately change to value stocks. While the authors found no evidence to show that hedge funds have more superior ability to recognize mispriced securities among stocks than other institutional investors. Their conclusion could support our hypothesis of funding is an essential feature of stock price fluctuations, also warns us that to treat funding from different institutions as the same feature would cause noise.

Jiang and Verardo in (Ye, Jiang, Yang, & Yan, 2017) conducted research on how herding behavior affects the stock price. Their sample consisted of all actively managed U.S. equity funds from 1990 to 2009. The monthly fund returns and other fund characteristics were obtained from the CRSP Mutual Fund database. Fund stock holding data came from the Thomson Reuters Mutual Fund Holdings database. They modeled data using regression models and presented the result by descriptive statistics. The behaviors they analyzed were different from other previous works; for instance, they analyzed if herding behavior related to the termination for a fund manager. However, we found very few previous works related to analyzing the employment states of fund managers, thus it causes difficulty to compare their work with others. Herding behavior is one of the most commonly seen behaviors in stock-market activities. By digging deep into the fund manager's performance and behaviors, they found a significant performance gap between herding and anti-herding funds inexperienced managers. Similar to other financial

domain research papers, their conclusions from behavior analysis are valuable to our work.

Wermers et al. in (Wermers et al., 1999) leveraged a study on how mutual fund herding impact on stock prices. Most of the fund-holding data were obtained from the CDA database. While the monthly returns and month-end prices were from the CRSP daily files. They exploited financial data modeling on the gathered data. The strengths of their work are that authors leveraged a thorough study on herding behaviors. Their analysis not limited to general herding behaviors in the stock market, but also included the comparison between large stocks and small stocks. Besides, they also performed analysis on herding behavior of different oriented funds. However, it is a relatively outdated previous work. The research questions limited the range of study in mutual funds only, while some investment strategies were not available in this kind of funds such as short-selling small stock portfolios. Similar to other financial domain paper, the most valuable part of this study was the phenomenon and conclusion from their research works. They found that herding behavior does not increase monotonically by funds trading in one stock, but slightly decreases with the increase of the trading activities performed by funds. Besides, they also concluded that herding behavior is more common in growth-oriented funds than income-oriented funds. For our work, we know another criterion to classify funds, and it might be useful when we are collecting funds data as a potential feature for the users to perform analysis.

Hendricks and Singhal in (Hendricks & Singhal, 2009) performed an empirical analysis about how supply chain disruptions affect the stock price. They leveraged buy-and-hold abnormal returns (BHARs) on collected data. The data sample they used was an

extension of the sample collected by Hendricks and Singhal (2003) for their short-window event study. The authors performed a study on long-run stock price which was a valuable subdomain in stock prices analysis while has few references. However, it is a particular research direction on supply chain disruptions while such data is often difficult to access. Different from other papers we reviewed in financial domain, the authors of this paper leveraged a study on long-run stock price performance. The situation they analyzed was the effect of supply chain disruptions. If we could access the related data, their findings would be significant to our research, especially on the long-run stock price prediction. One of the important findings from their statistical analysis work was: the risks of disruptions were associated with increases in financial leverage, it inspired us to focus more on the financing activities.

Zhang conducted a thorough research on non-competitive markets and heterogeneous investors. The research dataset was post-war asset pricing datasets from the real world. The author performed both discrete-time model and continuous-time model on the dataset, set a homogeneous agent rational expectation model for the baseline. The strength of this paper is that it has a solid foundation of statistics and financial domain background knowledge.

This paper is a specific researched on monopolistic traders. Monopolistic trading behaviour is a very common symptom in China; the original purpose of retrieving information in this paper is to eliminate the particular case and increase the generality of our proposed solution, while we found some significant findings related to market phenomena such as asset price bubbles and flash crashes.

## 2.3 Description of Our Dataset

In this section, we will describe the dataset in detail. This dataset consists of 3558 stocks from Chinese stock market. Besides the daily price data, daily fundamental data of each stock ID, we also collected the suspending and resuming history, top 10 shareholders, etc. We list two reasons that we choose two years as the time span of this dataset: 1. Most of the investors perform stock market price trend analysis using the data within the latest two years. 2. Using more recent data would benefit the analysis result.

We collected data through the open-sourced API namely Tushare ("Tushare API," 2018), meanwhile, we also leveraged web-scraping technique to collect data from Sina Finance web pages, SWS Research website.

### 2.3.1 Data Structure

**Figure 1 Dataset Structure**

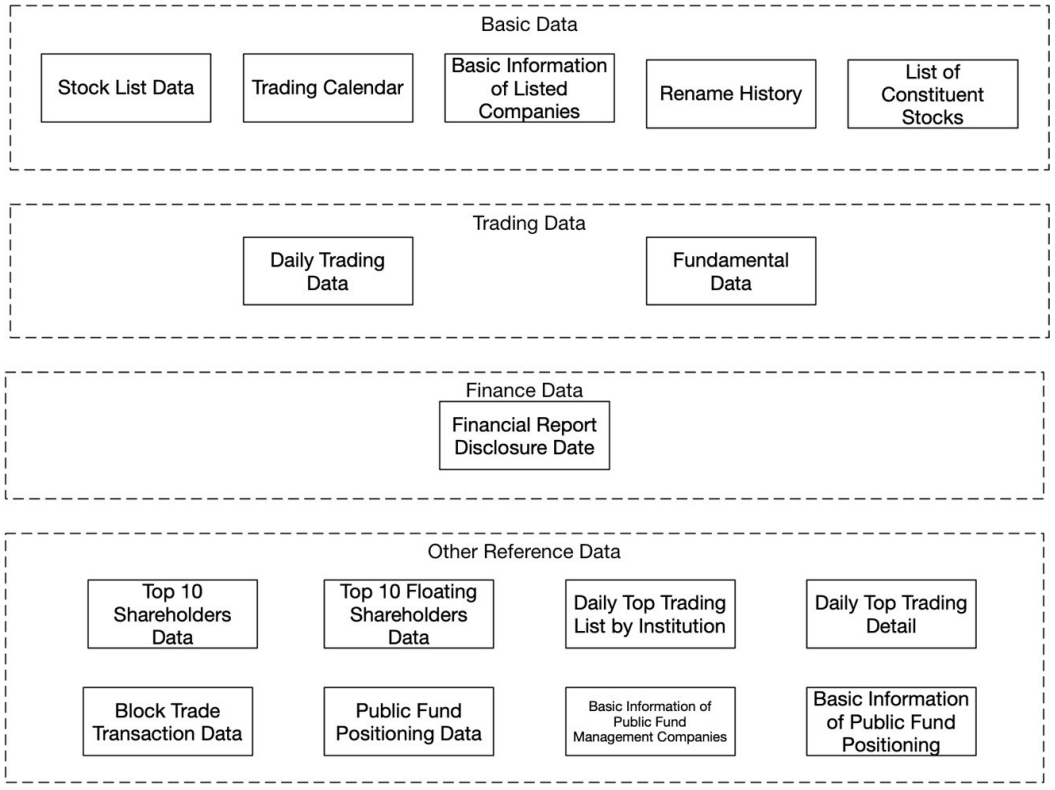


Figure 1 illustrates all the data tables in the dataset.

We collected four categories of data in this dataset: basic data, trading data, finance data, and other reference data.

All the data tables can be linked by a field called “Stock ID.” It is a unique stock identifier registered in Chinese Stock market.

Basic Data is the basic information that the researchers might need when exploring the data. It consists of Stock List Data, Trading Calendar, Basic Information of Listed Companies, Rename History and List of Constituent Stocks.

Stock List Data: this data table lists the basic information of all the stocks. It has both Chinese name and English name, as well as other important information such as industry, market type, list/delist date and stock exchange, etc. While the most useful column is stock ID, researchers can store the list and look up information in other data tables.

Trading Calendar: trading calendar data table is also for lookup usage. To look up if a day is a trading date or not. Users can filter the calendar by different stock exchange ID (SSE or SZSE).

Basic Information of Listed Companies: information about listed companies such as geography information and line of business. This data table is also arranged by stock ID.

Rename History: history of renaming the stocks, including the start date and end date of the name also the reason for changing. While the stock ID never changes with the stock name.

List of Constituent Stocks: if a stock is constituent stock can be counted as a feature. Users can also get the information about if the constituent stock is newly included.

The category called trading data consists of two data types; one is daily trading data; another one is the fundamental data. They are the core data of this dataset; it consists of 2-year stock trading data from Jan 2017 to Dec 2018.

Daily Trading Data: daily trading data is arranged by stock ID, one stock ID per CSV file. It consists of 2-year trading data in daily basis from Jan 2017 to Dec 2018, and if the stock were listed after Jan 2017, the date range would be from the listed date to Dec 2018. If the stock were delisted before Dec 2018, the data range would be from Jan 2017 to delist date. If the stock was listed after Jan 2017 and delisted before Dec 2018, the data range will be from listed date to delisted date. Trading data includes the basic price data to calculate the technical indices.

Fundamental Data: daily fundamental data is also arranged by stock ID, one stock ID per CSV file. It consists of 2 years of fundamental data on a daily basis from Jan 2017 to Dec 2018; if the stock were listed after Jan 2017, the date range would be from the listed date to Dec 2018. If the stock were delisted before Dec 2018, the data range would be from Jan 2017 to delist date. If the stock was listed after Jan 2017 and delisted before Dec 2018, the data range will be from listed date to delisted date. Different from trading data, the fundamental data are often used to perform analysis straightforward rather than calculation.

The third category is the finance data. There wasn't much finance data available on-line; we can only get the financial report disclosure date to support the related analysis.

Financial Report Disclosure Date: all the financial report disclosure date data are arranged within one data table. While researchers can still look up the related information

by stock ID, this data table does not include the detailed data of financial reports but only the scheduled disclosure date and actual disclosure date.

Besides, this dataset also consists of abundant reference data that highly expand the research opportunities. There are eight data tables of other reference data available. This data might be used to support related analysis or for feature extension usage.

Top 10 Shareholders Data: data of all the stocks are stored in one data table. Users can group by stock ID, announcement date, or end date. It is also possible to query by Shareholder name when the same shareholder holds multiple stocks in the top 10 chart. Holding amount and holding ratio is available for analysis.

Top 10 Floating Shareholders Data: different from top 10 shareholder chart, this data table does not include holding ratio since it is for floating shareholders while users can still group the data by stock ID, announcement and end date, shareholder name.

Daily Top Trading List by Institution: since one institution might operate multiple times in a day, this data table of the trading transaction is grouped by institutions. Top 10 buyers and top 10 sellers are listed in one same data table may need a further arrangement for analysis one direction trading.

Daily Top Trading Detail: the top trading transactions detail of all stocks are stored in one same data table. This data table is transaction-based; the information embedded in this table is more detailed than the daily top trading list by institutions. Besides the amount and ratio data, the nominated reason is also included in the data table.

Block Trade Transaction Data: not only top trading transactions are important to stock price trend analysis, but block trade transaction data is also essential.

Public Fund Positioning Data: public fund positioning status is often considered as an important feature of stock price analysis; it has been proved correlating to the stability of stock performance. This data table includes the market value and volume, instead of grouping by stock ID, this data table is grouped by fund ID while researchers can still rearrange the data into stock ID-based structure as the extended features for further analysis.

Basic Information of Public Fund Management Companies: most of the information in this data table are descriptive data about fund management companies.

Basic Information of Public Fund Positioning: most of the information in this data table are features of the fund. Users can exploit fund ID to other data tables for further analysis.

### 2.3.2 Basic Data

First, we collected the basic data of the Chinese stock market. The function of basic data is to facilitate data analysis tasks, when researchers using this dataset, they won't have to extract basic information mapping table or trading calendar anymore.

The basic data consists of stock list, trading calendar, basic information of listed companies, renamed history, constituent stock information.

**Table 1 Basic Data**

| Table Name | Field |
|---|---|
| Stock List | Stock ID, Stock name, Geographic info, Industry, Full name, English name, Market type, Stock exchange ID, Currency, List status, List date, Delist date, If the stock is HS constituent |
| Trading Calendar | Stock exchange ID, Calendar date, If the date is open for trading, Pervious trading date |
| Basic Information of Listed Companies | Stock ID, Stock exchange ID, Corporate representative, General manager, Secretary, Authorized capital, Registration date, Province, City, Introduction, Website, Email, Office address, Number of employees, Main business, Business scope |
| Renamed History | Stock ID, Stock name, Start date, End date, Announcement date, Rename reason |
| Constituent Stock Information | Stock ID, Constituent type, Included date, Excluded date, If the stock is new |

For the stock list data, we list the descriptions of each field in the table below.

**Table 2 Stock List Data**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Stock name | String | Short Chinese name of the stock |
| Geographic info | String | Where the company registered |
| Full name | String | Full Chinese name of the stock |
| English name | String | English name of the stock |
| Market type | String | If the stock is on Growth Enterprise Market Board(GEM), Small and Medium Enterprise Board(SME) or Main Board |
| Stock exchange ID | String | The identifier of the organized marketplace for share trading.<br>SZSE for Shenzhen Stock Exchange and<br>SSE for Shanghai Stock Exchange |
| Currency | String | Currency of trading |
| List status | String | L for listed stock, D for delisted stock |
| List date | String | The date of a stock listed |
| Delist date | String | The date of a stock delisted |
| If the stock is HS constituent stock | String | N for not HS constituent stock,<br>H for Shanghai constituent stock,<br>S for Shenzhen constituent stock |

Blow is the trading calendar data. The trading calendar is different from normal calendars so the users would not have to check the public holidays of China.

**Table 3 Trading Calendar**

| Field | Type | Description |
|---|---|---|
| Stock exchange ID | String | The identifier of the organized marketplace for share trading. SZSE for Shenzhen Stock Exchange and SSE for Shanghai Stock Exchange |
| Calendar date | String | Calendar date in YYYYMMDD format |
| If the date is open for trading | Integer | 1 for open and 0 for closed |
| Previous trading date | String | Previous trading date in YYYYMMDD format |

We also collected the basic information of listed companies.

**Table 4 Basic Information of Listed Companies**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Stock exchange ID | String | The identifier of the organized marketplace for share trading.<br>SZSE for Shenzhen Stock Exchange |
| Corporate | String | The corporate representative of the company |
| General manager | String | The general manager of the company |
| Secretary | String | The secretary of the chairman of the board |
| Authorized capital | Float | The authorized capital of the company |
| Registration date | String | When did the company register |
| Province | String | Which province does the company locate |
| City | String | Which city does the company locate |
| Introduction | String | The introduction of the company |
| Website | String | The website of the company |
| Email | String | The email of the company |
| Office address | String | The office address of the company |
| Number of employees | Integer | Number of employees working in the company |
| Main business | String | Main business of the company |
| Line of business | String | Line of business scope |

When analyzing the specific stock, we might encounter the stock name changed and it would possibly affect the analysis result. Thus, we also collected the name changing history of stocks.

The constituent stock is another special stock type of Chinese stock market; they can be regarded as a label on some of the stocks. We also collected the list of constituent stocks.

**Table 5 Rename History**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Stock name | String | Short Chinese name of the stock |
| Start date | String | Start date of using this name |
| End date | String | End date of using this name |
| Announcement date | String | The date of rename announcement published |
| Change reason | Float | The reason of changing the stock name |

**Table 6 List of Constituent Stocks**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |

| | | |
|---|---|---|
| If the stock is HS constituent stock | String | N for not HS constituent stock, H for Shanghai constituent stock, S for Shenzhen constituent stock |
| Start date | String | Start date of being listed in constituent stock |
| End date | String | End date of being listed in constituent stock |
| If it is new? | Integer | If it is a new constituent stock, 1 for yes, 0 for no. |

### 2.3.3 Trading Data

The data structure of this section is one file per stock ID on a daily basis. We collected daily trading data and daily fundamental data. The time span of the data collection is from Jan 1st 2017 till now.

Below is the daily trading data.

**Table 7 Daily Trading Data**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Trading date | String | Trading date in YYYYMMDD format |
| Opening price | Float | Opening price of stock exchange |

| | | |
|---|---|---|
| Highest price | Float | Highest price of the day |
| Lowest price | Float | Lowest price of the day |
| Closing price | Float | Closing price of stock exchange |
| Previous closing price | Float | Previous closing price of stock exchange |
| Price change | Float | Price change of the day |
| Price change percentage | Float | Price change percentage of the day |
| Volume | Float | Volume of stock exchange in trading date |
| Amount | Float | Amount of stock exchange in trading date |

Fundamental data are often exploited to perform the top-down analysis or the bottom down analysis. We also structured the data to the daily basis per stock ID. And they share the same timespan with trading data.

**Table 8 Fundamental Data**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Trading date | String | Trading date in YYYYMMDD format |

| | | |
|---|---|---|
| Closing price | Float | Closing price of stock exchange |
| Turnover rate | Float | One of the metrics to indicate the negotiability of a stock |
| Free turnover rate | Float | One of the metrics to indicate the negotiability of a stock |
| Volume ratio | Float | The metrics to measure the volume of a stock |
| Price-to-earning ratio | Float | Price/EPS, EPS is the abbreviation of Earning per share |
| Price-to-earning ratio TTM | Float | TTM PE |
| Price-to-book ratio | Float | Price/Asset |
| Price-to-sales ratio | Float | Price/sales price per share |
| Price-to-sales TTM | Float | TTM PS |
| Total share capital | Float | The total amount of share capital |
| Circulating shares | Float | The total amount of circulating shares |
| Tradable circulating shares | Float | The total amount of tradable circulating shares |
| Aggregate market value | Float | Total market value of the stock |
| Circulation market value | Float | Circulation market value of the stock |

### 2.3.4 Finance Data

This section is the finance data, such as income statement and balance sheet of each stock ID.

Financial report disclosure schedule might also affect the stock price, the data are stored in one table for all stocks.

**Table 9 Financial Report Disclosure Date**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Latest disclosure date | String | The latest disclosure date of financial report in YYYYMMDD format |
| Reporting period | String | The last day of reporting period in YYYYMMDD format |
| Scheduled disclosure date | String | The scheduled disclosure date of financial report in YYYYMMDD format |
| Actual disclosure date | String | The actual disclosure date of financial report in YYYYMMDD format |
| Disclosure modification date | String | The record of modified disclosure date, in YYYYMMDD format |

### 2.3.5 Other Reference Data

We also collect other reference data such as the top 10 shareholders data per stock ID. Below is the structure of top 10 shareholders data of each stock.

**Table 10 Top 10 Shareholders Data**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Announcement date | String | Announcement date in YYYYMMDD format |
| End date | String | Reporting date in YYYYMMDD format |
| Shareholder name | String | Name of the shareholder |
| Holding amount | Float | Stock holding amount (per unit of stock) |
| Holding ratio | Float | Stock holding ratio |

Besides, we also collect the top 10 floating shareholders data for the stocks in basic information scope for comparison purpose.

**Table 11 Top 10 Floating Shareholders Data**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Announcement date | String | Announcement date in YYYYMMDD format |
| End date | String | Reporting date in YYYYMMDD format |
| Shareholder name | String | Name of the shareholder |
| Holding amount | Float | Stock holding amount (per unit of stock) |

We collect the daily top trading list of buying and selling, both detail and group by institution.

**Table 12 Daily Top Trading List by Institution**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Trading date | String | Trading date in YYYYMMDD format |
| Institution name | String | The name of trading institution |
| Trading amount - buy | Float | Amount of sell (unit of 10k RMB) |

| | | |
|---|---|---|
| Trade ratio - buy | Float | Ratio of buy amount to total turnover amount |
| Trading amount - sell | Float | Amount of sell (unit of 10k RMB) |
| Trade ratio - sell | Float | Ratio of sell amount to total turnover amount |
| Net turnover | Float | Net turnover amount (unit of 10k RMB) |

Below is the data structure of daily top trading transaction detail.

**Table 13 Daily Top Transaction Detail**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Trading date | String | Trading date in YYYYMMDD format |
| Stock name | String | Short Chinese name of the stock |
| Closing price | Float | Closing price of the stock on the corresponding trading date |
| Price change percentage | Float | Price change percentage of the stock on the corresponding trading date |
| Turnover rate | Float | Turnover rate of the trading transaction |
| Amount - overall | Float | Overall trading amount of the trading |
| On-list amount - sell | Float | Amount of the trading transaction for selling |
| On-list amount - buy | Float | Amount of the trading transaction for buying |

| | | |
|---|---|---|
| On-list turnover | Float | Turnover of the trading transaction |
| On-list net trading amount | Float | Net trading amount of the trading transaction |
| On-list net trading ratio | Float | Ratio of net trading amount to overall trading amount |
| On-list net turnover ratio | Float | Ratio of on-list net turnover to overall turnover |
| Circulation market | Float | Circulation market value of the stock |
| Reason | String | Reason of being nominated. |

**Table 14 Block Trade Transaction Data**

| Field | Type | Description |
|---|---|---|
| Stock ID | String | Stock identifier |
| Trading date | String | Trading date of the transaction in YYYYMMDD format |
| Price | Float | Transaction price |
| Volume | Float | Transaction volume (in 10k unit) |
| Amount | Float | Transaction amount (price x volume) |
| Buyer | String | Buying institution name |
| Seller | String | Selling institution name |

Besides the shareholder related data, the block trade data is also considered as one of the factors that may affect the stock price trend that worth to investigate.

Since many of the investors mentioned how fund positioning affect stock market price trend, we also collect the fund positioning data as an important part of reference data. Please be aware that the fund data are public fund data only, which can also be fund on public financial web sites.

The basic information of fund management company is for further data mining purpose. The data structure is illustrated as the table below.

Besides, the basic information on fund positioning data is summarized in one data table. This is a positioning transaction-based data table.

**Table 15 Public Fund Positioning Data**

| Field | Type | Description |
|---|---|---|
| Fund ID | String | Public fund identifier |
| Announcement date | String | Announcement date of positioning in YYYYMMDD format |
| End date | String | The end date of positioning in YYYYMMDD format |
| Stock ID | String | Stock identifier |
| Market value | Float | Positioning market value (Yuan) |
| Volume | Float | Positioning volume (per unit of stock) |

| | | |
|---|---|---|
| Market value ratio | Float | The ratio of occupied market value of positioning to overall market value |
| Circulation market value ratio | Float | The ratio of occupied circulation market value of positioning to overall circulation market value |

## 2.4 Research Opportunity

Since we have collected a variety of data, the research opportunity is abundant. First, the daily trading data is available; the researchers can use the fundamental price information to calculate most of the technical indices. Moreover, researchers can also model the technical indices with fundamental prices in two years to time sequence and make the price or trend prediction.

Not only can the price and technical indices be used as features, but other information gathered in the dataset can also potentially be used as features and serves for data mining purpose.

For example, many previous works involve sentiment analysis in their proposed solutions. With the essential information in our dataset, researchers can perform web-scraping to get the related public information from websites. Or they could leverage the news scraping on social media to supervise how social media post affect the stock market price, which makes a real-time sentiment analysis system on the stock market possible.

# Chapter 3: Survey of Related works

In this section, we will introduce the previous works. We reviewed related work in two different domains: technical and financial, respectively. While the financial domain literature review can be found in chapter 2.2 for providing the direction of data collection, this part is the literature review of the technical domain.

## 3.1 Technical Related Works

Kim and Han in (Kim & Han, 2000) built a new hybrid model of artificial neural networks (ANN) and used genetic algorithms (GAs) approach to feature discretization for predicting stock price index. The research data used in this study is technical indicators and the direction of change in the daily Korea stock price index (KOSPI). The total number of samples is 2928 trading days, from January 1989 to December 1998. Table 16 gives selected features and their formulas (Achelis, 1995; Chang, Jung, Yeon, Jun, Shin & Kim, 1996; Choi, 1995; Edwards & Magee, 1997; Gifford, 1995). They also applied optimization of feature discretization, closely related to the dimensionality reduction.

The strengths of their work are that they introduced GA to optimize the ANN, also listed the selected features in Table 16. However, we also found some weaknesses existed in this paper. First, the amount of input features and processing elements in the hidden layer is 12 and not adjustable. Another limitation is in the learning process of ANN; the authors only focused on two factors in optimization. While they still believed that GA has great potential for feature discretization optimization. Our initialized feature pool refers to the selected features in Table 16. The algorithm they used to improve the ANN performance was GA, which is popularly used to optimize relevant feature subset or

determine the number of processing elements and hidden layers. So, we include ANN for model performance comparison.

Piramuthu in (Piramuthu, 2004) conducted a thorough evaluation of different feature selection methods for data mining applications. He used for datasets which were credit approval data, loan defaults data, web traffic data, tam and kiang data, and compared how different feature selection methods optimized decision tree performance. The feature selection methods he compared included probabilistic distance measure: the Bhattacharyya measure, the Matusita measure, the divergence measure, the Mahalanobis distance measure, and the Patrick-Fisher measure. For inter-class distance measures: the Minkowski distance measure, city block distance measure, Euclidean distance measure, the Chebychev distance measure, and the nonlinear (Parzen and hyper-spherical kernel) distance measure. The strength of this paper is that the author evaluated both probabilistic distance-based and several inter-class feature selection methods. Besides, the author performed the evaluation based on different datasets, which reinforced the strength of this paper. However, the evaluation algorithm was a decision tree only. We cannot conclude if the feature selection methods will still perform the same on a larger dataset or a more complex model. This paper introduced a method for feature selection. Since there are a large number of features in the stock market, irrelevant features will affect the performance, so we would like to investigate the feature selection approaches. The author also found that the nonlinear measure often performed well in most cases.

Hassan and Nath in (Hassan & Nath, 2005) applied Hidden Markov Model (HMM) on the stock market forecasting on stock prices of four different Airlines. They reduce states of the model into four states: opening price, closing price, the highest price, and the

lowest price. The strong point of this paper is that the approach does not need expert knowledge to build a prediction model. While this work is limited within the industry of Airlines, and evaluated on a very small dataset, may not lead to a prediction model with generality. One of the approaches in stock market prediction related works could be exploited to do the comparison work. The authors selected maximum 2 years as the date range of training and testing dataset, which provided us a date range reference for our evaluation part.

Lei in (Lei, 2018) exploited Wavelet Neural Network (WNN) to predict stock price trend. The author also applied Rough Set (RS) for attribute reduction as an optimization. Rough Set was exploited to reduce the stock price trend feature dimensions. It was also used to determine the structure of Wavelet Neural Network. The dataset of this work consists of 5 famous stock market indices. SSE Composite Index (China), CSI 300 Index (China), All Ordinaries Index (Australian), Nikkei 225 Index (Japan) and Dow Jones Index (USA). The model evaluation was based on different stock market indices, the result was convincing with generality. By using Rough Set for optimizing the feature dimension before processing reduces the computational complexity. However, the author only stressed the parameter adjustment in discussion part but didn't specify the weakness of the model itself. Meanwhile, we also found that the evaluations were performed on indices, the same model may not have the same performance if applied on a specific stock. The features table and calculation formula are worth taking as a reference. They can also include RS as a method for attribute discretization before processing the data.

Lee in (M. C. Lee, 2009) used the support vector machine (SVM) with a hybrid feature selection method to perform the stock trend prediction. The dataset in this research

project is a sub data set of NASDAQ Index from Taiwan Economic Journal database (TEJD, 2008). The feature selection part was using a hybrid method, supported sequential forward search (SSFS) played the role of the wrapper. Another advantage of this work is that they designed a detailed procedure of parameter adjustment with performance under different parameter values. The clear structure of feature selection model is also heuristic to the primary stage of model structuring. One of the limitations was that the author completed the performance evaluation of SVM to compare with back-propagation neural network (BPNN) only, while did not compare with other machine learning algorithms. Table 2 listed the results of F-score and average accuracy rate of selected features. The author also found that the combination of the SVM-based model and F _SSFS served as a promising method in stock trend prediction.

Sirignano and Cont leveraged a deep learning approach trained on a universal feature set of financial markets in (Sirignano & Cont, 2018). The data set they used was a high-frequency electronic buy and sell records of all transactions, and cancellations of orders for approximately 1000 NASDAQ stocks through the exchange's order book. The NN consists of 3 layers with LSTM units followed by a feed-forward layer with rectified linear units (ReLUs) at last, with stochastic gradient descent (SGD) algorithm as an optimization. A fruitful paper on modeling mega data. Their universal model was able to generalize to stocks outside of the training sample. Though they mentioned the advantages of a universal model, the training cost was still expensive. Meanwhile, due to the inexplicit programming of the deep learning algorithm, we don't know if there are useless features adulterated when feeding the data into the model. It would be better if they perform a feature selection part before training the model, and it is also an effective

way to reduce the computational complexity. First, the paper proved that the price information in the financial market has universal features. The features they extracted were trained from all stocks, which also proved the value of our work in stock price trend analysis. They also proved that to build a large model without overfitting on financial data is possible.

Ni et al. in (Ni, Ni, & Gao, 2011) predicted stock price trend by exploiting SVM and performed fractal feature selection for optimization. The dataset they used is Shanghai Stock Exchange Composite Index (SSECI) with 19 technical indicators as features. Before processing the data, they optimized the input data by performing feature selection. When finding the best parameter combination, they also used a grid search method which is k-cross-validation. Besides, the evaluation of different feature selection methods is also comprehensive. As the authors mentioned in their conclusion part, they only considered the technical indicators but not macro and micro factors in financial domain. The source of datasets that authors used were similar to our dataset, which makes their evaluation results useful to our research. They also mentioned a method called k-cross-validation when testing hyper-parameter combinations.

McNally et al. in (McNally, Roche, & Caton, 2018) leveraged RNN and LSTM on predicting the price of Bitcoin, optimized by using Boruta algorithm for feature engineering part, it works similarly to the random forest classifier. Besides feature selection, they also used Bayesian optimization to select LSTM parameters. The Bitcoin dataset ranged from the 19th of August 2013 to 19th of July 2016. Used multiple optimization methods to improve the performance of deep learning methods. The primary problem of their work is overfitting. The research problem of predicting Bitcoin price

trend has some similarities with stock market price prediction. Hidden features and noises embedded in the price data are threats of this work, the authors treated the research question as a time sequence problem. The best part of this paper is feature engineering and optimization part; we could replicate the methods they exploited in our data pre-processing.

Weng et al. in (Weng, Lu, Wang, Megahed, & Martinez, 2018) focused on short-term stock prices prediction by using ensemble methods of four commonly used machine learning models. The dataset for this project is five sets of data, they obtained these datasets from three open-sourced APIs and the TTR R package. The four commonly used machine learning models are a neural network regression ensemble (NNRE), a Random Forest with unpruned regression trees as base learners (RFR), AdaBoost with unpruned regression trees as base learners (BRT) and a support vector regression ensemble (SVRE). A thorough study of ensemble methods specified for short-term stock price prediction. With background knowledge, authors selected eight technical indicators in this study then performed a thoughtful evaluation of five datasets. The primary contribution of this paper is that they developed a platform for investors using R, which does not need users to input their own data but call API to fetch the data from online source straightforward. From the research perspective, they only evaluated the prediction of the price for 1 up to 10 days ahead but did not evaluate longer terms than two trading weeks or a shorter term than 1 day. The primary limitation of their research was that they only analyzed 20 U.S.-based stocks, the model might not be generalized to other stock market or need further revalidation to see if it suffered from overfitting problems. The core content that related

to our work is the feature extraction and evaluation. They illustrated how they performed feature extraction in detail and also listed the formula for evaluation.

Kara et al. in (Kara, Acar Boyacioglu, & Baykan, 2011) also exploited ANN and SVM in predicting the stock price index movement. The entire data set covers the period from January 2, 1997, to December 31, 2007, of Istanbul Stock Exchange. The primary strength of this work is their detailed record of parameter adjustment procedures. While the weaknesses of this work are: neither the technical indicator nor the model structure has novelty, and the authors didn't explain how their model performed better than other models in previous works, thus more validation works on other datasets would help. They explained how ANN and SVM work with stock market features, also recorded the parameter adjustment. The implementation part of our research could benefit from this previous work.

Jeon et al. in (Jeon, Hong, & Chang, 2018) performed research on millisecond interval-based big dataset by using pattern graph tracking to complete stock price prediction task. The dataset they used is a millisecond interval-based big dataset of historical stock data from KOSCOM, from August 2014 to October 2014, 10G-15G capacity. The author applied Euclidean distance, Dynamic Time Warping (DTW) for pattern recognition. For feature selection, they used stepwise regression. The authors completed the prediction task by ANN, and Hadoop and RHive for big data processing. Evaluation section is based on the result processed by a combination of SAX and Jaro-Winkler distance. Before processing the data, they generated aggregated data at five-minute intervals from discrete data. The primary strength of this work is the explicit structure of the whole implementation procedure. While they exploited a relatively old model, another weakness

is the overall time span of the training data is extremely short. It is difficult to access the millisecond interval-based data in real life, so the model is not as practical as a daily based data model. The evaluation is only based on three specific stocks in the Republic of Korea. But this work is highly recommended because rather than performing prediction on a small amount of data, this is one of the latest papers in stock price prediction using big data. The SAX and Jaro-Winkler distance methods are worth taking as a reference in our evaluation part.

Huang et al. in (C. F. Huang, Chang, Cheng, & Chang, 2012) applied a fuzzy-GA model to complete the stock selection task. They used the constituent stocks of the 200 largest market capitalization listed in the Taiwan Stock Exchange as the investment universe. Besides, the yearly financial statement data and stock returns were retrieved from the TEJ (Taiwan Economic Journal Co. Ltd., http://www.tej.com.tw/) database for the period of time from 1995 to 2009. For optimization, they conducted the fuzzy membership function with GA-optimized model parameters and extracted features for stock scoring purpose. The authors proposed an optimized model for stock selection and scoring. Different from the prediction model, the authors more focused on stock rankings, selection and performance evaluation, their structure is more practical among investors. But in the model validation part, they did not compare the model with existed algorithms but the statistics of the benchmark, which made it challenging to identify if GA would outperform other algorithms. The most valuable part of their work was the attributes they used in their stock selection model. The authors listed both formula and the references of each attribute. Besides the attributes, they also listed the statistics of benchmarks, it provides us a structure of evaluating machine learning models.

Fischer and Krauss in (Fischer & Krauss, 2018) applied long short-term memory (LSTM) on financial market prediction. The dataset they used is S&P 500 index constituents from Thomson Reuters. They obtained all month-end constituent lists for the S&P 500 from Dec 1989 to Sep 2015, then consolidate the lists into a binary matrix to eliminate survivor bias. The authors also used RMSprop as an optimizer, which is a mini-batch version of rprop. The primary strength of this work is that the authors used the latest deep learning technique to perform financial market predictions. On the other hand, they relied on LSTM technique, lack of background knowledge in financial domain. Though the LSTM outperformed the standard DNN and logistic regression algorithms, while the author did not mention the effort to train an LSTM with long-time dependencies. Their works indicated that LSTM is suitable for financial time series prediction tasks. With a thorough evaluation work, they drew a conclusion that LSTM outperforms the standard DNN and logistic regression marginally. It provided us a direction of choosing an algorithm to model the data if the goal is investigating the time series problem in the stock market.

Tsai and Hsiao in (Tsai & Hsiao, 2010) combined multiple feature selection methods for stock prediction. The data source is Taiwan Economic Journal (TEJ) database. The time range of the data is from the first quarter of 2000 to the second quarter of 2007. They exploited sliding window method combined with multi-layer perceptron (MLP) artificial neural networks with the back-propagation learning algorithm as a baseline prediction model. Besides they also applied principal component analysis (PCA) for dimension reduction, Genetic Algorithms (GA) and the classification and regression trees (CART) for feature selection. Unlike other previous works that took technical indices in consideration only, the data set they analyzed included both fundamental and

macroeconomic indices. The authors also compared the feature selection method combinations. Also, the validation part was done by combining the model performance stats with statistical analysis. The principal component analysis they performed was the basic method. There is another variance of PCA approaches such as asymmetric PCA and kernel PCA. We took a similar structure to the literature review part of this work. Another part worth taking as reference was the fundamental and macroeconomic indices.

Pimenta et al. in (Pimenta, Nametala, Guimarães, & Carrano, 2018) leveraged an automated investing method by using multi-objective genetic programming and applied it in the stock market. The dataset was obtained from Brazilian stock exchange market (BOVESPA), and the primary techniques they exploited were a combination of multi-objective optimization, genetic programming, and technical trading rules. For optimization, they leveraged genetic programming (GP) to optimize decision rules. The novelty of this paper was in the evaluation part. They included a historical period, which was a critical moment of Brazilian politics and economics when performing validation. This approach reinforced the generalization strength of their proposed model. When selecting the sub-dataset for evaluation, they also set criteria to ensure more assets liquidity. While the baseline of the comparison was too basic and fundamental, and the authors didn't perform any comparison with other existing models. The author listed the parameters of their automated system. We consider using the same overall structure to design a prediction model to fit the model on other financial market data, which is a practical approach to increase the model generality.

Huang and Tsai in (C. L. Huang & Tsai, 2009) conducted a filter-based feature selection assembled with a hybrid self-organizing feature map (SOFM) support vector regression

(SVR) model to forecast Taiwan index futures (FITX) trend. They divided the training samples into clusters to marginally to improve the training efficiency. The authors proposed a comprehensive model which was a combination of two novel machine learning techniques in stock market analysis. Besides, the optimizer of feature selection was also applied before the data processing to improve the prediction accuracy and reduce the computational complexity of processing daily stock index data. Though they optimized the feature selection part and split the sample data into small clusters, it was already strenuous to train daily stock index data of this model. It would be difficult for this model to predict trading activities in shorter time intervals since the data volume would be increased drastically. Moreover, the evaluation part is not strong enough since they set a single SVR model as a baseline, but didn't compare the performance with other previous works, which caused difficulty for future researchers to identify the advantages of SOFM-SVR model why it outperforms other algorithms. Overall, their work is a good comparison with other previous works since it has a common structure. We would take their technical attributes and compare with attributes from other works, to identify the similarities and gaps between each work.

Thakur and Kumar in (Thakur & Kumar, 2018) also developed a hybrid financial trading support system by exploiting multi-category classifiers and random forest (RAF). They conducted their research on stock indices from NASDAQ, DOW JONES, S&P 500, NIFTY 50 and NIFTY BANK. The authors proposed a hybrid model combined random forest (RF) algorithms with weighted multicategory generalized eigenvalue support vector machine (WMGEPSVM) to generate "Buy/Hold/Sell" signals. Before processing the data, they used Random Forest (RF) for feature pruning. The authors proposed a

practical model designed for real-life investment activities which could generate three basic signals for investors to refer to. They also performed a thorough comparison between related algorithms, reinforced the strengths of their evaluation part. While they didn't mention the time and computational complexity of their works. Meanwhile, the unignorably issue of their work was the lack of financial domain knowledge background. The investors regard the indices data as one of the attributes, but could not take the signal from indices to operate a specific stock straightforward. Though the system of advising trading activity and calculating profit is relatively naive, while the signals that generated from their system still worth referring to. Besides, they also listed the technical attributes so we could compare the attributes with other works and find the most commonly used attributes in the stock market price or trend prediction domain.

Hsu in (Hsu, 2013) assembled feature selection with a back propagation neural network (BNN) combined with genetic programming to predict the stock/futures price. The dataset in this research project was obtained from Taiwan Stock Exchange Corporation (TWSE). The authors have introduced the description of the background knowledge in detail. While the weakness of their work is that it is a lack of data set description. This is a combination of model that proposed by other previous works. Though we didn't see the novelty of this work, we can still conclude that genetic programming (GP) algorithm is admitted in stock market research domain. To reinforce the validation strengths, it would be good to consider adding GP models into evaluation if the model is predicting a specific price.

Hafezi et al. in (Hafezi, Shahrabi, & Hadavandi, 2015) built a bat-neural network multi-agent system (BN-NMAS) to predict stock price. The dataset was obtained from the

deutsche bundes-bank. They also applied bat algorithm (BA) for optimizing neural network weights. The authors illustrated their overall structure and logic of system design in clear flowcharts. While there was very few previous works that had performed on DAX data, it would be difficult to recognize if the model they proposed still has the generality if migrated on other datasets. The system design and feature selection logic are fascinating which worth referring to. Their findings in optimization algorithms are also valuable for the research in stock market prices prediction research domain, it is worth trying bat algorithm (BA) when constructing neural network models.

Long et al. in (Long, Lu, & Cui, 2018) conducted deep learning approach to predict the stock price movement. The dataset they used is Chinese stock market index CSI 300. For predicting the stock price movement, they constructed a multi-filter neural network (MFNN) with stochastic gradient descent (SGD) and back propagation optimizer for learning NN parameters. The strength of this paper is that the authors exploited a novel model with a hybrid model constructed by different kinds of neural networks, it provides an inspiration of constructing hybrid neural network structures. However, they used a regular optimizer and did not consider the time and computational complexity of their proposed model. Their work was a combination of different NNs, which was a valuable reference of feature mapping and how to deal with overfitting problems.

Atsalakis and Valavanis in (Atsalakis & Valavanis, 2009) proposed a solution of a neuro-fuzzy system, which is composed of an Adaptive Neuro Fuzzy Inference System (ANFIS) controller to achieve short-term stock price trend prediction. The noticeable strength of this work is the evaluation part. Not only did they compare their proposed system with the popular data models, but also compared with investment strategies. While the

weakness that we found from their proposed solution is that their solution architecture is lack of optimization part, which might limit their model performance. Since our proposed solution is also focusing on short-term stock price trend prediction, this work is heuristic for our system design. Meanwhile, by comparing with the popular trading strategies from investors, their work inspired us to compare the strategies used by investors with techniques used by researchers.

Nekoeiqachkanloo et al. in (Nekoeiqachkanloo, Ghojogh, Pasand, & Crowley, 2019) proposed a system with two different approaches for stock investment. The strengths of their proposed solution are obvious. First, it is a comprehensive system that consists of data pre-processing and two different algorithms to suggest the best investment portions. Second, the system also embedded with a forecasting component which also retains the features of time series. Last but not least, their input features are a mix of fundamental features and technical indices which aims to fill in the gap between financial domain and technical domain. However, their work has a weakness in evaluation part. Instead of evaluating the proposed system on a large dataset, they chose 25 well-known stocks. There is a high possibility that the well-known stocks might potentially share some common hidden features. Thus, some other related works randomly sampled stocks from datasets to perform the evaluation as a denoise method. The data pre-processing part before feeding the technical indices into time series forecasting component is heuristic to our system design.

As another related latest work, Idrees et al. (Idrees, Alam, & Agarwal, 2019) published a time series-based prediction approach for the volatility of the stock market. ARIMA is not a new approach in time series prediction research domain, their work is more

focusing on feature engineering side. Before feeding the features into ARIMA models, they designed three steps for feature engineering: Analyze the time series, identify if the time series is stationary or not, perform estimation by plot ACF and PACF charts and look for parameters. The only weakness of their proposed solution is that the authors did not perform any customization on existing ARIMA model, which might limit the system performance to be improved. Their proposed solution stressed the importance of feature selection again, the good evaluation result indicated that even the data model is not state-of-the-art, as long as embedded with a feature engineering step, the prediction result can still be promising.

**Table 16 Comparative Analysis Table**

| Work | Dataset | Prediction Model | Input Variables | Feature Selection or Optimizer |
|---|---|---|---|---|
| (Nekoeiqachkanloo et al., 2019) | Dataset of New York Stock Exchange (NYSE) | Two approaches: Markowitz portfolio theory and fuzzy investment counselor | Average Directional Index (ADI) and Stop and Reverse (SAR), 4 types of prices and volume, fundamental features | Three methods of data preprocess |
| (Idrees et al., 2019) | Dataset from India stock exchanges: NSE and BSE | Auto Regressive Integrated Moving Average (ARIMA) | Index value formed into time sequence | Three steps of feature engineering: Analyze, |

| | | | | |
|---|---|---|---|---|
| | | | | identify and estimation |
| (McNally et al., 2018) | Bitcoin dataset ranged from the 19th of August 2013 to 19th of July 2016. | Recurrent neural network (RNN) and long short-term memory (LSTM) | 5 days and 10 days moving average (MA) of price | Boruta algorithm |
| (Weng et al., 2018) | Five sets of data are obtained from three open source APIs and the TTR R package | Neural networks regression ensemble (NNRE), random forest regression (RFR), boosted regression tree (BRT), support vector regression ensemble (SVRE) | 4 stages of different number of technical indicators | N/A |
| (Lei, 2018) | SSE Composite (China), CSI 300 (China), All Ordinaries (Australian), Nikkei 225(Japan) and Dow Jones (USA) | Rough Set (RS) and Wavelet Neural Network (WNN). | 15 technical features | Rough Set (RS) |
| (Sirignano & Cont, 2018) | Detailed trading records of approximately | 3 layers of long short-term memory (LSTM) units with a feed-forward layer | Price in time-series and the history of the order book over | Stochastic gradient descent (SGD) algorithm |

| | | | | |
|---|---|---|---|---|
| | 1000 NASDAQ stocks | of rectified linear units (ReLUs) | many observation lags | |
| (Fischer & Krauss, 2018) | S&P 500 index constituents from Thomson Reuters | Long short-term memory (LSTM) | 3 kinds of performance characteristics | RMSprop |
| (Jeon et al., 2018) | A millisecond interval based big dataset of historical stock data from KOSCOM, from August 2014 to October 2014 | Artificial neural network (ANN) for prediction. Hadoop and RHive for big data processing. | 4 types of price: trading, opening, low, high | Stepwise regression |
| (Pimenta et al., 2018) | Data were obtained from Brazil stock exchange market (BOVESPA) | A combination of multi-objective optimization, genetic programming, and technical trading rules. | 12 technical indicators | Genetic programming (GP) to optimize decision rules. |
| (Thakur & Kumar, 2018) | Stock indices from NASDAQ, DOW JONES, S&P 500, NIFTY 50 and NIFTY BANK. | Weighted multicategory generalized eigenvalue support vector machine (WMGEPSVM) | 25 technical indicators | Random forest (RF) for feature pruning. |

| | | | | |
|---|---|---|---|---|
| (Long et al., 2018) | Chinese stock market index CSI 300 | Multi-filters neural network (MFNN) | Open price, close price, highest price, lowest price, volume, amount | Stochastic gradient descent (SGD) with back propagation optimizer |
| (Hafezi et al., 2015) | The dataset was obtained from the deutsche bundesbank. | Bat-neural network multi-agent system (BNNMAS) | 20 features | Bat algorithm (BA) |
| (Hsu, 2013) | Dataset was obtained from Taiwan Stock Exchange Corporation (TWSE). | Backpropagation neural network | 15 technical indicators | Genetic programming |
| (C. F. Huang et al., 2012) | The constituent stocks of the 200 largest market capitalizations listed in the TSE as the investment universe. | Fuzzy genetic algorithm (Fuzzy-GA) model | 15 technical attributes | Fuzzy membership function with GA-optimized model parameters |
| (Ni et al., 2011) | Shanghai Stock Exchange Composite | Support vector machine (SVM) | 19 technical indicators | Fractal feature selection |

| | | | | |
|---|---|---|---|---|
| | Index (SSECI) | | | |
| (Kara et al., 2011) | The entire data set covers Istanbul Stock Exchange data of the period from January 2, 1997 to December 31, 2007. | Artificial neural networks (ANN) and support vector machines (SVM). | 10 technical indicators | N/A |
| (Tsai & Hsiao, 2010) | Data source is Taiwan Economic Journal (TEJ) database. | Multi-layer perceptron (MLP) artificial neural networks (ANN) | The fundamental and macroeconomic indices | The CART (Classification and Regression Trees) |
| (C. L. Huang & Tsai, 2009) | Taiwan index futures (FITX) | Self-organizing feature map (SOFM) and support vector regression (SVR) | 13 technical attributes | Filter-based feature selection. |
| (M. C. Lee, 2009) | NASDAQ Index | Support vector machine (SVM) | 17 feature variables of currency | Supported sequential forward search (SSFS) |
| (Atsalakis & Valavanis, 2009) | The dataset of Athens and the New York Stock Exchange (NYSE) | Neuro-fuzzy based methodology, Adaptive Neuro Fuzzy Inference System (ANFIS) technique | Price sequence | N/A |
| (Hassan & | Stock price of | Hidden Markov | 4 input features | Reduce the |

| | | | | |
|---|---|---|---|---|
| Nath, 2005) | four different Airlines | Models (HMM) | of a stock | states to 4 states of prices |
| (Piramuthu, 2004) | Credit approval data, loan default data, web traffic data, tam and kiang data | Distance measure of probabilistic and inter-class | 10 features after feature selection | Distance measure |
| (Kim & Han, 2000) | KOSPI | A new hybrid model of artificial neural network (ANN) and genetic algorithms (GAs) | 13 technical indices | Feature discretization |

### 3.2 Comparative Analysis

This part is the detailed comparative analysis according to the Table 16.

The table above includes five columns, the first column is the author name and year of publication. The second column is the datasets that previous works used. The third column concludes the prediction models of related works; meanwhile, the fourth column is the input variables i.e., input features. The last column might not be applicable for all the associated works since it records the feature selection methods or optimizers of previous works, some of the works do not include feature engineering or optimization part, we noted the cell value of these works as "N/A".

From the comparative analysis table, we can see, though the related works are using stock datasets, despite stock market data from different countries, most of them are using index

data from the stock exchange. The stock index data often limits the data volume, for example, SSE and CSI 300 index from Chinese stock market only includes 300 stocks, while actually there are different trading boards in the stock market but those 300 stocks are only included in main board. To proper train a deep learning model, it would be more secure to have a large training dataset, as long as the data are putrefied and in good quality, the larger, the better. Besides the data volume concern, index data often have limited information segments, which leads to a limited number of available features and cause difficulty on feature selection.

The input variables are also diverse; most of the previous works used 10 or more technical indices calculated based on available price data; others use four basic prices as features to train the model. While we can conclude that for machine learning approaches, all the features of training datasets are technical indices. For HMM model, since the data has to transform between states, the author limited the feature numbers to boost the training efficiency.

Besides, most of the related works choose to add a feature selection algorithm. This symptom stresses the importance of feature engineering in building a machine learning prediction solution architecture.

### 3.3 Gap Analysis

In this section, we will discuss the gaps we found from the description and comparison contents of related works above.

Besides the technical indices, a few previous works focused on real-world investment indices. The features for investors selected are processed based on common technical indices.

For instance, instead of focusing on numbers, the investors often more focus on if the index value is above zero or below zero, or the fluctuation percentage compares with a previous trading date. Similar to the value of common technical indices, these processed features are also proved to be useful when pooling the stocks in good qualities or predicting the price trend.

The gaps we find between the research papers in the investment domain and technical domain are data pre-processing.

Technical research papers tend to more focus on building the models. When they select the features, they will list all the features mentioned in previous works and go through the feature selection algorithm then select best voted 10 to 15 features. While in investment domain, the researchers show more interests in behavior analysis, such as how herding behaviors affect the stock performance, or how the percentage of inside directors hold the firm's common stock affects the performance of a certain stock. These behaviors often need a pre-processing procedure of standard technical indices and investment experience to recognize.

During their studies, they often perform a thoroughly statistical analysis based on a special dataset and conclude new features rather than performing feature selections.

From the findings above, we know that the features or behaviors being focused on the financial domain are seldom being investigated in the technical domain, and the financial domain research paper also seldom introduced the machine learning or deep learning

algorithms to train their model straight forward without applying data pre-processing procedures as investors do.

Some data such as the percentage of a certain index fluctuation has been proved to be effective on stock performance; we believed that by extracting new features from these data, then combine the features with existed common technical indices will benefit the existing and well-tested models.

# Chapter 4: Design of Proposed Solution

The system design part includes gap analysis, problem statement, and proposed solution. Besides, we also introduce the architecture design and algorithmic and implementation details.

## 4.1 Problem Statement

We addressed the three research questions in different aspects.

### 4.1.1 RQ1: How does feature engineering benefit model prediction accuracy?

The first research question is about feature engineering. We would like to know how feature selection method benefits the performance of prediction models.

From the abundant previous works, we can conclude that stock price data embedded with a high level of noise, and there are also correlations between features, which makes the price prediction notoriously difficult. That is also the primary reason for most of the previous works introduced the feature engineering part as an optimization module.

### 4.1.2 RQ2: How do findings from financial domain benefit prediction model design?

The second research question is evaluating the effectiveness of findings we extracted from financial domain.

Different from previous works, besides the common evaluation of data models such as the training costs and scores, our evaluation part will emphasize the effectiveness of newly added features that we extracted from financial domain.

We will introduce some features from financial domain. While we only obtained some specific findings from previous research works, and the related raw data needs to be processed into usable features. After extracting related features from financial domain, we will combine the features with other common technical indices for voting the features with a high impact.

There are numerous features said to be effective from financial domain, it would be impossible for us to cover all of them. Thus, how to appropriately convert the findings from the financial domain to a data processing module of our system design is a hidden research question that we must be facing.

### 4.1.3 RQ3: What is the best algorithm for predicting short-term price trend?

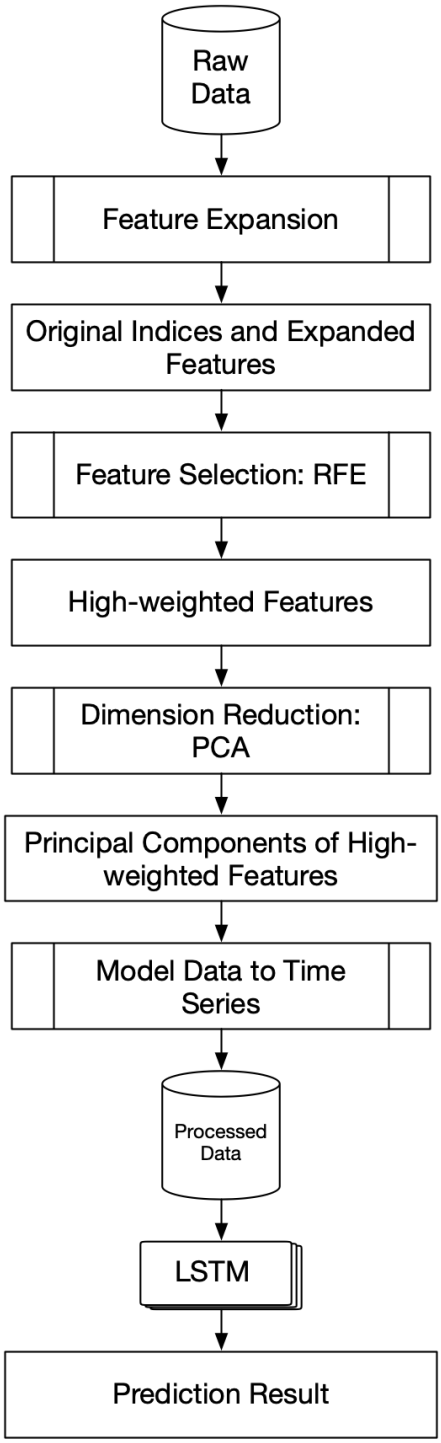
The third research question is the algorithm selection. Which algorithm are we going to use to model our data?

Conclude from previous works; researchers are putting efforts on exact price prediction. While we decompose the problem into predicting the trend and then an exact number, this paper will focus on the first step. Hence this objective has been converted to resolve a binary classification problem, meanwhile, finding an effective way to eliminate the negative effect brought by the high level of noise. Our approach is to decompose the complex problem into sub-problems which have fewer dependencies and resolve them one by one, then compile the resolutions into an ensemble model as an aiding system for investing behavior reference.

In the previous works, researchers have been used a variety of models for predicting stock price trend. While most of the best-performed models are based on machine

learning technique, thus in this work, we will compare our approach with the outperformed machine learning models in evaluation part and find the solution for this research question.

**Figure 2 High-level Architecture of Proposed Solution**



## 4.2 Technical Background – Technical Indices

In this section, we elaborate the most commonly used technical indices that conclude from related works.

When building the model, most of the previous works illustrated their technical indices. We found 15 the most frequent indices. The indices definitions refer to the appendix of related work (Hsu, 2013).

1) Stochastic indicator K

The n-day stochastic indicator K is defined as:

$$K\_n_i = \frac{2}{3} \times K\_n_{i-1} + \frac{1}{3} \times \frac{CP_i - LP\_n_i}{HP\_n_i} \times 100$$

Note the highest price in previous n days as $HP\_n_i$, and $LP\_n_i$ as the lowest price in previous n days. $CP_i$ is the closing price of day i.

2) Stochastic indicator D

The n-day stochastic indicator D

$$D\_n_i = \frac{2}{3} \times D\_n_{(i-1)} + \frac{1}{3} \times K\_n_i$$

Where $K\_n_i$ is the n-day stochastic indicator *K* of day *i*.

3) Williams overbought/oversold index

The n-day Williams overbought/oversold index is a momentum indicator that measures overbought and oversold levels.

$$WMS\%R\_n_i = \frac{HP\_n_i - CP\_n_i}{HP\_n_i - LP\_n_i}$$

4) Commodity channel index

The commodity channel index is used to identify cyclical turns in commodities.

We define the typical price as the formula below:

$$TP_i = \frac{HP_i + LP_i + CP_i}{3}$$

Then we calculate the n-day simple moving average of the typical price:

$$SMATP\_n_i = \frac{\sum_{j=i-n-1}^{i} TP_j}{n}$$

And the n-day mean deviation is noted by *MD_n*:

$$MD\_n_i = \frac{\sum_{j=i-n-1}^{i} \left| TP_j - SMATP\_n_i \right|}{n}$$

The n-day commodity channel index is calculated as:

$$CCI\_n_i = \frac{TP_i - SMATP\_n_i}{0.015 \times MD\_n_i}$$

5) Relative strength index

The relative strength index is a momentum oscillator that compares the magnitude of recent gains to the magnitude of recent losses.

$$G_i = \begin{cases} CP_i - CP_{i-1}, & if\ CP_i > CP_{i-1} \\ 0 \quad\quad\quad\quad\quad , & otherwise \end{cases}$$

6) Moving average convergence/divergence

The moving average convergence/divergence is a momentum indicator that shows the relationship between two moving averages.

First step is to calculate the demand index (*DI*):

$$DI_i = (HP_i + LP_i + 2 \times CP_i)/4$$

We also need to calculate the 12-day and 26-day exponential moving average:

$$EMA\_12_i = \frac{11}{13} \times EMA\_12_{i-1} + \frac{2}{13} \times DI_i$$

And

$$EMA\_26_i = \frac{25}{27} \times EMA\_26_{i-1} + \frac{2}{27} \times DI_i$$

Hence, we use $DIF_i$ to indicate the difference between *EMA_12* and *EMA_26*:

$$DIF_i = EMA\_12_i - EMA\_26_i$$

The $MACD_i$ is calculated as below:

$$MACD_i = \frac{8}{10} \times MACD_{i-1} + \frac{2}{10} \times DIF_i$$

7) 10-day moving average

The 10-day moving average is the mean price of the futures over the most recent 10 days and is calculated by:

$$MA\_10_i = \frac{\sum_{j=i-9}^{i} CP_j}{10}$$

8) Momentum

Momentum measures change in stock price over last n days

$$MTM_i = \frac{CP_i}{CP_{i-n}} \times 100$$

9) Rate of Change

The n-day rate of change measures the percent changes of the current price relative to the price of n days ago and is calculated by:

$$ROC\_n_i = \frac{CP_i - CP_{i-n}}{CP_{i-n}} \times 100$$

10) Psychological line

The psychological line is a volatility indicator based on the number of time intervals that the market was up during the preceding period and is calculated by:

$$PSY\_n_i = \frac{TDU\_n_i}{n} \times 100\%$$

The $TDU\_n_i$ is the total number of days that has price rises in previous n days.

11) AR

n-day A ratio means the n-day buying/selling momentum indicator which is calculated as:

$$AR\_n_i = \frac{\sum_{j=i-n-1}^{i}(HP_j - OP_j)}{\sum_{j=i-n-1}^{i}(OP_j - LP_j)}$$

12) BR

n-day B ratio means the n-day buying/selling willingness indicator and is defined as:

$$BR\_n_i = \frac{\sum_{j=i-n-1}^{i}(HP_j - OP_{j-1})}{\sum_{j=i-n-1}^{i}(OP_{j-1} - LP_j)}$$

13) Volume ratio

The n-day volume ratio is calculated by:

$$VR\_n_i = \frac{TVU\_n_i - TVF\_n_i/2}{TVD\_n_i - TVF\_n_i/2} \times 100\%$$

Where the *TVU* represents the total trade volumes of stock price rising, and *TVD* is the total trade volumes of stock prices falling, *TVF* represents the total trade volumes of stock prices holding in previous n days.

14) Accumulation/distribution oscillator

$$AD_i = \frac{HP_i - CP_{i-1}}{HP_i - LP_i}$$

15) 5-day bias

The 5-day bias is the deviation between the closing price and the 5-day moving average *MA_5*

$$BIAS\_5_i = \frac{CP_i - MA\_5_i}{MA\_5_i}$$

### 4.3 Proposed Solution

The high-level architecture of our proposed solution could be separated into three parts. First is the feature selection part, guarantee the selected features are all effective. Second,

we look into the data and perform the dimensionality reduction. And the last part which is the main contribution of our work is to build a prediction model of target stocks.

There are ways to classify different categories of stocks. Some investors prefer long-term investment, while others show more interest in short-term investment. It is common to see the stock-related company report shows an average performance, while the stock price is increasing drastically; this is one of the phenomena that indicate the stock price prediction has no fixed rules, thus find effective features before train the data model is necessary.

In this project, we focus on short-term price trend prediction.

Currently, we only have the raw data with no labels; the very first step is to label the data. We mark the price trend by comparing the current closing price with the closing price of n trading days ago, the range of n is from 1 to 10 since our research is focusing on the short-term. If the price trend goes up, we mark it as 1 or mark as 0 in the opposite case. To be more specified, we use the indices from the indices of $n-1_{th}$ day to predict the price trend of the $n_{th}$ day.

According to the previous works, some researchers who applied both financial domain knowledge and technical methods on stock data were using rules to filter the high-quality stocks. We referred to their works and exploited their rules to contribute to our feature extension design.

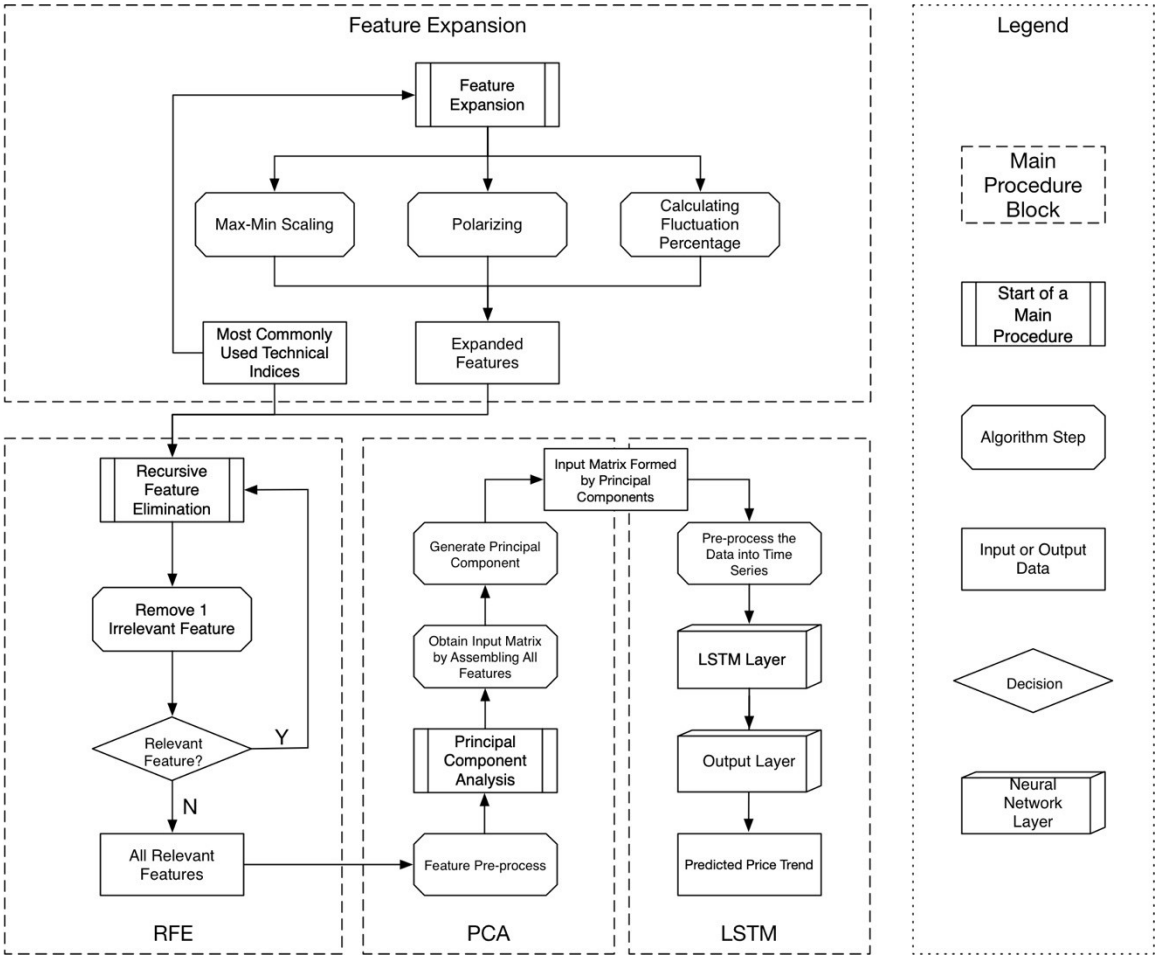
However, to ensure the best performance of the prediction model, we will look into the data first. There are a large number of features in the raw data; if we involve all the features into our consideration, it will not only drastically increase the computational complexity but will also cause side effects if we would like to perform unsupervised

learning in further research. So we leverage the recursive feature elimination (RFE) to ensure all the selected features are effective.

Since we found most of the previous works in the technical domain were analyzing all the stocks, while in the financial domain, researchers prefer to analyse the specific scenario of investment, to fill the gap between the two domains, we decide to apply a feature extension based on the findings we gathered from the financial domain before we start the RFE procedure.

Since we plan to model the data into time series, the number of the features, the more complex the training procedure will be. So, we will leverage the dimensionality reduction by using randomized PCA at the beginning of our proposed solution architecture.

**Figure 3 Detailed Technical Design**




## 4.4 Detailed Technical Design Elaboration

This part is the elaboration of the detailed technical design from data processing to prediction, including the data exploration detail based on Figure 3.

We split the content by main procedures, each procedure consists of algorithm steps. Algorithmic details are elaborated in the next section. The contents of this section will focus on illustrating the data workflow.

From the technical background, we know the most commonly used technical indices, then feed them into feature extension procedure to get the expanded feature set. We will

select the most effective *i* features from the expanded feature set. Then we will feed the data with *i* selected features into PCA algorithm to reduce the dimension into *j* features. After we get the best combination of *i* and *j*, we process the data into finalized the feature set and feed them into the LSTM model to get the price trend prediction result.

The novelty of our proposed solution is that we will not only apply the technical method on raw data but also apply the feature extension that used among stock market investors.

### 4.4.1 Feature Extension

The first main procedure in Figure 3 is Feature extension. In this block, the input data is the most commonly used technical indices concluded from related works.

The three feature extension methods are max-min scaling, polarizing, and calculating fluctuation percentage. Be aware that not all the technical indices are applicable for all three of the feature extension methods; this procedure only applies the meaningful extension methods on technical indices. The technical indices calculation formulas are elaborated in the Technical Background section; we choose the meaningful extension methods according to how the indices calculated.

The technical indices and the corresponding feature extension methods are illustrated in Table 17.

**Table 17 Feature Extension Method Selection**

| Feature | Polarize | Max-Min Scale | Fluctuation percentage |
|---|---|---|---|
| Price change | | | |
| Price change percentage | | | |
| Volume | | √ | |
| Amount | | √ | |
| SMA 10 | | √ | √ |
| MACD | √ | | |
| MACD SIGNAL | √ | | |
| MACD HIST | √ | | |
| CCI 24 | √ | | |
| MTM 10 | √ | | √ |
| ROC 10 | √ | | √ |
| RSI 5 | | √ | √ |
| WNR 9 | √ | √ | |
| SLOWK | | √ | √ |
| SLOWD | | √ | √ |
| ADOSC | √ | √ | |
| AR 26 | | √ | |
| BR 26 | | √ | |
| VR 26 | | √ | √ |
| BIAS 20 | √ | | |

After the feature extension procedure, the expanded features will be combined with most commonly used technical indices, i.e., input data with output data, and feed into RFE block as input data in the next step.

### 4.4.2 Recursive Feature Elimination

After the feature extension above, we explore the most effective *i* features by using Recursive Feature Elimination (RFE) algorithm. We estimate all the features by two attributes, coefficient and feature importance. We also limit the features that remove from the pool by one, which means we will remove one feature at each step and retain all the relevant features.

Then the output of RFE block will be the input of the next step, which refers to PCA.

### 4.4.3 Principal Component Analysis

The very first step before leverage PCA is features pre-process. Because some of the features after RFE are percentage data, while others are very large numbers, i.e. the output from RFE are in different units. It will affect the principal component extraction result. Thus, before feeding the data into PCA algorithm, a feature pre-processing is necessary. We also illustrate the effectiveness and methods comparison in evaluation section.

After performing feature pre-processing, the next step is to feed the processed data with selected *i* features into PCA algorithm to reduce the feature matrix scale into *j* features. This step is to retain as many effective features as possible and meanwhile eliminate the computational complexity of training the model.

This research work also evaluates the best combination of *i* and *j* which has relatively better prediction accuracy, meanwhile, cuts the computational consumption. The result can be found in the evaluation section as well.

After the PCA step, the system will get a reshaped matrix with *j* columns.

### 4.4.4 Long Short-Term Memory

PCA reduced the scale of input data, while the data pre-processing is mandatory before feeding the data into LSTM layer.

The reason of adding the data pre-processing step before LSTM model is that the input matrix formed by principal components has no time steps. While one of the most important parameters of training an LSTM is the number of time steps. Hence, we have to model the matrix into corresponding time steps as for both training and testing dataset.

After performing the data pre-processing part, the last step is to feed the training data into LSTM, and evaluate the performance using testing data.

As a variant neural network of RNN, even with one LSTM layer, the NN structure is still a deep neural network since it can process sequential data and memorizes its hidden states through time. An LSTM layer is composed of one or more LSTM units, an LSTM unit consists of cells and gates to perform classification and prediction based on time series data.

The LSTM structure is formed by two layers. Input dimension is determined by j after PCA algorithm. The first layer is the input LSTM layer and the second layer is the output layer.

The final output will be 0 or 1 indicates if the stock price trend prediction result is going down or going up, as a supporting suggestion for the investors to perform the next investment decision.

## 4.5 Design Discussion

Feature extension is one of the novelties of our proposed price trend predicting system. In feature extension procedure, we use technical indices collaborate with the heuristic processing methods learned from investors, which fills the gap between financial research area and technical research area.

Since we proposed a system of price trend prediction, feature engineering is extremely important to the final prediction result. Not only the feature extension method is helpful to guarantee we do not miss the potentially correlated feature, but also feature selection method is necessary for pooling the effective features. The more irrelevant features are fed into the model, the more noise would be introduced. Each main procedure is carefully considered contributing to the whole system design.

Besides feature engineering part, we also leverage LSTM, the state-of-the-art deep learning method for time-series prediction, which guarantees the prediction model can capture both complex hidden pattern and the time-series related pattern.

It is known that training cost of deep learning models is expansive in both time and hardware aspects; another advantage of our system design is the optimization procedure—PCA. It can retain the principal components of the features while reducing the scale of the feature matrix, thus help the system to save the training cost of processing the large time-series feature matrix.

## 4.6 Algorithm Elaboration

We elaborate the algorithm design in this part. Different from the previous section, this section comprehensively explains the algorithms we exploit in perspectives of terminologies, parameters, as well as optimizers.

From the legend on the right side of Figure 3, we note the algorithm steps as octagons, all of them can be found in this algorithm elaboration section.

Before dive deep into the algorithm steps, here is the brief introduction of data pre-processing: since we will go through the supervised learning algorithms, we also need to program the ground truth. The ground truth of this project is programmed by comparing the closing price of current trading date with the closing price of the previous trading date the users want to compare with. Label the price increase as 1, else the ground truth will be labeled as 0. Because this research work is not only focused on predicting price trend of a specific period of time but short-term in general, the ground truth processing is according to a range of trading days. While the algorithms will not change with the prediction term length, we can regard the term length as a parameter.

The algorithmic detail is elaborated, respectively, the first algorithm is the hybrid feature engineering part for preparing high-quality training and testing data. It corresponds to the Feature extension, RFE and PCA blocks in Figure 3. And the second algorithm is the LSTM procedure block, including time-series data pre-processing, NN constructing, training, and testing.

### 4.6.1 Algorithm 1: Short-term Stock Market Price Trend Prediction - Hybrid Feature Engineering Using FE+RFE+PCA

The function FE () is corresponding to the feature extension block.

For the feature extension procedure, we apply three different processing methods to translate the findings from the financial domain to a technical module in our system design. While not all the indices are applicable for expanding, we only choose the proper method(s) for certain features to perform the feature extension according to Table 17.

Normalize method preserves the relative frequencies of the terms, and transform the technical indices into the range of [0, 1]. Polarize is a method often used by real world investors, sometimes they prefer to consider if the technical index value is above or below zero, we program some of the features using polarize method and prepare for RFE. Max min scale is a transform method often used as an alternative to zero mean and unit variance scaling. The fourth method is fluctuation percentage, we transform the technical indices fluctuation percentage into the range of [-1, 1].

The function RFE () in the first algorithm refers to recursive feature elimination. Before we perform the training data scale reduction, we will have to make sure that the features we selected are effective. Ineffective features will not only drag down the classification precision, but also add more computational complexity. For the feature selection part, we choose recursive feature elimination (RFE).

As (Weng et al., 2018) introduced, the RFE algorithm can be split into ranking algorithm, resampling and external validation.

For the ranking algorithm, it fits the model to the features and rank by the importance to the model. We set the parameter to retain *i* numbers of features, and at each iteration of

feature selection retains $S_i$ top ranked features, then refit the model and assess the performance again to begin another iteration. The ranking algorithm will eventually determine the top $S_i$ features.

The RFE algorithm is known to have suffered from over-fitting problem. To eliminate the over-fitting issue, we will run the RFE algorithm multiple times on randomly selected stocks as training set and ensure all the features we select are high-weighted. This procedure is called data resampling. Resampling can be built as an optimization step as an outer layer of RFE algorithm.

The last part of our hybrid feature engineering algorithm is for optimization purpose. PCA () refers to Principal Component Analysis.

For the training data matrix scale reduction, we apply Randomized Principal Com-ponent Analysis (PCA) before we decide the features of classification model.

Financial ratios of a listed company are used to present the growth ability, earning ability, solvency ability, etc. Each financial ratio consists of a set of technical indices, each time we add a technical index (or feature) will add another column of data into the data matrix and will result in low training efficiency and redundancy. If non-relevant or less relevant features are included in training data, it will also decrease the precision of classification.

As explained in (Pang, Zhou, Wang, Lin, & Chang, 2018), PCA is an algorithm that often used in feature engineering, it will transform the original variables into new variables with most information retained. The new generated variables are principal components. Below is the definition of principal components.

$$\begin{cases} Y_1 = \overrightarrow{\alpha_1}^T \cdot \vec{X} = \alpha_{11}X_1 + \alpha_{12}X_2 + \cdots + \alpha_{1n}X_n \\ Y_2 = \overrightarrow{\alpha_2}^T \cdot \vec{X} = \alpha_{21}X_1 + \alpha_{22}X_2 + \cdots + \alpha_{2n}X_n \\ \cdots \\ Y_n = \overrightarrow{\alpha_n}^T \cdot \vec{X} = \alpha_{n1}X_1 + \alpha_{n2}X_2 + \cdots + \alpha_{nn}X_n \end{cases}$$

$X_i$ is the original variable, $Y_i$ is the principal component and $\vec{\alpha}_i$ is the coefficient vector. By minimizing $Var(Y_i)$ with the constraint conditions of $\overrightarrow{\alpha_1}^T \cdot \vec{X} = 1$ and $Cov(Y_i, Y_j) = \overrightarrow{\alpha_i}^T \cdot \overrightarrow{\alpha_i} = 0, j = 1,2,\cdots, i-1$, where $\sum = (\sigma_{ij})_{n\times n}$ is the covariance matrix of $\vec{X}$.

The next step is the selection of principal components. The covariance matrix of $\vec{X} = (X_1, X_2, \cdots X_n)^3 \sum = (\sigma_{ij})_{n\times n}$, is a symmetric non-negative definite matrix. Thus, this matrix has n characteristic roots $\lambda_1, \lambda_2, \ldots, \lambda_n$ and n characteristic vectors.

All the roots $\lambda \geq 0$, besides, the orthogonal unit eigenvectors are $\overrightarrow{e_1}, \overrightarrow{e_2}, \cdots, \overrightarrow{e_n}$. The $i_{th}$ principal component of $X_1, X_2, \ldots, X_n$ can be illustrated as:

$$Y_i = e_{i1}X_1 + e_{i2}X_2 + \cdots + e_{in}X_n, i = 1,2,\cdots, n$$

With $Cov(Y_i, Y_j) = \overrightarrow{e_i}^T \cdot \sum \overrightarrow{e_i} = 0, i \neq j$ and $Var(Y_i) = \overrightarrow{e_i}^T \cdot \sum \overrightarrow{e_i} = \lambda_i$, the first accumulated contribution rate of principal components $p$ is noted as:

$$ACR(p) = \sum_{i=1}^{p} \lambda_i / \sum_{i=1}^{n} \lambda_i$$

The above equation represents the explanation power of principal components ex-tracted by PCA method for original data. If an ACR is below 85%, the PCA method would be unsuitable due to a loss of original information. Because the covariance matrix is sensitive to the order of magnitudes of data, there should be a data standardize procedure before performing the PCA. The commonly used standardize methods are mean-standardization and normal-standardization and could be noted as below respectively:

- Mean-standardization: $X_{ij}{}^* = X_{ij}/\overline{X_j}$, which $\overline{X_j}$ represents the mean value.
- Normal-standardization: $X_{ij}{}^* = (X_{ij} - \overline{X_j})/s_j$, which $\overline{X_j}$ represents the mean value, and $s_j$ is the standard deviation.

The array *fe_array* is defined according to the Table 17, row number maps to the features, column 0, 1, 2, 3 note for the extension methods of normalize, polarize, max min scale and fluctuation percentage respectively. Then we fill in the values for the array by the rule where 0 stands for no necessity to expand and 1 for features need to apply the corresponding extension methods.

The final algorithm of data preprocessing using RFE and PCA can be illustrated as Algorithm 1.

**Algorithm 1** Short-term Stock Market Price Trend Prediction - Hybrid Feature Engineering Using FE + RFE + PCA

$fe\_array = fe[i, 3]$

**function** FE($f$) ▷ (Feature Expansion, $f[i]$ indicates $i_{th}$ feature)
    **for** $minrange[0, 3]$ **do**
        **if** $fe\_array[i-1, m] == 1$ **then**
            Feature expansion method
        **end if**
    **end for**
    **return** df_X_FE ▷ (df_X_FE is the processed data frame after feature expansion)
**end function**

**function** RFE($df$) ▷ (Recursive feature elimination function)
    Tune the model on the training set with all features
    Calculate model performance with testing samples
    Ranking the weight of different features
    **for** Each subset **do**
        Retain $i$ most weighted features
        Tune the model on the training set with all features
        Calculate model performance with testing samples
    **end for**
    Calculate performance profile over testing samples
    Estimating the features by final testing dataset
    Fit the final model based on selected features using the original training set
    **return** df_X_RFE ▷ (df_X_RFE is the processed data frame after RFE algorithm)
**end function**

**function** PCA($df$) ▷ (Leverage optimization algorithm PCA to reduce dimension from $i$ to $j$)
    n_components=$j$, whiten=False, copy=True, batch_size=200
    **return** df_X_PCA ▷ (df_X_PCA is the optimized data frame after PCA algorithm)
**end function**

**function** MAIN( ) ▷ (Main function)
    FE($f[i]$)
    DATAPARTITION(df_all, method = resampling)
    RFE(df_X_FE)
    PCA(df_X_RFE)
    **return** df_X_PCA
**end function**

### 4.6.2 Algorithm 2: Price Trend Prediction Model Using LSTM

After the principal component extraction, we will get the scale-reduced matrix, which means *i* most effective features are converted into *j* principal components for training the prediction model.

We exploit an LSTM model, and added a conversion procedure for our stock price dataset. The detail algorithm design is illustrated in Alg 2.

The function *TIMESERIESCONVERSION* () converts the principal components matrix into time series by shifting the input data frame according to the number of time steps i.e. term length in this project. The processed dataset consists of input sequence and forecast sequence. In this project, the parameter of *lag* is 1, because the model is detecting the pattern of features fluctuation in daily basis. Meanwhile, the *NTIMESTEPS* is varied from 1 trading day to 10 trading days.

We omit the function description of *DATAPARTITION (), FITMODEL (), EVALUATE MODE ()* since the functions above are regular steps without customization.

The NN structure design, optimizer decision and other parameters are illustrated in function *MODELCOMPILE ()*.

**Algorithm 2** Price Trend Prediction Model Using LSTM

```
function TimeSeriesConversion(df, term_length, lag)        ▷ Convert the training data matrix from Alg1 to time series
    cols = list()
    for i in range (term_length, 0, -1) do                 ▷ input sequence
        shift df by i
        append shifted df to cols
    end for
    for i in range (0, lag) do                             ▷ forecast sequence
        shift df by -i
        append shifted df to cols
    end for
    df_X_TS = concat(cols, axis = 1)                       ▷ put all sequences together
     return df_X_TS
end function

function ModelCompile(j)                                   ▷ Define NN structure and compile
    Stack_method = Sequential()
    Layer_1 = LSTM(50, input_shape=(train_X.shape[1], train_X.shape[2]))
    Layer_2 = Dense(1)
    Loss_Function=mae
    Optimizer=adam
    Metrics=f1, metrics.binary_accuracy, metrics.mean_squared_error, metrics.mean_absolute_error
     return LSTMmodel
end function

function Main( )                                           ▷ Main Function
    TimeSeriesConversion(df_X_PCA, N_TIME_STEPS, LAG)
    DataPartition(df_X_TS, method = resampling)
    ModelCompile(j)
    FitModel(X, y, epochs=50, batch_size=3000)
    EvaluateModel(X_test, y_test)
end function
```

## 4.7 Use Case of Proposed Solution

In this section, we elaborate the use case of our proposed solution, i.e., how we implement the proposed solution as an application.

The major purpose of this use case is to build a lite, easy-to-access application; meanwhile, we prefer an all-python implementation to retain the consistency of system components.

The overall architecture of the use case design is illustrated in Figure 4.

The application consists of three layers: data collection & storage, data processing, graphical user interface (GUI).

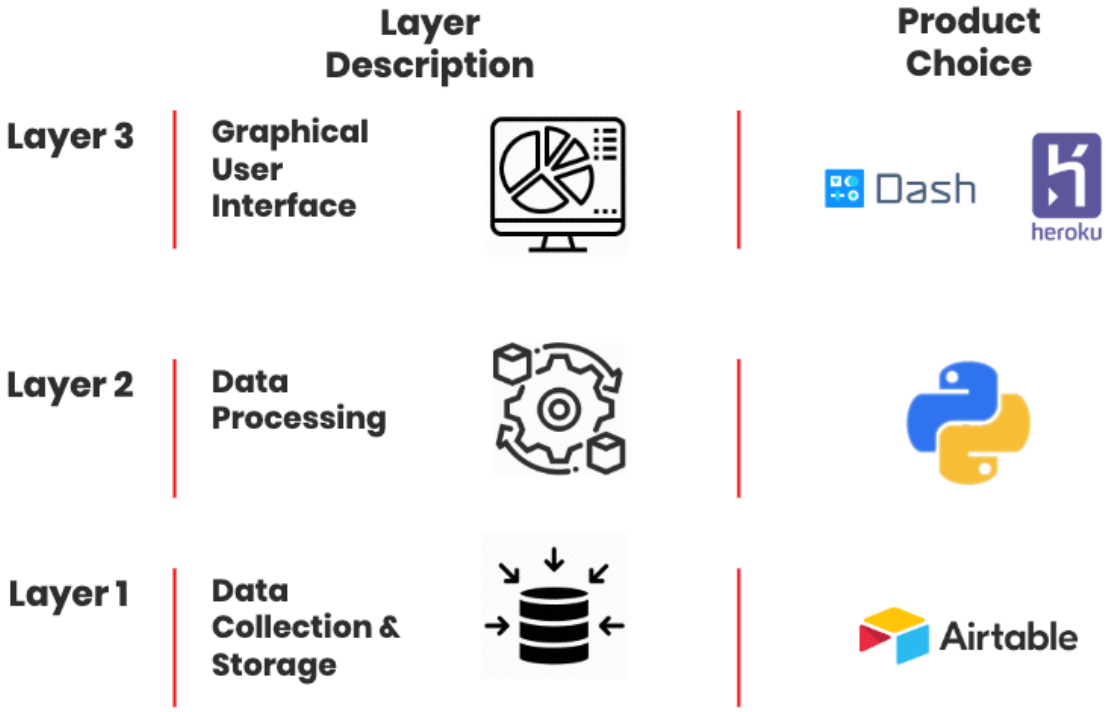
To achieve the purpose of building an easy-to-access application, we prefer to build a web application, so that users can access the application anywhere anytime with the URL.

The first layer is the basic layer of this web application, data collection & storage. For the demo application, we only apply the code of data storage part, while it would be easy to slightly modify the data collection code and collect daily stock data from Tushare API then store to the database.

The second layer is data processing. In this layer, deploy the python codes from Chapter 4.6.

The third layer is the graphical user interface for user input and result output. Demo version web application has a GUI for users to fill in the stock ID, trade date, prediction time range, with an output of the prediction result.

**Figure 4 Use Case Architecture Design**




### 4.7.1 Related Applications

We reviewed the most recent stock market price trend related works; most of them omit the detailed design elaboration of how to integrate their proposed solution with a practical application.

The authors of previous work (Zubair, Fazal, Fazal, & Kundi, 2019) implement the stock market trend prediction system using R software, we will illustrate the advantages and disadvantages of their application designs.

Both the algorithm and the user interface in the aforementioned work are in R console. The advantage of this system is obvious, it is easy to implement, meanwhile, all the system components are in the same platform, compare with cross-platform implementation, this approach will save the time of data transforming via interfaces. But

implement all the components within R console also causes some weaknesses in the meantime. The user interface of their recommendation system is difficult to understand for the users who are not familiar with R software, and it is impossible to access their recommend system without all the algorithms and components being deployed locally.

### 4.7.2 Application Deployment and GUI Explanation

This section illustrates the application decision-making and the reasons for choosing certain products.

For data storage, we choose Airtable (Airtable, 2019) as it can store different types of data, even image. In the start-up stage, it would be more flexible if we plan to add more types of data into the database to further extend the application functionalities. For instance, if we plan to construct a CNN model to analyze the price trend line graphs, we can get the training data straight from the same database without linking the data from a different source. Another advantage of using Airtable as a database is that the data structure of Airtable is flexible. We can regard Airtable as a No-SQL database with a comprehensive GUI since the data are in json format. The flexibility of Airtable provides us the convenience to test the data structure, and it is the first step of making the decision of dataset architecture for a mature product.

We choose Heroku (Heroku, 2019) to deploy the web application, and use Plotly Dash (Dash, 2019) to develop the user interface layer.

Plotly Dash is a python-based library, it can integrate very well with Pandas data frame. For integrating Airtable with Plotly Dash, we also exploit a python library called airtable-

python-wrapper. And by using HTML, CSS and JavaScript, user can easily style the web application via the normal procedure for web page development.

The Figure 5 is the GUI of our use case web application.

First of all, select the start date of the price trend prediction period, then select the prediction time range from three options: every other day, weekly, bi-weekly. Then fill in the stock ID of which the user would like to predict and click the Submit button.

The result will show in the Prediction Result section.

### 4.7.3 Potential of the Use Case

This section is a discussion about the potential of this use case. From the current available function, we can see, actually, there is a high potential in extending the application functionalities.

Since Plotly Dash is a powerful library for data visualization; meanwhile, data visualization also plays an important role in stock analysis. We can add line graphs for stock price and technical indices in the future as previous products since our web application has already embedded the price trend prediction functionality which distinct from other existed stock market analysis products.

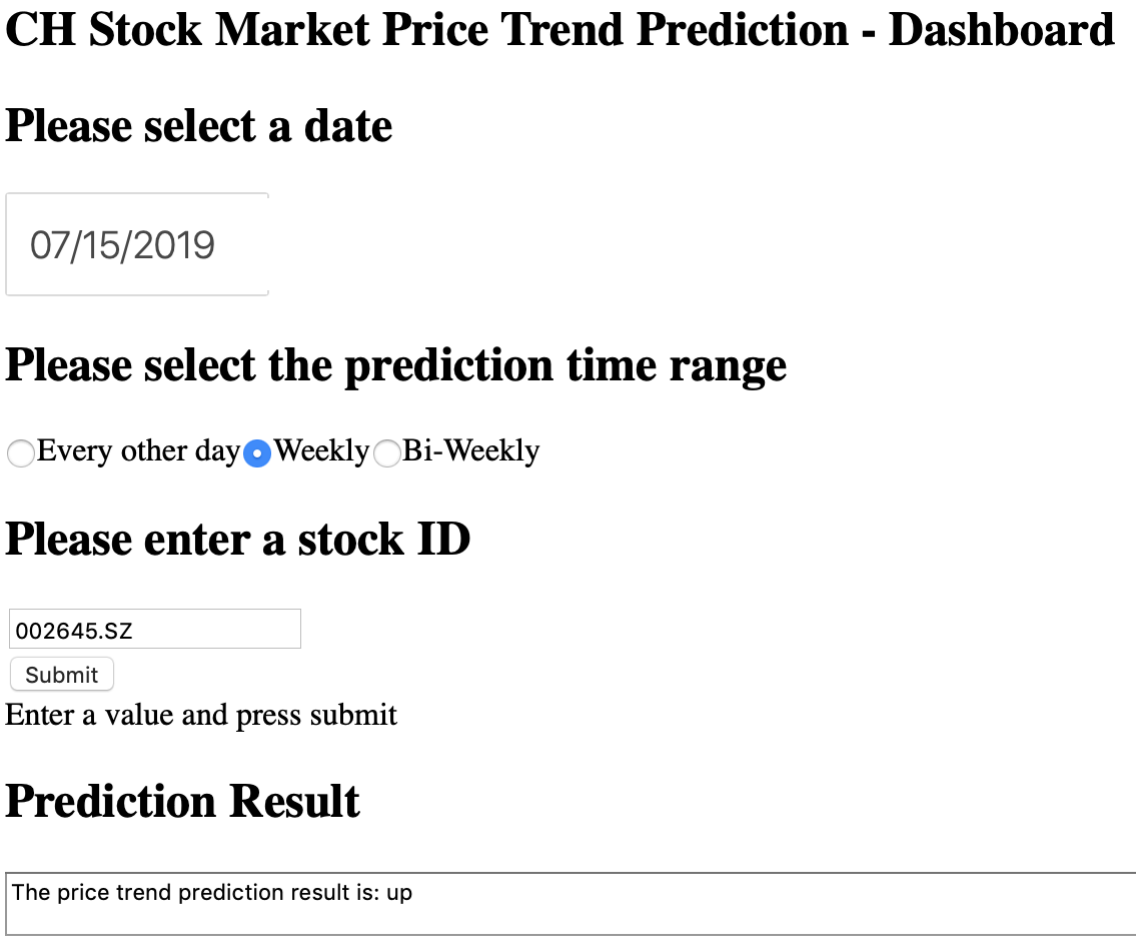
Moreover, it is also possible to upgrade the data collection and storage layer. As we mentioned in previous section, flexibility is the major reason that we choose Airtable as the database product, because our product is still in the start-up stage, the data structure is not maturely defined yet. While as the application develops, it would be better to store the stock market price data into a relational database. Heroku also offers the Postgres

database service, which prevents most of the integration issues at the structure design stage.

For image data for pattern recognition, and text data for sentiment analysis, we would store them into a No-SQL database such as Mongo DB.

With high potential and flexibility, we discussed above, we believe this lite and easy-to-access web application for stock market analysis can highly benefit individual investors.

**Figure 5 Web Application GUI**



# Chapter 5: Evaluation

Some procedures impact the efficiency but do not affect the accuracy or precision and vice-versa, while other procedures may affect both efficiency and prediction result. To fully evaluate our algorithm design we structure the evaluation part by main procedures, and evaluate how each procedure affects the algorithm performance.

We evaluated the entire algorithm on a macOS laptop with 2.2 GHz Intel Core i7 processor, embedded 16 GB 1600 MHz DDR3 memory.

In this section, we introduce the evaluation part in detail. In the implementation part, we know that we have expanded 20 features into 54 features, while we retain 30 features that are the most effective. In this section, we record the evaluation detail of feature selection part.

The contents of this section are split into three main parts for each step in implementation. While before the detail illustration of evaluation procedures, we begin this part with introducing how we split the dataset. Test procedure including two parts, one testing dataset is for feature selection and another one is for models testing. We note the feature selection dataset and model testing dataset as DS_test_f and DS_test_m, respectively.

We randomly select two thirds of the stock data by stock ID for RFE training and notes the dataset as DS_train_f, all the data consist of full technical indices and expanded features throughout 2018. The estimator of RFE algorithm is SVR with linear kernels. We rank the 54 features by voting and get 30 effective features then process them using PCA algorithm to perform dimension reduction and reduce the features into 20 principal components. The rest of stock data forms the testing dataset DS_test_f to validate the effectiveness of principal components we extracted from selected features.

We reform all the data from 2018 as the training dataset of the data model and noted as DS_train_m.

The model testing dataset DS_test_m consists of the first 3 months of data in 2019, which has no overlap with the dataset we exploited in previous steps. This approach is to prevent the hidden problem caused by overfitting.

### 5.1 Term Length

To build an efficient prediction model, instead of the approach of modeling the data to time series, we determined to use one day ahead indices data to predict the price trend of the next day.

We tested the RFE algorithm on a range of short-term from one day to two weeks (ten trading days), to evaluate how commonly used technical indices correlated to the price trend.

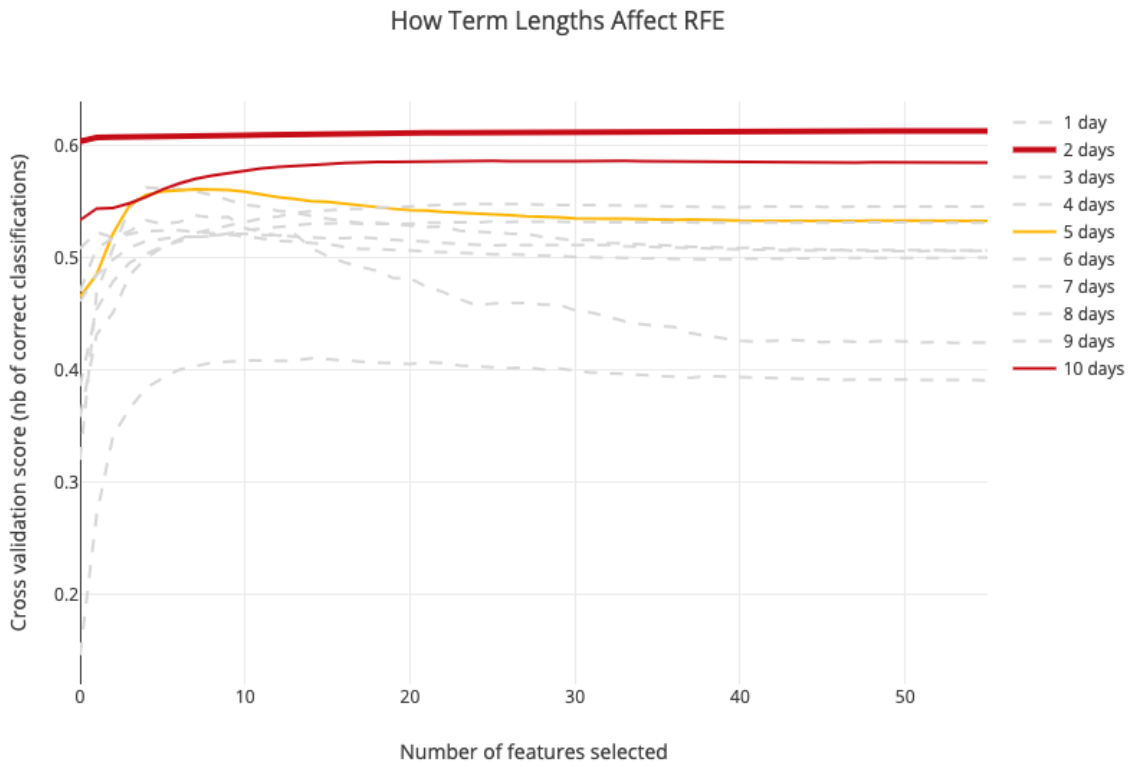
For evaluating the prediction term length, we fully expanded the features as the Table 17 above, and feed them to RFE.

During the test, we found that different length of term has a different level of sensitive-ness to the same indices set.

We get the close price of the first trading date, and compare it with the close price of the *n_th* trading date. Since we are predicting the price trend, we do not consider the term lengths if the cross-validation score is below 0.5. And after the test, as we can see from the Fig 4, there are three term lengths that are most sensitive to the indices we selected from the related works. They are $n = \{2, 5, 10\}$, which indicates that price trend

prediction of every other day, one week and two weeks using the indices set are likely to be more reliable.

**Figure 6 How Do Term Lengths Affect the Cross-validation Score of RFE**




While these three curves have different symptoms, for the length of two weeks, the cross-validation score increases with the number of features selected. If the prediction term length is one week, the cross-validation score will decrease if selected over 8 features. For every other day price trend prediction, the best cross validation score is achieved by selecting 48 features. Biweekly prediction requires 29 features to achieve the best score. In the Table 18, we listed the top 15 effective features for these three period lengths. Interestingly, if we predict the price trend of every other day, the cross-validation score merely fluctuates with the number of features selected. So, in the next step, we will evaluate the RFE result for these three term lengths.

We compare the output feature set of RFE with the all-original feature set as a baseline, the all-original feature set consists of n features and we choose *n* most effective features from RFE output features to evaluate the result using linear SVR. We used two different approaches to evaluate feature effectiveness. The first method is to combine all the data into one large matrix and evaluate them by running RFE algorithm once. Another method is to run RFE for each individual stock and calculate the most effective features by voting.

**Figure 7 Confusion Matrix of Validating Feature Extension Effectiveness**

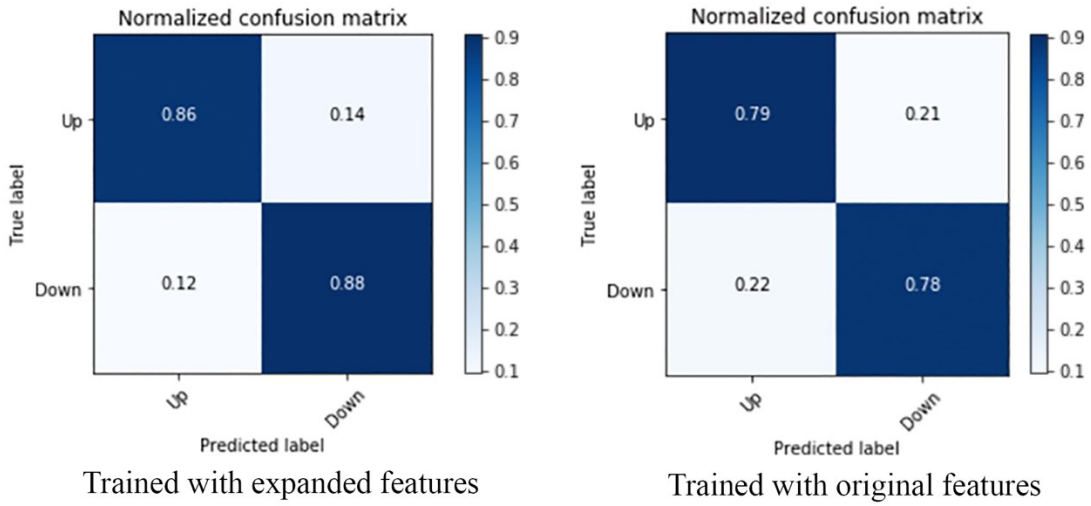
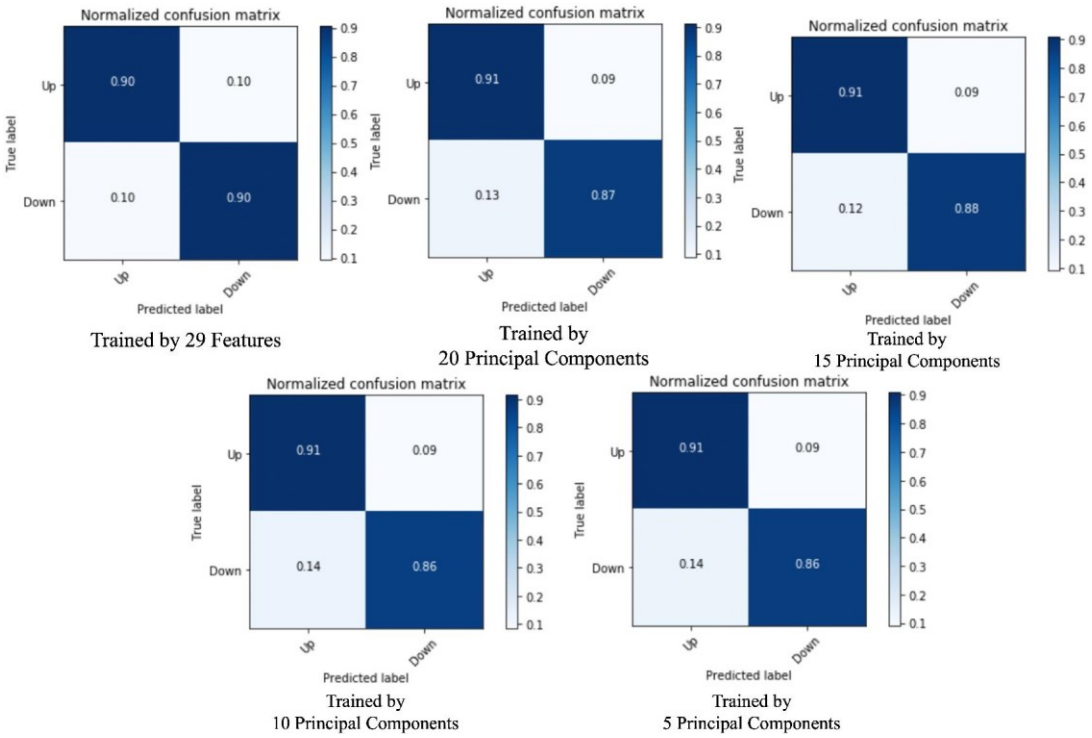



**Table 18 Effective Features Corresponding to Term Lengths**

| Relevant Ranking | Every Other Day | Weekly | Bi-weekly |
|---|---|---|---|
| 1st | **up_down** | **SLOWK_maxmin** | **MTM_10_plr** |
| 2nd | **change** | **SLOWK** | **ROC_10_plr** |
| 3rd | **pct_chg** | **SLOWD_maxmin** | **WNR_9** |
| 4th | **low** | **RSI_5_maxmin** | **WNR_9_maxmin** |
| 5th | **RSI_5_flc** | **SLOWD** | **SLOWK** |
| 6th | **open** | **RSI_5** | **SLOWK_maxmin** |
| 7th | **amount** | **SLOWK_flc** | **ROC_10** |
| 8th | **amount_maxmin** | **WNR_9_maxmin** | **SLOWD_flc** |
| 9th | **vol** | WNR_9 | **WNR_9_flc** |
| 10th | **BIAS_20_maxmin** | CCI_24 | **RSI_5** |

| | | | |
|---|---|---|---|
| 11th | **high** | BIAS_20_maxmin | **BIAS_20_maxmin** |
| 12th | **vol_maxmin** | BIAS_20 | **RSI_5_maxmin** |
| 13th | **ROC_10** | ADOSC_maxmin | **BIAS_20** |
| 14th | **ADOSC_maxmin** | ADOSC | **SMA_10** |
| 15th | **ADOSC** | WNR_9_flc | **SLOWD** |
| ... | ... | | ... |
| Number of Features | 48 features selected | 8 features selected | 29 features selected |

**Figure 8 How Does the Number of Principal Component Affect Evaluation Result**




## 5.2 Feature Extension and RFE

From the result of the previous subsection, we can see that when predicting the price trend for every other day or biweekly, the best result is achieved by selecting a large number of features. Within the selected features, some features processed from extension methods have better ranks than original features, which proves that the feature extension method is useful for optimizing the model.

The feature extension affects both precision and efficiency, while in this part, we only discuss the precision aspect and leave efficiency part in the next step since PCA is the most effective method for training efficiency optimization in our design. We involved an evaluation of how feature extension affects RFE, and use the test result to measure the improvement of involving feature extension.

In this subsection, we would test the effectiveness of feature extension: if polarize, max-min scale and calculate fluctuation percentage works better than original technical indices. The best case to leverage this test is the weekly prediction since it has the least effective feature selected. From the result we got from the last section, we know the best cross-validation score appears when selecting 8 features. The test consists of two steps, the first step is to test the feature set formed by original features only, in this case, only SLOWK, SLOWD, and RSI_5 are included. Next step is to test the feature set of all 8 features we selected in the previous subsection. We leveraged the test by defining the simplest DNN model with three layers.

The normalized confusion matrix of testing the two feature sets are illustrated in Figure 7. The left one is the confusion matrix of the feature set with expanded features, and the right one besides is the test result of using original features only.

Both precision of true positive and true negative has been improved by 7% and 10% respectively, which proves that our feature extension method design is reasonably effective.

**Figure 9 Relationship Between Feature Number and Training Time**

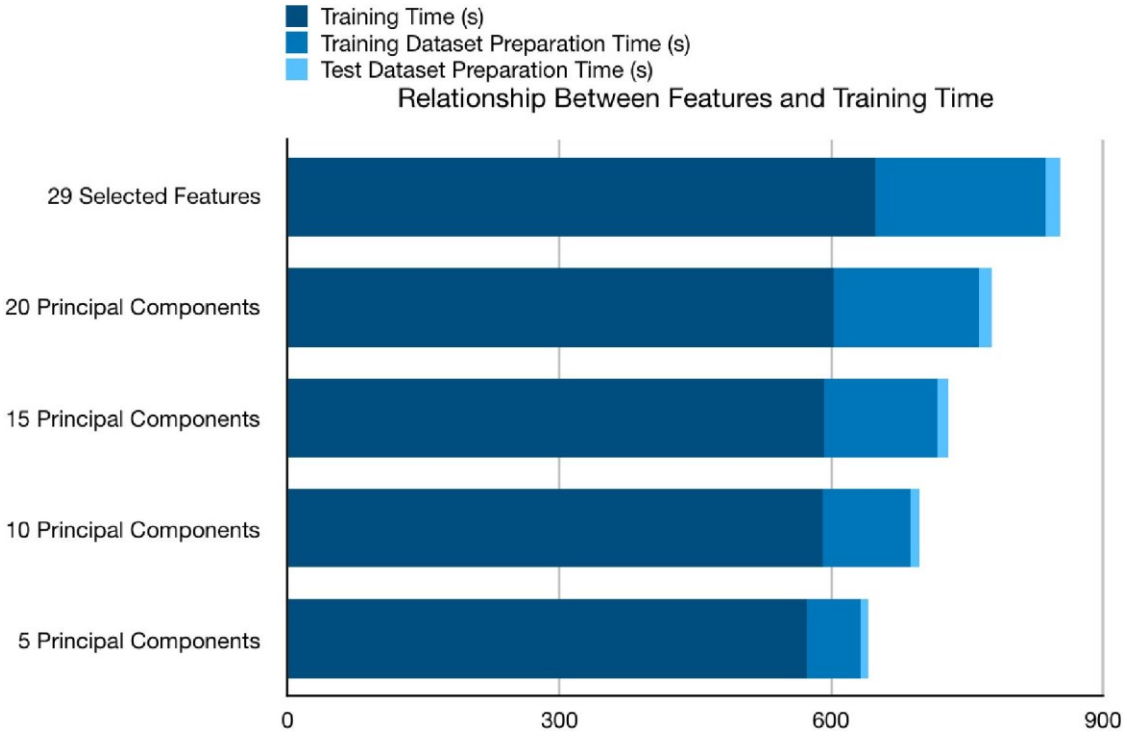
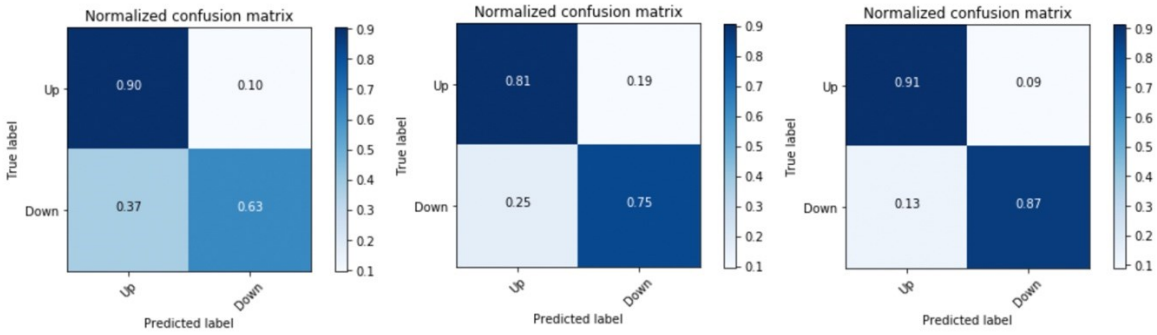



**Figure 10 Confusion Matrices of Different Feature Pre-processing Methods**




Without Feature Pre-processing　　Normalization　　Max-min Scaling

## 5.3 Feature Reduction Using Principal Component Analysis

PCA will affect the algorithm performance on both prediction accuracy and training efficiency aspect, while this part should be evaluated with NN model, so we also defined

a simplest DNN model with three layers as we used in the previous step to perform the evaluation.

This part introduces the evaluation method and result of the optimization part of the model from computational efficiency and accuracy impact perspectives.

**Table 19 Relationship Between the Number of Principal Components and Training Efficiency**

| Number of Features | Training Dataset Preparation Time (s) | Test Dataset Preparation Time (s) | Training Time (s) | Sum (s) |
|---|---|---|---|---|
| 29 Selected Features | 187.46 | 16.30 | 648.53 | 852.29 |
| 20 Principal Components | 160.29 | 14.24 | 602.68 | 777.21 |
| 15 Principal Components | 125.20 | 12.18 | 591.93 | 729.31 |
| 10 Principal Components | 96.54 | 10.37 | 590.76 | 697.67 |
| 5 Principal Components | 59.37 | 8.22 | 572.88 | 640.47 |

**Table 20 How Does the Number of Selected Features Affect the Prediction Accuracy**

| Number of Selected | 5 Principal Components | 10 Principal Components | 15 Principal Components | 20 Principal Components | 29 Selected Features |
|---|---|---|---|---|---|
| Accuracy | 89.03% | 89.35% | 89.39% | 89.30% | 90.29% |

In this section, we will choose bi-weekly prediction to perform a use case analysis, since it has a smoothly increasing cross validation score curve, moreover, unlike every other day prediction, it has excluded more than 20 ineffective features already. In the first step, we select all 29 effective features and train the NN model without performing PCA. It creates a baseline of the accuracy and training time for comparison. To evaluate the accuracy and efficiency, we keep the number of principal component as 5, 10, 15, 20, 25. The Table 19 recorded how number of features affect the model training efficiency, then use the stack bar chart in Figure 9 to illustrate how PCA affect the training efficiency.

We also listed the confusion matrix of each test in Figure 8.

The stack bar chart shows that the overall time spends on training the model is decreasing by the number of selected features, while the PCA method is significantly effective on optimizing training dataset preparation. For the time spent on training stage, PCA is not as effective as data preparation stage. While there is the possibility that the optimization effect of PCA is not drastic enough because of the simple structure of NN model. Table 20 indicates that the overall prediction accuracy is not drastically affected by reducing the dimension. However, the accuracy could not fully support if the PCA has no side effect to model prediction, so we looked into the confusion matrices of test results

**Table 21 Accuracy and Efficiency Analysis on Feature Pre-processing Procedures**

| Feature Pre-processing | Overall Accuracy (%) | Training Dataset Preparation Time (s) | Testing Dataset Preparation Time(s) | Training Time (s) | Sum (s) |
|---|---|---|---|---|---|
| Max-min Scaling | 89.30 | 160.28 | 14.24 | 602.68 | 777.20 |
| Normalization | 78.17 | 157.63 | 14.73 | 596.22 | 768.58 |
| N/A | 78.88 | 142.17 | 13.00 | 595.52 | 750.69 |

using different number of selected features. From Figure 8 we can conclude that PCA does not have a severe negative impact on prediction precision. The true positive rate and false positive rate are barely be affected, while the false negative and true negative rate are influenced by 2% to 4%.

Besides evaluating how the number of selected features affects the training efficiency and model performance, we also leveraged a test upon how data pre-processing procedures affect the training procedure and predicting result. Normalizing and max-min scaling are the most commonly seen data pre-procedure performed before PCA, since the measure units of features are varied and it is said that it could increase the training efficiency afterwards.

We leveraged another test on adding pre-procedures before extracting 20 principal components from original dataset, and make the comparison in the aspects of time elapse of training stage and prediction precision.

However, the test results lead to different conclusions. In the Table 21 we can conclude that feature pre-processing does not have a significant impact on training efficiency, but it influences the model prediction accuracy.

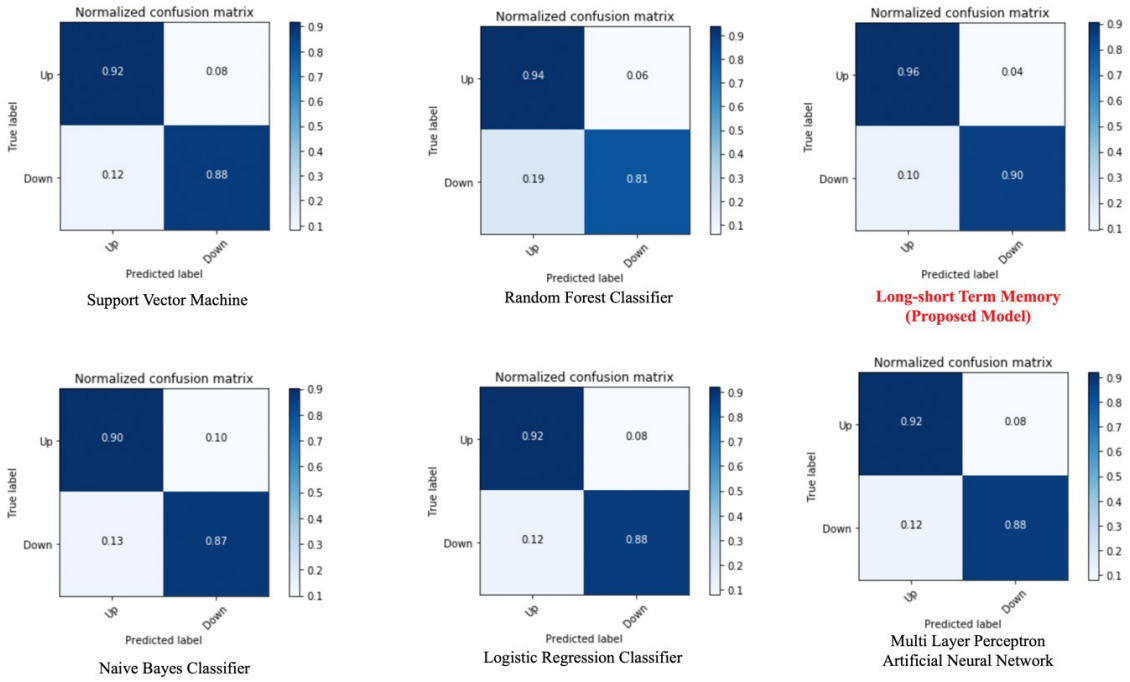
Moreover, the first confusion matrix in Figure 10 indicates that without any feature pre-processing procedure, the false negative rate and true negative rate are severely affected, while the true positive rate and false positive rate are not affected. If performs the normalization before PCA, both true positive rate and true negative rate are decreasing by approximately 10%.

This test also proved that the best feature pre-processing method for our feature set is exploiting max-min scale.

## 5.4 Model Performance Comparison

In this part, we compared our model with other approaches and the most related works.

**Figure 11 Model Prediction Comparison - Confusion Matrices**



### 5.4.1 Comparison with Related Works

From the previous works, we found the most commonly exploited models for short-term stock market price trend prediction are Support Vector Machine (SVM), Multilayer Perceptron Artificial Neural Network (MLP), Naive Bayes Classifier (NB), Random Forest Classifier (RAF) and Logistic Regression Classifier (LR).

The test case of comparison is also bi-weekly price trend prediction, to evaluate the best result of all models, we keep all 29 features selected by RFE algorithm.

For MLP evaluation, to test if the number of hidden layers would affect the metric scores, we noted layer number as $n$ and tested $n = \{1, 3, 5\}$, 150 training epochs for all the tests, found slight differences in the model performance, which indicates that the variable of MLP layer number hardly affects the metric scores.

From the confusion matrices in Figure 11, we can see all the machine learning models perform well when training with the full feature set we selected by RFE.

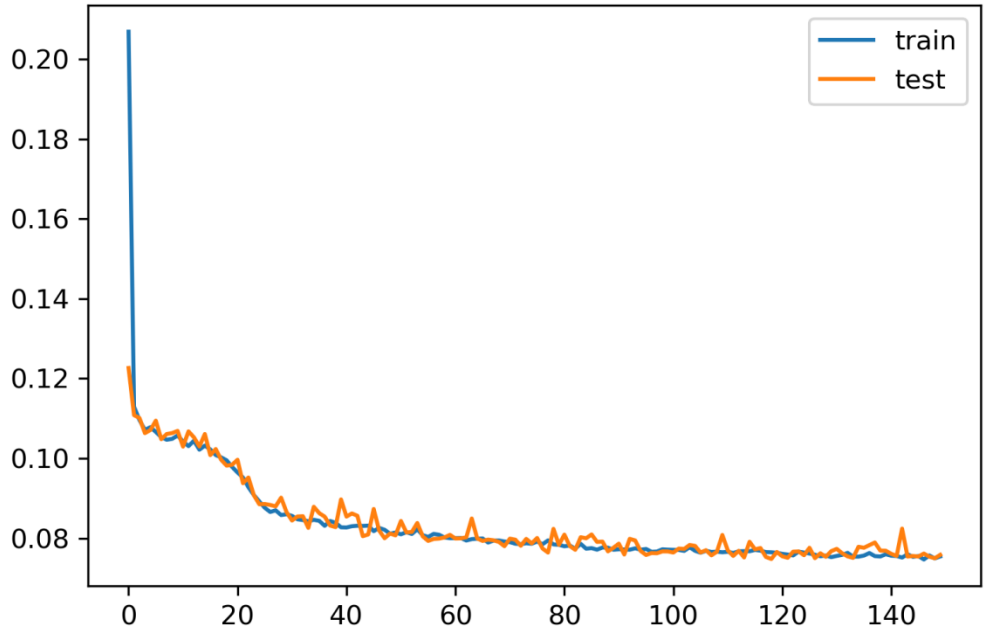
From the perspective of training time, training the NB model got the best efficiency. LR algorithm cost less training time than other algorithms while it can achieve a similar prediction result with other costly models such as SVM and MLP. RAF algorithm achieved a relatively high true-positive rate while poor perform in predicting negative labels.

For our proposed LSTM model, it achieves a binary accuracy of 93.25%, which is a significantly high precision of predicting the bi-weekly price trend.

We also pre-processed data through PCA and got 5 principal components, then trained for 150 epochs. The learning curve of our proposed solution is illustrated as Figure 12.

Confusion matrix is the figure on the right in Figure 13, detailed metrics scores can be found in Table 24.

**Figure 12 Learning Curve of Proposed Solution**

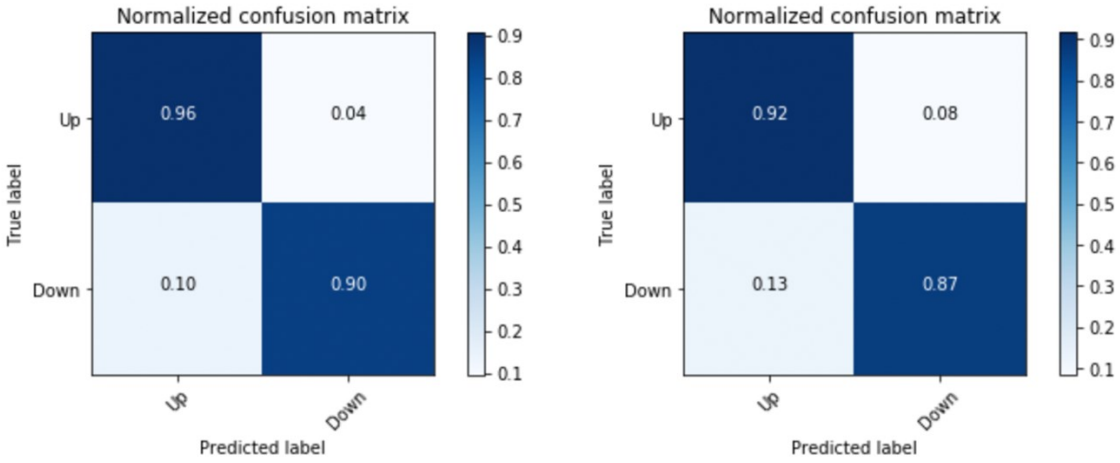



The detailed evaluate results are recorded in Table 22 below. We will also initiate a discussion upon the evaluation result in the next section.

**Table 22 Model Performance Comparison – Metric Scores**

| Model | F1 Score | Binary Accuracy | TPR (recall) | TNR (specificity) | FPR (fall-out) | FNR (miss rate) |
|---|---|---|---|---|---|---|
| LR | 0.90 | 0.90 | 0.92 | 0.88 | 0.08 | 0.12 |
| SVM | 0.90 | 0.90 | 0.92 | 0.88 | 0.08 | 0.12 |
| NB | 0.89 | 0.89 | 0.90 | 0.87 | 0.10 | 0.13 |
| MLP (Single hidden layer) | 0.90 | 0.90 | 0.92 | 0.88 | 0.08 | 0.12 |
| MLP (Three hidden layers) | 0.90 | 0.90 | 0.92 | 0.87 | 0.08 | 0.13 |
| MLP (Five hidden layers) | 0.90 | 0.90 | 0.92 | 0.88 | 0.08 | 0.12 |
| RAF | 0.88 | 0.88 | 0.94 | 0.81 | 0.06 | 0.19 |
| LSTM (Proposed Model) | 0.93 | 0.93 | 0.96 | 0.90 | 0.04 | 0.10 |

**Figure 13 Proposed Model Prediction Precision Comparison - Confusion Matrices**




**LSTM Model**
**Trained by 29 Features**

**LSTM Model**
**Trained by 5 Principal Components**

Because the result structure of our proposed solution is different from most of the related works, it would be difficult to make naïve comparison with previous works. For example, it is hard to find the exact accuracy number of price trend prediction in most of the related works since the authors prefer to show the gain rate of simulated investment. Gain rate is a processed number based on simulated investment tests, sometimes one correct investment decision with a large trading volume can achieve a high gain rate regardless of the price trend prediction accuracy. Besides, it is also a unique and heuristic innovation in our proposed solution, we transform the problem of predicting an exact price straight forward to two sequential problems, i.e., predicting the price trend first, focus on building an accurate binary classification model, construct a solid foundation for predicting the exact price change in future works.

Besides the different result structure, the datasets that previous works researched on are also different from our work. Some of the previous works involve news data to perform

sentiment analysis and exploit SE part as another system component to support their prediction model.

The latest related work that can compare is (Zubair et al., 2019), the authors take multiple r-square for model accuracy measurement. Multiple r-square is also called the coefficient of determination, it shows the strength of predictor variables explaining the variation in stock return (Nagar, Anurag; Hahsler, 2012). They used three datasets (KSE 100 Index, Lucky Cement Stock, Engro Fertilizer Limited) to evaluate the proposed multiple regression model, and achieved 95%, 89% and 97% respectively. Except for KSE 100 Index, the dataset choice in this related work is individual stocks; thus, we choose the evaluation result of the first dataset of their proposed model.

We listed the leading stock price trend prediction model performance in Table 23, from the comparable metrics, the metric scores of our proposed solution are generally better than other related works. Instead of concluding arbitrarily that our proposed model outperformed other models in related works, we first look into the dataset column of Table 23. By looking into the dataset used by each work (Khaidem & Dey, 2016) only trained and test their proposed solution on three individual stocks, which is difficult to prove the generalization of their proposed model. (Ayo, 2014) leveraged analysis on the stock data from New York Stock Exchange (NYSE), while the weakness is they only performed analysis on closing price, which is a feature embedded with high noise. (Zubair et al., 2019) trained their proposed model on both individual stocks and index price, but as we have mentioned in the previous section, index price only consists of limited number of features and stock IDs, which will further affect the model training quality. For our proposed solution, we collected sufficient data from Chinese stock

market, and applied FE + RFE algorithm on the original indices to get more effective features, the comprehensive evaluation result of 3558 stock IDs can reasonably explain the generalization and effectiveness of our proposed solution in Chinese stock market. However, the authors of (Khaidem & Dey, 2016) and (Ayo, 2014) chose to analyze the stock market in United States, (Zubair et al., 2019) performed analysis on Pakistani stock market price, and we obtained the dataset from Chinese stock market, the policies of different countries might impact the model performance, which needs further research to validate.

**Table 23 Comparison of Proposed Solution with Related Works**

| Related Work | Dataset | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|---|
| (Khaidem & Dey, 2016) | Stock price data of AAPL, GE and Samsung Electronics Co. Ltd. | Random forest | 0.83 | 0.82 | 0.81 |
| (Ayo, 2014) | Close price of stock data from New York Stock Exchange (NYSE) | ARIMA | 0.90 | 0.91 | 0.92 |
| (Zubair et al., 2019) | KSE 100 Index<br>Lucky Cement Stock<br>Engro Fertilizer Limited | Multiple Regression | 0.94 | 0.95 | 0.93 |
| *(Proposed Solution)* | *Price data of 3558 stock ID from 2017 to 2018 collected from Chinese stock market* | *Proposed Model – FE+RFE+ PCA+LSTM* | 0.93 | 0.96 | 0.96 |

### 5.4.2 Proposed Model Evaluation - PCA Effectiveness

Besides comparing the performance across popular machine learning models, we also evaluated how PCA algorithm optimizes the training procedure of the proposed LSTM model. We recorded the confusion matrices comparison between training the model by 29 features and by 5 principal components in Figure 13.

The model training using the full 29 features takes 28.5s per epoch on average. While it only takes 18s on average per epoch training on the feature set of 5 principal components. PCA has significantly improved the training efficiency of LSTM model by 36.8%. The detailed metrics data are listed in Table 24. We will leverage a discussion in the next section about complexity analysis.

**Table 24 Proposed Model Performance Comparison - With and Without PCA**

| Metrics Name | LSTM Trained on 29 Features | LSTM Trained on 5 Principal Components |
|---|---|---|
| Loss | 0.0702 | 0.0848 |
| F1 Score | 0.9323 | 0.9194 |
| Binary Accuracy | 0.9325 | 0.9193 |
| MSE | 0.0669 | 0.0772 |
| MAE | 0.0702 | 0.0848 |
| TPR | 0.96 | 0.92 |
| TNR | 0.90 | 0.91 |
| FPR | 0.04 | 0.08 |
| FNR | 0.10 | 0.09 |

## 5.5 Discussions and Implications

In this section, we will discuss the findings from the results we got from the evaluations above. The discussion contents are formed by the related findings and answers back to the research questions.

### 5.5.1 RQ1: How does feature engineering benefit model prediction accuracy?

As we illustrated in the proposed solution part, the algorithm for feature engineering in this project was RFE. The curves in Figure 6 obviously show that when the feature number reaches a certain threshold, the cross-validation score will no longer increase and would even drop with more features selected. The thresholds are varied from different term lengths.

This finding shows that over selected features will only overload the hardware resources and increasing training time but not contributes to the model prediction accuracy and might have a negative impact on the prediction task.

From the confusion matrices of different model prediction precision in Figure 11 we can also conclude that with a well-selected feature set, even a simple classifier such as Naive Bayes Classifier can also achieve a relatively accurate prediction result. It also proved that the feature engineering plays an important role in data preparation and model design part.

### 5.5.2 RQ2: How do findings from financial domain benefit prediction model design?

We translated the most helpful findings from financial domain into technical processing, which could benefit our research project. We called this procedure as feature extension.

Table 18 records the top 15 features that selected by RFE after feature extension procedures. From the effective features of three different time lengths, we can see that the top feature of weekly and biweekly price trend prediction is both extended features. Meanwhile, for biweekly prediction, 8 of the top 15 effective features are expanded features.

Besides, none of the three feature extension methods is an extravagant pre-processing. They are useful in different level when predicting the price trend of varied term lengths.

The confusion matrices in 5 illustrate that by applying the feature extension technique, the recall and specificity have been improved by 7% and 10% respectively. This result indicates that the knowledge we extracted from financial domain then converted them into technical procedures significantly benefits the model performance.

### 5.5.3 RQ3: What is the best algorithm for predicting short-term price trend?

From the test result, we got from the evaluation section, the confusion matrices in 9 and detailed metrics score in Table 22, our proposed LSTM model has outperformed other models in all metrics scores.

In predicting up labels, only RAF got a competitive recall of 0.94. While RAF also got the lowest specificity among all the prediction models. Other models exploited from related works got almost the same metric scores, which also proves that our RFE algorithm plays a crucial role in guarantee the prediction accuracy.

The LSTM model proposed in this research project has outperformed other models in overall binary accuracy by 3% to 5%. As the prediction accuracy getting higher, the wrongly predicted labels might be contradicted to the normal pattern and are difficult to be recognized by only applying ML techniques. Hence it would be tougher for improving the prediction accuracy when the FN and FP labels fall in unusual patterns and difficult to learn. While our proposed model even outperforms other models in predicting TP labels by 2% to 6% and the recall has reached a rate as high as 96%, which is a very promising result. Our proposed model also improved recognition accuracy on down price trend and is the only model whose specificity has reached 90% among all the models used by most related works.

There are reasons why the LSTM model has an outstanding performance in predicting short-term price trend.

LSTM can model much more time steps than RNN does, meanwhile, without suffering from the vanishing gradient problem, while the drawback of LSTM is that the dimension of training data matrix will grow fast with the number of time steps.

For long-term predictions, the computational complexity grows crazily when the feature set is already too large. While for short-term prediction the training data matrix dimension is still in an acceptable range.

Another reason for the LSTM model outperforms than other models are because the price trend prediction is a time-series problem. LSTM model retains the time dependencies of some features, which is the advantage that other models lack.

### 5.5.4 Complexity Analysis of Proposed Solution

This section analyzes the complexity of our proposed solution.

The Long Short-term Memory is different other NNs, it is a variant of standard RNN which also has time steps with memory and gate architecture. In the previous work (Zhang, 2016), the author performed an analysis of the RNN architecture complexity. They introduced a method to regard RNN as a directed acyclic graph, and proposed a concept of recurrent depth which helps perform the analysis on the intricacy of RNN.

The recurrent depth is a positive rational number, we denote it as $d_{rc}$. As the growth of $n$, $d_{rc}$ measures the nonlinear transformation average maximum number of each time step. We then unfold the directed acyclic graph of RNN and denote the processed graph as $g_c$, meanwhile, denote $C(g_c)$ as the set of directed cycles in this graph. For the vertex $v$, we note $\sigma_s(v)$ as the sum of edge weights and $l(v)$ as the length. The equation below is proved under a mild assumption which could be found in the appendix of (Zhang, 2016).

$$d_{rc} = max_{v \in C(g_c)} \frac{l(v)}{\sigma_s(v)}$$

They also found that another crucial factor that impacts the performance of LSTM, which is the recurrent skip coefficients. We note $s_{rc}$ as the reciprocal of recurrent skip coefficient. Please be aware that $s_{rc}$ is also a positive rational number.

$$s_{rc} = min_{v \in C(g_c)} \frac{\sigma_s(v)}{l(v)}$$

According to the above definition, our proposed model is a 2-layers stacked LSTM which $d_{rc} = 2$ and $s_{rc} = 1$. From the experiments performed in previous work, the authors also found that when facing the problems of long-term dependency, LSTMs may benefit from decreasing the reciprocal of recurrent skip coefficients and from increasing recurrent

depth. The empirical findings above mentioned are useful to enhance the performance of our proposed model further.

### 5.5.5 Other Findings

#### 5.5.5.1 Choose a proper pre-processing method for the feature set

Since our feature set was based on feature extension using three different methods, not only the measure units of different features are varied, but also the scale.

Back to the Figure 10, if train the model without feature pre-processing, the specificity would be extremely poor. With adding a normalization procedure, recall and specificity were greatly balanced but still not ideal. By performing max-min scale as the pre-processing method, we eventually got the highest precision score, which stressed the importance of choosing the right data-preprocessing method before performing dimension reduction or model training.

#### 5.5.5.2 Term length significantly affects the price trend prediction result

The impact brought by term lengths is also a heuristic finding from our evaluation part. At the beginning of the research, we determined to define a general model for predicting the price trend of short-term (from one day ahead to bi-weekly). While as the RFE result shown in the Figure 6, the feature selection procedure is most effective in predicting price trend of every other day, weekly and biweekly. Meanwhile, one day ahead price trend is proved to be highly unpredictable. The cross-validation score of one day ahead price trend prediction could never reach 50%, which appears to be worse than random guessing.

From the features selected by RFE in Table 18 shows that some of the selected features are related to the term length. Below is a discussion based on three cases:

For every other day, the RFE effectiveness is not significant, but the features which have the highest covariance are price changes from the previous trading date. One assumption of this symptom is that the price trend has inertia brought from the previous trading day, other features have far less impact on price trend.

For weekly and bi-weekly price trend prediction, some of the selected features are calculated based on the data of the same term length of prediction timespan. Another assumption of increasing the generalization of prediction model is to add the flexibility of calculating the indices based on user-defined term lengths before performing RFE, in another word, define the term length as a parameter and calculate some of the indices based on this parameter and put into feature pool.

#### 5.5.5.3 How does PCA algorithm affect the model performance

The objective of introducing PCA algorithm into the model design is to improve the training efficiency of data model, meanwhile, eliminate the side effect on evaluation metrics.

By testing the PCA procedure on MLP model, we got the timing data in the Table 19. Despite significant time saving on data preparation procedure but look into the training procedure only, from training the model on a full feature set, performing the training on 5 principal components improves the efficiency by 11.66%.

For our proposed LSTM model, it even improved the training efficiency by 36.8%, which apparently to be a significant optimization on data model training.

While every coin has two sides, by performing a dimension reduction from 29 features to 5 principal components is almost an extreme operation. In the aspect of binary accuracy, the binary accuracy of MLP has dropped from 90.29% to 89.03%, and for LSTM it has dropped from 93.25% to 91.93%. If we analyze more detailed metrics, we can see the specificity of MLP has dropped by 4%, meanwhile, the recall of LSTM has dropped by 4%. It might be costly for sacrificing the prediction precision if the training time is still acceptable.

#### 5.5.5.4 Lower rate of TN than TP

From all the evaluation results, the recalls are higher than specificities. One possible cause is the imbalanced label since we have 10:7 positive label to negative label. In our approach, sampling the data is not an appropriate approach since it will break the time series. Sampling by stocks which has the balanced label of price trend will also cause other problems, such as insufficient training data.

# Chapter 6: Future Work

Though we have achieved a decent prediction result from our proposed model, this research project still has much potential in future research.

First of all, the objective of building the model to perform short-term price trend prediction is to complete the very first step of stock market price prediction. With a reliable trend prediction, we can perform the price prediction in a more reliable way.

While what threats our proposed model the most is 10% of FPR. The next step is to look into the data of 10% FP labels and try to address the issue of the wrong prediction and optimize the model by either add a rule-based layer or keep researching and find a better parameter set of our proposed model.

During the evaluation procedure, we also found that the RFE algorithm is not sensitive to the term lengths other than two-day, weekly, biweekly. Get more in-depth research into what technical indices would influence the irregular term lengths would be one possible future research direction.

During our research, we only involved some knowledge from the financial domain but already got a promising improvement, it proved that the related financial domain knowledge cooperates with technical indices will benefit the price trend prediction greatly. Thus, we plan to build filters for pre-classify different kinds of stocks and see if this approach can further optimize the prediction result.

Moreover, by combining the sentiment analysis technique like the algorithm in previous work (Nagar, Anurag; Hahsler, 2012) with our proposed deep learning model, there is also a high potential to develop a more comprehensive prediction system which is trained by diverse types of information such as Tweets, news, and other text-based data.

# Chapter 7: Conclusion

This work consists of three parts: the Chinese stock market dataset, stock price trend prediction model, use case of the proposed solution. There are three major contributions of this research work. First, by researching into the techniques often used by real-world investors, we develop a new algorithm component and name it as Feature Extension which is proved to be effective. Second, we apply the FE algorithm with RFE followed by PCA to build a feature engineering procedure which is both effective and efficient. The system is customized by assembling the aforementioned feature engineering procedure with an LSTM prediction model, achieved a significant high prediction accuracy that outperforms the leading models in most related works. The third contribution is the comprehensive evaluation in this work. By comparing the most frequently used machine learning models with our proposed LSTM model under the feature engineering part of our proposed system, we conclude many heuristic findings that could be future research questions in both technical and financial research domains. Besides the three major contributions above, we also have other contributions: 1) We made a dataset contribution. In this project, after doing a comprehensive literature review in financial domain we determine the information segments that are useful for stock market analysis, then we collect, clean-up and structure the two years of Chinese stock market data for future research. 2) We developed a web application based on the proposed solution as a use case, the advantage of this web application is expansible, flexible, and easy-to-access. There is a high potential to develop this web application into a mature product for individual investors.

Our proposed solution is unique from previous works because rather than propose a state-of-the-art LSTM model, we proposed a fine-tuned deep learning prediction system. By researching into the observations from previous works, we fill in the gaps between investors and researchers by proposing a feature extension algorithm before RFE and get a noticeable improvement in the whole model performance. Thus, this work proves the significant contribution of feature engineering in data pre-processing for training machine learning models.

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