Developing Cryptocurrency Price Forecasting Model and Trading Strategies

: Focus on Predictability Driven Asset Allocation

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: Focus on Predictability Driven Asset Allocation

A dissertation
submitted to the Department of Investment Information Engineering and the Graduate School of Yonsei University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Hyun Sun Kim

December 2023

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December 2023

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ABSTRACT

Developing Cryptocurrency Price Forecasting Model and Trading Strategies: Focus on Predictability Driven Asset Allocation

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This study aims to enhance investment opportunities in cryptocurrencies by providing a rationale for investment decisions. Our goal is to improve the predictability of five prominent cryptocurrencies – Bitcoin, Ethereum, Ripple, Litecoin, and EOS – and evaluate the effectiveness of trading strategies based on the prediction model.

In Part 1 of the study, we aimed to propose the best-performing prediction model for each cryptocurrency by year. We examined three methodologies – ARIMA, LSTM, and Prophet – from traditional statistics and artificial intelligence across varying periods and time intervals. Among these approaches, Prophet generally demonstrated superior performance, while LSTM outperformed it only in the 2022 Ethereum and EOS predictions. In most cases, training on the previous 28 days' price history at a 15-minute interval yielded the highest performance.

In Part 2 of the study, we developed trading strategies based on the best-performing prediction model from Part 1. The simple idea is to assign more weight to more predictable assets. We used MAPE as a metric to assess predictability, determining asset allocation accordingly. We recommended purchasing the cryptocurrency when the forecasting model indicated an upward trend, with the investment amount based on its relative predictability. Our experimental results demonstrate that the proposed trading strategy yields annual returns of 19%, which is significantly higher than an equal portfolio employing a buy-and-hold strategy (-1.1%).

The cryptocurrency trading model introduced in this paper holds two significant points. Firstly, it facilitates the transition of cryptocurrencies from speculative assets to bona fide investment instruments. Secondly, it plays a pivotal role in advancing deep learning-based investment strategies by offering reasonable evidence for portfolio allocation. This process addresses the black box issue, a notable weakness in deep learning, providing greater transparency to the model.

Keywords: Cryptocurrencies, Time-series Analysis, Price forecasting, Deep Learning, Trading Strategy

CHAPTER 1.

Introduction

1.1 Motivation

Since the introduction of Bitcoin in 2009, the cryptocurrency landscape has continually seen the emergence of numerous alternatives that diverge from the original Bitcoin consensus mechanism. Despite Bitcoin's initial intention to serve as an alternative to traditional currency, cryptocurrencies have been actively traded as investment assets today (Taleb, 2021). The cryptocurrency market has undergone several cycles of rapid ascent and descent, currently representing slightly less than 1% of the global stock market size and reaching up to 2.5% at its peak.

While the current prospect of cryptocurrencies serving as a mainstream currency is low, their attractiveness as an investment option is heightened by significant price volatility. This introduces new opportunities from a portfolio perspective under the assumption of normal operation. However, analyzing cryptocurrencies poses challenges due to their inherent volatility and limited intrinsic value assessment (Kim, 2023). Consequently, many investors approach cryptocurrency speculatively, lacking sufficient logical grounds for investment decisions, resulting in market disruptions and substantial economic losses for individuals.

Therefore, this study begins by questioning whether it is possible to anticipate short-term trends in cryptocurrency and apply them directly to trading. We have applied traditional statistical methodologies used for time-series data analysis and AI-based methods, which have gained recent attention and technological advancements, to perform prediction tasks under various learning conditions. The study aims to select the best-performing model and subsequently utilize it to formulate a trading strategy.

This endeavor seeks to establish a logical foundation for cryptocurrency investments and also aims to assist novice cryptocurrency investors with limited prior knowledge or trading experience in developing investment guidelines.

1.2 Objectives

The goal of this study is to effectively incorporate cryptocurrencies as an investment asset. We aim to explore models capable of predicting cryptocurrency prices on a daily basis and validate the effectiveness of portfolio strategies derived from these forecasts.

In Part 1, our objective is to find superior models for cryptocurrency price prediction, which are nonlinear time-series data. We employ three representative methods from traditional statistics and artificial intelligence: ARIMA, LSTM, and the most recently introduced statistical-based AI software, Prophet. By applying diverse learning conditions to each method, we compare their predictive capabilities, aiming to identify the best-performing model for each cryptocurrency annually.

In Part 2, we apply the optimal prediction models identified in Part 1 to design trading strategies. We propose to use error values from Part 1 models to determine the weight assigned to each asset. The principle that more invest to more predictable asset works here. We execute buy orders based on upward signals provided by the models, proportionate to their relative predictability. Upon concluding the testing period, we demonstrate the effectiveness of the investment strategy utilizing prediction models through a comparison with a portfolio evenly composed and operated with a Buy-and-Hold strategy.

1.3 Organization of the Thesis

This paper is structured as follows. Chapter2 provides a literature review on cryptocurrency fundamentals, its market, statistical techniques, and Artificial Intelligence techniques for market understanding and prediction. Chapter3 proposes AutoRegressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM) and Prophet as the methodology to find best available cryptocurrency price prediction model. Chapter4 is about the empirical analysis starting with the overall flow of experiment. It shows the data used in the study, progress of the experiment applying ARIMA, LSTM and Prophet with varying learning conditions and the best-performing prediction model as a result. Chapter5 proposes a cryptocurrency trading model leveraging the findings in Chapter4. The profitability assessment is also made in this chapter by comparison with equal-weighted portfolio taking buy and hold strategy. Finally, Chapter 6 consists of the conclusion of this study.

Chapter 2.

Literature Review

2.1 Cryptocurrency

Researchers from different organizations have their own definitions of cryptocurrencies. Focusing on the core technology and inventor's intention, Bech and Garratt (2017) defined cryptocurrency as a type of digital currency which blockchain-based distributed ledger technology (DLT) system underlies. DLT enables nodes in a network to securely propose, validate and record state changes to a synchronized ledger enabling entities to conduct transactions without inevitably leaning on a central authority to preserve a single original copy of the ledger. That made cryptocurrency can be issued by anyone other than a central bank and exchanges are processed in a decentralized manner in which transactions occur directly between payer and payee without the need for trusted intermediary. Satoshi Nakamoto (2008) who created the world's first cryptocurrency, Bitcoin also stated that controls central bank or government put could trigger inflation and it cause the erosion of asset values. Bitcoin can be safe-haven by excluding the central authorities in the process.

Commodity money is valued by its inherent commodity and the value of fiat currency is determined by government's credit while cryptocurrency is guaranteed by underlying knowledge and technology (trust and proof). When the backbone does not obtain consent from users, cryptocurrency cannot function as a popular currency because it fails to satisfy the requirements for currency, means of payment or medium of exchange, store of value and unit of account. For these reasons, Bouri et al. (2020) concluded cryptocurrencies are more like very high-risk, speculative assets than a standard currency in general.

Since Bitcoin's first launch in 2009, thousands of altcoins have been created discovering the possibilities of decentralized digital currency. Most altcoins are trying to target any perceived shortcomings that Bitcoin has and come up with benefits in newer versions. Other than limited function of Bitcoin, Ethereum, the second-largest cryptocurrency by market capitalization, has broad range of applications including smart contracts and decentralized finance (DeFi). Ripple targets to replace the commission fee for various exchange transactions such as SWIFT, traditional interbank transfer fees. Binance coin tries to overcome the security risks associated with cryptocurrencies and the operational immaturity of new financial industry.

According to Coinmarketcap, there are 22,904 cryptocurrencies in existence as of October 2023, only around 8,878 cryptos are active while the rest are dead. They form 1.07 trillion-dollar market. Figure 1. shows historical data on global market capitalization and 24-hour trading volume. The total market value is calculated by aggregating the dollar market capitalization of all active cryptocurrencies including stablecoins and tokens. From the figure 1, we can observe how the market experiences exponential growth and widespread popularity in 2017 and a huge bubble burst in early 2018. In the pandemic period, total market value raised dramatically in 2020 and it lasted till early November 2021 excluding two months in between. In the year 2021, the market has been very volatile but consistently at high levels in history hitting the highest record $3 trillion. After that, it had shrunk, reached to $1 trillion size in October 2023. Figure 2 shows how much each of several dominant cryptocurrencies takes up the whole market. Bitcoin, Ethereum and

Ripple have accounted for the majority of the total market capitalization. Also, Top 10 altcoins by market capitalization are shown in Table 1.

Table 1. Top10 cryptocurrencies by Market Cap as of Oct 2023

NAME	Symbol	Price	Market Cap	Circulating Supply
Bitcoin	BTC	$28,357.23	$553,878,062,488	19,516,068 BTC
Ethereum	ETH	$1,589.24	$191,160,624,828	120,260,916 ETH
Binance Coin	BNB	$213.65	$32,412,221,222	151,705,758 BNB
Ripple	XRP	$0.4912	$26,258,361,815	53,441,027,384 XRP
Solana	SOL	$24.00	$10,003,667,354	416,384,521 SOL
Cardano	ADA	$0.2505	$8,825,953,110	35,218,635,342 ADA
Dogecoin	DOGE	$0.05984	$8,466,174,362	141,444,936,384 DOGE
Tron	TRX	$0.0886	$7,872,445,688	88,925,380,673 TRX
Toncoin	TON	$1.95	$6,702,261,554	3,431,892,088 TON
Polygon	MATIC	$0.53	$4,930,659,115	9,299,803,031 MATIC

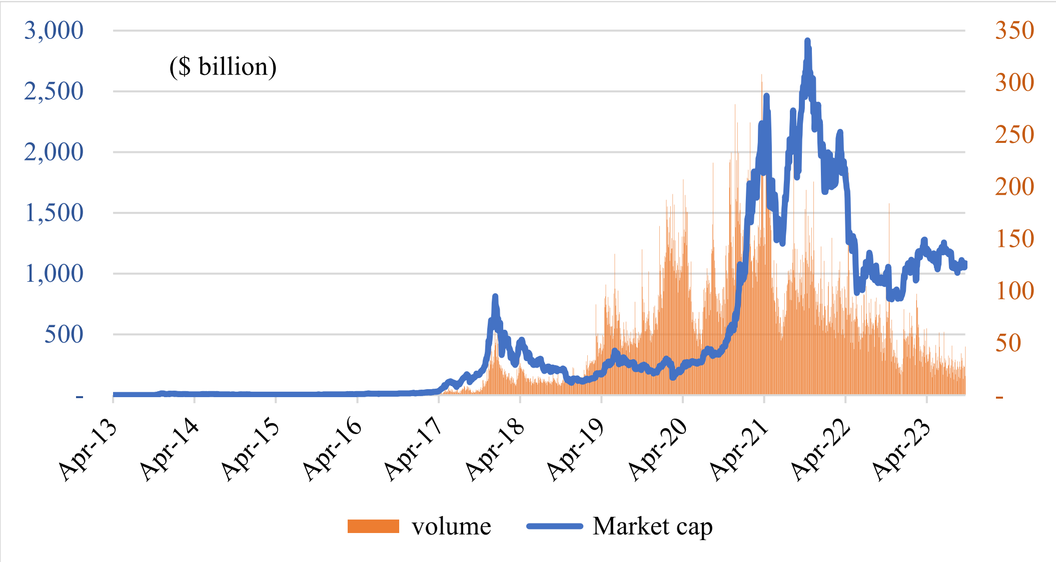

Figure 1. Total market capitalization and volume of cryptocurrency market, USD

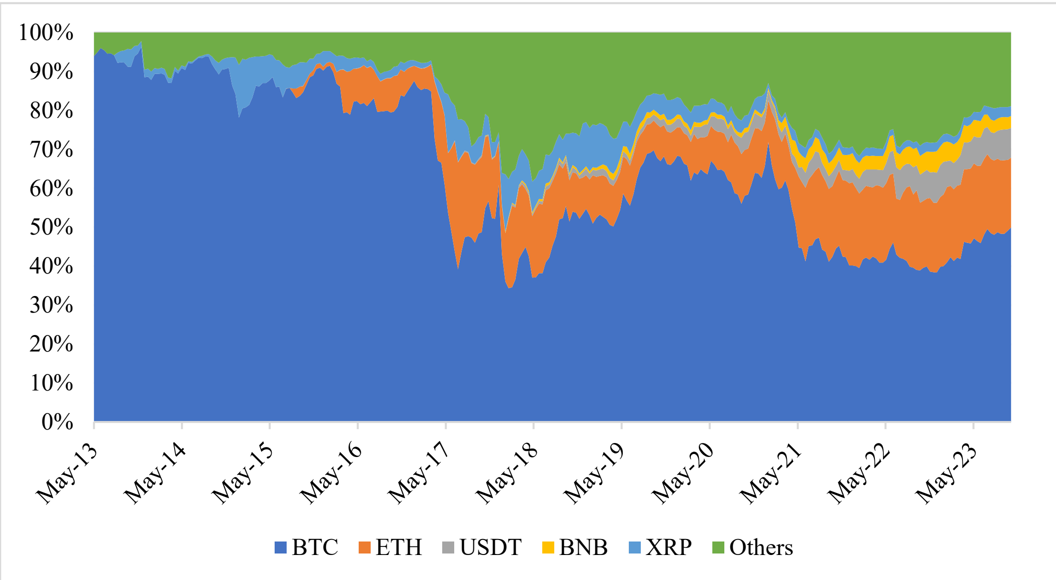

Figure 2. Market dominance of top 5 cryptocurrencies

2.2 Study on Cryptocurrency Market

With the advent of Bitcoin in 2009, cryptocurrency market was launched. But it was not much popular in early times. It began to get worldwide attention since the end of 2013, when Litecoin and Ripple showed significant instability in price, Bitcoin was beginning to see signs of price hike at the same time. Therefore, before the rapid expansion of the cryptocurrency market, main research topic was nature of cryptocurrency itself such as Bitcoin Fundamentals, Mining and Network Security, Blockchain Applications. Their primary focus is to determine whether Bitcoin is a currency or it has potential by investigating its technical character and market record.

Grinberg (2011) studied the economic aspects of bitcoin and pointed out that bitcoin has a competitive advantage in micropayments because it is divisible to eight decimal places. But he concluded that there will be limit in further adoption for broader use due to the emergence of a competing virtual currency and governmental. Wu and Pandey (2014) examined bitcoin's capacity as a currency and its effectiveness as an investment asset. The results suggest it can play a prominent part in boosting the efficiency of an investor's portfolio while it may be less useful as a currency. Carrick (2016) analyzed the volatility and value of Bitcoin relative to legal tender of emerging market and looked over ways in which Bitcoin can make up emerging market currencies. The results suggest that it has a potential to role as a complement to emerging market's lawful money but not a substitute.

The second research stream since 2014, the year cryptocurrency prices start to soar had been seen, is to identify factors impact on cryptocurrency price. Focusing on the similarity with stock trading, two basic approaches used in traditional financial investment asset studies, fundamental analysis and technical analysis have been applied to crypto price analysis. However, there is a significant difference between them. Cryptocurrencies are backed by nothing, neither hard assets nor cash flow of an underlying entity. That means it is hard to evaluate their fundamentals and price of most cryptocurrencies relies on market circumstance or supply and demand factor. Many studies have identified and categorized influential factors in cryptocurrency pricing as technology, supply and demand, economics and investors' attributes.

Leshno and Strack (2020) indicated Bitcoin's decentralized system and a unique combination of anonymous miners and profit-driven incentives have encouraged investors to participate freely in the Bitcoin market. Ciaian et al. (2016) demonstrated an increase in the number of Bitcoins available for transactions may result in Bitcoin price volatility and a massive speculative price bubble. Van Wijk (2013) investigated the influence of macroeconomic factors on bitcoin price and suggested that factors such as the stock market index, exchange rates and oil prices impacted its value. Polasik et al. (2015) observed that increased trading against the US dollar led the exponential growth of Bitcoin price. Dickinson et al. (2017) proved the exchange rate has a significant and negative relationship with the price of Bitcoin. Anamika et al (2021) indicated that fear in the equity market had a positive correlation with Bitcoin, Ethereum and Litecoin returns. Investors consider cryptocurrency as an alternative asset when experiencing bearish sentiment, in consquence of the increase in cryptocurrency prices. After experiencing surging price and extreme market volatility in 2017, there have been studies to focus on qualitative factors such as investor sentiment. Figa-Talamanca and Patacca (2020) tried to explain Wikipedia views, which represented online information queries, had a positive and statistically significant effect on the Bitcoin price. Panagiotidis et al. (2018) identified Google Search as the most important variable for explaining Bitcoin returns, and it was found to be a good predictor of cryptocurrency prices (Chuffart, 2022).

Having been through COVID-19, which began in early 2020, studies to investigate the impact of the pandemic on cryptocurrency price, market volatility and relationship between cryptocurrencies have been conducted. Katsiampa et al. (2022) examined high-frequency connectedness between Bitcoin and 32 most tradable cryptocurrencies during the period. They provide evidence of the positive contagion effect in the market.

Findings from above studies play a key role in next subject which tries to predict and model the price of cryptocurrencies in addition to analyze the volatility of the cryptocurrency market. The simple idea is to reflect the determinants into the model to represent price dynamics. However, the market is complex and dynamic that the prediction is considered as one of the most challenging forecasting tasks in the financial domain at present. Most creditable research cast it as a time-series prediction example since the base is to leverage historical and current price data to forecast future prices over a period or a specific point in the future. There are mainly two approaches to design the model. One is using traditional statistical and the other is using artificial intelligence techniques.

Statistical techniques use mathematical equations to encode information acquired from the data (Kaufman 2013). With the advancement of big data technology and artificial intelligence, lots of studies have applied machine learning models to classification and prediction problems. Since they have capacity to dynamically make selections and combinations among an enormous number of characteristics and to understand complicated, high-dimensional correlations between features and goals. The details of previous research on them are as follow in Chapter 2.3 and 2.4.

The current research interest on cryptocurrency market is trading. It means the behavior of buying and selling of cryptocurrencies with the purpose of profit making. Based on the definition, studies on the cryptocurrency trading are summed in four major categories. Cross-asset or cryptocurrency-only portfolio composition, trading strategies, bubbles and crash analysis and market behavior.

In the field of structuring portfolio, research point is to examine whether there are connectedness or contagion among assets and market factors. Ji et al. (2019) examined interdependence via return and volatility spillovers across Bitcoin and five largest altcoins. They found Litecoin and Bitcoin have the most significant effect on other cryptocurrencies. Hale et al. (2018) suggested that Bitcoin prices fluctuate swiftly after CME issues futures congruous with pricing dynamics. Specifically, they pointed out that the sharp upswing and subsequent decline in prices after the bring-out of futures is explicable with trading behavior in the cryptocurrency market. Bedi and Nashier (2020) tried to prove Bitcoin 's diversification capabilities for a global portfolio which is spread across six asset classes dealing in five major fiat currencies, Great Britain Pound, US Dollar, Chinese Yuan, Euro and Japanese Yen. They employed modified Conditional VAR (Value-at-Risk) and Standard Deviation as a risk measurement to optimize portfolio across three asset allocation strategies. The result of study also provided understandings on the sharp disparity in Bitcoin trading volumes across lawful fiat currencies from a portfolio theory perspective.

Caporale and Plastun (2018) suggested the method which can detect bubbles in market. Several parametric and non-parametric tests verified the fact that price patterns exist after overreactions which captured the price changes on next day in both of negative and positive directions are more significant than after normal days. The results also indicated there would not be available profit opportunities due to the overreaction captured in the cryptocurrency market which support that cannot be evidence of the Efficient Market Hypothesis.

Figure 3 shows major milestones in cryptocurrency market research.

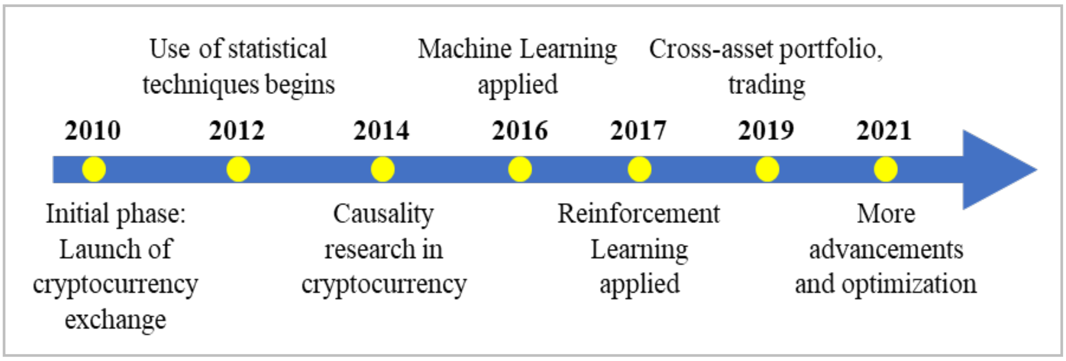

Figure 3. Major milestones in cryptocurrency market research

2.3 Study on Statistical Techniques for Cryptocurrency Market

The traditional approaches for cryptocurrency normally applied econometric and statistical models. According to Brooks (2019), econometric approaches apply combination of an economic theories and statistical to make estimation and forecast the values of economic variables. A linear statistical model-based approach tracks the linear relationship between explanatory variables and prices. If there exist multiple explanatory variables, multiple linear models can help to model the linear relationship between explanatory (independent) variables and response (dependent) variables possible. The commonly used statistical for time-series analysis is the ARIMA (Autoregressive Moving-Average model). Fang et al. (2020) summarized that while examining the fluctuations of cryptocurrency using econometrics, researchers normally utilize statistical models on time-series data. The most widely used ones among these models are the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model, multivariate linear regression, multivariate VAR (Vector Autoregressive) model, and extended vector autoregressive model.

Classical approaches such as Holt–Winters exponential smoothing by Chatfield and Yar (1988) were used previously to forecast time-series data. They depend on linear assumptions. In this approach, input data are separated into several trends and are used for forecasting features which have seasonal effects. However, the classical way has somewhat limitations on precise forecasting cryptocurrency price when there is no seasonality in cryptocurrency price movement.

Bakar et al. (2019) used a moving-average (MA) method, 2-day, 3-day, 4-day, and 7-day calculations, to predict the bitcoin price. The study concluded that the 2-day moving average method performs better with the lowest MAE (Mean Absolute Error) percentage for all observation periods.

Caporale and Zekokh (2019) used Markov-switching GARCH models to estimate the variation in four cryptocurrencies - Bitcoin, Ethereum, Litecoin and Ripple. The study concluded that the standard GARCH model may lead wrong predictions which can cause ineffective risk management.

Badenhorst (2018) studied whether the volumes of spot and derivative market cause volatility in bitcoin price. He used the ARCH (1, 1) and Granger-causality method for analysis. The result suggested that there exists uncertain relationship between the derivative market and cryptocurrency volatility, whereas price volatility is affected in positive direction significantly by the spot trading volumes.

Ogbonna et al. (2018) applied the fractional cointegration method in VAR to identify the persistence and dependence of bitcoin on other thirteen top-ranked altcoins before and after the cryptocurrency markets crash over 2017 to 2018. The results showed that after the crash, there probably exists higher persistence of shocks since cryptocurrency traders have speculation in the minds. They also found non-mean reversions tendency which implies possibilities of further price falls in cryptocurrency prices.

Table 2 summarizes the statistical techniques for cryptocurrency market studies.

Financial data, multiple internal and external factors and sentiment analysis were used in the research and the most common cryptocurrency studied was Bitcoin.

Table 2. Summary of statistical techniques for cryptocurrency market research.

Researchers	Methodology	Data	Target variables	Performance metric
Abu Bakar et al., (2019)	MA	daily data of Bitcoin	Price prediction	MAE
Caporale and Zekokh (2019)	Markov-switching GARCH	daily data of BTC, ETH, LTC, XRP	Modeling volatility, prediction of VaR and ES	P-values
Badenhorst (2018)	Granger-causality And ARCH	daily data of Bitcoin	Volatility prediction, return	SD, skewness, min and max
Ogbonna et al. (2018)	Fractional cointegration technique in VAR set-up	daily data of top-ranked 13 cryptocurrencies	Volatility trends	Dependency of the paired variables
Bartolucci et al., (2020)	Granger-causality	Sentiment and BTC, ETH	Price prediction	Mean, SD, Min–Max
Vieira (2017)	Regression analysis	daily data of Bitcoin	Asymmetrical impacts on price volatility	test-stat, P-value
Sovbetov (2018)	ADF unit-root test and bound testing approach	weekly data of BTC, ETH, DASH, LTC, XMR	Market beta, trading volume, and volatility	Crypto50 index price
Roy et al.,	ARIMA, AR,	daily data of	Price	Accuracy

(2018)	MA	Bitcoin	prediction	
Abbatemarco et al., (2018)	Vector error Correction	daily data of Bitcoin	Price prediction	Cost and revenues databases
Bhambhwani et al., (2019)	Dynamic OLS (ordinary least squares)	weekly average of BTC, ETH, LTC, DASH, XMR	Price prediction	Least squares method
Anupriya and Garg (2018)	ARIMA	daily OHLC of Bitcoin	Seasonality and trend	Accuracy
Bystrom and Krygier (2018)	Correlations, regressions, VAR, impulse response	daily, weekly, monthly data of Bitcoin	Prediction of volatility	RMSE, PSE, QL loss function and the R^2LOG loss function
Ardia et al., (2019)	MSGARCH	daily Bitcoin mid prices	Volatility dynamics of bitcoin's log returns	Mean, median, SD, skewness, kurtosis, VaR forecasting
Troster et al., (2019)	GARCH and GAS	daily data of Bitcoin	Bitcoin returns and risk	RMSE
Alahmari (2019)	ARIMA	daily, weekly, monthly data of BTC, XRP, ETH	Price prediction	MAE, MSE, RMSE
Kjærland et al., (2018)	AR distributed Lag, GARCH	Sentiment-based data, BTC	Determinants of BTC price dynamics	Variance inflation factors

2.4 Study on Artificial Intelligence Techniques for Cryptocurrency Market

According to Domingos (2012), machine learning and deep learning mainly emphasize their competitive characteristics as automatic learning ability and adaptation from the provided example data without human intervention. The fact that cryptocurrency is quite volatile and hard to understand its moving pattern motivated researchers to apply artificial intelligence methods to cryptocurrency concerns. El-Bannany et al. (2020) said that considering the similarity with the stock, adopting AI methods used to traditional asset price prediction to cryptocurrency market can help raising the accuracy rate. Thus, in recent years, AI techniques are the most spotlighted approaches in cryptocurrency price forecasting.

Most popular method for analyzing nonlinear and time series data such as cryptocurrency price is recurrent neural networks (RNNs) which will be explained minutely in chapter 3.1. As it processes sequences of inputs and identify patterns and relationships in the data over time, prediction becomes possible based on the work. Other AI techniques that can be applied for nonlinear and time series data include Prophet, support vector machine, decision trees, random forests, and gradient boosting, etc. These techniques can be used to find correlation or causality between factors and asset pairs and build models predicting future trends. They are also useful in finance, healthcare, and weather forecasting.

Using AI as a main tool, there have been a lot of studies to target explaining the market in more detail and improving prediction performance by combining various variables into a model as follows.

Datsenko et al. (2019) proposed a short-term forecasting model for price of Bitcoin, Ripple and Ethereum using binary autoregression tree which combines classification and ARIMA. Simulation results showed that the algorithm surpasses other traditional approaches.

Li et al., (2019) analyzed Twitter signals to forecast price volatility applying ZClassic. An hourly basis Tweets were collected for three and half weeks and each tweet was classified as positive, neutral or negative. Tweets were classified to create a weighted or unweighted index as a next step. The model was trained by an extreme Gradient Boosting regression tree model and compared with historic price movements. Mohanty et al. (2018) also served the Twitter data for bitcoin price prediction using LSTM (Long Short-Term Memory). Twitter data was used to estimate public mood. In this method, some conspicuous features from the blockchain were selected as major impact factors on Bitcoin's demand and supply. After that, they are used to train a model which enhanced the predictive performance. It showed high accuracy and good precision.

Andreotti et al. (2019) used hidden Markov models to explain historical change of cryptocurrencies and LSTM to predict future movements. A genetic algorithm was applied to additional parameter optimization of the hybrid technique. The simulation results indicated the lowest MAE, MSE and RMSE compared with ARIMA and conventional LSTM, traditional approaches of time-series prediction, proving the effectiveness of the proposed model. Internal details of bitcoin transactions were not accounted for in this model. They continuously work on finding internal details of bitcoin transactions reflecting additional features.

Kwon et al. (2019) proposed an LSTM model to classify cryptocurrency price time-series. They encoded past price data into a three-dimensional price tensor which represented the past movement of cryptocurrencies and applied a grid search- based k-cross validation to find out the best fitted parameters in the LSTM model. LSTM outperformed GB (Gradient Boosting) and other machine learning models in comparison results.

Chen et al. (2020) make comparison between two statistical techniques, LDA (Linear Discriminant Analysis) and logistic regression, and complicated machine learning approaches, including QDA (Quadratic Discriminant Analysis), LSTM, RF, XGBoost and SVM, on forecasting daily bitcoin price by high-dimensional features. Measured by average prediction accuracy, machine learning models showed better performance than statistical models of 62.2% over 53.05%. Among them, LSTM showed best performance generating an accuracy of 67.2%. Table 3 summarizes the AI techniques for cryptocurrency market studies.

Table 3 summarizes the AI techniques for cryptocurrency market studies.

Table 3. Summary of AI techniques for cryptocurrency market research.

Researchers	Methodology	Data	Target variables	Performance metric
Datsenko et al. (2019)	Binary autoregressive tree	Daily log return data of BTC, XRP, ETH	Short-term forecasting of prices	RMSE
Chen et al. (2020)	XGBoost, quadratic discriminant analysis, RF, LSTM, SVM	Daily, 5 min interval BTC price	5 min interval and daily price	Accuracy, precision, recall, F1 score
Mohanty et al. (2018)	Time-series analysis using bidirectional LSTM	Market and social sentiment	future price fluctuation prediction	-
Andreotti et al. (2019)	Hybrid model of hidden Markov and optimized LSTM	BTC market data: orders and trades, technical indicators	Price prediction	Mean, SD
Kwon et al. (2019)	LSTM, GB	10 min data of BTC, ETH, XRP, KRW	Classification	F1-score, recall, precision
Chen et al. (2020)	XGBoost, quadratic discriminant analysis, RF, LSTM, SVM	Daily, 5 min interval BTC price	5 min interval and daily price	Accuracy, precision, recall, F1 score
Li et al., (2019)	XGBoost	Sentiment-based on Twitter, trading volume	Predicting	Correlation coefficients, Adjusted SD

Madan et al., (2015)	Binomial logistic regression, SVM, RF, binomial GLM	Daily, 10 min, 10 s price of BTC	10 min interval price change	Sensitivity, specificity, precision, accuracy
Hitam et al., (2019)	Optimized SVM–PSO	Daily BTC, LTC, ETH	OHLC	Accuracy
McNally et al., (2018)	LSTM, RNN	Daily BTC	Closing price	RMSE, sensitivity

Chapter 3.

Methodology Review

3.1 AutoRegressive Integrated Moving Average (ARIMA)

Yule (1927) introduced the concept of the autoregressive (AR) model, while Walker (1931) put forth the idea of the moving average (MA) model. The AR model involves constructing a linear combination of several past observations of a random variable. It essentially represents a linear regression model for predicting the current value, x_t, using the previous values, from x_1 to x_{t-1}. When we refer to an AR (P) model, we mean a model of autoregressive order P, which specifies the number of past observations considered in the model. The formula for the AR model is defined as follows:

$$\begin{cases} x_t = \emptyset_0 + \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + \varepsilon_t \\ \emptyset_p \neq 0 \\ E(\varepsilon_t) = 0,\ Var(\varepsilon_t) = \sigma_z^2,\ E(\varepsilon_t \varepsilon_s) = 0,\ s \neq t \\ E(x_s \varepsilon_t) = 0,\ \forall_s < t \end{cases}$$

The Moving Average (MA) model represents a linear combination of past prediction errors, or random disturbances, spanning various time intervals, which collectively describe the current predicted value. It articulates the sequence by attributing different weights to random components from the same period and previous periods. Importantly, the MA model retains its stability across all conditions. When we refer to an MA (q) model, we are indicating a moving average model of order q, signifying the number of past time intervals considered in the model. The definition of the MA model is as follows:

$$\begin{cases} x_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \\ \theta_q \neq 0 \\ E(\varepsilon_t) = 0,\ Var(\varepsilon_t) = \sigma_\varepsilon^2,\ E(\varepsilon_t \varepsilon_s) = 0,\ s \neq t \end{cases}$$

AutoRegressive Moving Average Models (ARMA) represent a fusion of both AutoRegressive (AR) and Moving Average (MA) models. In essence, an ARMA model comprises a composite of multiple AR processes and MA processes. Notably, when the value of q is set to 0, an ARMA (p, q) model simplifies into an AR (p) model. Conversely, when the value of p is set to 0, the ARMA (p, q) model simplifies into an MA (q) model.

The ARIMA model, famously known as the Box-Jenkins model, was introduced by Box and Jenkins (1970). This model is typically denoted as ARIMA (p, d, q). The ARIMA framework is a versatile tool that can effectively model both stationary and non-stationary time series data. Non-stationary time series, characterized by unstable mean and variance due to factors like volatility and periodicity, require a transformation. To address this, the differencing method is often applied initially to convert non-stationary time series into a stationary form. Subsequently, the ARIMA model is established using the resulting stationary time series data. The formula defining the ARIMA model is as follows:

$$\begin{cases} \Phi(B)\nabla^d x_t = \Theta(B)\varepsilon_t \\ E(\varepsilon_t) = 0,\ Var(\varepsilon_t) = \sigma_z^2,\ E(\varepsilon_t\varepsilon_s) = 0,\ s \neq t \\ Ex_s\varepsilon_t = 0,\ \forall s < t \end{cases}$$

The value of a time series at a given moment, denoted as time 't,' can be expressed as a multiple linear combination of past data from the preceding 'p' periods (x_{t-1}, x_{t-2}, x_{t-p}) and the prediction errors from the prior 'q' periods (ε_{t-1}, ε_{t-2}, and so forth, up to ε_{t-p}). It is generally assumed that the error term ε_t consists of independent and identically distributed variables drawn from a normal distribution with a mean of zero.

3.2 Long Short-Term Memory (LSTM)

The LSTM model, as introduced by Hochreiter and Schmidhuber in 1997, is a robust recurrent neural system specifically engineered to tackle the challenges of gradient instability (vanishing or exploding) that commonly manifest during the learning of long-term dependencies. These difficulties persist even when the time intervals between events are notably extensive, a point which the authors addressed in their work. In essence, this challenge can be mitigated by employing a concept known as a constant error carousel (CEC). The CEC serves as a mechanism for preserving the error signal within each cell unit. It's worth noting that these cells themselves function as recurrent networks, characterized by a compelling architectural design. This design extends the CEC with additional elements, namely the input gate and output gate, which collectively form what is referred to as the memory cell. Furthermore, the presence of self-recurrent connections underscores the existence of feedback mechanisms with a one-time step delay.

A standard LSTM unit consists of several key components: a cell, an input gate, an output gate, and, introduced later, a forget gate. Initially absent from the LSTM network, the forget gate was proposed by Gers and colleagues (2000). Its purpose is to enable the network to reset its state, enhancing its adaptability. The cell's unique ability lies in its capacity to retain information over variable time spans, while the three gates effectively control the flow of information associated with the cell.

In short, the LSTM structure comprises a series of interconnected sub-networks, often referred to as memory blocks. The core concept underpinning these memory blocks is the preservation of their internal state across time, along with the regulation of information flow through non-linear gating components. The provided Figure 4 illustrates the layout of a standard LSTM block, encompassing the gating mechanisms, the input signal denoted as $x^{(t)}$, the output signal designated as $y^{(t)}$, the activation functions, and the incorporation of peephole connections (Gers and Schmidhuber, 2000). Notably, the block's output feeds back into its input, creating a recurrent loop, and all gating components are integral to this process.

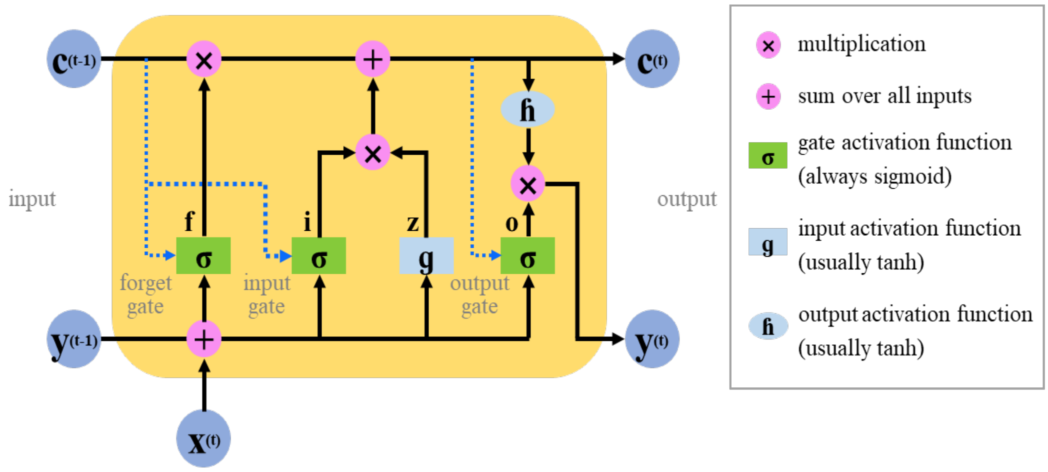

Figure 4. LSTM Structure

To elucidate the inner workings of the LSTM model, consider a network comprising N processing blocks and M inputs. The forward pass within this recurrent neural system is delineated as follows.

In the block input step, the focus lies on refreshing the block's input element, achieved by merging the current input $x^{(t)}$ with the prior iteration's output from the LSTM unit, denoted as $y^{(t-1)}$. This process can be carried out as illustrated below:

$$z^{(t)} = g(W_z x^{(t)} + R_z y^{(t-1)} + b_z)$$

Where W_z and R_z represent the weights connected with $x^{(t)}$ and $y^{(t-1)}$, respectively, whereas b_z corresponds to the bias weight vector.

In input gate, it undergoes an update process, which involves the fusion of the present input x(t), the prior iteration's output from the LSTM unit, $y^{(t-1)}$, and the cell value $c^{(t-1)}$. The procedure is depicted by the following equation:

$$i^{(t)} = \sigma(W_i x^{(t)} + R_i y^{(t-1)} + p_i \times c^{(t-1)} + b_i)$$

where × signifies the element-wise multiplication of two vectors, W_i, R_i, and p_i being the weights related to $x^{(t)}$, $y^{(t-1)}$, and $c^{(t-1)}$, respectively. Meanwhile, b_i signifies the bias vector connected with this element.

In preceding stages, the LSTM layer plays a crucial role in deciding what information is to be preserved within the network's cell states, $c^{(t)}$. This encompasses the determination of the candidate values, $z^{(t)}$, which might be incorporated into the cell states, along with the activation values, $i^{(t)}$, governing the input gates.

In forget gate, the LSTM unit assesses which information should be excluded from its prior cell states, $c^{(t-1)}$. Hence, the calculation of the activation values, $f^{(t)}$, pertaining to the forget gates at time step t, takes into account the existing input, $x^{(t)}$, the outputs, $y^{(t-1)}$, and the state $c^{(t-1)}$ of the memory cells from the previous time step (t−1). Additionally, it considers the peephole connections and the bias terms, b_f, associated with the forget gates. This operation can be executed as below:

$$f^{(t)} = \sigma(W_f x^{(t)} + R_f y^{(t-1)} + p_f \times c^{(t-1)} + b_f)$$

where W_f, R_f, and p_f represent the weights connected to $x^{(t)}$, $y^{(t-1)}$, and $c^{(t-1)}$, respectively. In addition, b_f signifies the bias weight vector associated with this component.

In cell stage, the cell value is calculated by integrating the block input $z^{(t)}$, the input gate value $i^{(t)}$, and the forget gate value $f^{(t)}$, all in conjunction with the previous cell value. This process is illustrated as follows:

$$c^{(t)} = z^{(t)} \times i^{(t)} + c^{(t-1)} \times f^{(t)})$$

In output gate, itself is determined by merging the present input $x^{(t)}$, the previous output of the LSTM unit $y^{(t-1)}$, and the cell value $c^{(t-1)}$ from the prior iteration. This process is represented as follows:

$$o^{(t)} = \sigma(W_o x^{(t)} + R_o y^{(t-1)} + p_o \times c^{(t)} + b_o)$$

where W_o, R_o, and p_o represent the weights connected to $x^{(t)}$, $y^{(t-1)}$, and $c^{(t-1)}$, respectively. Additionally, b_o signifies the bias weight vector associated with this component.

Finally, the block output is determined by blending the present cell value, $c^{(t)}$, with the current output gate value, in accordance with the following expression:

$$y^{(t)} = g\left(c^{(t)}\right) \times o^{(t)}$$

In the previously described procedures, σ, g, and h represent element-wise non-linear activation functions. The gate activation function is typically represented by the logistic sigmoid $\sigma(x) = \frac{1}{1+e^{1-x}}$, while for block input and output activation, the hyperbolic tangent function g(x) = h(x) = tanh(x) is frequently applied.

It is worth noting that the effectiveness of this architecture served as an inspiration for the authors in the work of Kumar Srivastava et al. (2015). They drew upon the gating mechanism and incorporated it into what they referred to as "highway networks." These highway networks were designed to facilitate a smooth and uninterrupted flow of information across numerous layers. This can be viewed as an additional demonstration of the practicality and effectiveness of gating mechanisms.

While the standard LSTM model already demonstrates excellent performance, numerous studies have explored avenues for enhancing its capabilities. For instance, Su and Kuo (2019) introduced the Extended LSTM model, which further improves prediction accuracy in various application domains by enhancing memory capacity. This underscores that even a state-of-the-art architecture like LSTM can still benefit from theoretical advancements. The pursuit of model improvements has been ongoing, as observed in the work of Bayer et al. (2009). These authors sought architectural alternatives to LSTM to optimize sequence learning capabilities. They succeeded in evolving memory cell structures capable of learning context-sensitive formal languages through gradient descent, achieving performance levels in many ways comparable to LSTM. In a different vein, the study by Bellec et al. (2018) delved into recurrent networks of spiking neurons, leading to the development of Long Short-Term Memory Spiking Neural Networks (LSNN) that include adapting neurons. In comparative tests where the size of LSNN was similar to that of LSTM, it was revealed that the performance of LSNN is very much in line with that of LSTM. These examples emphasize the remarkable accuracy and enduring effectiveness of the LSTM architecture.

3.3 Prophet

The Prophet is an open-source solution designed for handling seasonal time series data with strength and precision. Developed by the Core Data Science team at Facebook and introduced by Taylor and Letham in 2017, this model is renowned for its resilience in dealing with missing data, changes in trends, and outliers, as highlighted in the work by Rodriguez and colleagues in 2018. It relies on time series decomposition to forecast and model the data. The components of the model are detailed as follows.

$$y(t) = g(t) + s(t) + h(t) + \varepsilon$$

where $g(t)$ is a trend item, $s(t)$ is a term related to seasonality, $h(t)$ is a holiday component, and ε is an error meaning stochastic volatility term.

The trend element, g(t) encapsulates the fundamental trajectory of the time series, indicating whether it exhibits a gradual rise or fall across time. To represent this aspect, a piecewise linear regression model is employed, offering adaptability in how the trend aligns with the data. In this model, it is presumed that the trend can be expressed as a series of linear segments. Each segment's slope is determined by the changepoints within the data, which denote the specific moments in the time series where the trend's direction undergoes a shift. It follows improved logistic growth function to fit the non-periodic fluctuations in the time series as below.

$$g(t) = \frac{C(t)}{1 + \exp\left(-(k + a(t)^T\delta)\right)(t - (m + a(t)^T)\gamma)}$$

$$a(t) = \begin{cases} 1, & t > s_j \\ 0, & otherwise \end{cases}$$

C stands for the model's capacity, which is the maximum level of growth saturation. The function involves time 't,' denoted as a function of "k +a(t)^T δ", symbolizing the model's growth rate as time progresses. Likewise, (m + a(t)^T) γ represents an adjustment or offset. The term s_j marks a specific discontinuity point at which the growth rate shifts and δ quantifies the magnitude of this alteration in the growth rate at the transition point.

The seasonality element, s(t) encapsulates recurring patterns within the data, such as those occurring on a weekly or monthly basis. This element is represented using the Fourier series, enabling versatile modeling of various types of seasonal patterns.

$$s(t) = \sum_{n=1}^{N} (a_n \sin(\frac{2\pi nt}{p}) + b_n \cos(\frac{2\pi nt}{p}))$$

Where, 'p' signifies a constant time interval, while 'N' denotes the count of intervals to be incorporated into the model. 'a_n' and 'b_n' are the parameters that require estimation.

For the holiday component, h(t), the impact of various holidays within a year on the time series' trend alteration is treated as an individual model. For each of these models, a distinct dummy variable is established.

$$h(t) = Z(t)k = \sum_{i=1}^{L} k_i \times 1_{\{t \in D_i\}}$$

where k_i stands for the holiday effect on the forecast value and D_i stands for a dummy variable. The model operates by receiving a list of dates, which can include predefined dates for US holidays or user-defined dates. For each date within the list, when it aligns with the forecast, the model adjusts to the forecast by either adding or subtracting values from both the growth and seasonality terms. These adjustments are determined based on historical data regarding the specific holiday dates identified.

Prophet employs Bayesian inference to gauge the posterior distribution of model parameters. This process relies on a Markov Chain Monte Carlo (MCMC) algorithm, which extracts samples from the posterior distribution of these parameters. The algorithm assesses the posterior distribution by employing the likelihood function provided below:

$$p(y|\theta) = \prod_{t=1}^{T} N(y(t)|g(t), \sigma)$$

where y(t) represents the recorded value of the time series at time t, while g(t) stands for the forecasted value of the time series at the same time point. The noise parameter is denoted by σ, and θ represents the collection of model parameters, encompassing both trend and seasonality components. The algorithm employs this likelihood function to calculate the posterior distribution of the model parameters by applying Bayes' theorem:

$$p(\theta|y) = p(y|\theta) \times \frac{p(\theta)}{p(y)}$$

In this equation, p(θ|y) signifies the posterior distribution of the model parameters, p(y|θ) denotes the likelihood function, p(θ) represents the prior distribution of the model parameters, and p(y) stands for the marginal likelihood.

Moreover, the model provides the flexibility to incorporate supplementary regressors. Regressors are external factors that could potentially impact the time series, such as holidays, meteorological patterns, or marketing initiatives. The incorporation of these regressors into the model has the potential to enhance forecast accuracy. Incorporating regressors into the model entails defining both the regressor matrix and the coefficients for these regressors. The regressor matrix takes the form of a T x N, where T indicates the count of time points, and N represents the number of regressors. Each column in that signifies a distinct regressor variable. The coefficients for the regressors are determined through a linear regression model, which establishes a relationship between the time series and the regressor matrix. The final model can be expressed as follows:

$$y(t) = g(t) + s(t) + \sum_{j=1}^{N} X(j,t) \times \beta(j) + \varepsilon$$

X(j,t) refers to the j^{th} regressor variable at time t, β(j) signifies the coefficient associated with the j^{th} regressor variable, and ε represents the error term.

Prophet offers several key benefits. First, it provides adaptability in modifying the periodicity and allows for diverse trend assumptions within time series. Secondly, it eliminates the need to manually input missing data as the model automatically manages such gaps. It delivers timely predictions and allows for parameter adjustments to enhance model performance in varying scenarios.

PART I.

Developing Cryptocurrency Price Forecasting Model

Chapter 4.

Empirical Study (Part I)

4.1 Proposed Model

In this study, we aim to demonstrate the short-term predictability of cryptocurrencies and the potential for improved profitability in trading by utilizing the proposed model.

In the forecasting phase, we initially selected five major cryptocurrencies: Bitcoin, Ethereum, Ripple, Litecoin and EOS. A fundamental requirement for any investment asset is its integrity, free from any form of fraud. Without this essential trust, efforts to understand, analyze, or predict such assets become futile. Therefore, we established two conservative selection guidelines based on past encounters with deception, such as the Terra collapse and FTX scam. The first requirement is that cryptocurrencies should have a trading history of at least five years on crypto exchanges. Additionally, we prioritize cryptocurrencies with consistently larger market capitalization or a sustained presence in the market. While these criteria are neither a firm guarantee nor a necessary and sufficient condition of their impeccability, they serve as a useful supplement to filter out potential fraud. Following these guidelines means evaluating the capability of these cryptocurrencies to withstand threats, contributing to the market's trust in them.

We collect one-minute interval price history of the subjects. Based on this data, we attempt to vary the learning conditions through different time intervals and learning periods. More details of empirical data will be provided in the following chapter 4.2.

Focusing on the non-linear and time series nature of cryptocurrency price history, we propose to employ three methodologies: the autoregressive integrated moving average

(ARIMA), a classic statistical approach for handling time-series data; long short-term memory (LSTM), a deep learning method suitable for sequential data; and Prophet, a novel time series analysis method developed by Facebook (Meta). The parameters used will be explained in the following chapter 4.3.

Also, we divided the entire experiment period into years to enhance the accuracy and eligibility of the model in the volatile cryptocurrency market. Subsequently, we identified the best prediction model for each cryptocurrency within each year, selecting the model based on the lowest average error from 20 target dates of every year. Table 4 displays the randomly selected target dates by year.

Table 4. Random selection of target dates by year

Index	2017	2018	2019	2020	2021	2022
1	2017-11-02	2018-01-14	2019-01-14	2020-01-14	2021-01-14	2022-01-14
2	2017-11-05	2018-02-04	2019-02-04	2020-02-04	2021-02-04	2022-02-04
3	2017-11-09	2018-03-10	2019-03-10	2020-03-09	2021-03-10	2022-03-10
4	2017-11-12	2018-04-02	2019-04-02	2020-04-01	2021-04-02	2022-04-02
5	2017-11-13	2018-04-12	2019-04-12	2020-04-11	2021-04-12	2022-04-12
6	2017-11-14	2018-04-15	2019-04-15	2020-04-14	2021-04-15	2022-04-15
7	2017-11-19	2018-05-27	2019-05-27	2020-05-26	2021-05-27	2022-05-27
8	2017-11-22	2018-06-21	2019-06-21	2020-06-20	2021-06-21	2022-06-21
9	2017-11-29	2018-06-24	2019-06-24	2020-06-23	2021-06-24	2022-06-24
10	2017-12-04	2018-08-18	2019-08-18	2020-08-17	2021-08-18	2022-08-18
11	2017-12-05	2018-09-24	2019-09-24	2020-09-23	2021-09-24	2022-09-24
12	2017-12-11	2018-09-25	2019-09-25	2020-09-24	2021-09-25	2022-09-25

13	2017-12-12	2018-09-29	2019-09-29	2020-09-28	2021-09-29	2022-09-29
14	2017-12-15	2018-10-03	2019-10-03	2020-10-02	2021-10-03	2022-10-03
15	2017-12-21	2018-11-06	2019-11-06	2020-11-05	2021-11-06	2022-11-06
16	2017-12-22	2018-11-23	2019-11-23	2020-11-22	2021-11-23	2022-11-23
17	2017-12-23	2018-11-25	2019-11-25	2020-11-24	2021-11-25	2022-11-25
18	2017-12-24	2018-12-03	2019-12-03	2020-12-02	2021-12-03	2022-12-03
19	2017-12-27	2018-12-06	2019-12-06	2020-12-05	2021-12-06	2022-12-06
20	2017-12-28	2018-12-19	2019-12-19	2020-12-18	2021-12-19	2022-12-19

Time Interval	Learning Period
15min	7 days
60min	28 days
180min	60 days

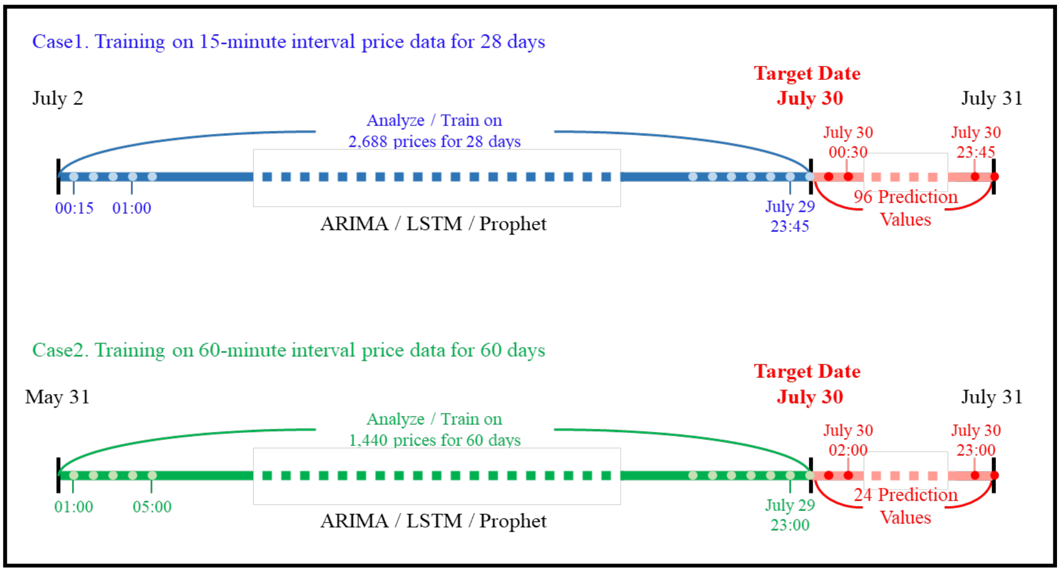

Figure 5. How the prediction model works

Figure 5 illustrates the design of the prediction model. As mentioned above, we randomly selected 20 target dates per year, total 120 days from the entire period. For each methodology, we conducted training using price data from the D-learning period to D-1 (the day before target date) and generated one-day predictions for the corresponding target date. As an example, we think about the Prophet learning case using 15-minute interval price for 28 days as a dataset to forecast the target date of July 30, 2021. The model is trained on 15-minute interval prices for 28 days, beginning at 00:15 on July 2, 2021, and ending at 24:00 on July 29, 2021. As a result, it provides a total of 96 15-minute interval prediction values for July 30, 2021. In total, there are 9 different learning conditions for each of the 3 methodologies by year, examining 5 cryptocurrencies. This resulted in a total of 540 cases per year by combining three time intervals (15min, 60min, 180min), three learning periods (7days, 28days, 60days), three methods (ARIMA, LSTM, Prophet), and 20 target dates at the end of the experiment over each cryptocurrency.

As a final step, we compared the assessment values of each prediction model by MAPE, MSE, L_APE and L_SE which will be explained in chapter 4.4.1 to find the best one. The experiment flow is outlined in Figure 6.

We used Intel i7-10700 (CPU), NVIDIA GeForce GTX 1660 SUPER (GPU), statsmodels and torch library for the empirical analysis of this study.

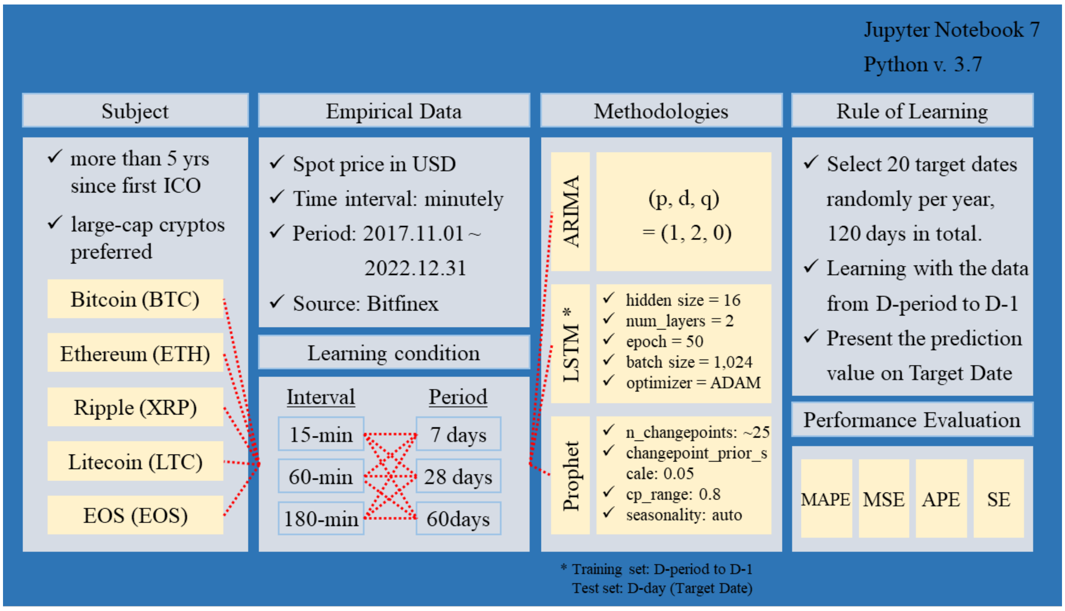

Figure 6. Experiment Process of Part1

4.2 Empirical Data

We collected minute-by-minute historical price data for five major cryptocurrencies—Bitcoin, Ethereum, Ripple, Litecoin, and EOS—spanning from November 1, 2017, to December 31, 2022, from Bitfinex. Given our goal to vary learning conditions using different interval data, we extracted prices at 15-minute, 60-minute, and 180-minute intervals from the original one-minute price data. The cryptocurrency market operates 24 hours a day, 365 days a year, ensuring there are no missing values in our dataset, eliminating the need for interpolation. Additionally, ARIMA and Prophet models do not require preprocessing, while min-max normalization is applied to the LSTM model.

Table 5. Empirical Data used in Part 1

Dataset	Interval	Start Date	End Date	Source
SPOT price in USD (BTC, ETH, XRP, LTC, EOS)	1-minute	2017.11.01	2022.12.31	Bitfinex

Table 6 provides an overview of the 5 cryptocurrencies that are the subjects of our experiment. For Bitcoin, XRP and Litecoin, they did not undergo a traditional Initial Coin Offering (ICO). Instead, they were created through a process called mining or initially distributed by developers through a combination of strategies. In Table 6, the term 'first ICO' refers to the beginning year of trade in the open market.

Table 6. Overview of 5 cryptocurrencies.

NAME	Symbol	First ICO	Rank by MC	Current Price (Oct 2023)	Market Cap
Bitcoin	BTC	2009	# 1	$28,357.23	$553,878,062,488
Ethereum	ETH	2014	# 2	$1,589.24	$191,160,624,828
Ripple	XRP	2012	# 5	$0.4912	$26,258,361,815
Litecoin	LTC	2011	# 17	$67.85	$5,008,985,981
EOS	EOS	2017	# 60	$0.6182	$684,415,947

Table 7. Descriptive Statistics for 5 cryptocurrencies during the experiment period.

Statistics	BTC	ETH	XRP	LTC	EOS
MIN	3191.30	82.83	0.1151	22.82	0.529
25%	8206.09	226.76	0.2987	56.09	1.936
50%	15467.48	759.95	0.4136	80.12	2.994
75%	29942.27	1834.29	0.6315	129.46	4.864
MAX	68789.63	4891.70	3.8419	412.96	22.890
MEAN	20903.29	1206.82	0.5195	99.27	3.816
STD	15888.99	1129.73	0.3426	59.83	2.966

Subsequently, Figure 7 depicts their historical prices and Table 7 presents descriptive statistics. Both Bitcoin and Ethereum, the top-ranked cryptocurrencies by market capitalization, reached their highest prices in November 2021 and their lowest in December 2018. Also, the historical movement of Bitcoin, Ethereum, and cryptocurrency market looks similar from 2018 to 2023 as shown in Figure 1 and Figure7.

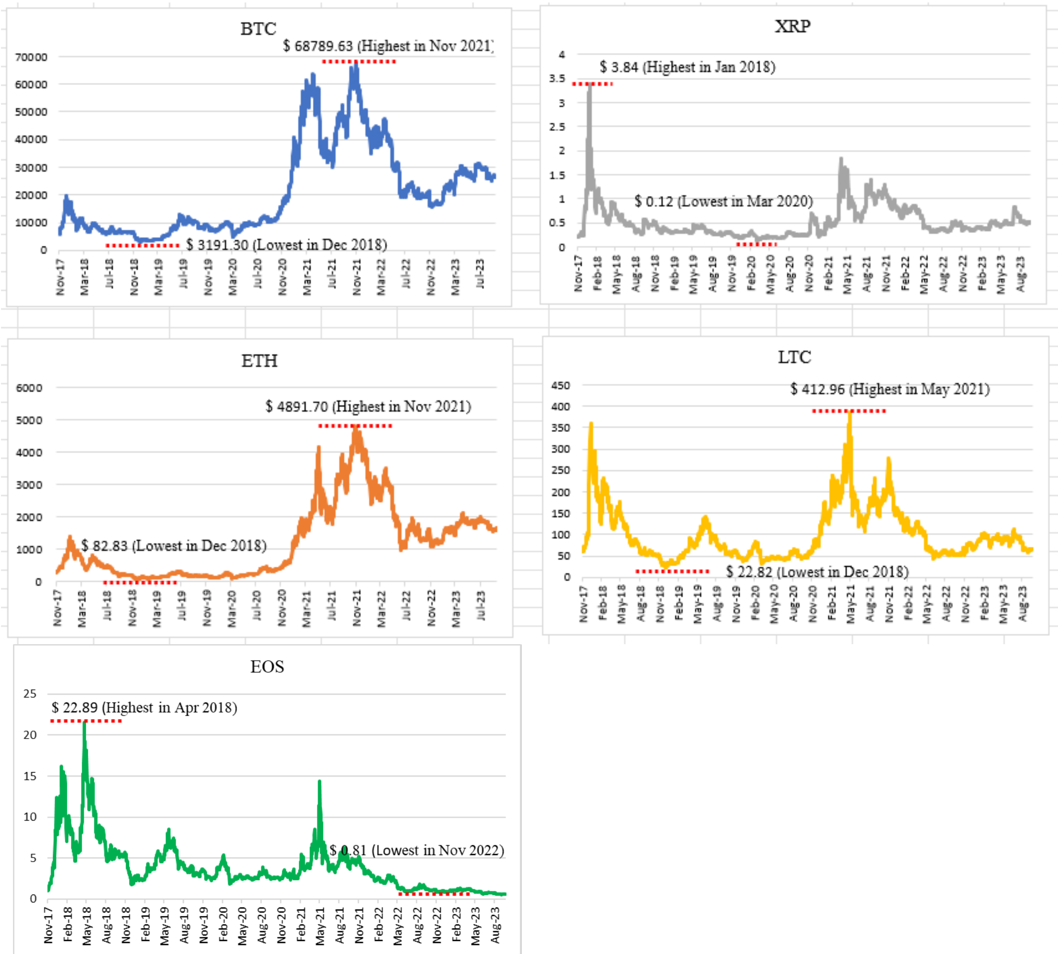

Figure 7. Historical prices of 5 cryptocurrencies.

4.3 Finding Best Parameters in Price Prediction

As our experiment emphasizes varying learning conditions to find the best-performing prediction model, the parameters for each methodology remain consistent across these diverse conditions. We set the parameters simplistically, allowing the machine to automatically detect the characteristics of the training data and present results across the varied conditions.

4.3.1 ARIMA

The ARIMA model presupposes the use of stationary data, indicating that the average variance of the data remains constant. Non-stationary data needs to undergo differencing to achieve stationarity. The ARIMA method, a statistical approach represented by three parameters, incorporates the autoregressive (AR) process from previous periods, integrates the data (I) to enhance predictability, and maintains the moving average (MA) process for improved forecasting. That principle is reflected in three orders, (p, d, q). To determine (p, d, q) for the data used in the experiment, we tried several combinations of (p, d, q) which passed the ADF test. Among the combinations, ARIMA (p, d, q) = (1, 2, 0) was the best model with a small error rate.

4.3.2 LSTM

The second model used is LSTM, which is commonly employed in deep learning time series prediction. Unlike ARIMA and Prophet, LSTM has a structure where sequence data is input, and sequence data is output. To predict our target output sequence, the length of the input sequence was set to twice the length of the output sequence when constructing the training dataset. For instance, if a 15-minute time interval is used, resulting in 96 time sequences in the output, the input is set to 192 time sequences to compose the dataset. As deep learning models are significantly influenced by the scale of the data, a min-max scaler was utilized to fix the data distribution from 0 to 1.

Table 8. Structure of LSTM

Layer (type)	Input shape	Output shape	Number of parameters
lstm_encoder-1	[1024, 192, 1]	[1024, 192, 16], [1, 1024, 16], [1, 1024, 16]	1,216
lstm_decoder-2	[1024, 1], [1, 1024, 16], [1, 1024, 16]	[1024, 1, 1], [1, 1024, 16], [1, 1024, 16]	1,233
Total params: 2,449	Trainable params: 2,449	Non-trainable params:0	

Table 8 shows the structure of the LSTM used in the experiment. It was developed and trained using Python 3.7. Two LSTM layers were arranged within the LSTM model. Following batch normalization, the t+1 value was forecasted through the dense layer. The structure of the created model is outlined below. The provided structure corresponds to the model configuration with a batch size of 1024 and a time interval set to 15. Given the time interval of 15, the input shape yields 192 time sequences, and the output concatenates the first tensor value repeated 96 times to generate a final output of 96 time sequences.

The hidden size was set to 16, the number of layers was set to 2, and epoch was set to 50. The batch size was set to 1,024 and the learning rate was set to 0.01. The loss function was MSE (Mean Squared Error), and the optimization function was Adam.

Table 9. Parameters for LSTM model training

Parameter	**Value**
Hidden size	16
Number of layers	2
Epoch	50
Batch size	1,024
Learning rate	0.01
Loss function	MSE
Optimizer	ADAM

4.3.3 Prophet

Prophet mandates data in the specific format of a data frame with a "ds" (date stamp) and "y" (value to be forecasted). We converted the timestamp to the 'YYYY-MM-DD HH:MM:SS' format. The next consideration involves parameters. Prophet provides several adjustable parameters related to trend, seasonality, and holiday factors. Given our experiment's focus on short-term learning within a maximum of 60 days, we chose not to directly include seasonality and holiday components, such as 'holidays_prior_scale' and 'seasonality_prior_scale'. If seasonality and holiday effects are present in the training data, the machine autonomously detects and integrates them into the model without requiring manual adjustments. The number of potential changepoints which are uniformly placed in the first 80% of the time series was set to 25. changepoint_prior_scale, which represents the flexibility of the model was set to 0.05.

Table 10. Parameters for Prophet model training

Parameter	**Value**
n_changepoints	25
changepoint_range	0.8 (80%)
changepoint_prior_scale	0.05
seasonality	Auto
holidays	Auto
interval_width	0.8

4.4 Empirical Study Results

4.4.1 Evaluation Metrics

A critical aspect of forecasting involves measuring the forecasting error to determine its performance. According to Makridakis and Wheelwright (1989), accuracy may be described as the "goodness of fit" or the ability of the forecasting model to accurately replicate known data. To measure the accuracy of prediction model, we used Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Absolute Percentage Error (APE), and Squared Error (SE).

Mean Squared Error (MSE) indicates the average squared difference between the estimated values and the actual value. The smaller the MSE value, the more stable the model. However, interpreting the MSE value can be misleading, for the MSE will accentuate large error terms.

$$MSE = \frac{\sum_{t=1}^{n}(X_t - \widehat{X_t})^2}{n}, \quad X_t: Actual\ value, \quad \widehat{X_t}: Forecast\ value$$

Mean Absolute Percentage Error (MAPE) is calculated by the following equation. It regarded as a better error measurement than MSE because it does not accentuate large errors.

$$MAPE = \frac{\sum_{t=1}^{n}\left[\frac{|X_t - \widehat{X_t}|}{X_t}\right]}{n} \times 100\%$$

Similar way to MAPE, we calculated Absolute Percentage Error (APE), the difference between the actual and forecasted values, divided by the actual value, for the last prediction. APE can contribute to the design of trading strategies for the Part 2 study, particularly since we execute only one transaction per day, and the last prediction value serves as the criterion for positioning.

$$L\_APE = \frac{\left|X_L - \widehat{X_L}\right|}{X_L} \times 100\% \, ,$$

$X_L: Actual\ value\ of\ the\ last\ point, \quad \widehat{X_L}: Forecast\ value\ of\ the\ last\ point$

Similar way to MSE, we calculated Squared Error (SE) which indicates squared difference between the estimated value and the actual value for the last point.

$$L\_SE = (X_L - \widehat{X_L})^2$$

We calculate the average of 20 MSEs, 20 MAPEs, 20 L_APEs and 20 L_SEs from each target date by the methodologies to conclude the year's error value.

4.4.2 Experimental Results

Table 11 presents a summary of Bitcoin predictions in 2017 under various conditions as an example. Among the 27 models, the one developed using the Prophet algorithm with training data at 60-minute interval prices over a 28-day period demonstrated the superior performance, boasting the lowest values across all metrics, including MAPE, MSE, L_APE, and L_SE. Consequently, we assert that the optimal prediction model for Bitcoin in 2017 is the Prophet model with a 60-minute interval for 28 days. It is important to note that this is an exceptional case, achieving the lowest values across all metrics. Typically, we would need to prioritize a single criterion among the four types of measurements since the result (rank) depends on the selected metric.

Table 11. Bitcoin predictions in 2017 across varying learning conditions.

Train-Days	Time Interval	Metho-dology	MAPE	MSE	L_APE	L_SE
7	15	Prophet	7.34	1,958,545	8.62	2,536,734
7	15	LSTM	10.84	3,004,893	10.86	3,034,297
7	15	ARIMA	22.09	25,830,389	43.47	74,019,086
7	60	Prophet	7.30	1,951,353	8.30	2,402,344
7	60	LSTM	9.89	2,602,112	9.85	2,694,035
7	60	ARIMA	13.89	7,740,635	24.85	20,400,688

7	180	Prophet	5.96	1,349,654	6.25	1,383,787
7	180	ARIMA	8.46	2,493,039	12.36	4,627,937
7	180	LSTM	8.75	2,436,936	8.22	2,368,622
28	15	Prophet	6.50	1,317,631	7.76	1,607,462
28	15	LSTM	8.37	1,974,841	10.66	2,830,328
28	15	ARIMA	22.04	26,063,245	43.25	74,650,304
28	60	Prophet	5.75	1,046,490	7.19	1,173,928
28	60	LSTM	12.15	3,586,614	12.53	3,895,711
28	60	ARIMA	13.50	7,097,493	24.07	18,716,417
28	180	Prophet	6.76	1,777,946	8.11	2,086,683
28	180	ARIMA	7.55	1,983,760	10.74	3,550,611
28	180	LSTM	10.09	2,787,785	10.44	3,673,861
60	15	LSTM	9.64	2,585,083	11.08	3,303,587
60	15	Prophet	11.03	3,422,493	11.86	3,917,755
60	15	ARIMA	22.01	25,985,315	43.18	74,431,002
60	60	LSTM	9.29	1,931,858	10.87	2,215,056
60	60	Prophet	10.78	3,408,004	11.44	3,761,749
60	60	ARIMA	13.51	7,071,054	24.10	18,646,699
60	180	ARIMA	7.45	1,940,585	10.54	3,460,154
60	180	LSTM	9.65	2,010,881	9.46	1,627,547
60	180	Prophet	11.50	3,875,472	11.83	4,203,248

Table 12 summarizes the best-performing forecasting model for each cryptocurrency within each year, with MAPE as the chosen evaluation criterion. The selection of evaluation criteria hinges on the specific prediction purpose. In our Part 1 study, the goal is to establish a baseline for building trading strategies in Part 2. In terms of that, MAPE has several strong points. It provides a straightforward and easy-to-understand measure of the accuracy of the models, expressing the prediction error as a percentage of the actual value, making it intuitive for interpretation. Also, it is scale-independent, meaning it can be used to compare the accuracy of predictions across different cryptocurrencies with varying price ranges. This is particularly useful when dealing with diverse datasets. On the contrary to this, one drawback of MSE is its sensitivity to the scale of the data. Given the significant differences in price ranges among the five cryptocurrencies in our experiment (e.g., Bitcoin reaching nearly $70,000 while Ripple maintains its highest record below $4), we chose MAPE as the criterion. In addition, MAPE captures the performance of all prediction traces on the target date, a feature lacking in both L_APE and L_SE. They only assess the accuracy of the last value. When designing a trading strategy to execute transactions once a day based on the last forecasting value, L_APE or L_SE could also be considered as assessment criteria.

The experiment results consistently highlight Prophet's superior performance compared to other methodologies and utilizing 15-minute interval prices for predicting future movements is the most effective. Notably, extending the training period to 60 days did not result in improved outcomes. Given the model's one-day prediction horizon, extending the training period did not yield any additional benefits.

Generally, the MAPE value exhibited a decreasing trend over time. There is an inverse relationship between the market capitalization of a cryptocurrency and its MAPE value, indicating that cryptocurrencies with larger market capitalization tend to have lower MAPE values. Bitcoin exhibited the lowest MAPE value compared to the other cryptocurrencies, suggesting a relatively higher accuracy in the forecasting model for Bitcoin.

Table 12. Summary of the best-performing model within each year by MAPE

	Year	**Train days**	**Time Interval**	**Methodology**	**MAPE**
BTC	2017	28	60	Prophet	5.749
BTC	2018	28	15	Prophet	3.015
BTC	2019	7	60	Prophet	2.603
BTC	2020	28	15	Prophet	2.497
BTC	2021	28	15	LSTM	1.782
BTC	2022	28	15	LSTM	1.631
ETH	2017	28	15	Prophet	5.633
ETH	2018	7	180	Prophet	4.437
ETH	2019	28	15	Prophet	3.539
ETH	2020	28	15	Prophet	2.610
ETH	2021	28	15	Prophet	3.477
ETH	2022	7	180	LSTM	2.958

XRP	2017	28	180	Prophet	6.626
XRP	2018	28	15	Prophet	5.943
XRP	2019	7	15	Prophet	2.885
XRP	2020	28	15	Prophet	2.933
XRP	2021	7	15	Prophet	3.838
XRP	2022	7	15	Prophet	3.338
LTC	2017	28	15	Prophet	6.571
LTC	2018	28	15	Prophet	4.370
LTC	2019	28	15	Prophet	3.985
LTC	2020	7	15	Prophet	3.348
LTC	2021	7	15	Prophet	4.569
LTC	2022	28	15	Prophet	3.268
EOS	2017	28	15	Prophet	9.855
EOS	2018	28	15	Prophet	5.745
EOS	2019	28	15	Prophet	3.980
EOS	2020	7	15	Prophet	3.303
EOS	2021	7	15	Prophet	3.564
EOS	2022	28	15	LSTM	2.767

4.5 Concluding Remarks

The primary goal of Part 1 is to determine the most effective prediction model for each cryptocurrency annually, setting the foundation for the development of trading strategies in Part 2. Our approach involves parameter variation, employing three methodologies—ARIMA from traditional statistics, LSTM, and Prophet from artificial intelligence. Furthermore, we varied learning conditions, testing each methodology on different datasets with distinct time intervals and learning periods. This is the distinguished point of our study from previous research. Instead of optimizing a single method through hyperparameter tuning or incorporating more causal variables to the model, we explored various models to find out the most suitable one for short term prediction.

Prophet generally outperformed other models, with 15-minute interval data proving to be the most effective for generating accurate predictions. Additionally, training over a longer period did not exhibit strengths in the outcomes; high achievements were observed from datasets over 28 days at the longest. The performance is assessed with MAPE, which is a scale-independent metric, providing intuitive interpretation.

Based upon the experiment result of Part 1 study, we try to build trading strategies in the next chapter.

PART II.

Developing Cryptocurrency Trading Strategies

Chapter 5.

Empirical Study (Part II)

5.1 Proposed Model

Our study aims to validate the short-term predictive power of cryptocurrencies and construct an effective investment portfolio based on these predictions. In Part 1, the forecasting phase, we identified parameters for each cryptocurrency's superior annual performance, determined by the MAPE value. In this section, we leverage the findings from Part 1 to formulate cryptocurrency trading strategies, substantiating the efficacy of our prediction-based portfolio.

Figure 8 outlines the experimental process in the Part 2 study. It involves forecasting, asset allocation (determining investment weights on individual cryptocurrency), position taking, and assessing returns in that order.

We devised four investment plans. Two of the four investment plans leverage the MAPE value as a determinant for establishing the investment weight of the portfolio. The underlying principle for both approaches is to assign a higher weight to more predictable assets. The key distinction between these two plans lies in the MAPE used for asset allocation. One utilizes the MAPE calculated on predictions by the previous year’s best model, updating the portfolio weight once a year. In contrast, the other plan utilizes the MAPE for daily predictions on the trading date, employing the best model from the previous year, resulting in daily portfolio rebalancing. The third strategy relies solely on signals (upward or downward) from the Part 1 prediction model, maintaining equal proportions between the five cryptocurrencies. The fourth approach adopts a buy-and-hold strategy with an equal proportion portfolio for a comparison. We assess the effectiveness of each strategy using metrics such as total return, annual return, Maximum Draw Down (MDD), and Standard Deviation (SD).

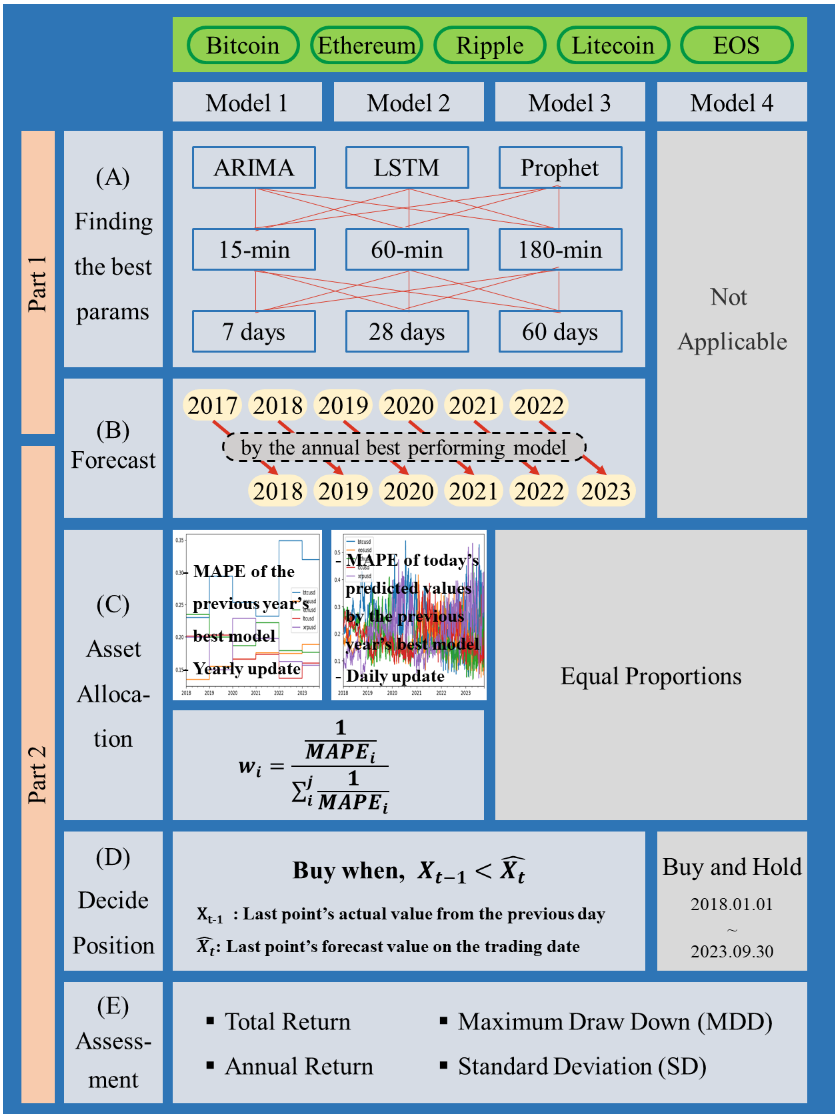

Figure 8. Diagram of overall experiment process

The following rules were consistently applied throughout the trading simulation experiment.

1. We generate daily predictions and make corresponding daily decisions on whether to buy the cryptocurrency or not throughout the testing period.

2. The forecasting for the current year employs the best-performing model from the previous year. For example, the daily prediction for EOS in 2018 uses the Prophet algorithm with training data at 15-minute interval prices over a 28-day period. Similarly, the daily prediction for Ethereum in 2023 utilizes LSTM with 180-minute interval prices for 7 days.

3. We explored two approaches to using MAPE as a weight determinant.

   - MAPE 1 (Trading Model 1)

   The annual asset allocation is determined by the MAPE values from the previous year and is rebalanced annually. For example, the MAPE obtained from the best-performing model of Bitcoin in 2018 dictates the investment weight allocated to Bitcoin in 2019.

   - MAPE 2 (Trading Model 2)

   The Daily MAPE and the subsequent weight determination are consistently updated with daily prediction results from the previous year's optimal model. For instance, the MAPE value influencing asset allocation on November 24, 2021, is derived from the prediction outcomes of the best model from the preceding year, specifically targeting that date. This methodology is consistently applied for weight allocation on the subsequent day.

Figure 9 illustrates the difference between Model 1 and Model 2.

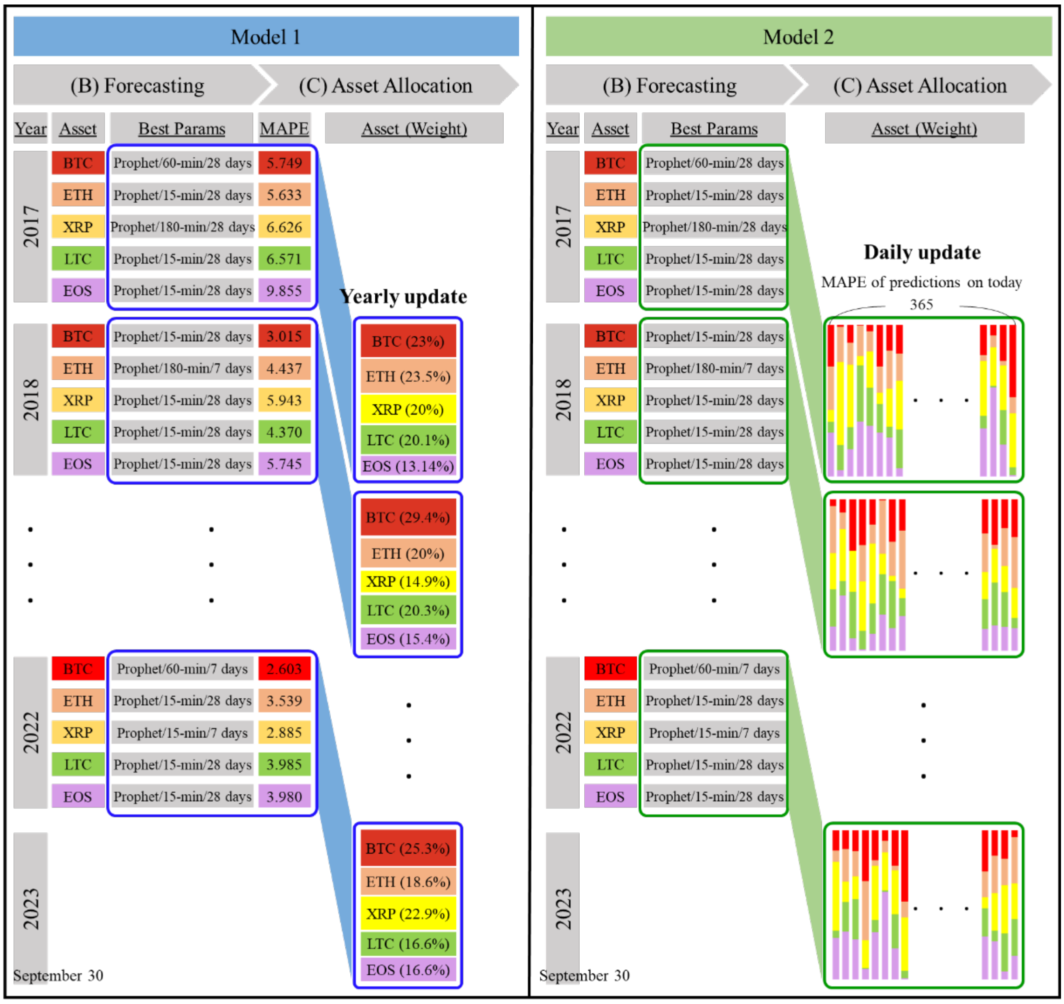

Figure 9. How Model 1 and Model 2 determine their own asset allocation

4. How to utilize MAPE as a weight determinant, in other words, a concrete logic for asset allocation needs to be established in this step. As previously mentioned, we assign more weight to the cryptocurrency for which our verified prediction model performs well, ensuring a higher return. The determination of the weight for asset i (w_i) is outlined by the following equation.

$$w_i = \frac{\frac{1}{MAPE_i}}{\sum_i^j \frac{1}{MAPE_i}}$$

5. The models generate predictions on the trading date based on their respective training intervals. When the last point's forecasted value on the trading date ($\widehat{X_t}$) exceeds the last point's actual value from the previous day (X_{t-1}), we purchase the asset in the amount of w_i.

6. We execute transactions once a day at the closing point of each day when there is a buy signal.

7. At the end of the testing period, we evaluate the profitability of Models 1 to 4 based on total returns, annual returns, Maximum Drawdown (MDD), and Standard Deviation (SD).

5.2 Empirical Data

The data used in Part 2 study is same with the one used in Part 1 study. 1-minute interval prices of five cryptocurrencies from January 1, 2023, to September 30, 2023, has been collected additionally as testing period is from January 1, 2018 to September 30, 2023. Min-max normalization for LSTM model was the only pre-processing done for the data treatment likewise Part 1 study.

Table 13. Empirical data used in Part 2 study.

Dataset	Interval	Start Date	End Date	Source
SPOT price in USD (BTC, ETH, XRP, LTC, EOS)	1-minute	2017.11.01	2023.09.30	Bitfinex

In 2023, the average prices of Bitcoin, Ethereum, Ripple and Litecoin have increased compared to the previous year. The highest and lowest prices for them remain unchanged; however, EOS has set a new record low at $ 0.53.

5.3 Trading Simulation

Table 14 provides a snapshot of the essential elements utilized in the trading simulation conducted during the period from January 1, 2018, to January 3, 2018. In accordance with the previously outlined trading rules, transactions were initiated once a day at the closing point of each day, specifically when a buy signal was detected.

Table 14. Related Factors for trading simulation

Trade Date	Asset	X_{t-1}	Params for Prediction	$\widehat{X_t}$	MAPE	Position	Weight_1	Weight_2
2018-01-01	BTC	13,753.00	Prophet/60-min/28 days	14,416.90	3.82	Buy	23%	21%
	ETH	736.50	Prophet/15-min/28 days	780.57	2.67	Buy	24%	30%
	XRP	1.97	Prophet/180-min/28 days	2.08	10.20	Buy	20%	8%
	LTC	225.15	Prophet/15-min/28 days	228.00	3.65	Buy	20%	22%
	EOS	7.66	Prophet/15-min/28 days	7.37	4.57	-	13%	18%
2018-01-02	BTC	13,428.00	Prophet/60-min/28 days	13,759.84	3.37	Buy	23%	24%
	ETH	755.13	Prophet/15-min/28 days	795.37	2.74	Buy	24%	30%
	XRP	2.07	Prophet/180-min/28 days	2.24	11.51	Buy	20%	7%
	LTC	223.77	Prophet/15-min/28 days	238.70	3.74	Buy	20%	22%
	EOS	7.64	Prophet/15-min/28 days	8.25	4.54	Buy	13%	18%
2018-01-03	BTC	14,709.00	Prophet/60-min/28 days	13,406.41	3.34	-	23%	25%
	ETH	856.30	Prophet/15-min/28 days	876.61	2.87	Buy	24%	29%
	XRP	2.18	Prophet/180-min/28 days	2.44	13.30	Buy	20%	6%
	LTC	250.52	Prophet/15-min/28 days	227.80	3.97	-	20%	21%
	EOS	8.31	Prophet/15-min/28 days	8.40	4.49	Buy	13%	19%

For the trade executed on January 1, 2018, the best-performing parameters from the preceding year for each cryptocurrency were initially arranged. Two critical factors, the values at the last point and the MAPE were obtained from the one-day prediction provided by the model. Specifically, Ethereum exhibited a MAPE of 2.67 based on 96 prediction values, while Ripple's MAPE of 10.20 was determined from a dataset comprising 8 prediction values. These metrics were instrumental in the context of Model 2, one of the three strategies designed to determine the optimal method of asset allocation. Model 2 dynamically rebalances daily with predictions obtained each day. In contrast, Model 1, which follows the MAPE of the best-performing model from the previous year, is reflected in the 'Weight_1' column on Table 14. This weight remains constant throughout the observed period, providing stability in asset allocation for the entirety of the year. These strategies were strategically employed during the trading step. For Bitcoin, Ethereum, Ripple, and Litecoin—four out of five cryptocurrencies—the position was set to 'buy' as the forecasted value on January 1, 2018, 24:00, exceeded those recorded on December 31, 2017, 24:00. Conversely, for EOS, as the forecasted value of $7.37 on the first day was lower than the previous day's price of $7.66, we opted not to initiate a buy position.

We extended the experimental period to September 2023 to ensure the attainment of more generalizable results. As a part of that, Table 15 illustrates the annual asset allocation applied to Trading Model 1 and Figure 10 graphically represents this allocation. Table 16 also provides how the daily MAPE influences the daily weight determination in Trading Model 2 over the period from January 1 to 10, 2018. Figure 11 depicts the daily status in graph.

Table 15. Annual asset allocation determined by MAPE applied to Trading Model 1

Trade Year	2018		2019		2020	
Asset	MAPE	Weight	MAPE	Weight	MAPE	Weight
BTC	5.749	0.230	3.015	0.294	2.603	0.253
ETH	5.633	0.235	4.437	0.200	3.539	0.186
XRP	6.626	0.200	5.943	0.149	2.885	0.229
LTC	6.571	0.201	4.37	0.203	3.985	0.166
EOS	9.855	0.134	5.745	0.154	3.98	0.166
		1		1		1
Trade Year	**2021**		**2022**		**2023**	
Asset	**MAPE**	**Weight**	**MAPE**	**Weight**	**MAPE**	**Weight**
BTC	2.497	0.232	1.782	0.349	1.631	0.320
ETH	2.61	0.222	3.477	0.179	2.958	0.176
XRP	2.933	0.198	3.838	0.162	3.338	0.156
LTC	3.348	0.173	4.569	0.136	3.268	0.160
EOS	3.303	0.175	3.564	0.174	2.767	0.188
		1		1		1

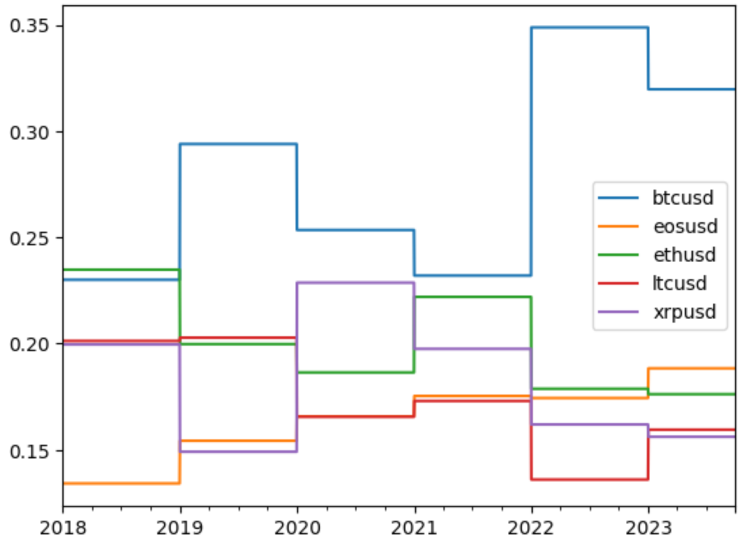

Figure 10. Annual weight on each cryptocurrency in Trading Model 1

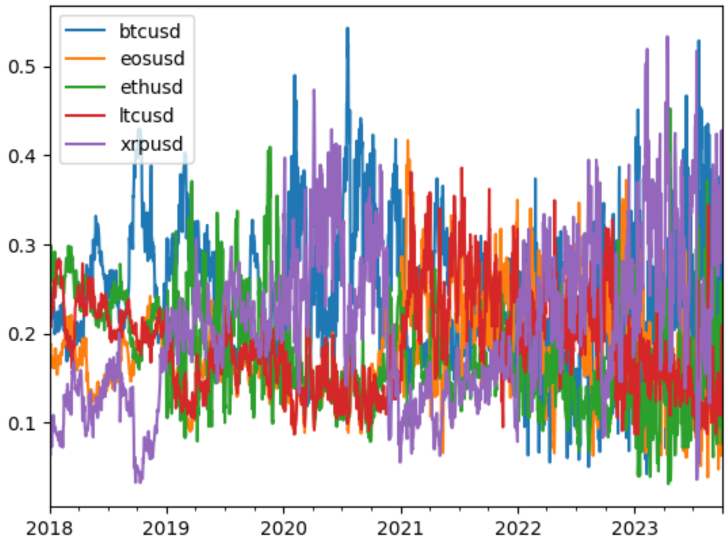

Figure 11. Daily weight on each cryptocurrency in Trading Model 2

Table 16. Daily MAPE and Daily weight employed in Trading Model 2.

D_MAPE	BTC	ETH	XRP	LTC	EOS
2018-01-01	3.820	2.673	10.200	3.651	4.571
2018-01-02	3.368	2.740	11.511	3.743	4.536
2018-01-03	3.337	2.867	13.299	3.973	4.485
2018-01-04	3.548	2.738	10.023	3.916	4.289
2018-01-05	3.428	2.558	8.320	3.574	4.428
2018-01-06	3.409	2.530	8.589	3.150	4.193
2018-01-07	3.132	2.446	9.599	3.097	4.078
2018-01-08	2.792	2.445	9.620	3.151	4.141
2018-01-09	3.026	2.599	8.373	3.102	4.185
2018-01-10	2.988	2.658	7.399	2.914	4.047
D_Weight	**BTC**	**ETH**	**XRP**	**LTC**	**EOS**
2018-01-01	0.213	0.305	0.080	0.223	0.178
2018-01-02	0.240	0.295	0.070	0.216	0.178
2018-01-03	0.250	0.291	0.063	0.210	0.186
2018-01-04	0.228	0.296	0.081	0.207	0.189
2018-01-05	0.223	0.299	0.092	0.214	0.173
2018-01-06	0.216	0.290	0.086	0.233	0.175
2018-01-07	0.228	0.292	0.074	0.231	0.175
2018-01-08	0.250	0.286	0.073	0.222	0.169
2018-01-09	0.237	0.276	0.086	0.231	0.171
2018-01-10	0.233	0.262	0.094	0.239	0.172

5.4 Empirical Study Results

We conducted a back test on four investment plans, and the results are presented in Figure 12. This figure provides an overview of the total return observed across the period from January 1, 2018, to September 30, 2023.

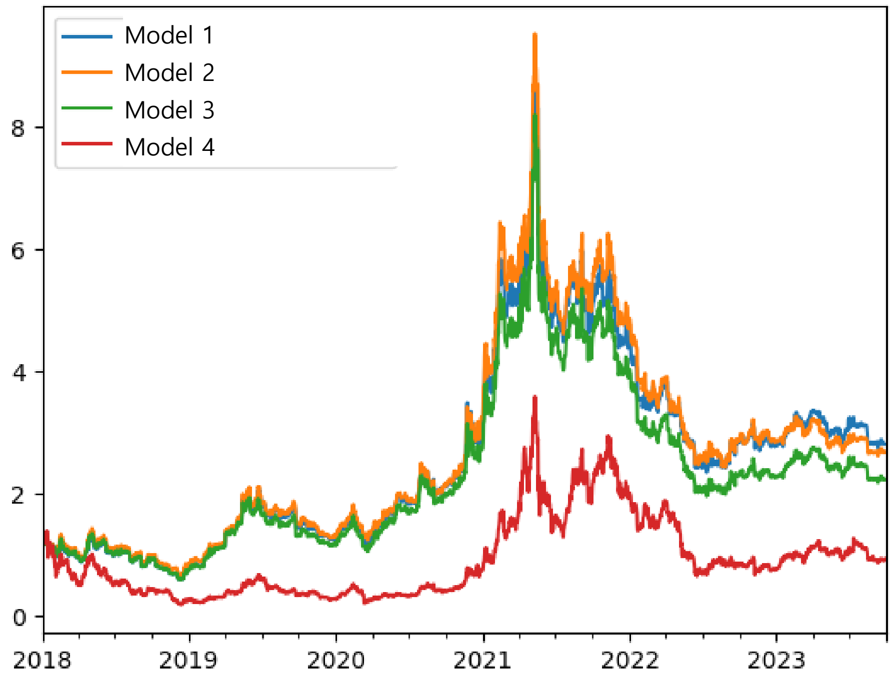

Figure 12. Total return Comparison of 4 investment plans

The vertical axis of the graph represents the portfolio value, starting with a baseline of '1'. As illustrated in the figure, before 2023, Model 2—an active portfolio adjusting its composition based on current prediction errors—achieved the highest performance among the four plans. Model 1 also demonstrated robust performance within its own portfolio, leveraging a prediction error-driven logic. The primary distinction between Model 1 and Model 2 lies in their approaches to utilizing prediction errors, with Model 1 assuming the effectiveness of the Mean Absolute Percentage Error (MAPE) from the previous year for the current year. However, starting in 2023, Model 1 notably outperformed the others, securing the highest rank in cumulation. Model 3, employing equal proportions based on the prediction signals, secured the third position, while Model 4, implementing a buy-and-hold strategy, ranked last among the four plans.

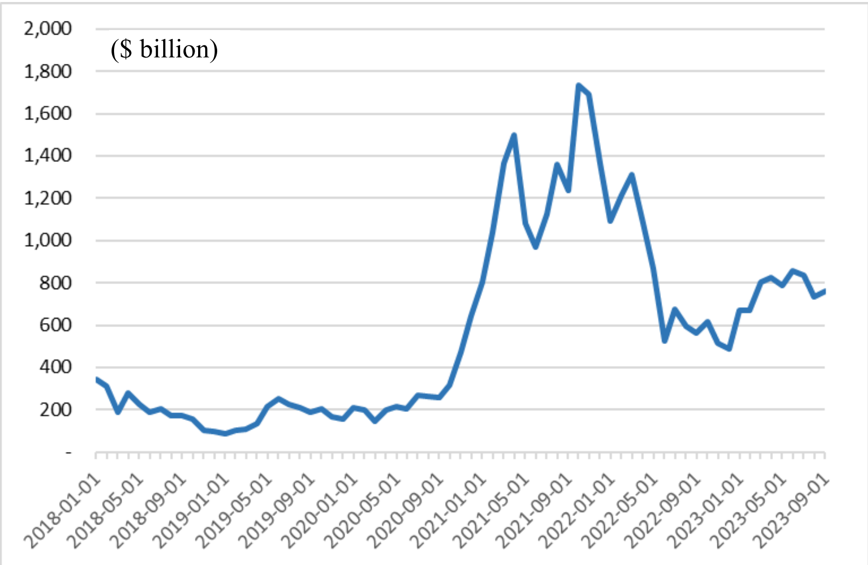

Figure 13. Market cap of 5 cryptocurrencies during Jan 2018 to Sep 2023.

Figure 13 illustrates the market capitalization of five cryptocurrencies throughout the test period for reference. Referring to Figure 12, a noticeable gap emerges between the three proposed models leveraging prediction methodologies and the passive fourth model. The larger the gap, the more bullish the market appears. In the middle of 2021, when the crypto market reached its peak, our trading strategy also demonstrated the most superior performance. Conversely, from 2018 to the end of 2020, during market downturns, the gap is relatively moderate. These observations suggest that there are more opportunities to enhance profits in a brisk market environment.

Table 17. Profitability Assessment

	Model 1	Model 2	Model 3	Model 4
Total Return	1.817	1.691	1.238	-0.061
Annual Return	0.197	0.188	0.150	-0.011
MDD	-0.737	-0.744	-0.761	-0.867
STD	0.027	0.027	0.028	0.045

Table 17 provides a numerical summary of the results. Maximum Drawdown (MDD), representing the maximum observed loss from a peak to a trough of a portfolio before a new peak is attained, aligns with our intuitive understanding from figure 12. Specifically, the profitability index is ordered as Model 1, Model 2, Model 3, and Model 4, with higher values indicating better performance in total and annual return. However, MDD and STD of risk metrics reveal the reverse order, suggesting that the models' performance in risk management follows the sequence of Model 4, Model 3, Model 2, and Model 1.

5.5 Concluding Remarks

In part 2 study, we conducted experiments to assess the effectiveness of our trading strategies. Building on the findings from Part 1, we then devised trading strategies that specifically emphasized asset allocation. The guiding principle throughout the process remained 'More investment in more predictable assets'. Operating under the assumption that the best-performing model from the previous year provides the most accurate estimation of the current movement, we followed the direction signal and employed the MAPE of the models to determine the allocation of assets.

We proposed three distinct options for asset allocation. The first involved determining weights based on yearly MAPE from Part 1, the second rebalanced daily with the everyday predictions, and the third assigned equal proportions to each subject while following directional signals indicating upward or downward movements.

Upon conclusion of the testing period, we observed that Model 1, which rebalance its portfolio once a year, yielded the largest profit. Model 2 secured the second position. Notably, Model 2, the more active strategy, effectively capitalized on opportunities in a bullish market. This suggests that continuous portfolio restructuring in response to market changes holds strong potential for earning profits compared to a static approach. Building on the insights gained from the Part 2 study, there exists further potential for the development and refinement of our strategy.

Chapter 6.

Conclusion

6.1 Concluding Remarks& Implication

As evidenced by numerous previous studies, attempts to predict the future value of cryptocurrencies and capitalize on subsequent investment opportunities have been widespread. While traditional approaches continue to yield results in this novel asset class, innovative methodologies leveraging artificial intelligence have shown remarkable success. However, predicting the future still remains a challenging endeavor. As part of the broader effort to categorize cryptocurrencies as investment assets, not speculative, we proposed a prediction model and corresponding trading strategies.

In Part 1 of our study, our objective was to identify the best parameters by the year for producing accurate estimations of each cryptocurrency's value. We selected five cryptocurrencies considered less prone to fraud as a first step. Using various methodologies (ARIMA, LSTM, Prophet), training data intervals (15-minute, 60-minute, 180-minute), and training periods (7 days, 28 days, 60 days), we aimed to determine optimal learning conditions. The assessment metric, Mean Absolute Percentage Error (MAPE), guided our prioritization of the most effective model. Overall, Prophet among the three methodologies, 15-minute interval prices, and a training period of 28 days emerged as the most effective parameters.

In Part 2 of our study, we aimed to develop and validate a trading strategy based on the findings from Part 1. We established a fundamental principle: 'More investment in more predictable assets.' Three investment plans, driven by prediction power, were devised. They allocated investment weight inversely proportionate to prediction errors. Model 1 used MAPE from the previous year's best model, adjusting asset allocation once a year. Model 2 employed daily MAPE values from everyday predictions, responding to volatile markets with agility. Model 3 relied solely on directional signals with an equally invested portfolio, while Model 4, buy-and-hold strategy with an equal portfolio, was also assessed for a comparison.

Experimental results indicated that Model 1 demonstrated superior performance among the four plans, achieving the highest total and annual returns. Model 2 secured the second position, and Model 3 followed behind Model 2. Model 4 ranked last. Notably, in bullish markets, the gap between the three proposed models and Model 4 widened. Additionally, the risk metrics, including standard deviation and Maximum Drawdown, showed higher values in the order of Model 4 to Model 1, in complete opposition to the profitability metrics. This suggests potential opportunities to amplify profits through strategy refinement.

Our study holds several implications. Firstly, in the pursuit of optimal parameters, we adopted a learning condition variation approach instead of introducing an abundance of causal factors or fine-tuning hyperparameters within a single model. This approach facilitates quick and flexible responses to changing conditions Secondly, by deliberately selecting subjects with diverse sizes and characteristics, we pursued the portfolio effect. Thirdly, our distinctive approach utilizing MAPE as a weight determinant offers a logical foundation for asset allocation. In deep learning-based portfolio strategies, the blackbox problem, which fails to provide a rationale for the output, is consistently recognized as a fatal flaw.

The cryptocurrency trading model developed in this study not only assists speculative traders who invest without rationale but also contributes to the ongoing elaboration of advanced trading strategies.

6.2 Further Studies

In Part 1 of the study which centered on fortifying predictive efficacy, we identified three critical aspects that enhance the logical coherence and quality of our research. Firstly, we employed a random selection of 20 target dates for model validation. However, validating the model across each trading day would impart greater credibility to the best-performing model and holds the potential to significantly impact trading results. Consequently, securing ample resources to conduct a thorough examination bolsters the robustness of our conclusions. Secondly, as we endeavored to augment the predictive capabilities of our models in Part 1 through diverse methodologies, it is crucial to emphasize that the effectiveness of these models relies on the hyperparameter tuning process. The outcomes of this tuning process may exert influence on both trading positions and weight determinations, thereby shaping the overall robustness and reliability of our prediction model. Lastly, our conclusions are derived from the conditions we set. Comparisons with the best-performing models from previous studies lend higher conviction to the logical development of our research.

During the trading phase, it's noteworthy that we did not account for slippage and transaction fees associated with each transaction. The inclusion of these elements is imperative for achieving more accurate results. Additionally, while we utilized the buy and hold option as a point of comparison, exploring alternatives such as traditional portfolio strategies or options that assign higher weights to the least predictable cryptocurrencies could offer new insights and perspectives in our research.

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국문초록

암호화폐 가격 예측 모델과 거래 전략의 개발: 예측력 기반의 자산 배분 전략을 중심으로

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비트코인의 등장으로 시작된 암호화폐의 역사는 대안화폐의 검증 과정이기보다 새로운 금융 투자 상품의 시장 역사로 축적되고 있다. 문제는 지난 몇 년 간 반복된 암호화폐 가격의 폭등과 폭락 속에서 투기적 거래가 심화되는 양상을 보인다는 것이다. 그 원인 중 하나는 내재가치 평가가 제한적인 암호화폐의 본질적 특성으로, 이를 보완하고자 암호화폐 투자에 합리적 근거를 제시하려는 연구들이 다수 진행되고 있다.

본 연구는 예측 오차에 근거하여 5 개 주요 암호화폐의 투자 비중을 결정하는 거래 전략을 제안하고자 한다.

Part1 에서는 연도 별로 각 암호화폐의 가격을 가장 잘 예측하는 모델을 찾기 위해 ARIMA 와 LSTM, Prophet 에 학습 조건을 달리 하며 예측을 실행하였다. 3 가지 방법 중 대체적으로 Prophet 이 가장 우수한 예측 성과를

보였고, 28 일 동안 15 분 간격의 가격을 바탕으로 학습하였을 때 가장 정확한 예측이 이루어졌다.

Part2 에서는 Part1 에서 확인된 예측 모델을 기반으로 암호화폐 거래 모델을 개발하는 것을 목표로 삼았다. 예측 성과가 높은 암호화폐에 더 큰 투자 비중을 두는 것을 기본 원리로 하여 포트폴리오를 설계하였다. 예측 모델이 제시하는 상승 신호에 따라 예측 오차의 상대적 크기만큼 해당 암호화폐를 매수하였다. 이러한 전략에 따라 2018 년부터 2023 년 9 월말까지 운용된 포트폴리오는 연평균 19%의 수익률을 보여, 균등 비율로 구성한 포트폴리오를 매수 후 보유 (Buy and hold) 전략으로 운용하였을 때에 (−1.1%) 비하여 월등히 높은 결과를 끌어내었다.

본 연구는 암호화폐를 투기의 영역에서 투자 대상으로 재정립하는 시도라는 점에서 의미가 있다. 또한 예측 오차를 기반으로 투자 가중치를 설정하여, 딥러닝에 의한 자산 분배의 주요 단점인 블랙박스 문제를 해소하고 가중치 분배에 대한 근거를 제시했다는 시사점을 지닌다.

주제어: 암호화폐, 시계열 분석, 가격 예측, 딥러닝, 투자 전략