

RO1

- Good report!
- Update the verb tenses and GANTT chart,
- Update your title on p. 2
and on page headers
- Mention ensemble learning

FYP Proposal

Personalized Algorithmic Trading using Machine Learning / Deep Learning models

OR: "Personalize Algo-trading Using Ensemble Learning"

MUN Sun Bin, KWOK Ue Nam, KONG Kin Cheung and HO Yat Man Peter

RO1

Advised by

Prof. David Rossiter

Submitted in partial fulfillment of the requirements for COMP 4981

in the

Department of Computer Science

The Hong Kong University of Science and Technology

2021-2022

1. Introduction

1.1 Overview

1.1.1 Market Bubble Growth

~~Stock~~
Due to recent advances and convenience of
Being benefited by the technology enhancement on mobile technologies, investors
nowadays are much easier to enter the stock market through mobile applications developed
by the security brokers. With a coincidence of the COVID-19 pandemic, Governments are
many central banks are rapidly debasing their currencies to hold off imminent
undergoing quantitative easing to support their economies. As a result, a large amount of
economic collapse and maintain the status quo.
capital has flowed into the stock market as more people stepped into it to keep their assets
~~savings will continue to be eroded by~~ and more people fear that the value of their hard-earned
valuable over inflation [18]. However, many of them are not experienced in the stock or
security market, in which they have inadequate knowledge and resources (Investment
and time)
Capital or Time) to manage their investments. Most are also unaware that the global
elite have planned for decades to make the whole global financial system implode
so that they can have a "Great Reset" and bring in a new blockchain-based
system in which proof of work is done through human brain activity [20, 21].

1.1.2 Machine Learning and Deep Learning in Trading

Machine Learning (ML) is a study of constructing a model operating under complex algorithms which will improve over the iterative learning process without programmed instructions.

Further stretching, Deep Learning (DL) is an extension of Machine Learning that makes use of multiple artificial neural networks to return higher-level features of the data. The field studies constructing algorithms to perform like the neural network in the human brain.

In recent years, both Machine Learning and Deep Learning models ~~are~~ ^{have been} applied to a vast range of industries, including the financial industry. Some popular models used by quantitative analysts and data scientists ~~used~~ for stock prediction include:

1. Convolutional Neural Network (CNN)
2. Long Short-Term Memory (LSTM)
Short-term
3. Recurrent Neural Network (RNN)
4. Reinforcement Learning (RL)
5. Q-Learning (reinforcement learning *model* without the agent)

1.1.3 Algorithmic Trading

Among all the practical applications of ML and DL in the financial industry such as fraud detection, market insights, and financial advisory, algorithmic trading (or electronic trading) plays a great role. According to Coherent Market Insights, the equity market *is expected to* contribute \$8.61 billion *of* *in* the Algo-trading market share by 2027[14]. Moreover, Coalition Greenwich reported that the top 12 investment banks profited around USD 2 billion from *the* portfolio and algorithmic trading in 2020[15].

Because the *trading markets* is a vibrant, fast-paced, and hard to predict environment, algorithmic trading is of great use with its higher entry speed, concrete execution protocol, *and lower degree of bias and emotion compared to human-initiated trading, and less prone to human bias.* Based on the input data, the model will be trained to accurately predict the price and be applied to the real market to form a profitable portfolio.

With the diverse pool of strategies, we propose a comprehensive trading pipeline with the *ensemble* selection of algorithms/strategies and suggest what type of strategies are the most appropriate for each user. Our team plans to apply the unique 'voting system' by first filtering out the outlier predictions and rearrange the contribution of different models in the final price decision. The predicted value of each stock will then determine how to distribute the stocks *in a portfolio* and determine whether it has an apt risk level and offers maximum profit.

1.2 Objective

1.2.1 General goal overview

The objective of our project is to develop a user-friendly algorithmic trading pipeline with a diverse choice of models for stock price prediction and portfolio distribution that can beat the market by more than 5%. Moreover, when comparing our project to other existing Robo-advisors or algorithmic trading platforms, we hope that our final product can be better in terms of two prospects. Firstly, with the help of ensemble learning, i.e., using multiple machine learning models and different trading strategies, we would like to achieve higher accuracy in stock price prediction when comparing the existing Robo-advisors in the market. Secondly, we would like to develop a truly automated platform that does not require users to make any judgments or choices during investing. To achieve the above two goals, we have designed the following objective.

1. Database Implementation

The database stores the training data, test data, and machine learning models.

- Historical data is ~~being~~ stored for training the models and testing the models
- Real-time data is ~~being~~ pushed into the database constantly through APIs,
keeping the database updated.
- While the user is ~~being~~ classified, the dedicated model will be retrieved for the ~~making~~ choices according to his risk level.
corresponding risk.

one
or
several
APIs?

2. Machine Learning Models Training

To have a ~~better~~ performance in trading, having ~~an~~ accurate stock price prediction is very important. One of the ways to achieve this is to use multiple models to predict different results and then combine ^s _^ the results to produce the final prediction of the stock price. The method we use here is to filter out some of the outliers/top and bottom-n

the remaining predictions. Our results and then average it out. The method of averaging out can be done with weighting. The weighting can be figured out by 2 approaches:

1. Based on every prediction, higher weighting would be assigned to the data in the main cluster.
2. Based on previous training history, the models with better performance would be assigned with the higher weighting.

3. Risk Quantification

To adequately categorize users' To be more familiar with the users' profile and the risk-bearing level, we will design a survey to understand users' financial situations and investment preferences survey for the user to obtain the information of users and then classify them into

different risk levels. After knowing the risk level and the area of interest of the users, we would select a few corresponding potential stocks for price and trend prediction.

With the price prediction results and the users' profiles, the platform will automatically trade the selected stocks.

4. Portfolio Presentation

We are building a user's A user-friendly web dashboard will be built for visualizing the portfolio and the

performance of our models compared with the US stock market. It contains the following parts:

- (a) ^{A pie} Pie chart is used to visualize the distribution of stocks currently held in a user portfolio.
- (b) Multi-line charts are used to compare the performance between our strategies and the "buy and hold" strategy.

1.2.3 Objectives plans

To achieve the first objective, we would get historical data from the US stock market. We scraped X years of data from the US stock market to build the database. After training the models, we will filter out some of the models that return top and bottom n-results and use the best results of the remaining models to calculate the average for stock price prediction.

To achieve the second objective, a virtual machine is needed for building the database, and ideally, it should be able to constantly push new data into the database.

To achieve the last three objectives, a web application with an intuitive UI is being built to perform most of the interaction with the users.

1.2.4 Potential Challenges

As mentioned above, the financial market is so uncertain and difficult to predict, we can foresee that one of the major challenges would be how to train an accurate and reliable stock price prediction model. As mentioned above, we plan to use different machine learning models to predict stock prices independently and then apply filtered weighting. The major challenge would be how to decide which models to be dropped out and how to allocate the weighting of the fund results of the models.

1.3 Literature Review

There exist many methods of algorithmic trading and also quant firms with electronic trading execution systems. We build on two main areas of related work: Existing Algo-trading companies, and the technologies currently used.

1.3.1 Existing Algo-Trading Companies

Wealthfront

Some companies use algorithmic trading to perform portfolio management. Machine Learning models deployed in each firm tend to make decisions based on low-risk/high-return rules. One example of a company using Robo-advisor (¹⁷ A digital platform providing ¹⁸ algorithmic financial planning without any human supervision) is Wealthfront. ¹⁹ Wealthfront users set investing goals and duration before placing the seed money, then the platform takes care of the rest. It automatically manages portfolios while also allowing customized portfolios of single stocks, ETFs, and other funds. However, Wealthfront provides a rigid list of stocks in creating a portfolio, and users ²⁰ do not get to have a 'personalized' portfolio upon their will [19].

Aqumon

Other than Wealthfront, another Asia's leading platform ^{One of} ^{trading} ⁵ ^{link} Aqumon ²¹ ^{has rapidly} ^{ed} ⁱⁿ ^{the} ^{expected outcome of this project,} is in rapid development recently. Aqumon looks similar to the expected outcome of this project, with four major functions which are: Long Term Asset Allocation Portfolios, SmartStock Thematic Stock Portfolios, Stock Trading, and Cash Management Portfolios. One of the selling points for Aqumon is that they claim that their portfolios are built using the Nobel-winning Markowitz Efficient Frontier and Black-Litterman Model.

One of the advantages of Aqumon is that they provide various combinations of ETFs for the user to choose from, ²² the users are given advice based on their risk-bearing level but the users can make their own choices. However, financial-market newcomers ²³ might not know how to make a rational decision. ²⁴ Therefore, our project aims to provide a fully automated trading platform that does all the trading decisions in the back end without asking for users' decisions.

1.3.2 ~~Literature Review~~ on Stock Price Prediction Model ⁵

Research on predicting stock prices was conducted by implementing two major techniques:

- 1) Machine Learning Methods and 2) Deep Learning Techniques. This is because these

techniques can help us to predict the price movement in the future. The accuracy may not be high but better than a wild guess.

Machine Learning Methods

There are several common techniques in the machine learning field that are used for stock price prediction such as Support Vector Machine (SVM) [2,4,12], Random Forest (RF) [7,13], and Multiple Linear Regression (MLR) [10,12]. SVM and RF are practical and useful methods for classification in making trading actions (Buy/Sell/Hold) but they are not able to give a numerical prediction on the stock price. MLR is effective for finding the relationship between the historical data and the future price but it is limited to linear relationships, which Deep Learning can overcome. Hybrid models [7,13] combined with data mining methods and machine learning methods are also used to enhance the improvement.

In [9], three machine learning methods ~~are being~~ ^{were} implemented, including Extended Hill Climbing (EHC), Grid Method (GC), and Differential Evolution Method (DEM).

These models are compared based on an annualized rate of return from strategy and two risk measures, annualized standard deviation, and the maximum drawdown.

Deep Learning Methods

Other than machine learning methods, deep learning has drawn our attention as well. Artificial Neural Network (ANN)^s [13], Convolutional Neural Network (CNN)^s [1,3,5,11] and Recurrent Neural Network (RNN)^s [3,5,6,8] are the generally used deep learning methods to tackle price prediction problems. The major advantage of a neural network is that it can solve more complicated problems as the hidden layers in the neural network can extract more features from the data. [1] and [11] used CNN to predict stock price movement by using 1-D price data as input data. CNN is capable of capturing features from the data in

The form of both 1-D and 2-D, which can be used to capture the pattern in the stock price data.

Other than CNN, as stock price data is time-series data, RNN may be useful as well for time

Long Short-term
series data. Long Short Term Memory (LSTM) [3,5,6,8], an improved version of RNN, could *can also*

be a good choice to handle time-series data. However, the design of LSTM is more focused on historical data, which may not be very effective for predicting future events. Moreover, deep learning methods are quite sensitive to noise which exists a lot in stock data.

Therefore, hybrid models [3,5] were *being* applied in deep learning methods as well. These models are generally better than standalone models.

The existing research and products *always* apply one single model on the prediction of price trends. They focus on optimizing the models or making comparisons between models.

they usually do not use ensemble learning, i.e., they do
However, it does not consist of any fusion or integration of the results from different models.

Thus, in we are spreading
which is included in our project and it should be able to spread out the prediction error from
so as to
different models such that lowering the risk.

As mentioned above, algorithmic trading is the new generation of trading business. On top of

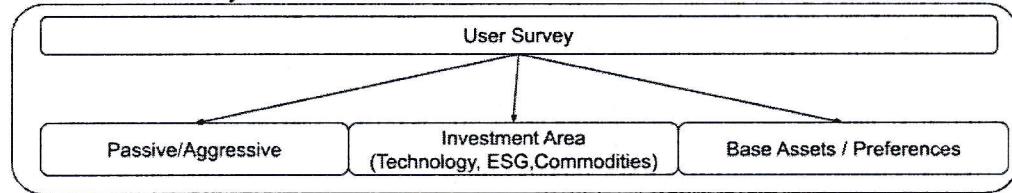
the current systems and algorithms implemented, we focus on developing the pipeline to
use
in application that
generate the optimal combination of multiple algorithms and study whether such procedures
will yield a higher return in the trading market.

2. Methodology

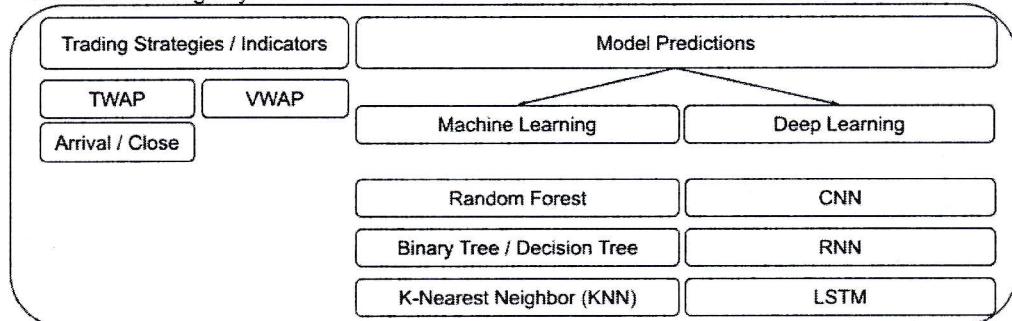
- Try to match the verb tenses to the current status of each part.

2.1 Design

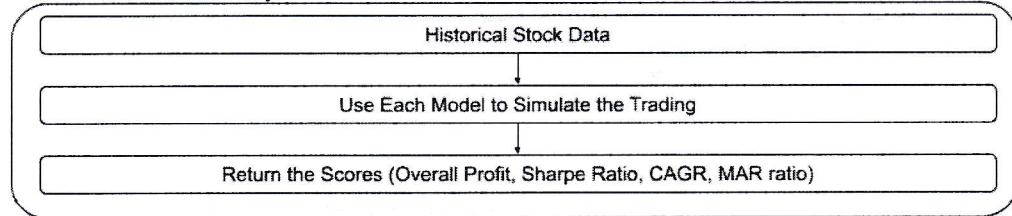
1. User Portfolio Layer



2. Model Training Layer



3. Model Evaluation Layer



4. Portfolio Management / Stock Allocation

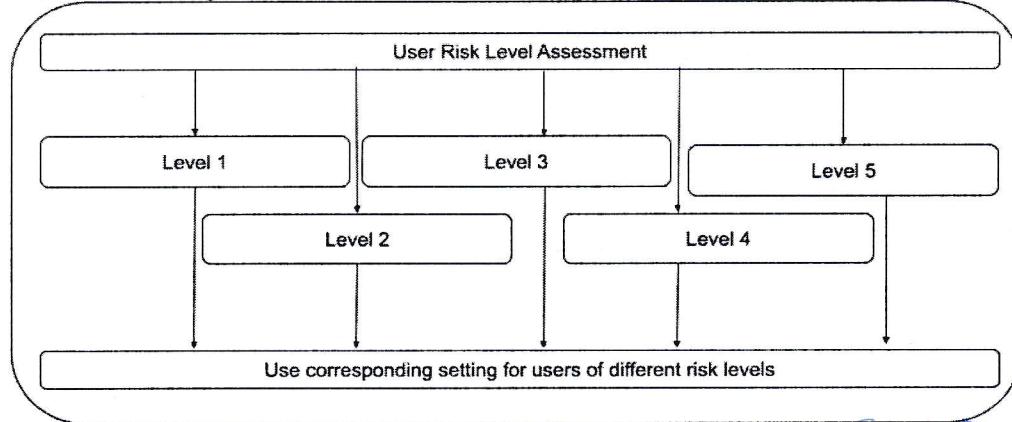


Figure 1. The initial design of the Customized portfolio pipeline "name"

Use a smaller
font size

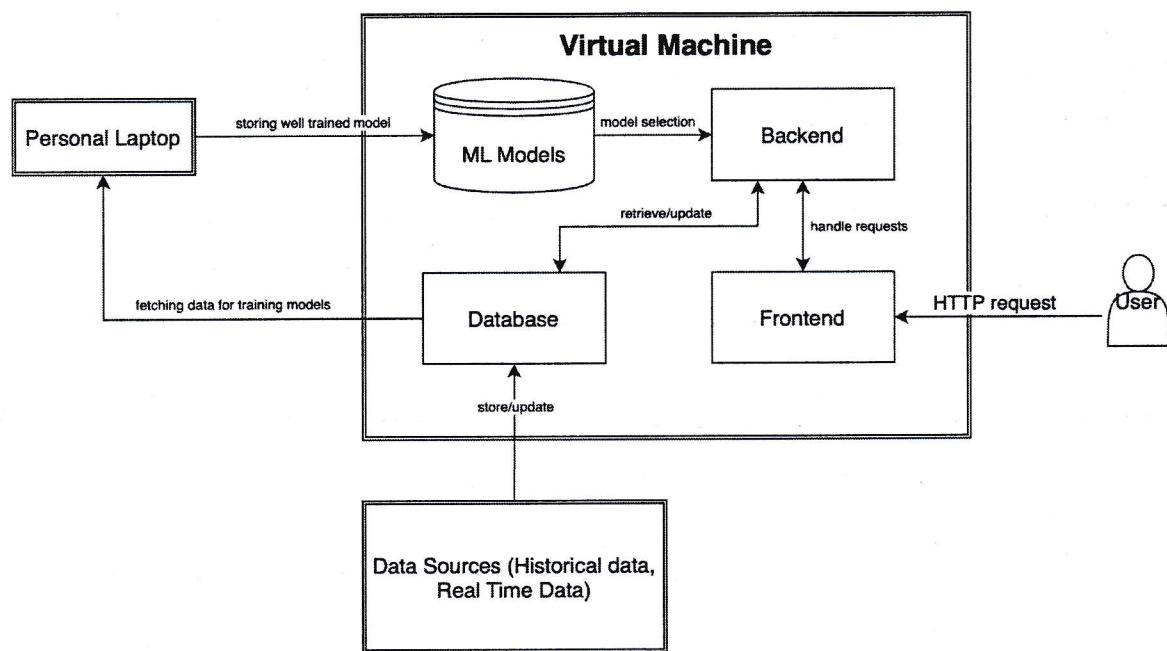


Figure 2. Initial Design of System Architecture for our platform

3 similar font

The pipeline our team designed goes through the following steps:

2.1.1. User preference survey

Users will first be given a series of questionnaires related to their preference in specific fields and style of investment. All the responses will be recorded in the database and will classify users on a scale of 1 to 5 (1 being extremely passive and 5 being extremely active/risky).



Figure 2. Example of possible question choices [17]

Example questions:

- I am looking for the long term / short term investment
- I prefer stocks that recently claimed IPOs / start-ups
- I wouldn't mind higher risk if the portfolio promises a higher return (high risk - high return)
- I would like to invest along with ETF indexes (safer)
- I would like to invest in technology-related funds
- I would like to invest on ESG related businesses

Around 20 questions will be asked for the user to categorize users.

you
can
put the
details
in the
appendix
→ one for the
survey
→ one for the
results

2.1.2 User classification & Asset deposit

After the user has completed all the questionnaires, the pipeline finalizes the following regarding the user :

- Which type of portfolio the user expects from the “name”
- Which category (Blockchain, traveling, Semiconductors, Artificial Intelligence, Cloud, Biotechnology, Social Media, Entertainment, Retail, Franchise, Real estate, Telecommunication, Energy & Resources, Commodity, Luxury goods, etc) user prefer investing on
- How much of a risk the user is willing to take (user risk level assessment)
- Whether the user is looking for long term investment or HFT (High-Frequency Trading)

If the user wishes to adjust the level on their own, they can re-take the survey (from section 2.1.1) to re-adjust their category.

- Seed money balance

After the pipeline returns the list of information above, the user can take them into account in their trading activities.

2.2 Implementation

- focus on how you implement what you designed

2.2.1 User survey - Input form

An input form will be included in the web application. The result will be sent back to the database and then decide the strategy/algorithm used in the backend based on the corresponding risk level the user has chosen.

2.2.2 Model training/testing/evaluation

We will use Jupyter Notebook or Google Colab for our major model training and testing tools. We will try out various models such as Random Forest (RF), Multiple Linear Regression (MLR), Long Short Term Memory (LSTM), and Convolutional Neural Network (CNN) with hyperparameters tuning.

Evaluation of the models will be compared to other research papers as we aim for better performance than other models. Evaluation will also be done on the entire platform so that we can check if our platform can outperform other existing platforms.

2.2.3 Data Storage

A database is needed for storing the historical data of one/more stocks. It is essential to the models' training and evaluation. MySQL database is the first option since our team is familiar with it and it is suitable for time series data like stocks' price data. For historical data, our target is to find free data with around 20 years of stock prices. For real-time data, we will try to extract data from different brokers' APIs, for example, Interactive Broker, First Trade, FUTU, and then store it in the database for later use. If we could not afford the charges of real-time data, we may use free data from the internet with a little delay of the data (i.e. 1-day delay). *[Provide citations for each data source you use.]*

Historical data will be stored in our database as a backup in case of any modification of the data source. Before the training, necessary data preprocessing such as normalization and removing outliers will be conducted for removing the effect on the scale of different features.

2.2.4 Graphic User Interface (GUI)

A web application will be built to present the portfolio of the user in a dashboard view. There are numerous templates available online and we can choose one and then modify it to suit our needs. There are also many functions available online so that we can simply integrate them into our application. HTML/CSS/Javascript or ReactJS are the possible options for developing the web application. Some examples are below:

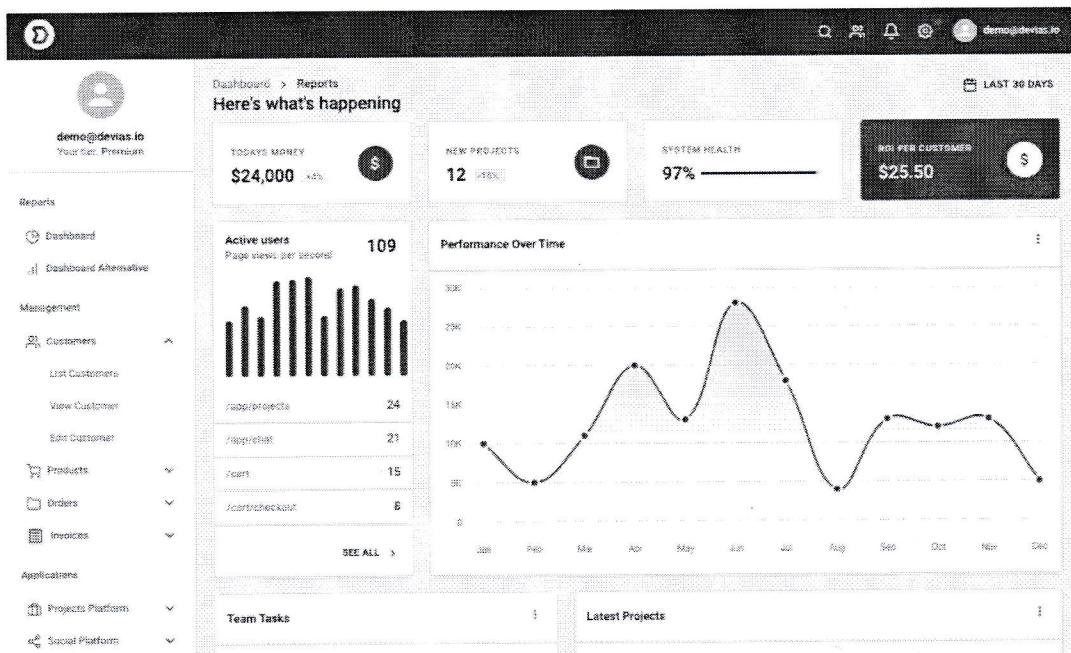


Figure 3. Dashboard Design Template - 1

source: <https://material-ui.com/store/collections/free-react-dashboard/>

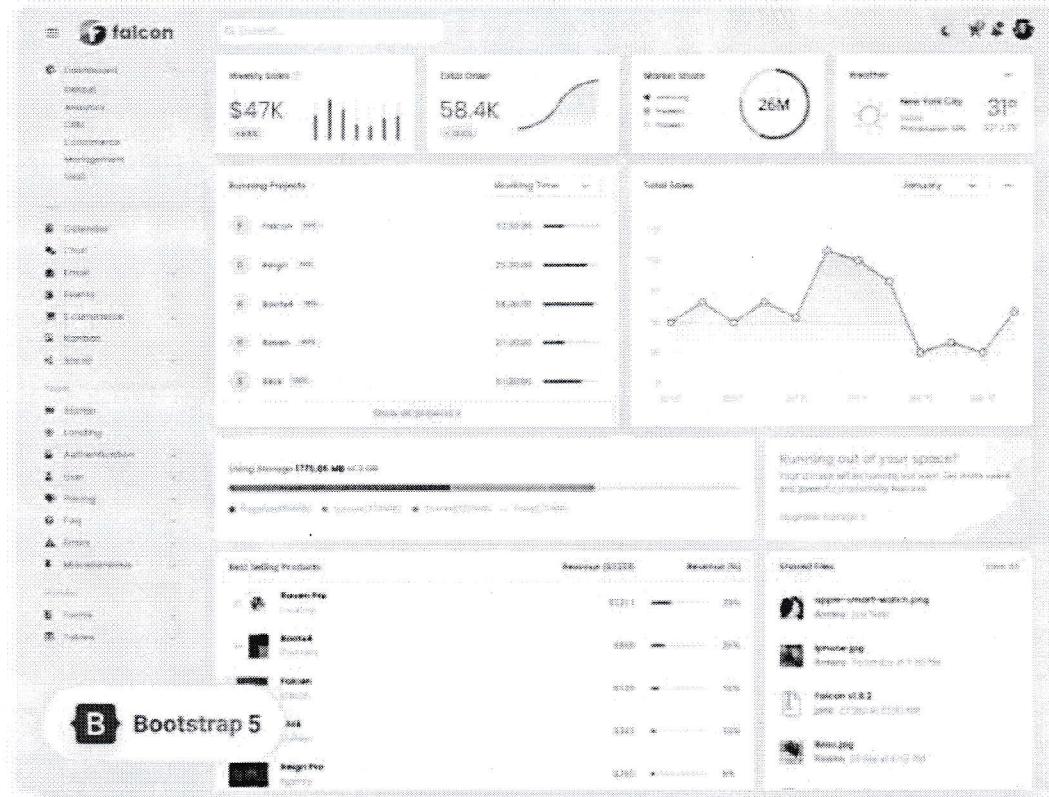


Figure 4. Dashboard Design Template - 2

source: <https://themes.getbootstrap.com/product/falcon-admin-dashboard-webapp-template/>

2.3 Testing (Backtest)

Testing will be done on both the Price Prediction Model and Our Entire Platform with 3-5 years of historical data.

To evaluate the performance of the model, we will use a simulator to simulate the trading process. After we train a model, historical and unseen testing data will be fed into the model for generating testing results (list of buying and selling), like in CSV format. Then, the results will be imported into a simulator and start simulating the trading process and calculating the corresponding profit and some performance indicators mentioned above such as CAGR, Sharpe Ratio, and Annual Income.

2.3.1 Testing on Price Prediction Models

For the historical data we have, we will first set a cut-off date as the date to separate the dataset. The data before the cut-off date would be used to train the model while the data later than the date will be used to test the model. The performance of the model would be assessed by the various Indicators such as Model Accuracy Score, Model Trend Score,

3. Project Planning

3.1 Distribution of work

Very good!

But try to squeeze it onto one A4 page,

Task	Peter	Anthony	Sun	Thomas
Project Designing				
1. Database Design	○	●	○	○
2. GUI Design	●	○	○	○
Model Training & Testing				
3. CNN	○	●	○	○
4. RNN	○	●	○	○
5. LSTM	○	○	●	○
6. Random Forest	○	○	●	○
7. KNN Algo	○	○	●	○
8. Decision Tree	○	○	○	●
9. SVM	○	○	○	●
Database Implementation				
10. Database set up on VM	○	○	○	●
11. Database Structure	○	○	●	○
API Data Extraction				
12. Apt Dataset Selection	○	○	●	○
13. Database Storage Automation	○	○	○	●
14. Data API & Pipeline Connectivity	○	●	○	○
GUI Implementation				
15. User portfolio	●	○	○	○
16. Pie chart distribution	●	○	○	○
17. Trend line analysis	●	○	○	○
18. Returned portfolio dashboard	●	○	○	○
Model Evaluation				
19. Backtesting - Model	○	●	●	○
20. Backtesting - User	○	●	●	●
21. Further Evaluation	●	●	●	●
Other				
22. Poster Design <i>Video Trailer</i>	●	●	●	●

3.2 Gantt Chart

*- Good, but try to fit the chart on one A4 page
 - Also update the chart to match the current status.*

Tasks	2021					2022				
	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	
Project Designing										
1. Database Design	█									
2. GUI Design	█									
Model Training & Testing										
3. Model Building - Different files for a Department different model		█	█	█	█	█				
4. Model Testing - CNN		█	█	█						
5. Model Testing - RNN		█	█							
6. Model Testing - LSTM				█	█	█				
7. Model Testing - Random Forest				█	█	█				
8. Model Testing - KNN Algo		█	█	█	█	█				
9. Model Testing - Decision Tree				█	█	█				
Database Implementation										
10. Database set up on VM			█	█	█	█				
11. Database Structure				█	█					
API Data Extraction										
12. Apt Dataset Selection		█	█	█						
13. Database Storage Automation				█	█	█	█			
14. Data API & Pipeline Connectivity			█	█	█					
GUI Implementation										
15. User portfolio					█					
16. Pie chart distribution						█				
17. Trend line analysis							█			
18. Returned portfolio dashboard							█			
Model Evaluation										
19. Backtesting - Model							█	█		
20. Backtesting - User							█	█		
21. Further Evaluation							█	█		
Other										

4. Required Hardware and Software

4.1 Hardware

- 4 Laptops

4.2 Software

- Jupyter / Google Colab
- Python
- Virtual Machine (AWS)

For testing
Programming language
For hosting the DB and server

- React JS?
- HTML / CSS / Javascript?
- Any others?
- Git

For building the front end

For software version management

5. Reference

- Very good, but the IEEE style is more popular
in the CSE Dept. → see the CT website*
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16 Personalities

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6. Appendix

6.1 Meeting Minutes *of the 1st Meeting*

1st Meeting Minutes

Date: 7 Aug 2021

Time: 11:00 - 11:57

Via: Discord

Participants:

KWOK, Ue Nam (20597580 unkwo)

HO, Yat Man Peter (20606082 ympho)

KONG, Kin Cheung (20595166 kckongaa)

MUN, Sun Bin (20455378 sbmun)

Meeting Discussion:

1. Contact the professor
2. Starting to prepare the proposal (Due on 17 Sept)
 - o Due on 17 Sept
 - o Suggested page number: 6
 - o The task for this week: Overview - Sun and Thomas
 - o The task for this week: Objective - Peter and Anthony
3. Discussing the direction
 - o More focusing on Machine Learning
4. Schedule meeting 3-4 weeks later for discussing different methodologies
5. Regular meeting (Sunday 10 am)
6. Focusing on the pipeline (X on the GUI or application platform/server)
 - o Data Extraction (Where to get stock data?)
 - o Data Preprocessing
 - o Model Design (Different algorithms and strategies)
 - o Model Training
 - o Evaluation (Evaluation Method? Simulate the trading once)

Main focus: devising the unique algorithm for the stock prediction

Task Distribution:

1.1 Overview - Sun, Thomas

1.2 Objective - Peter, Anthony

1.3 - Altogether next week

Research Distribution:

- Sun: Algorithm for trading (VWAP, TWAP...) + some previous Python/ML implementation of these algorithms
- Thomas: Sentiment analysis/NLP
- Peter: previous FYP possible competitor
- Anthony: CNN or DNN (LSTM) for stock price data

Next Meeting: 14 Aug 2021

Minutes of the
6.2 1 2nd Meeting Minutes

Date: 14 Aug 2021

Time: 10:30 - 11:30

Via: Discord

Participants:

KWOK, Use Nam (20597580 unkwok)
HO, Yat Man Peter (20606082 ympho)
KONG, Kin Cheung (20595166 kckongaa)
MUN, Sun Bin (20455378 sbmun)

Meeting Discussion:

1. Confirmation on using US Stock Market
2. Brainstorm on the final product
 - More focus on a trading model
 - Multiple Models for different combinations
 - Base on Users' risk level
 - Should we add Sentiment Analysis by NLP
 - Collaborative Filtering for User Classification (SVM, CF, etc...)
3. Visualization of fund results the Product and the Logic Flow
4. Email to Professor (Seek Advice and Share our Ideas)

Task Distribution:

1. FYP Report - Overview (Sun and Anthony)
2. FYP Report - Objective (Peter and Thomas)

Next Meeting: 1 Sept 2021 15:00-16:00