CRYPTOCURRENCY QUANTITATIVE TRADING STRATEGY BASED ON MACHINE LEARNING APPROACH

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CRYPTOCURRENCY QUANTITATIVE TRADING STRATEGY BASED ON MACHINE LEARNING APPROACH

by

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My master's journey has been fraught with numerous challenges. With my wife away for her doctoral research, I had to juggle studies, article - writing, and childcare. there have been sleepless nights with a crying child, days balancing my mother's medical records and thesis draft. The beeps of my father-in-law's hospital monitor and my son's laughter wove into life's unexpected rhythm. This situation compelled me to take a year off.

Yet when the wisdom lights burn past midnight, when ideas spark in academic debates, when Professor Tahir and I see our paper published—all the struggles fade. They become time's own presents.

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LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
ANN	Artificial Neural Networks
AR	Autoregression
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GRU	Gated Recurrent Unit

STRATEGI DAGANGAN KUANTITATIF MATA WANG KRIPTO BERDASARKAN PENDEKATAN PEMBELAJARAN MESIN

ABSTRAK

Mata wang kripto ialah pasaran penting yang tidak boleh diabaikan, dan kajian pengurusan aset dengan harga tidak menentu ini adalah penting. Dagangan kuantitatif menggunakan data harga sejarah aset dan model matematik untuk merumus strategi dagangan serta mengujinya terhadap data sejarah, bagi meningkatkan kawalan dan mengurangkan risiko. Ramalan trend harga adalah teknologi utama bidang ini. Berbanding kaedah ekonometrik tradisional, model LSTM direka khusus untuk memproses data jujukan dan mampu menangkap kebergantungan jangka panjang dalam siri masa, dengan fungsi ingatan yang mengekal dan mengaplikasi maklumat jangka panjang pada keputusan semasa. Ketiadaan data kewangan fundamental seperti saham bagi mata wang kripto menjadikan penggunaan pelbagai penunjuk teknikal amat penting untuk menganalisis trend harganya. Walaupun model ekonometrik tradisional dan implementasi asas LSTM menunjukkan potensi, ia sering gagal menangkap corak kompleks dan tak linear dalam pasaran mata wang kripto, terutamanya tanpa penunjuk teknikal. Untuk menangani jurang ini, tesis ini menggunakan model LSTM untuk meramal trend harga mata wang kripto dengan menggabungkan harga sejarahnya bersama pelbagai penunjuk teknikal sebagai ciri kajian. Enam eksperimen kawalan direka bagi membandingkan kesan pelbagai penunjuk teknikal sebagai ciri terhadap model. Hasil akhir menunjukkan model LSTM yang digabungkan dengan penunjuk teknikal berkesan meningkatkan ketepatan ramalan, namun bukan semua penunjuk teknikal menyumbang kepada penambahbaikan model tersebut.

CRYPTOCURRENCY QUANTITATIVE TRADING STRATEGY BASED ON MACHINE LEARNING APPROACH

ABSTRACT

Cryptocurrency is undoubtedly a significant market that cannot be ignored, and studying how to manage such an asset with volatile price fluctuations is an important issue. Quantitative trading can utilize historical asset price data along with mathematical models to formulate trading strategies and can test these strategies against historical data, greatly enhancing controllability and risk reduction. Price trend prediction is the key technology within this field. Compared to traditional econometric methods, the LSTM model is explicitly designed for sequence data processing and can capture long-term dependencies in time series. It possesses memory functions that can retain long-term information and apply it to current decisions. Cryptocurrencies do not have financial data like stocks as a basis for fundamental analysis, so using various technical indicators to analyze the trend of cryptocurrency prices is particularly important. While traditional econometric models and basic LSTM implementations have shown some promise, they often fail to capture the complex, nonlinear patterns present in cryptocurrency markets, particularly when technical indicators are excluded. To address this gap, this thesis adopts the LSTM model to predict the price trends of cryptocurrencies by combining their historical prices with various technical indicators as features for research. We designed six control experiments to compare the impact of different technical indicators as features on the model. The final results indicate that the LSTM model combined with technical indicators can effectively improve prediction accuracy, but not all technical indicators contribute to the improvement of the model.

CHAPTER 1

INTRODUCTION

1.1 Background of the study

Currency, a non-physical fiction, plays an important role in human development, so much so that when Karl Marx wanted to study the course of human development, he first started with money. The nature and origin of money are discussed in the first volume of his "Das Kapital." The invention of currency has played a crucial role in advancing human civilization. Since the rise of capitalism, the way people interact and communicate has undergone a revolution, with virtually all social activities now taking place within an economic cycle facilitated by currency.

However, in recent times, this remarkable invention has encountered new challenges. With the collapse of the Bretton Woods system, which was considered the world's most credible monetary framework, we have also entered an era characterized by large-scale, unanchored currency issuance. (Dooley et al., 2003) After the collapse of the Bretton Woods system, the price of gold was no longer constrained by the official fixed exchange rate and began to be determined by market supply and demand. In the early 1970s, the price of gold experienced a significant increase, from about 35 U.S. dollars per ounce in 1971 to a historical high of 850 U.S. dollars per ounce in 1980. During this period, the U.S. dollar, as the most credible currency in the world, was also criticized by central banks of various countries. (Dooley et al., 2004).

Every operation of the Federal Reserve on the dollar affected the economic situation of other countries, such as the Asian financial crisis in 1998, which was influenced by it. In the early 21st century, the 2008 subprime mortgage crisis further exacerbated public distrust of centralized financial systems and government monetary policies. (Bordo et al., 2007). Many people began seeking alternative financial solutions to reduce their dependence on traditional banks and government institutions. These economic and financial crises intensified the demand for reform of the financial system. People began to seek a new financial system that is more transparent, secure, and resilient to risks. It was against this backdrop that, in 2008, an individual or group using the pseudonym Satoshi Nakamoto published the Bitcoin white paper "Bitcoin: A Peer-to-Peer Electronic Cash System". (Guo & Yu, 2022; Zheng et al., 2017; Casino et al., 2019).

The design goal of Bitcoin was to create a decentralized currency system not controlled by any single government, bank, or central authority. Thus, the first decentralized cryptocurrency system in human history was born. With the advent of Bitcoin, a vast market consisting of various cryptocurrencies was also born. Undoubtedly, cryptocurrencies have become one of the important components of the global financial system today. In November 2023, the SEC (United States Securities and Exchange Commission) approved the first Bitcoin spot ETF, an event that directly led to a surge in the prices of cryptocurrencies in 2024, with Bitcoin, the leading effect, rising from $27621 on May 11, 2023 to $61637 on May 9, 2024. It nearly tripled in a year. According to the Coin Market Cap website, the global crypto market cap is $2.28T and everyday trade volume over $64.74B. Therefore, we need to analyse and predict the market through scientific methods in order to better manage these assets.

1.2 Problem Statement

Cryptocurrency markets pose unique challenges for price prediction due to their extreme volatility, sentiment-driven behavior, absence of fundamental valuation metrics, and 24/7 trading nature. These characteristics differentiate them significantly from traditional financial markets such as equities or forex, where standard econometric models often rely on more stable structures and predictable patterns. (Sabry et al., 2020; Khedr et al., 2021)

Therefore, we must analyze and predict the market through scientific methods to better manage these assets. Quantitative trading strategies represent a rigorous scientific framework that employs mathematical models to supplant subjective judgments and human decision-making. The core premise is to leverage mathematical algorithms and historical data to identify recurring patterns with predictive power for profitable investment opportunities. (Patel et al., 2022; John et al., 2024)

The most crucial aspect of Quantitative Trading is price prediction technology; hence, a significant amount of time is invested in this field (Chan, 2021; DeFusco et al., 2015). In order to address these problems, people began to try to use econometric models. Traditional econometric model forecasting, such as AR (Autoregression), affects price forecasting. Although the AR model can predict linear time series, the AR requires that the series be stationary and the autocorrelation coefficient is greater than 0.5. It is only suitable for predicting economic phenomena related to their own previous periods. The ARMA (Autoregressive Moving Average) model combines the advantages of AR and MA models, considering historical observations and prediction errors to forecast future values, making predictions on time series data more comprehensive and accurate. Based on ARMA, the ARIMA (Autoregressive Integrated Moving Average) also incorporates a differencing method to stabilize non-stationary data. The SVAR (Structure Vector Autoregression) model can capture the instantaneous structural relationships among various variables within the model system, which allows the model to be more explanatory. However, these methods have some flaws. For example, the ARIMA model does not perform as well in long-term prediction as it does in short-term prediction. In addition, it cannot identify underlying dynamics within various time series.

The SVAR model is primarily intended to investigate the interrelationships and causalities among diverse economic variables, yet it is not ideally suited for addressing financial time-series issues. While it can capture the long-term equilibrium relationships among variables, it may not be as effective as LSTM in handling long-term dependencies. Moreover, the SVAR model relies on linear assumptions to capture relationships among variables. This can be limiting when dealing with complex and nonlinear relationships inherent in financial data. (Hao et al., 2022; Ariyo et al., 2014; Hiransha et al., 2018).

Nevertheless, deep learning models, distinguished by their vast feature quantity and inherent learning capabilities, have significantly enhanced prediction precision compared to traditional econometric models (Ma & Yan,2022; Sheng, et al., 2022). Unlike traditional linear statistical models like ARMA, machine learning techniques excel at capturing the nonlinear dynamics of highly volatile cryptocurrency prices. While ANNs (Artificial Neural Networks) offer robust performance in handling vast datasets and intricate problems, they overlook the interdependencies within time series data. The RNN (Recurrent Neural Network), however, effectively addresses this issue of data correlation. Yet, RNNs encounter the challenge of gradient vanishing, which the LSTM (Long Short-Term Memory) model adeptly overcomes. Nonetheless, a single LSTM may falter when confronted with intricate financial data. Hence, this study endeavors to devise a quantitative analysis framework for cryptocurrency trading, leveraging technical indicators and the LSTM model.

The LSTM model surpasses the predictive capabilities of traditional ARCH or GARCH models (Liu & Lin, 2018) as these latter nonlinear approaches are only precise when the data aligns with a specified distribution model, thereby restricting their applicability by imposing a predefined distribution on the data. (Davis & Jagannathan, 2020; Wang et al., 2022)

While LSTM networks have demonstrated potential in modeling temporal dependencies in cryptocurrency prices, most existing implementations rely solely on raw price data, and the model often fail to account for crucial market signals such as momentum, trend strength, and trading volume. This narrow input scope limits the model's ability to fully capture market dynamics, such as momentum, trend strength, and trading volume signals. Technical indicators—such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and On-Balance Volume (OBV)—provide enriched representations of these factors. Integrating these indicators as input features enables LSTM models to better interpret market behavior, leading to significantly improved prediction accuracy, as demonstrated by recent empirical studies. (Kang et al., 2025; Penmetsa et al., 2023; Lee et al., 2024)

1.3 Research Question

Therefore, this study addresses this gap by proposing a hybrid LSTM framework that incorporates a comprehensive set of technical indicators, aiming to enhance the model’s predictive performance and better reflect market behavior. Based on this motivation, the study is guided by the following research questions:

RQ1: Does incorporating technical indicators into LSTM models improve prediction accuracy compared to using only price data?

RQ2: Which combinations of technical indicators contribute most significantly to reducing prediction error?

RQ3: Can the hybrid LSTM model outperform traditional econometric models in forecasting cryptocurrency prices?

1.4 Objectives of the Study

From the problem statement in Section 1.2, the LSTM model has advantages in price prediction. Thus, this research aims to forecast cryptocurrency prices by combining LSTM models with technical indicators. This approach aims to provide more accurate predictions for the cryptocurrency market.

To accomplish this, the research comprises the following objectives:

The first objective is to construct a robust feature set by integrating historical Bitcoin price data with technical indicators:

This involves gathering comprehensive historical Bitcoin price data and applying technical indicator formulas to transform it into the required feature sets for the LSTM models.

The second objective is to compare the predictive performance of LSTM models using different combinations of technical indicators:

This includes designing controlled tests to identify which combinations of technical indicators contribute most significantly to the accuracy of cryptocurrency price forecasts by the LSTM models

The third objective is to determine the optimal set of technical indicators that maximize the predictive accuracy of the LSTM models:

This entails finding the best mix of indicators that improve price forecasting accuracy, thereby enhancing the practical utility of the LSTM models in quantitative trading.

1.5 Significance of the Study

This research will focus on finding a scientific investment method that can reduce investment risk, increase controllability, increase investment income, and reflect the practical significance. Thus, the research question will ask how to use machine learning to predict price trends to guide cryptocurrency investment.

1.6 Organization of the Chapters

Chapter 2 provides a comprehensive review and comparative analysis of existing literature. Chapter 3 delves into the methodology, outlining the specific approach to address the research questions. Chapter 4 outlines the experimental setup and delves into the findings and discussions stemming from the conducted experiments. Lastly, Chapter 5 discusses and analyzes the experimental results. Chapter 6 summarizes the thesis, highlighting key findings and limitations, and outlines potential avenues for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This literature review begins by outlining the foundations of modern quantitative trading strategies, which provide a broader context for financial market prediction. It then narrows the focus to time-series forecasting methods, starting with traditional models and progressing to Recurrent Neural Networks (RNNs), which are well-suited for sequential data. Within this framework, Long Short-Term Memory (LSTM) networks are introduced as a specialized RNN variant capable of capturing long-term dependencies in financial time series. Finally, the review concentrates on recent research involving LSTM models for cryptocurrency price prediction, highlighting both opportunities and limitations in this emerging domain.

2.2 Quantitative Trading Strategies

The quantitative trading strategy, at its core, utilizes sophisticated mathematical models to supersede subjective human judgments. This approach focuses on guiding investment decisions through the utilization of mathematical models and computer technology, aiming to sieve through vast historical data to identify various "high-probability" events that promise excess returns. Based on these insights, investment strategies are formulated accordingly. Quantitative trading strategies are grounded in rigorous mathematical models and computer programs, ensuring the discipline and systematic nature of trading. Through systematic and disciplined data processing, these strategies can more accurately reflect market conditions, minimizing errors introduced by human judgments. Consequently, quantitative trading significantly mitigates the impact of investors' emotional fluctuations, preventing irrational investment decisions during periods of extreme market euphoria or pessimism.(Velu, 2020; Ta et al., 2020; Tulchinsky, 2019; Chan, 2021; DeFusco et al., 2015). Modern quantitative trading is divided into several categories, and we will introduce these strategies in the following.

2.2.1 Based on Price Strategies

Pricing strategies are typically based on price data to predict future market trends and make trading decisions accordingly. Momentum strategy and trend strategy are two common types of pricing strategies. While both do focus on future price trends, they differ in their emphasis and implementation.

Trend strategy involves identifying and following the main trends in the market. Investors look for established trends and then trade to profit from the continuation of these trends. Tools such as moving averages, trend lines, and channels may be used to identify and track trends in a trend strategy.

Based on the fundamental method of trend strategies, let us discuss the timing of buying and selling within this strategy. The Trend strategy’s Buying Opportunity is after a period of consolidation or pullback, the market begins to climb gradually, forming a series of higher highs and higher lows. This upward progression indicates the start of an uptrend. Investors can enter a buy position when the price breaks through the previous high or on a dip to the vicinity of the upward trendline. Technical indicators such as moving averages and the Relative Strength Index (RSI) can also assist in identifying buying opportunities. For instance, a "golden cross" formed when a short-term moving average crosses above a long-term moving average or when the RSI enters the overbought zone and is poised to retreat towards the neutral line may signal a favorable buying opportunity. The Trend strategy’s Selling Opportunity is that the market gradually declines after a prolonged upward move, creating a series of lower lows and lower highs. This downward progression signals the beginning of a downtrend.

Investors can initiate a sell position when the price breaks below the previous low, or on a rebound towards the downtrend line. Technical indicators can also help pinpoint selling opportunities. For instance, a "death cross" formed when a short-term moving average crosses below a long-term moving average, or when the RSI enters the oversold zone and is poised to rebound towards the neutral line, may indicate a favorable selling opportunity (Fabozzi, et al., 2010; DeFusco et al., 2015; Drakopoulou, 2016; Fang et al., 2019; Yao et al., 2022; Tang et al., 2019).

Momentum's strategy is based on price changes of assets that have recently shown strong performance, assuming that prices have continuity in the short term, meaning stocks that have performed well in the past are likely to continue their upward trend for a while. Momentum strategy relies on specific thresholds or momentum rankings of momentum indicators. Identifying Momentum is typically measured by looking at the price movement over a specific period, such as the past few weeks or months. Technical indicators like the Momentum Oscillator or Rate of Change (ROC) can help quantify momentum and signal potential trading opportunities.

Based on the above description of the core ideas of momentum strategies, let us establish the timing for buying and selling within this strategy. The Momentum strategy's Buying opportunities look for assets that have exhibited strong upward momentum, characterized by a series of higher highs and higher lows. Consider buying when the momentum indicator reaches a new high or crosses above a significant level. Buying opportunities may also arise when an asset breaks out to new highs, indicating a continuation of the upward momentum. The Momentum strategy's Selling opportunities similarly, look for assets with strong downward momentum, marked by a series of lower lows and lower highs. Consider selling when the momentum indicator reaches a new low or crosses below a significant level. selling opportunities may emerge when an asset breaks down to new lows, signaling a continuation of the downward momentum. (Fabozzi et al., 2010; DeFusco et al., 2015; Drakopoulou, 2016; Ryou et al., 2020; Su, 2021; Pani & Fabozzi, 2021; Hanauer & Windmüller, 2023)

2.2.2 Based on Statistical Strategies

Statistical strategies are trading strategies that use mathematical and statistical methods to analyze and predict market price behavior. They typically include mean reversion and statistical arbitrage, identifying potential trading opportunities by analyzing historical data and market patterns.

The mean reversion strategy is based on the long-term pattern of price fluctuations, believing that stock prices will return to their intrinsic value in the long run. Therefore, the focus is not on price changes but on finding the mean of fluctuations. Identifying mean reversion is typically observed in assets that exhibit stable statistical properties over time. Technical indicators like Bollinger Bands, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) can help identify potential mean reversion opportunities. These indicators measure an asset's price deviation from its historical mean and signal when the price is overextended. Buying opportunities look for assets falling below their historical averages or mean values, indicating they may be oversold. Consider buying when the price approaches or breaches the lower Bollinger Band or when the RSI drops into oversold territory. Buying opportunities may also arise when the MACD line crosses above the signal line, indicating a potential reversal in the downward momentum.

Selling opportunities similarly, look for assets that have risen above their historical averages or mean values, suggesting they may be overbought. Consider selling when the price approaches or breaches the upper Bollinger Band or when the RSI rises into overbought territory. Selling opportunities may emerge when the MACD line crosses below the signal line, signaling a potential reversal in the upward momentum. (Poterba & Summers, 1988; Cecchetti, et al., 1988; Dai et al., 2021; Wood et al., 2021, 2021; Corbet et al., 2020; Rubaszek et al., 2020)

A statistical arbitrage strategy is a trading approach based on mathematical and statistical models that aim to capture excess returns by exploiting short-term deviations in market pricing efficiency. This strategy does not rely on the overall market environment but instead constructs portfolios by analyzing historical data of asset prices and utilizes mathematical techniques to make trading decisions, thereby achieving stable and relatively risk-free investment returns.

The core of the statistical arbitrage strategy lies in identifying asset pairs or portfolios with price correlations. These asset pairs or portfolios tend to maintain a stable price relationship in the absence of significant market changes. When the price relationship of these assets deviates from its equilibrium position, arbitrageurs will engage in corresponding trading operations, buying assets that are undervalued and selling those that are overvalued. Once the price relationship returns to equilibrium, the arbitrageurs will reverse their positions to profit.

The statistical arbitrage strategy is characterized by its market neutrality, meaning that the overall market trend does not influence the investment portfolio's performance. This allows the strategy to maintain stable returns in complex, volatile market environments. The strategy relies heavily on extensive historical data and complex statistical and mathematical models to make trading decisions. These models can capture the nuanced relationships between asset prices and provide precise trading signals for arbitrageurs. Compared to other investment strategies, statistical arbitrage strategies exhibit lower risk. Since they are based on historical data and models, they avoid the interference of human factors and emotional trading. Through analyzing historical price data and utilizing statistical and mathematical methods, we construct models to establish asset price relationships and determine the rules for generating trading signals. The buying and selling opportunities are then determined based on the trading signals generated by the model, specifying which assets to buy and sell as well as the quantities. Investors need to implement rigorous risk management measures, including setting stop-loss points and controlling positions, to mitigate potential market risks. (Krauss, 2017; Pole, 2011; Krauss, et al., 2017; Ramos-Requena et al., 2020; Brim, 2020; Sarmento & Horta, 2020; Fil & Kristoufek, 2020; Ngoyi & Ngongang, 2023)

2.2.3 Based on Portfolio Strategies

As Eugene F. Fama and others proposed the random walk and market efficiency hypothesis, they believe that because market participants will act immediately to exploit any new information, asset prices will quickly and accurately reflect all known information. All market information is already fully reflected in the price. Since the price has already reflected all information, further price analysis or prediction is theoretically impossible, or it is not possible to systematically obtain excess returns. Moreover, the change in stock prices is a random walk process, so the change in stock prices is unpredictable. Therefore, since prices are unpredictable, portfolio strategies have shifted from short-term price fluctuation predictions to long-term value creation and risk management. Several important economists in this area have won the Nobel Memorial Prize in Economic Sciences for their work in this area. Such as Harry Markowitz's modern portfolio theory (MPT), John Lintner, Jan Mossin, Jack Treynor, William F. Sharpe's capital asset pricing model (CAPM) and Myron Scholes, Robert Merton, and Fischer Black's Black-Scholes Option Pricing Model), Black-Scholes option pricing model, Eugene F. Fama and Kenneth R. French, Eugene F. Fama and Kenneth R. French proposed the three-factor and five-factor models. In the portfolio strategy, important methods include the Factor investment and Alpha strategy strategies. (Markowitz, 1991, 2010; Sharpe, 1964, 1992; Black & Scholes, 1973)

Factor investing strategies do not attempt to predict short-term price fluctuations but rather identify and exploit multiple factors that influence stock returns, such as the intrinsic value and fundamentals of a stock, including financial health, profitability, growth potential, etc. These factors are usually related to the company's long-term performance. The goal is to identify which factors significantly impact stock returns and construct portfolios with expected returns above the market average while reducing uncertain risks. The pursuit is for optimal returns on a risk-adjusted basis, rather than simply the highest returns. This involves considering the balance between risk and return, with investment decisions being more based on a long-term investment perspective rather than short-term market fluctuations. In a factor-based stock selection strategy, factor each quarter based on the latest factor weights are evaluated and adjusted each quarter based on the latest financial data and other quantitative indicators. Through these factors, investors attempt to predict future returns and risks of stocks, reflecting an in-depth analysis of their intrinsic value. The construction of a diversified investment portfolio aims to achieve expected returns above the market average while controlling risk. Risk is mitigated through diversification and the management of factor exposure. The timing for buying or selling thus becomes a comparison between the intrinsic value of a stock calculated by the multifactor model and its current market value. If the current market value is less than the estimated value, it indicates that the stock has potential for future growth and should be purchased, rather than focusing on when the stock will rise specifically. Conversely, if the market value exceeds the estimated value, the stock should be sold. (Maehashi et al., 2020; Feng & He, 2022; Pástor et al., 2021; Avramov et al., 2023; Leippold et al., 2022; Cao & You, 2024)

Alpha strategy within the framework of the Capital Asset Pricing Model (CAPM), Alpha can be expressed as:

$$\alpha = R_p - (R_f + \beta \times (R_m - R_f))$$

$$\beta = \frac{Cov(R_p, R_m)}{Var(R_m)}$$

where R_p is the actual return rate of the investment portfolio, R_f is the risk-free rate of return, R_m is the market rate of return, and β is the Beta coefficient. The Beta coefficient measures the volatility of an individual stock or portfolio relative to the entire market (such as the S&P 500 Index).

The Alpha value represents the excess return of an investment strategy relative to a benchmark index. The Beta value measures the volatility of a portfolio or asset relative to the overall market. A Beta of 1 means that the asset's volatility is consistent with the market; a Beta greater than 1 indicates that the asset's volatility is higher than the market, and consequently, the risk is also higher; a Beta less than 1 suggests that the asset's volatility is lower than the market, and accordingly, the risk is also lower. The objective of Alpha strategies is to achieve excess returns through stock selection and market timing, that is, to obtain returns above the market average while considering risk. The Beta value is an indicator for measuring market risk; therefore, when evaluating the performance of Alpha strategies, it is necessary to consider the impact of the Beta value on the portfolio's risk. Alpha strategy finds a portfolio with high and stable positive returns and then hedges the market risk (systematic risk) of the portfolio by selling the corresponding stock index futures contracts so that the beta value of the portfolio remains zero throughout the investment process, thus obtaining Alpha returns with low correlation with the market. Therefore, the Alpha strategy aims to achieve returns above the market average, while the Beta value represents the market risk premium. In practice, Alpha strategies need to pursue high Alpha while reasonably controlling the risks associated with Beta values. When evaluating the performance of Alpha strategies, risk-adjusted performance metrics are commonly used, such as the Sharpe Ratio, which considers the relationship between the excess return of a portfolio and its total risk (including market and non-market risks). The Beta value is an important factor in calculating the Sharpe Ratio. (Tulchinsky, 2019; Cong et al., 2021; Snow, 2020; Naffa & Fain, 2020; Spilak & Härdle, 2023; Jansen, 2020; Gültekin et al., 2020; Kristanti et al., 2022)

In quantitative trading, the ability to accurately forecast asset prices is fundamental to constructing profitable strategies. Unlike discretionary trading, quantitative approaches rely on systematic, data-driven models that require robust predictions to identify entry and exit points. Traditional statistical models such as ARIMA or GARCH have been widely used for financial time-series forecasting. However, they often fall short in capturing the nonlinear, non-stationary, and highly volatile nature of financial markets—particularly in the context of cryptocurrencies. To address these limitations, researchers have increasingly turned to machine learning and deep learning techniques. Among them, Recurrent Neural Networks (RNNs) have shown promise in modeling sequential dependencies in time-series data. The RNN model has achieved good results in forecasting stocks.

2.3 Forecasting Stock Prices Using RNN

The RNN model appeared earlier than the LSTM model. Traditional Recurrent Neural Network (RNN) models face issues of "vanishing gradients" and "exploding gradients" when dealing with long sequence data, preventing the network from effectively learning long-term dependencies. (Ribeiro et al., 2020; Sen & Mehtab, 2022).

To address this issue, the Long Short-Term Memory (LSTM) model was introduced. The LSTM model controls the flow of information by incorporating gating mechanisms, including input gates, forget gates, and output gates, allowing it to more effectively capture long-term dependencies within sequences. Despite this, traditional RNN models still play a significant role in quantitative trading. (Rumelhart, Hinton, & Williams, 1986; Sen & Mehtab, 2022; Turkoglu et al., 2021; Galimberti et al., 2023; Borawar et al., 2023)

In the 1990s, Kamijo et al. (1990) began to experiment with the RNN model to identify triangle patterns in stock price trends to assist investors in making better investment decisions. Tenti (1996) studied the model has performed well in the practical application of forex trading and applies to various markets and different types of currencies. Kermanshahi (1998) additionally applied the model to forecast Japan's electricity demand for the next ten years and to better plan the development of power production.

Quek et al. (2008) took this model and tried to apply it to options trading. this study introduces an innovative non-parametric approach leveraging a customized recurrent neural network (RNN) to forecast the future values of strategic assets, including gold, crude oil, and major currencies—assets whose significance in global financial markets has surged in recent years. The network's predictions, validated for both accuracy and computational efficiency, are integrated into a risk-mitigation framework designed to minimize exposure to market volatility. Empirical evaluations using real-world trading data for gold and foreign exchange markets demonstrate that our proposed system, combining the RNN model with a tailored hedging strategy, achieves an approximate 4.76% return on investment (ROI) for optimized portfolios.

Rather et al. (2015) crafted a hybrid model that seamlessly integrates recurrent neural networks (RNN) with an autoregressive moving average model. This innovative model exhibits a remarkable ability to capture intricate non-linear patterns within stock market data. The findings validate the precision of RNN in predictive performance. Notably, the proposed hybrid prediction model surpasses the RNN, demonstrating exceptional forecasting capabilities. Given its effectiveness in capturing intricate non-linear patterns that traditional models struggle with, the model stands as a promising solution in the realm of prediction-based modeling for nonlinear data.

Samarawickrama et al. (2017) conducted an experiment in the Sri Lankan stock market. This study compared three different models: RNN, GRU (Gate Recurrent Unit), and LSTM. The results indicated that LSTM have more stable accuracy. Qiu et al. (2020) designed a new model named hybrid RNN model is proposed by combining three-layer LSTM, three-layer GRU and one-layer ReLU, to overcome the limitations of traditional RNNs. 8 daily stocks from Shanghai Stock Exchange are used in experiments. The model is compared with traditional machine learning algorithms, such as support vector machine (SVM), k-nearest neighbor (KNN), naive Bayesian (NB), decision tree (DT), and logistic regression (LR). The results show that the hybrid RNN model achieves outstanding performance in terms of accuracy, stability, and robustness compared to traditional machine learning algorithms.

In a recent study conducted by Saud and Shakya (2020), an innovative examination was carried out on the parameter look-back period in the context of recurrent neural networks. Furthermore, a comparative analysis was undertaken to assess the performance of three deep learning models - Vanilla RNN, LSTM, and GRU - in predicting the stock prices of two leading and robust commercial banks listed on the Nepal Stock Exchange (NEPSE). This study provides a unique insight into the effectiveness of these models in stock price forecasting.

In Bao et al. (2021) research, a groundbreaking prediction methodology was introduced, involving the iterative integration of forecast errors into the historical neural network model through a three-step process. Initially, the neural network generates a preliminary prediction for the next day's value based on historical data. Subsequently, the neural network calculates the prediction error for the following day, taking into account past prediction errors. Ultimately, the initial predicted value and the prediction error are combined to yield the final prediction for the next day. Our approach employs popular recurrent neural network prediction methods, such as the Long Short-Term Memory Network Model and Gated Recurrent Unit. During simulations, we utilized historical stock prices from China spanning June 2010 to August 2017 as training data and data from September 2017 to April 2018 as test data. The experimental outcomes reveal that our proposed method incorporating forecast errors offers a more precise prediction of the stock's high price for the following day, indicating its superior performance compared to traditional models without forecast error integration.

An external influence on stock prices is macroeconomic factors, which refer to events occurring within a country that have an impact on the stock market. These factors often leave investors perplexed about the optimal timing for buying or selling stocks. One approach to assessing the potential of stock prices is through forecasting. In this study, they leverage the recurrent neural network (RNN) to predict stock prices for future periods. Pahlawan et al., (2021) thier research focuses on two variables: the daily closing stock price and the rupiah exchange rate against the dollar. they findings indicate a MAPE value of 1.546% for the RNN model without considering the foreign exchange rate and 1.558% for the RNN model that incorporates the rupiah-to-dollar exchange rate.

2.4 Forecasting Stock Prices Using LSTM

As elaborated earlier, traditional RNN architectures encounter challenges such as "vanishing gradients" and "exploding gradients" during the processing of lengthy sequence data, hindering their ability to effectively learn long-term dependencies. In order to overcome this limitation, the LSTM model was introduced. The LSTM model utilizes gating mechanisms, encompassing input gates, forget gates, and output gates, to regulate the flow of information, thus enabling it to capture long-term dependencies within sequences more efficiently. Consequently, we shifted our focus towards the exploration of the LSTM model. (Hochreiter & Schmidhuber, 1997; Yu, Si, Hu & Zhang, 2019; Mahajan et al., 2022; Sen & Mehtab, 2022;)

Nelson et al. (2017) delved into the application of LSTM networks in a scenario aimed at forecasting future stock price trends. Their methodology relied on historical pricing data, in addition to technical analysis indicators. Their findings reveal that this approach offers superior performance compared to traditional machine learning algorithms, achieving an average accuracy of 55.9% in predicting whether a specific stock's price is likely to increase or decrease in the imminent future.

Bao et al. (2017) have also introduced a hybrid model consisting of wavelet transforms (WT), stacked autoencoders (SAEs), and LSTM. The primary role of WT is to eliminate noise, while SAEs can increase the depth of their hidden layers based on automatic encoding to obtain better feature extraction abilities and training outcomes. Finally, the high-level denoised features are fed into the LSTM to forecast the price for the following day. The results demonstrate that this model surpasses other comparable models in both predictive accuracy and profitability.

Fischer and Krauss (2018) tested the performance of the LSTM model in predicting the price trends of the S&P 500 index constituents and compared it with traditional machine learning models. According to the experimental results, the LSTM model outperformed traditional machine learning models, With daily returns of 0.46 percent and a Sharpe ratio of 5.8 prior to transaction costs. Mehtab et al. (2021) also conducted a similar research experiment in NIFTY50. In their study, Borovkova and Tsiamas (2019) employed LSTM model in conjunction with technical indicators to forecast the performance of several major U.S. stock indices. Upon comparing the experimental results with Lasso and Ridge Logistic classifiers, it was found that the LSTM model outperformed them in terms of predictive capabilities.

In the face of the complexity of the stock market, traditional linear and stationary models often fail to accurately describe market behavior. Therefore, researchers have proposed a method that combines a specific ordered feature set with Convolutional Neural Networks (CNN) to handle this kind of non-linear and non-stationary data. Chen et al. (2016) employed a CNN model to extract more comprehensive data features, which proved effective upon validation through simulated trading using Taiwan Stock Index Futures data. Correlations between instances and features are utilized to order the features before they are presented as inputs to the CNN. Gunduz et al. (2017), through testing on the Istanbul Stock Exchange 100 Index stocks, the method combining a specific ordered feature set with CNN is able to effectively capture the correlations in the stock market.

Long et al. (2019) undertook some innovative work in feature engineering, proposing the Multi-filters Neural Network (MFNN) that can capture richer price market features. This approach proved to be superior to traditional machine learning models and single-structure network models through testing on China's CSI 300. Kim and Kim (2019) also conducted tests on the S&P 500 EFT and discovered that candlestick charts are suitable for price prediction. By incorporating image features, it is easier to achieve good results and reduce prediction errors. In their study, Chung and Shin (2020) propose a method to systematically optimize the parameters for the CNN model by using a genetic algorithm (GA) and test in KOSPI. Lee and Kim (2020) introduced a novel model called NuNet, which is an integrated neural network framework composed of two feature extractor modules. One is the ultra-high-dimensional market information feature extractor, and the other is the target index feature extractor. The model was validated in markets such as S&P 500, KOSPI 200, and FTSE100, and the test results showed that the profits were 2.57 times higher than the benchmark market profits, outperforming the buy-and-hold strategy. Zhou et al. (2022) made some new attempts to introduce The Bidirectional Gated Recurrent Unit (BGRU), this model is tested on Shanghai Composite Index, Shenzhen Composite index, CSI 300, Growth Enterprise Index, China National Petroleum Corporation (CNPC), China State Construction Engineering Corporation (CSCEC), China Railway Rolling stock Corporation (CRRC) and Shanghai Automotive Industry Corporation (SAIC).

Zaheer et al. (2023) conducted an experimental study focusing on the Shanghai Composite Index (000001), incorporating various comparisons with existing techniques. These techniques encompassed CNN, RNN, LSTM, CNN-RNN, and CNN-LSTM. The objective was to evaluate these models' capability in addressing the challenges posed by noise, nonlinearity, and volatility in stock market predictions. The findings of this experiment indicate a notable improvement over the preliminary tests.

Md et al., (2023) introduces a cutting-edge optimization technique for forecasting stock prices, leveraging a Multi-Layer Sequential Long Short-Term Memory (MLS-LSTM) model and test in S&P 500 index. The findings demonstrate that the MLS-LSTM algorithm significantly outperforms other conventional machine learning and deep learning algorithms in terms of prediction accuracy.

Xing et al., (2024) X designed a comparative experiment to forecast the price of a single stock, specifically NVIDIA, over the period spanning from 2019 to 2024. The experiment encompassed traditional neural network models, econometric models, and the state-of-the-art LSTM model. Based on the experimental outcomes, the LSTM model yielded promising results, exhibiting a Mean Absolute Error (MAE) of 14.3815, a Root Mean Square Error (RMSE) of 20.9397, and a coefficient of determination (R^2) of 0.9859. These findings indicate the effectiveness of the LSTM model in predicting stock prices.

Shi et al. (2024) Y postulates a plausible hypothesis that significant fluctuations in stock prices are primarily driven by high-volume transactions, which tend to occur in clusters of stocks sharing common characteristics, such as stocks from the same industry, region, concept, or exhibiting similar volatility patterns. Consequently, Y endeavors to predict such fluctuations by utilizing a novel hybrid model that combines a graph convolutional network (GCN) with an LSTM model. The proposed model achieves a commendable accuracy of 57.81%, significantly outperforming the baseline models.

Numerous studies have explored the application of LSTM models in forecasting stock prices with varying degrees of success. For instance, some models that incorporate only raw historical prices have shown limited predictive accuracy due to their inability to capture market dynamics such as momentum or volume fluctuations. In contrast, studies that enhance LSTM models with technical indicators—such as RSI, MACD, or moving averages—report significantly improved performance in terms of reduced RMSE and increased directional accuracy. Additionally, some researchers have proposed hybrid models combining LSTM with other techniques such as attention mechanisms or convolutional layers, further improving feature extraction and temporal awareness. These comparisons suggest that while LSTM outperforms traditional models like ARIMA in most cases, its effectiveness is highly dependent on the quality and diversity of input features as well as model architecture choices.

Table 2.1 presents a comprehensive overview of recent studies employing LSTM and its hybrid variations for stock price forecasting across different global markets. A clear trend emerges in favor of deep learning architectures, particularly LSTM, which consistently outperform traditional econometric methods due to their ability to capture nonlinear temporal dependencies. Notably, seminal studies such as Nelson et al. (2017), Fischer and Krauss (2018), and Mehtab et al. (2021) demonstrate the standalone effectiveness of LSTM models in various stock indices, including the Ibovespa, S&P 500, and NIFTY50.

However, a growing number of studies have moved beyond raw price inputs, integrating technical indicators to enrich feature representation and improve forecasting performance. For example, Borovkova and Tsiamas (2019), Md et al. (2023), and Xing et al. (2024) illustrate that combining LSTM with momentum, trend, and volume-based indicators leads to superior accuracy. This trend underlines the evolving consensus that price alone is insufficient to capture the complexity of financial markets, especially in high-volatility environments.

Moreover, hybrid models such as CNN-LSTM, GCN-LSTM, and FS-CNN-BGRU reflect efforts to leverage both spatial and sequential patterns in financial time