COMBINING TECHNICAL ANALYSIS AND DEEP LEARNING MODELS FOR STOCK MARKET TRADING

Mr. Phurinut Pholsri

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Computer Science
Department of Computer Engineering
FACULTY OF ENGINEERING
Chulalongkorn University
Academic Year 2022

การผสานการวิเคราะห์เชิงเทคนิคและแบบจำลองการเรียนรู้เชิงลึกสำหรับการซื้อขายหุ้น

นายภูริณัฐ พลศรี

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาวิทยาศาสตร์คอมพิวเตอร์ ภาควิชาวิศวกรรมคอมพิวเตอร์
คณะวิศวกรรมศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2565

Thesis Title	COMBINING TECHNICAL ANALYSIS AND DEEP LEARNING MODELS FOR STOCK MARKET TRADING
By	Mr. Phurinut Pholsri
Field of Study	Computer Science
Thesis Advisor	Assistant Professor Dr. PITTIPOL KANTAVAT

Accepted by the FACULTY OF ENGINEERING, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Science

.... Dean of the FACULTY OF ENGINEERING

(Professor Dr. SUPOT TEACHAVORASINSKUN)

THESIS COMMITTEE

.... Chairman

(Professor Dr. BOONSERM KIJSIRIKUL)

.... Thesis Advisor

(Assistant Professor Dr. PITTIPOL KANTAVAT)

.... External Examiner

(Assistant Professor Dr. Kridsda Nimmanunta)

ภูริณัฐ พลศรี : การผสานการวิเคราะห์เชิงเทคนิคและแบบจำลองการเรียนรู้เชิงลึกสำหรับการซื้อขายหุ้น. (COMBINING TECHNICAL ANALYSIS AND DEEP LEARNING MODELS FOR STOCK MARKET TRADING) อ.ที่ปรึกษาหลัก : ผู้ช่วยศาสตราจารย์ ดร.พิตติพล คันธวัฒน์

การออกหุ้นเป็นวิธีหนึ่งที่ใช้แสดงถึงการเป็นเจ้าของในบริษัท และการกระจายหุ้นอาจแตกต่างกันขึ้นอยู่กับว่าบริษัทเป็นบริษัทจำกัดหรือบริษัทสาธารณะ ตลาดหลักทรัพย์นั้นเสนอโอกาสในการได้รับผลตอบแทนสูง ซึ่งทำให้เป็นทางเลือกที่น่าสนใจสำหรับการลงทุน ก่อนการศึกษานี้จะมีวัตถุประสงค์เพื่อพัฒนาโมเดลทำนายราคาหุ้นที่สามารถช่วยให้มีผลการซื้อขายที่ได้กำไร ในการบรรลุวัตถุประสงค์นี้ การศึกษาเน้นการซื้อขายในระหว่างวันและตลอดชั่วโมง และใช้โมเดลแบบผสานที่รวมเอา Bidirectional Long Short-Term Memory (BiLSTM) และ Convolutional Neural Network (CNN) พร้อมกับตัวชี้วัดทางเทคนิค BiLSTM เป็นโครงสร้างของเครือข่ายประสาทเทียมที่สามารถประมวลผลข้อมูลลำดับได้ทั้งในทิศทางข้างหน้าและข้างหลัง ซึ่งทำให้โมเดลมีความสามารถในการจับความสัมพันธ์ภายในข้อมูลได้ดียิ่งขึ้น จากนั้นทำการประเมินประสิทธิภาพของโมเดลที่ได้ผลลัพธ์ออกมาโดยเปรียบเทียบกับการวิเคราะห์ทางเทคนิค การตรวจสอบทางประสิทธิภาพของโมเดลนี้ใช้หุ้นทางเทคโนโลยีที่ระบุในดัชนี NASDAQ เพื่อแสดงให้เห็นถึงว่าโมเดลผสมระหว่าง CNN และ BiLSTM สามารถทำให้มีผลการซื้อขายที่ได้กำไรในตลาดหลักทรัพย์ได้ดีกว่าการวิเคราะห์ทางเทคนิค

สาขาวิชา	วิทยาศาสตร์คอมพิวเตอร์	ลายมือชื่อนิสิต ....
ปีการศึกษา	2565	ลายมือชื่อ อ.ที่ปรึกษาหลัก ....

6370233921 : MAJOR COMPUTER SCIENCE

KEYWORD:

Phurinut Pholsri : COMBINING TECHNICAL ANALYSIS AND DEEP LEARNING MODELS FOR STOCK MARKET TRADING. Advisor: Asst. Prof. Dr. PITTIPOL KANTAVAT

The issuance of stocks constitutes a means by which ownership in a company is represented, and its distribution may vary depending on whether the company is limited or public. The stock market offers the potential for high returns, thereby serving as an attractive avenue for investment. Against this backdrop, the objective of this study is to develop a predictive model for stock prices that can facilitate profitable trading outcomes. To achieve this aim, the study focuses on intraday and hourly trading and utilizes a hybrid model that integrates Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Network (CNN) architectures, along with technical indicators. BiLSTM is a neural network architecture that possesses the capability to process sequential data in both forward and backward directions, thereby augmenting the model's ability to capture dependencies within the data. The efficacy of the resulting model is subsequently evaluated through a comparison with technical analysis. Empirical validation of the model is carried out using technology stocks that are listed on the NASDAQ index. The experimental findings demonstrate that the hybrid architecture of CNN and BiLSTM can outperform technical analysis in terms of achieving profitable trading outcomes in the stock market.

Field of Study:	Computer Science	Student's Signature ....
Academic Year:	2022	Advisor's Signature ....

ACKNOWLEDGEMENTS

วิทยานิพนธ์นี้สำเร็จลุล่วงได้ด้วยความกรุณาจาก อาจารย์ ดร. พิตติพล คันธวัฒน์ อาจารย์ที่ปรึกษาวิทยานิพนธ์ ซึ่งเป็นผู้ที่คอยให้คำปรึกษา ทั้งในด้านวิชาการและด้านอื่นๆ นอกจากนี้ยังเป็นผู้ช่วยตรวจทานให้คำแนะนำในการปรับปรุง วิทยานิพนธ์นี้จนสาเร็จไปได้ด้วยดี ผมจึงขอขอบพระคุณอาจารย์เป็นอย่างสูงมา ณ ที่นี้ด้วย ครับ

ขอขอบคุณ ศาสตราจารย์ ดร. บุญเสริม กิจศิริกุล และ ผู้ช่วยศาสตราจารย์ ดร. กฤษฎา นิมมานันทน์ ที่ให้เกียรติมาเป็นประธานกรรมการและกรรมการสอบวิทยานิพนธ์ และช่วยชี้แนะแนวทาง ในการปรับปรุงวิทยานิพนธ์ให้มีคุณภาพยิ่งขึ้น

ขอขอบคุณบริษัท Tech Globe Co.,Ltd สำหรับการสนับสนุนข้อมูลสำหรับการทำวิทยานิพนธ์

สุดท้ายนี้ขอขอบคุณ คุณพ่อ คุณแม่ ครอบครัว และเพื่อน ๆ ที่คอยให้กำลังใจและการสนับสนุนในการเรียนระดับปริญญาโท และการทำวิทยานิพนธ์เสมอมา จนกระทั่งวิทยานิพนธ์ฉบับนี้สำเร็จลุล่วงไปได้ด้วยดี

Phurinut Pholsri

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

Page

Chapter 1

Introduction

1.1 Introduction

Equity securities, commonly known as "stocks," are issued by companies to investors to represent ownership rights in the company, proportional to the shares held. The stocks of each company can be distributed to shareholders differently, depending on whether it is a limited company (Company Limited) or a public company (Public Company Limited). Only public companies allow the general public to own shares through trading in the stock market. The stock market is popular nowadays because it can provide relatively high returns, either in the form of price differences (Capital Gain/Loss) or dividends.

The value of stocks does not solely depend on a company's performance, as past events have shown. Factors such as government economic policies, global market trends, and even investor sentiment (Trader Sentiment) can cause stock values to fluctuate. To predict stock prices, many studies have attempted to develop various asset price prediction models, such as Autoregressive Integrated Moving Average (ARIMA) [1, 2], Random walk [1], Genetic algorithm (GA) [2], and later, Support Vector Machine (SVM) [1], which became very popular.

Artificial neural networks have also played a role in model development. Tsantekidis et al. [3] found that Convolutional Neural Networks (CNN) can predict stock prices more accurately than SVM. In the studies of Sisodia [4], Yang [5], and Wisaroot [6], it was discovered that using hybrid models results in better performance than using a single type of model. Therefore, in the field of stock price prediction, it is important to consider all possible factors and use various models to create a more accurate prediction.

Time series data is a commonly encountered type of data that changes over time and processing it can be difficult due to its dynamic nature. To address this, recurrent neural networks (RNNs) have gained popularity for processing time series data, with Long Short-Term Memory (LSTM) networks being particularly effective in capturing temporal dependencies. The advantages of using gated cells in LSTM networks have been further supported by Hasan et al. in their publication "LSTM Cells" [7]. The effectiveness of LSTM networks has been demonstrated in various time-series applications, including credit card fraud detection by Ibtissam [8], semantic similarity prediction by D. Meenakshi [9], and gamelan melody generation by Arry M. Syarif [10] among others.

In this research, the primary focus is directed towards the Bi-directional Long Short-Term Memory (Bi-LSTM) neural network architecture, which represents an extension of the LSTM network. The Bi-LSTM model processes the input sequence in both forward and backward directions, allowing it to capture contextual information from past and future time steps. This feature renders the Bi-LSTM network particularly well-suited for time series prediction tasks that rely on leveraging historical and future data. A recent investigation by Sunny et al. [11] implemented the Bi-LSTM model for predicting stock prices, demonstrating the efficacy of this model for prediction tasks. In further recent research, Ibrahim et al. [12] proposed a hybrid CNN-BiLSTM model for univariate time-series anomaly detection using artificial intelligence. This model captures both temporal and spatial features of input data, resulting in superior anomaly detection compared to traditional methods. The study's contribution to the field of time-series anomaly detection is noteworthy, and the reference may be valuable for future research in this area. Specifically, researchers seeking to improve traditional anomaly detection methods for time-series data can benefit from examining the proposed hybrid model.

In this study, we present a novel approach that integrates CNNs with LSTM and BiLSTM models for stock trading. To the best of our knowledge, no prior research has investigated the combined use of BiLSTM with these stocks. Our investigation aims to identify the optimal sequence structure for CNN-LSTM and CNN-BiLSTM models, with the ultimate goal of generating stock trading signals that outperform traditional long-term indicators in terms of average returns. Specifically, we focus on a 1-hour timeframe to explore the possibilities and optimize efficiency.

Chapter 2

Related Theory

2.1 Deep Learning

2.1.1 Artificial Neural Networks (ANN) [13]

Artificial Neural Networks (ANN) is one of the popular machine learning techniques. It is inspired by the neural networks in the human brain. The human nervous system is composed of numerous cells called neurons, and each neuron is connected to each other through axons (output axons) and dendrites (input axons). The area where the axons and dendrites are connected is called synapses. Synapses are constantly changing due to external stimuli, as this change is a learning mechanism found in living organisms.

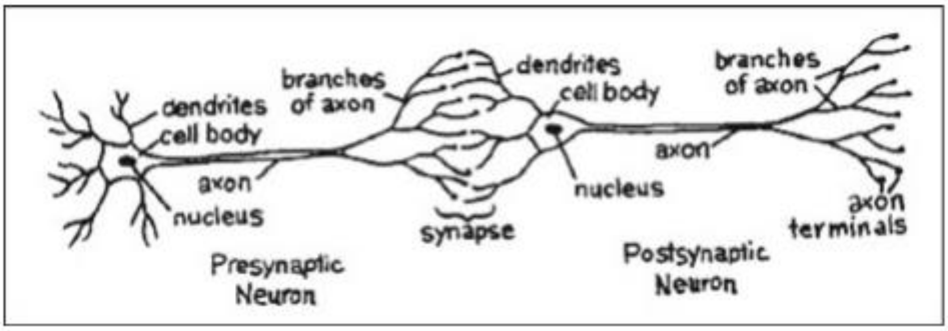

Figure 1 Simulation image depicting the biological neural network [13].

The concept of biological neural networks has been used to create artificial neural networks, where processing units replace neurons, and these processing units are interconnected similar to the axons and dendrites. Each interconnection is called an edge, and each edge has a weight value associated with it. This structure is depicted in Figure 2. When the artificial neural network is trained, the weights of the edges in the model undergo changes, enabling the model to learn and memorize patterns in the data. This results in an artificial neural network that can be further utilized.

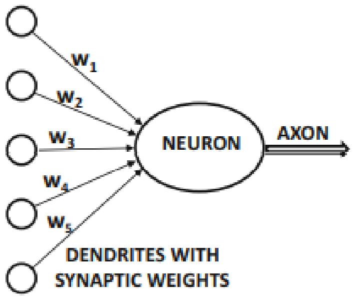

Figure 2 Simulation image of an artificial neural network [13].

2.1.2 Convolutional Neural Network (CNN) [14]

Convolutional Neural Network (CNN) is a highly popular model of artificial neural network because it can be applied to various fields such as Computer Vision, Speech Processing, Face Recognition, and many others. One of the key advantages of CNN is its ability to learn features from data without the need for human supervision.

In general, CNNs are similar to multi-layer perceptron (MLP) networks. They consist of multiple Convolution layers followed by Sub-sampling (pooling) layers, and the final layer is the Fully Connected Layer, as shown in Figure 3.

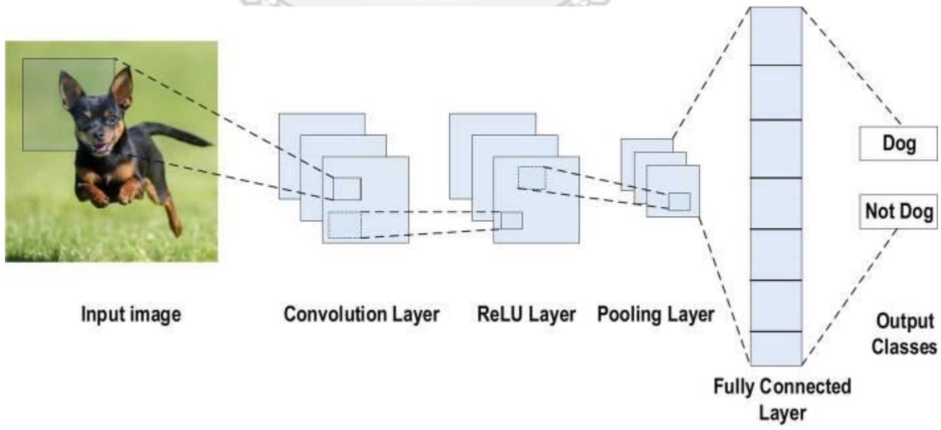

Figure 3 Example of CNN architecture for image classification [14].

The architectural structure of a CNN consists of numerous layers, also known as multi-building blocks. Each layer is composed of the following:

Convolution Layer: This is the most crucial part of the CNN architecture as it is the layer used for filters to create important features and influence the model's output. It utilizes kernels, which are grids with randomly generated numerical values. Each number represents the weight of each channel, which helps extract meaningful features from raw data.

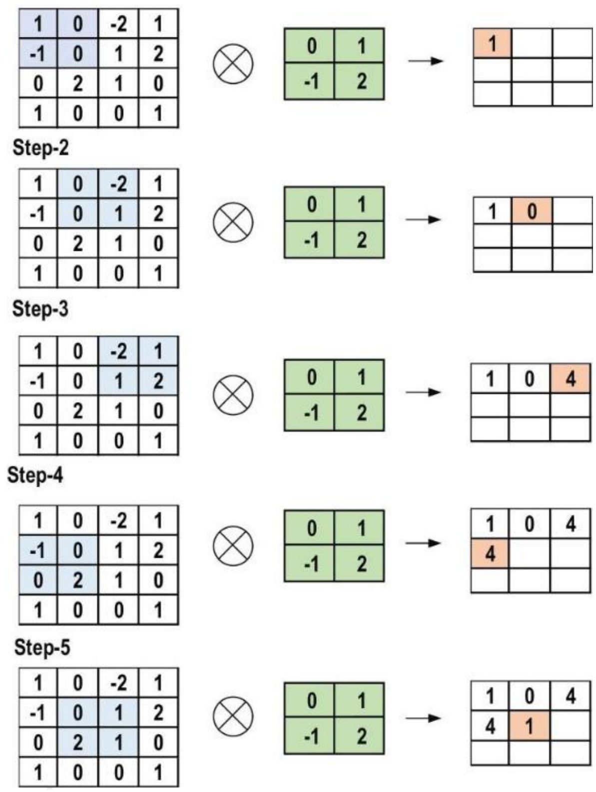

Figure 4 Example of Convolutional operation [14].

The main objective of a pooling layer is to downsample the features obtained after convolutional operations or to reduce the size of data while preserving their essential characteristics. It achieves this by randomly sampling sub-regions. There are various methods to accomplish this, such as average pooling, max pooling, global average pooling, and others.

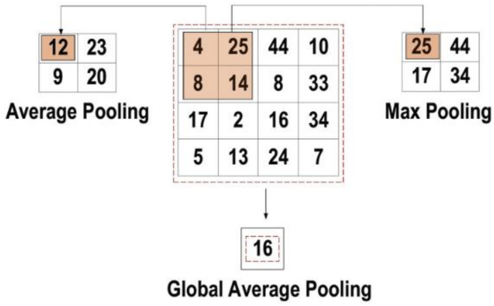

Figure 5 Examples of Average Pooling, Max Pooling, and Global Average Pooling [14].

Fully Connected Layers: Generally, this layer is the last layer of a CNN architecture. Within this layer, neurons are connected to all neurons of the previous layer. This technique is called Fully Connected (FC) and is characteristic of a CNN classifier. The input here is a vector generated from the extracted features in the previous layers. The output of the FC layer is the result of the CNN, as shown in Figure 6.

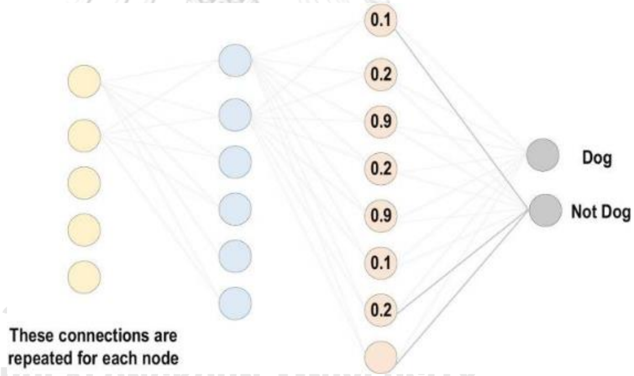

Figure 6 Example of Fully Connected Layer [14].

2.1.3 Long Short-Term Memory (LSTM) [15]

LSTM was introduced by Hochreiter and Schmidhuber in 1997 to address the issues of traditional RNNs, which often suffer from the vanishing gradient problem, preventing the models from effectively learning information from early stages. However, LSTM is designed to overcome this limitation and enable long-term learning and memory retention. The key component of LSTM is the cell state (C_t), which travels along the nodes of the LSTM and undergoes transformations through various input gates in each node.

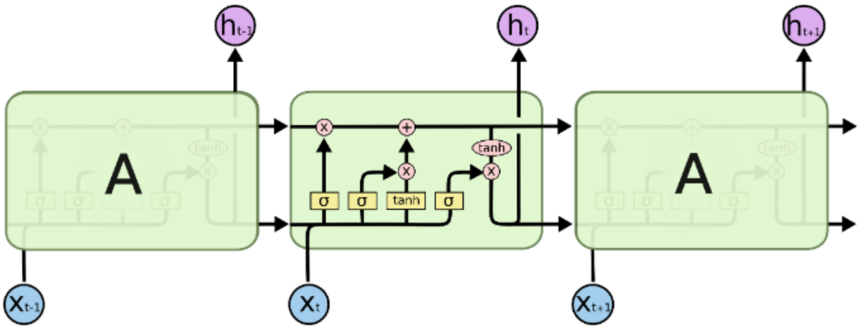

Figure 7 The architecture of LSTM [15].

For the initial step, the decision-making process for data filtering is performed using a Sigmoid layer called the 'Forget gate layer.' The Sigmoid function takes inputs h_{t-1} and x_t according to Equation (1), and the resulting output from the function is a value between 0 and 1. A value of 1 indicates that the data should be retained, while a value of 0 means the data should be completely discarded.

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

In the next part, the decision is made on what to store in the cell state, which consists of two components. The first component is the Sigmoid layer called the 'Input gate layer,' which determines what values to update. The second component is the Tanh layer, which represents the candidate layer. These two components are combined and used to update the cell state according to Equations (2) and (3).

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

$$\tilde{C}_t = \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{3}$$

In the final part, the decision is made on what will be taken out as the output. In this section, the values of h_{t-1} and x_t are computed and used in the Sigmoid function to obtain o_t, as shown in Equation (4). Then, C_t is multiplied by the output from the Tanh function, represented as o_t, according to Equation (5), to ensure that only the selected portion is included in the final output.

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t \right] + b_o \right) \tag{4}$$

$$h_t = o_t * \tanh\left(\mathrm{C_t} \right) \tag{5}$$

2.1.4 Bidirectional Long Short-Term Memory Networks [16]

A Bidirectional LSTM, also known as a BiLSTM, is a powerful sequence processing model composed of two LSTMs working in tandem. One LSTM processes the input sequence in the forward direction, while the other processes it in the backward direction. This bidirectional architecture enhances the network's understanding by incorporating both past and future information at each time step. By considering the words that come before and after a particular word in a sentence, BiLSTMs provide a richer context for the algorithm, leading to improved performance and comprehension.

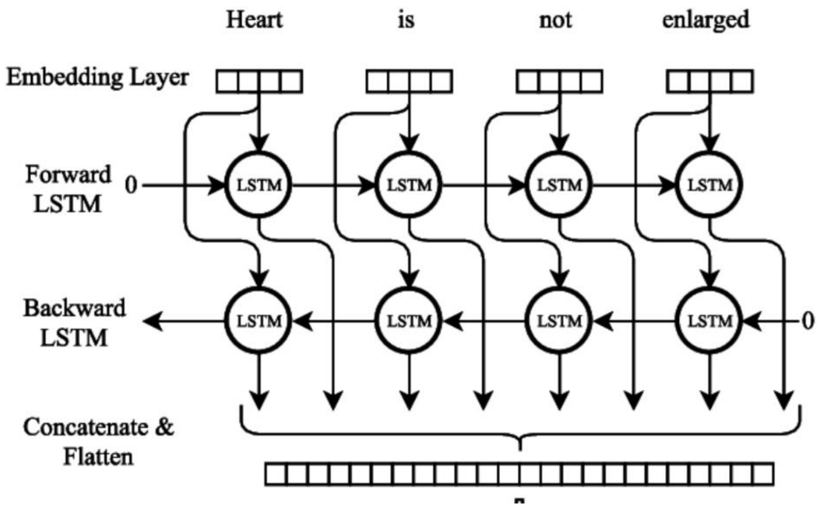

Figure 8 The architecture of BiLSTM [17].

2.2 Technical Analysis [18]

Certain types of assets, such as gold, currency, and oil, often rely on price and trading volume data from the past to predict future price trends. This approach is known as technical analysis and differs from fundamental analysis, which requires financial data for prediction. Technical analysis can be conducted in various forms, including:

1. Analyzing past price patterns, such as Double Top, Double Bottom, and Triangle patterns.
2. Creating trend lines to identify appropriate buying and selling prices, such as support and resistance lines.
3. Utilizing historical data to calculate technical indicators. In this research, the focus will be on Technical Indicators, which will be discussed in detail.

There are several types of technical indicators, but in this study, we will explain the specific type that is compared with the learning model framework.

2.2.1 Moving Average (MA)

Moving Average is a method of calculating the average using price data of stocks over a specified period N. Normally, a single average value is insufficient for analysis purposes. Therefore, the Moving Average method calculates multiple average values and plots them as a line graph by arranging the consecutive calculated average values. When the variable N has a larger value, it results in a smoother graph.

The commonly used Moving Average in analysis is the comparison between short-term Moving Average and long-term Moving Average. If the short-term Moving Average line intersects above the long-term Moving Average line, it is called a Golden Cross, indicating an uptrend or a buying point. Conversely, if the short-term Moving Average line crosses below the long-term Moving Average line, it is called a Dead Cross, indicating a downtrend or a selling point.

2.2.2 Moving Average Convergence/Divergence (MACD)

Moving Average Convergence/Divergence (MACD) is a method that illustrates the relationship between two periods of average prices. It calculates the difference between two lines of exponential moving averages with different time periods. Generally, a 12-day and a 26-day period are used.

The Signal line is an exponential moving average typically calculated over 9 days. When the MACD line crosses above the Signal line, it indicates a buying signal. Conversely, when the MACD line crosses below the Signal line, it indicates a selling signal.

2.2.3 Relative Strength Index (RSI)

Relative Strength Index (RSI) is a market indicator that measures the strength of the market, with a value ranging from 0 to 100. RSI is calculated based on the ratio of the upward price changes to the downward price changes over a specified period of time, according to Equation (6).

$$RSI = 100 - \frac{100}{1 + \frac{U_N}{D_N}} \tag{6}$$

Methods for analyzing buying and selling signals from RSI vary, but the most popular method is to analyze whether the market is overbought or oversold. When the RSI line crosses above 70, it indicates that the market is overbought, suggesting that the price may decline even if it is in an uptrend. Conversely, when the RSI line crosses below 30, it indicates that the market is oversold, indicating that the price may recover and increase even if it is in a downtrend.

2.2.4 Stochastic Oscillators

Stochastic Oscillators measure the volatility of prices and study the relationship between price movements within a certain period and the closing price. It is observed that if the price is increasing and has an upward trend, the closing price tends to be near the highest price. On the other hand, if the price is decreasing and has a downward trend, the closing price tends to be at the same level as the lowest price of the day. Typically, a 14-day period is used, and the oscillation ranges from 0% to 100%.

Stochastic Oscillators consist of two lines: %K and %D, which are calculated using Equation (7). The commonly used method for analyzing buying and selling signals from Stochastic Oscillators is as follows: When the %K line crosses above the %D line in the oversold region below 20%, it indicates a buying signal. Conversely, when the %K line crosses below the %D line in the overbought region above 80%, it indicates a selling signal.

$$\% K = 100\left(\frac{C_t - LL_{t(14-1)}}{HH_{t-(14-1)} - LL_{t-(14-1)}}\right) \quad (7)$$

C_t the latest closing price.

$LL_{t-(14-1)}$ the lowest price within a 14-day period.

$HH_{t-(14-1)}$ the highest price within a 14-day period.

$\% D$ the latest 3-day average of %K.

Chapter 3

Literature Review

The prediction of stock prices through machine learning techniques has gained significant attention in the field of financial analysis and investment decision-making. This increased interest is driven by the recognition that traditional statistical models often struggle to capture the complex patterns and dynamics present in financial time series data. Machine learning models, on the other hand, offer the advantage of being able to learn and adapt from historical data, enabling them to uncover hidden patterns and make more accurate predictions. Among the various machine learning techniques, LSTM neural networks have emerged as a popular choice for analyzing time series data, including stock prices. LSTM models are a type of RNN that are designed to overcome the limitations of traditional RNNs, which struggle with capturing long-term dependencies. LSTM networks incorporate memory cells and gating mechanisms that allow them to retain and selectively update information over longer sequences, making them particularly well-suited for analyzing financial data with longer time frames. Researchers have conducted several studies utilizing LSTM models for stock price prediction, showcasing their effectiveness. For example, Sisodia et al. [4] applied LSTM models to predict the prices of Nifty50 stocks, a stock market index in India. Their study demonstrated the ability of LSTM models to capture the underlying patterns and trends in stock prices, leading to accurate predictions. Similarly, Wisaroot et al. [6] focused on predicting crude oil prices using LSTM models. Crude oil prices are highly volatile and influenced by numerous factors, making them challenging to forecast accurately. However, the study showed that LSTM models were able to capture the complex dynamics of crude oil price movements, resulting in improved prediction accuracy. In another study by Z. He et al. [19], LSTM models were employed to predict daily gold prices. Gold prices are influenced by various economic and geopolitical factors, and accurately forecasting their movements is of great interest to investors. The study demonstrated that LSTM models could effectively capture the patterns and trends in gold prices, enabling accurate predictions.

While LSTM models have shown promise in stock price prediction, researchers have also explored other variants of RNNs. Sunny et al. [11] conducted a study to compare the performance of LSTM and BiLSTM models in predicting stock prices. BiLSTM models have the advantage of processing data in both forward and backward directions, allowing them to capture dependencies from the past and future simultaneously. The authors found that both LSTM and BiLSTM models outperformed other models in terms of predictive accuracy. Notably, the BiLSTM model exhibited even higher accuracy than the LSTM model, suggesting its potential for accurate forecasting of stock prices.

In addition to machine learning techniques, researchers have also explored the integration of traditional market analysis methods with neural network architecture to improve stock price prediction. Market profile theory, which examines price and volume data to identify market structures, has been combined with neural network models by Chen et al. [20]. By incorporating market profile theory into the neural network architecture, the study created a market profile indicator that considered both long-term and short-term trends. This combined approach led to improved forecasting performance and profitability, providing a comprehensive method to analyze financial markets.

Furthermore, Ganatra et al. [21] proposed the use of artificial neural networks for stock price prediction, highlighting their potential to outperform traditional techniques such as fundamental and technical analysis. They developed a spiking backpropagation multilayer neural network and optimized the accuracy of predictions by adjusting various network parameters. Their study demonstrated the potential of artificial neural networks in predicting unpredictable stock market prices, emphasizing the importance of considering various factors that affect their performance.

Considering the findings of these research studies, it becomes apparent that utilizing a hybrid neural network model, such as a BiLSTM or combining market profile theory with neural network architecture, can lead to more accurate predictions in stock market forecasting. These approaches leverage the strengths of different techniques to capture the complex dynamics of stock prices and provide valuable insights for investment decision-making. Therefore, in the present research, a hybrid neural network model that combines the advantages of LSTM and BiLSTM models, along with market profile theory, will be employed. The objective is to develop a comprehensive and robust approach for stock market forecasting that takes into account both the temporal dependencies in the data and the insights provided by market analysis techniques. By leveraging these methodologies, the aim is to achieve enhanced prediction accuracy and facilitate informed decision-making in financial markets.

Chapter 4

Methodology and Dataset

4.1 Proposed Method

The proposed methodology of this study involves an assessment of the predictive performance of three widely used neural network architectures, namely CNN, LSTM, and BiLSTM, for stock price prediction using technical indicators.

To evaluate the effectiveness of these models, four different configurations were considered: CNN-LSTM, LSTM-CNN, CNN-BiLSTM, and BiLSTM-CNN, as presented in Figures 1, 2, 3, and 4. Each configuration includes batch normalization, dense, and dropout layers, which are fundamental components of modern neural network architectures. Batch normalization is a layer that normalizes the input values of each mini-batch to mitigate the problem of internal covariate shift, thereby improving the stability and convergence of the model during training. Dense layers, also known as fully connected layers, connect all neurons from the previous layer to every neuron in the current layer, enabling the model to learn complex non-linear relationships between input features and output predictions. Dropout layers randomly remove some of the neurons during training, preventing the model from overfitting to the training data and improving its generalization capability. By incorporating these layers, the models' robustness and generalization capabilities are expected to be enhanced, enabling them to generate more accurate predictions of stock prices using technical indicators.

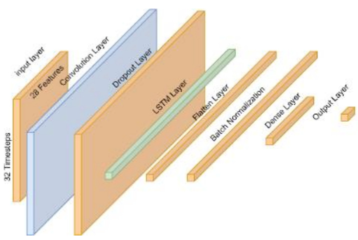

Figure 9 CNN-LSTM architecture.

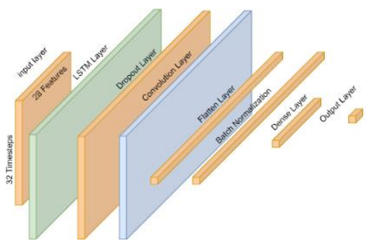

Figure 10 LSTM-CNN architecture

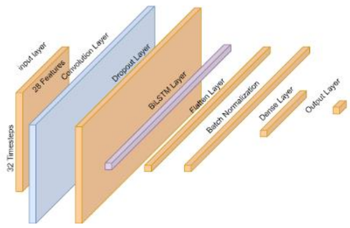

Figure 11 CNN-BiLSTM architecture

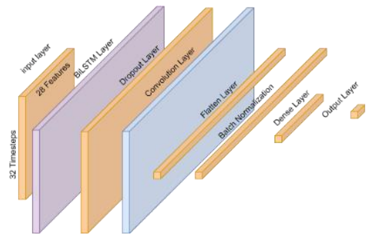

Figure 12 BiLSTM-CNN architecture

4.2 Experimental Dataset

This research project analyzed the stock prices of 12 select stocks, namely AMD, APA, DVN, GOOGL, MOS, MRNA, NFLX, NVDA, OXY, SQQQ, TQQQ, and TSLA. The study specifically concentrated on technology stocks that demonstrate notable growth potential and attract significant investor attention in the NASDAQ market. The data covers the period from 2019 to 2022 and includes the opening price, highest price, lowest price, closing price, and trading volume for each day. To calculate the technical indicators, the TA package [22] and methods proposed by Kumar et al. [23] were used, and the details of the technical indicators are shown in Table 1.

The collected data were divided into three groups: training data (first 3 weeks of the month), validation data (1 week after the training data), and testing data (1 year after the validation data), based on the time periods shown in Table II. The data in this section used 1-hour data, with the average number of data points used being 253 for training, 105 for validation, and 3,683 for testing, annually.

Table. 1 List of Indicators

Indicator Type	Indicator Name
Trend	Simple Moving Average (SMA)
	Moving Average Convergence (MACD)
	Average Directional Movement Index (ADX)
	Commodity Channel Index (CCI)
Momentum	Rate of Change (ROC)
	Relative Strength Index (RSI)
	True Strength Index (TSI)
	Stochastic RSI %K (%K)
	Stochastic RSI %D (%D)
	Williams %R (%R)
Volatility	Bollinger Bands (BB)
	Average True Range (ATR)
	Ulcer Index (UI)
Volume	Accumulation/Distribution Index (ADI)
	On-balance volume (OBV)
	Chaikin Money Flow (CMF)
	Force Index (FI)
	Money Flow Index (MFI)
	Volume-price trend (VPT)
	Volume Weighted Average Price (VWAP)

Table 2. Training, validation, and test data for the experiment

Dataset	2019		2020		2021		2022	
	Jan-Nov	Dec	Jan-Nov	Dec	Jan-Nov	Dec	Jan-Nov	Dec
2020								
2021								
2022								

Training Validation Test

4.3 Data Preprocessing and Labeling

Data transformation is necessary in this research due to the differences in the variable ranges. To prepare the data for neural network training, it will be transformed using the normalization method proposed by Kumar [24], which scales the data to the range of [0, 1] using the equation (8).

$$Scaled\ X_t = \left(\frac{X_t - X_{t-1}}{X_{max} - X_{min}}\right) \tag{8}$$

The label used in this research is the percentage change in the daily average price, calculated based on the previous day's closing price, as shown in equation 9.

$$y_t = \left(\frac{C_{t+1} - C_t}{C_t}\right) \tag{9}$$

Chapter 5

EXPERIMENT RESULTS

The performance of the neural network model was evaluated using two methods. The first method involved calculating the mean squared error (MSE), which measures the average squared difference between predicted and actual values. A lower MSE indicates better accuracy of the model in forecasting outcomes. The second method involved backtesting the model using a trading strategy to evaluate its profitability. Historical data was used to test the model, and signals to buy or sell were generated based on the percentage prediction of the daily average price change. A prediction value greater than 0 was interpreted as a buy signal, while a value less than 0 was interpreted as a sell signal.

Using both methods to evaluate the performance of the model is important to ensure its accuracy and profitability in a real trading environment. The predictive error measurement evaluates the accuracy and reliability of the model's predictions, while the trading strategy comparison assesses its profitability. The study compared four types of neural network models, CNN-LSTM, LSTM-CNN, CNN-BiLSTM, and BiLSTM-CNN, in interpreting buy-sell signals using a testing dataset. Additionally, traditional trading strategies such as buy-and-hold, RSI-based buy and sell signals, MACD-based buy and sell signals, SMA-based buy and sell signals, and Stochastics RSI %K and %D-based buy and sell signals were also compared to the neural network models.

5.1 Prediction Error

The objective of this study was to assess the performance of four different neural network models for sequence prediction tasks, namely BiLSTM-CNN, CNN-BiLSTM, LSTM-CNN, and CNN-LSTM, by utilizing the mean squared error (MSE) metric. The training and evaluation of these models were carried out using the configuration specified in Table 3. A grid search was conducted on the hyperparameters of the models, where the number of filters in the CNN layer (32, 64, 128, and 256), the number of nodes in the LSTM layer (32, 64, 128, and 256) were varied using validation data. The selection of the optimal hyperparameter configuration was based on the lowest MSE, which was determined through performance evaluation on test data.

Upon examination of Table 4, it becomes apparent that the mean squared error (MSE) values of all four models are indicative of their aptitude for trading, with the average MSE for the entire year 3 being ranked in order from BiLSTM-CNN, CNN-BiLSTM, LSTM-CNN, CNN-LSTM at 83.591×10^{-2}, 61.45×10^{-2}, 65.64×10^{-2}, and 52.96×10^{-2}, respectively. Nevertheless, in making an informed decision as to which model to employ, the return on investment (ROI) values presented in the Trading Performance section ought to serve as the paramount criterion.

Table 3. Model training configurations

Parameters	Configuration
Number of filters in the CNN layer	{32, 64, 128, 256}
Number of nodes in the LSTM layer	{32, 64, 128, 256}
Batch size	32
Optimize	Adam
Learning rate	1×10^{-4}

Table 4. Shows the MSE values of each stock in the test datasets for the year 2020, 2021, and 2022. The unit is 1x10^-2, and the bolded values indicate the minimum MSE for each dataset.

	2020				2021				2022			
STOCK	BiLSTM-CNN	CNN-BiLSTM	LSTM-CNN	CNN-LSTM	BiLSTM-CNN	CNN-BiLSTM	LSTM-CNN	CNN-LSTM	BiLSTM-CNN	CNN-BiLSTM	LSTM-CNN	CNN-LSTM
AMD	93.56	**27.41**	93.50	84.32	95.07	**30.67**	45.96	55.32	81.56	80.53	**27.74**	54.49
APA	**61.46**	74.58	61.98	70.69	83.43	74.47	**31.88**	50.42	97.20	**41.66**	83.40	67.94
DVN	83.98	98.86	100.03	**72.00**	**38.52**	74.42	54.99	59.97	49.03	38.01	**35.03**	44.97
GOOGL	85.79	89.04	94.70	**16.50**	75.27	62.59	78.46	**47.53**	92.40	83.17	93.56	**25.79**
MOS	94.68	98.67	99.88	**15.53**	54.20	**25.19**	88.43	58.82	91.76	**35.36**	47.27	61.92
MRNA	92.76	32.98	86.83	**17.74**	81.63	87.11	**42.65**	69.62	95.10	79.75	**29.37**	49.51
NFLX	81.12	79.45	**55.79**	56.42	77.26	68.28	53.93	**19.10**	86.28	**32.78**	37.04	59.53
NVDA	63.08	**48.38**	76.83	65.13	97.98	79.73	**22.53**	59.53	69.53	73.61	58.48	**54.12**
OXY	93.90	**45.83**	65.47	55.41	79.54	50.93	95.40	**14.26**	95.61	86.52	82.07	**61.09**
SQQQ	81.73	61.92	**47.85**	48.40	84.46	47.78	78.37	**43.64**	92.94	**26.23**	33.28	70.49
TQQQ	94.71	79.84	93.30	**50.52**	91.61	**61.38**	96.45	81.36	94.10	91.09	72.02	**50.19**
TSLA	67.77	**24.06**	55.56	54.39	87.66	**79.62**	85.81	91.48	82.36	**38.70**	57.42	51.22
Average	82.88	63.42	77.64	**50.59**	78.89	61.85	64.57	**54.25**	85.66	58.95	**54.27**	**54.27**

5.2 Trading Performance

The efficiency of trading is a measure of portfolio performance resulting from past trading at prices. In the trading simulation, investing $100 USD and buying stocks at the closing price of the day based on signals from the simulation model and selling all of them when a sell signal occurs. This research compares this trading strategy with traditional trading strategies such as buy-and-hold, RSI-based trading, MACD-based trading, SMA-based trading, and Stochastics RSI %K and %D-based trading.

The study empirically demonstrates the effectiveness of the employed trading strategies and offers insights into investment portfolio performance. ROI and Sharpe ratio serve as key performance indicators. ROI measures profitability, while Sharpe ratio evaluates risk-adjusted returns. Equations (10) and (11) provide specific formulations for these metrics, enabling evaluation and comparison of different strategies against the traditional buy-and-hold approach.

$$ROI = \frac{(Portfolio\,Value_i - Portfolio\,Value_{i-1})}{Portfolio\,Value_{i-1}} \quad (10)$$

$$Sharpe\ Ratio = \frac{(R_p - R_f)}{\sigma_p} \quad (11)$$

R_p is the average return of the investment portfolio

R_f is the risk-free rate of return (typically a government bond yield or a benchmark rate)

σ_p is the standard deviation of the portfolio's returns

Tables 5, 6, 7, and 8 present the ROI for each dataset, with green indicating a positive ROI and red indicating a negative ROI. The intensity of the color indicates the magnitude of the ROI, with darker shades of green representing higher profits and darker shades of red representing higher losses. Bold text denotes the highest ROI for each year, and parenthetical numbers indicate the ranking of the comparison models in stock trading.

The results displayed in Table 5 for the year 2020 demonstrate a net profit yielded by the average ROI. Notably, the BiLSTM-CNN model proved to be the most effective approach, with an average profit of 149.14% and a favorable average rank of 3.33. The Buy & Hold strategy ranked second as the most successful technique.

Table 6 presents the ROI outcomes for the year 2021, indicating that all models and trading techniques, with the exception of SQQQ, generated a net profit. The Buy and Hold strategy emerged as the most effective approach, producing an average ROI of 64.71 and an average rank of 3.33. The BiLSTM-CNN method also demonstrated comparable profitability, with an average ROI of 57.94 and an average rank of 3.58. Moreover, CNN- BiLSTM, LSTM-CNN, and CNN-LSTM models outperformed the original trading technique in terms of average ROI and rank values, except for Buy and Hold.

Table 7, which displays the results for 2022, shows an average ROI of 4 for both loss-making and profit-making methods. However, the mean ROI for the profit-making methods does not demonstrate a significant increase when compared to the figures of 2020 and 2021. Notably, three out of the four deep learning structures presented, namely CNN-BiLSTM, LSTM-CNN, and CNN-LSTM, outperformed the market and generated profits. In contrast, only two traditional trading methods, MACD and STO, demonstrated success in outperforming the market.

Table 8, it is noteworthy to mention the cumulative ROI of the three-year period derived from Table V, VI, and VII. A comprehensive analysis reveals that each strategy exhibits the capability to generate profits over the aforementioned timeframe. Notably, the BiLSTM CNN strategy emerges as the most lucrative option, boasting an impressive average ROI of 205.87% alongside a commendable average ranking of 2.75. Following closely behind, the Buy and Hold strategy secures the second position, delivering a respectable average ROI of 168.76% accompanied by an average ranking of 3.5. These findings shed light on the performance and profitability of the various strategies under consideration.

Table 5. Displays the ROI values of each trading strategy for the year 2020. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	91.85 (1)	78.72 (3)	37.03 (8)	37.95 (7)	88.34 (2)	-2.35 (9)	50.19 (4)	40.64 (6)	41.1 (5)
APA	1.86 (5)	27.77 (4)	-57.98 (9)	-23.64 (6)	-44.68 (8)	46.05 (3)	-40.1 (7)	52.82 (1)	51.96 (2)
DVN	-35.28 (3)	-55.72 (8)	-79.91 (9)	-40.02 (5)	-40.02 (4)	35.63 (1)	-47.27 (6)	22.85 (2)	-51.25 (7)
GOOGL	34.72 (1)	25.43 (3)	-1.31 (6)	17.25 (4)	26.33 (2)	7.99 (5)	-1.71 (7)	-4.1 (8)	-4.5 (9)
MOS	-1.36 (7)	27.88 (2)	34.25 (1)	11.76 (5)	9.92 (6)	14.58 (4)	-5.48 (8)	17.03 (3)	-14.77 (9)
MRNA	101.33 (6)	355.18 (3)	-40.37 (9)	141.64 (5)	486.69 (1)	163.34 (4)	43.83 (8)	360.59 (2)	61.25 (7)
NFLX	59.47 (6)	152.11 (1)	132.91 (2)	80.54 (3)	67.14 (5)	-25.84 (9)	57.29 (7)	1.58 (8)	70.98 (4)
NVDA	-5.69 (9)	124.88 (1)	68.67 (3)	44.39 (8)	121.15 (2)	46.29 (7)	47.73 (6)	48.52 (5)	54.52 (4)
OXY	-64.17 (8)	-31.54 (3)	-46.02 (5)	-68.58 (9)	-60.64 (7)	5.8 (2)	-58.75 (6)	89.89 (1)	-42.02 (4)
SQQQ	-43.83 (2)	-80.24 (8)	-73.25 (7)	-44.53 (3)	-86.14 (9)	-47.33 (4)	-35.8 (1)	-68.56 (5)	-72.24 (6)
TQQQ	100.37 (2)	54.54 (3)	-26.9 (9)	34.9 (7)	105.56 (1)	46.96 (5)	45.71 (6)	54.09 (4)	-12.87 (8)
TSLA	72.46 (9)	1110.72 (1)	254.19 (6)	149.45 (8)	677.83 (2)	401.75 (4)	158.06 (7)	496.34 (3)	299.92 (5)
Avg. ROI	25.98	149.14	16.78	28.43	112.62	57.74	17.81	92.64	31.84
Avg. Rank	4.92	3.33	6.17	5.83	4.08	4.75	6.08	4.00	5.83

Table 6. Displays the ROI values of each trading strategy for the year 2021. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	22.19 (4)	49.8 (2)	-10.02 (9)	13.87 (5)	55.12 (1)	3.17 (7)	-0.56 (8)	32.16 (3)	4.61 (6)
APA	123.37 (1)	23.03 (7)	46.8 (4)	109.82 (2)	63.83 (3)	38.87 (5)	2.46 (9)	14.93 (8)	26.78 (6)
DVN	86.99 (5)	96.35 (4)	136.9 (2)	133.17 (3)	141.81 (1)	30.96 (9)	76.14 (6)	31.71 (8)	67.98 (7)
GOOGL	43.54 (6)	71.66 (1)	62.93 (4)	63.02 (3)	67.54 (2)	21.56 (8)	45.5 (5)	9.17 (9)	21.93 (7)
MOS	47.05 (3)	43.09 (4)	26.28 (6)	7.49 (8)	50.71 (2)	33.43 (5)	53.78 (1)	-8.87 (9)	17.79 (7)
MRNA	123.9 (3)	93.71 (5)	-2.21 (8)	101.71 (4)	135.45 (2)	79.03 (6)	-23.44 (9)	161.85 (1)	51.77 (7)
NFLX	38.94 (1)	30.39 (3)	33.04 (2)	5.03 (7)	17.86 (5)	21.07 (4)	4.75 (8)	-13.76 (9)	14.21 (6)
NVDA	53.9 (6)	124.66 (2)	128.31 (1)	14.78 (9)	119.49 (3)	106.41 (4)	17.68 (8)	95.4 (5)	30.63 (7)
OXY	62.01 (3)	76.26 (2)	12.77 (8)	50.52 (5)	50.83 (4)	98.9 (1)	31.48 (6)	-18.2 (9)	19.5 (7)
SQQQ	-27.54 (4)	-60.61 (8)	-36.51 (5)	-3.97 (1)	-61.06 (9)	-16.51 (2)	-24.35 (3)	-52.88 (7)	-49.57 (6)
TQQQ	-12.31 (9)	95.53 (2)	127.42 (1)	13.24 (7)	94.08 (3)	85.35 (4)	25.29 (5)	9.45 (8)	22.34 (6)
TSLA	41.44 (4)	51.39 (3)	70.3 (1)	51.64 (2)	40.86 (5)	15.87 (6)	-0.13 (9)	15.72 (7)	1.31 (8)
Avg. ROI	50.29	57.94	49.67	46.69	64.71	43.18	17.38	23.06	19.11
Avg. Rank	4.08	3.58	4.25	4.67	3.33	5.08	6.42	6.92	6.67

Table 7. Displays the ROI values of each trading strategy for the year 2022. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	-20.88 (5)	-60.12 (9)	-46.72 (6)	8.86 (2)	-54.97 (8)	17.07 (1)	-7.21 (4)	-54.01 (7)	-3.45 (3)
APA	98.37 (1)	43.4 (6)	29.83 (7)	24.79 (8)	58.53 (5)	63.95 (4)	66.4 (3)	18.12 (9)	75.69 (2)
DVN	-11.28 (7)	85.25 (1)	25.59 (5)	-13.67 (8)	28.03 (3)	20.73 (6)	27.02 (4)	34.06 (2)	-20.39 (9)
GOOGL	-32.95 (6)	-34.7 (7)	-30.64 (5)	-21.7 (4)	-35.82 (9)	-4.46 (1)	-21.4 (3)	-35.15 (8)	-6.63 (2)
MOS	-4.52 (4)	-2.11 (3)	37.32 (1)	-9.25 (6)	12.49 (2)	-11.43 (7)	-12.29 (8)	-15.72 (9)	-9.23 (5)
MRNA	2.75 (3)	-30.31 (9)	-8.98 (6)	42.3 (1)	-22.98 (7)	-8.42 (5)	-25.96 (8)	1.4 (4)	5.76 (2)
NFLX	-18.94 (3)	-54.11 (9)	-33.31 (6)	-4.9 (1)	-49.63 (8)	-26.82 (4)	-10.93 (2)	-31.13 (5)	-34.31 (7)
NVDA	-66.06 (9)	12.85 (2)	-18.04 (4)	-32.85 (6)	-49.58 (8)	9.87 (3)	-21.6 (5)	-44.22 (7)	51.1 (1)
OXY	134.92 (2)	96.28 (3)	157.68 (1)	90.25 (4)	88.46 (5)	48.28 (7)	52.13 (6)	10.48 (8)	-5.67 (9)
SQQQ	146.07 (1)	65.01 (4)	80.42 (3)	36.87 (7)	62.8 (5)	92.32 (2)	11.8 (8)	-1.51 (9)	38 (6)
TQQQ	-44.1 (5)	-74 (8)	-20.72 (1)	-28.16 (3)	-76.02 (9)	-22.84 (2)	-62.05 (7)	-61.87 (6)	-38.12 (4)
TSLA	-37.71 (4)	-61.95 (7)	-14.83 (1)	-41.26 (5)	-63.42 (9)	-42.8 (6)	-62.01 (8)	-34.78 (3)	-33.84 (2)
Avg. ROI	12.14	-1.21	13.13	4.27	-8.51	11.29	-5.51	-17.86	1.58
Avg. Rank	4.17	5.67	3.83	4.58	6.5	4	5.5	6.42	4.33

Table 8. Displays the ROI values of the trading strategy for a total of 3 years. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	93.17 (1)	68.4 (3)	-19.72 (9)	60.69 (4)	88.43 (2)	17.87 (8)	42.4 (5)	18.75 (7)	42.22 (6)
APA	223.6 (1)	94.2 (5)	18.65 (9)	110.97 (4)	77.62 (7)	148.83 (3)	28.69 (8)	85.83 (6)	154.35 (2)
DVN	40.42 (8)	125.88 (2)	82.58 (5)	79.48 (6)	129.76 (1)	87.27 (4)	55.83 (7)	88.59 (3)	-3.72 (9)
GOOGL	45.31 (4)	62.4 (1)	30.99 (5)	58.56 (2)	57.99 (3)	25.05 (6)	22.35 (7)	-30.09 (9)	10.76 (8)
MOS	41.18 (4)	68.85 (3)	97.85 (1)	10 (7)	73.06 (2)	36.54 (5)	35.96 (6)	-7.59 (9)	-6.26 (8)
MRNA	227.98 (6)	418.58 (3)	-51.55 (9)	285.65 (4)	599.1 (1)	233.94 (5)	-5.63 (8)	523.79 (2)	118.78 (7)
NFLX	79.48 (4)	128.39 (2)	132.64 (1)	80.67 (3)	35.31 (7)	-31.62 (8)	51.08 (5)	-43.34 (9)	50.82 (6)
NVDA	-17.85 (9)	262.4 (1)	178.94 (3)	26.33 (8)	191 (2)	162.55 (4)	43.79 (7)	99.66 (6)	136.22 (5)
OXY	132.76 (3)	141 (2)	124.43 (4)	72.2 (7)	78.59 (6)	152.91 (1)	24.79 (8)	82.13 (5)	-28.2 (9)
SQQQ	74.7 (1)	-75.84 (6)	-29.35 (4)	-11.63 (3)	-84.46 (8)	28.42 (2)	-48.38 (5)	-122.97 (9)	-83.83 (7)
TQQQ	43.96 (5)	76.07 (4)	79.81 (3)	19.98 (6)	123.56 (1)	109.44 (2)	8.94 (7)	1.65 (8)	-28.66 (9)
TSLA	76.19 (9)	1100.16 (1)	309.66 (5)	159.83 (7)	655.21 (2)	374.72 (4)	95.91 (8)	477.16 (3)	267.31 (6)
Avg. ROI	88.41	205.87	79.58	79.39	168.82	112.2	29.68	97.84	52.52
Avg. Ranking	4.58	2.75	4.83	5.08	3.5	4.33	6.75	6.33	6.83

Tables 9, 10, and 11 present the Sharpe ratio for each dataset, with green indicating a positive Sharpe ratio and red indicating a negative Sharpe ratio. The intensity of the color indicates the magnitude of the Sharpe ratio, with darker shades of green representing higher profits and darker shades of red representing higher losses. Bold text denotes the highest Sharpe ratio for each year, and parenthetical numbers indicate the ranking of the comparison models in stock trading.

Table 9 presents the Sharpe ratio values for the year 2020. The analysis reveals that the Bi-LSTM strategy achieved the highest average Sharpe ratio of 2.2, with an average ranking of 3.33. Following closely were the SMA and Buy and Hold strategies, which exhibited average Sharpe ratios of 1.39 and 1.36, respectively. These strategies obtained average rankings of 4.08 and 4.00, respectively.

Table 10, the Sharpe ratio values for the year 2021 are presented. The findings indicate that the CNN-LSTM strategy demonstrated the highest average Sharpe ratio of 1.41, with an average ranking of 4. Trailing behind was the BiLSTM-CNN strategy, which achieved an average Sharpe ratio of 1.41 and an average ranking of 3.58. The Buy and Hold strategy followed suit with an average Sharpe ratio of 1.34 and an average ranking of 4.25.

Table 11 showcases the Sharpe ratio values for the year 2022. Notably, the CNN-LSTM strategy exhibited the highest average Sharpe ratio of 0.25, accompanied by an average ranking of 3.83. Subsequently, the MACD strategy emerged as the second-highest performer with an average Sharpe ratio of 0.22 and an average ranking of 4. It is worth mentioning that the Buy and Hold strategy failed to surpass the market returns during this period.

Table 9. Displays the Sharpe ratio values of each trading strategy for the year 2020. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	2.9 (1)	1.3 (4)	0.64 (7)	0.62 (8)	1.39 (2)	-0.06 (9)	1.07 (5)	0.92 (6)	1.33 (3)
APA	0.02 (5)	0.31 (4)	-0.57 (9)	-0.25 (6)	-0.36 (7)	0.53 (3)	-0.5 (8)	0.68 (1)	0.55 (2)
DVN	-0.33 (3)	-0.54 (6)	-0.89 (9)	-0.37 (4)	-0.37 (5)	0.46 (1)	-0.58 (7)	0.33 (2)	-0.65 (8)
GOOGL	0.94 (1)	0.73 (2)	-0.07 (7)	0.44 (4)	0.64 (3)	0.27 (5)	-0.05 (6)	-0.16 (9)	-0.13 (8)
MOS	-0.02 (7)	0.38 (2)	1.19 (1)	0.16 (5)	0.13 (6)	0.26 (4)	-0.1 (8)	0.36 (3)	-0.25 (9)
MRNA	1.42 (5)	3.16 (3)	-0.73 (9)	1.28 (6)	4.2 (1)	1.9 (4)	0.66 (8)	4.01 (2)	0.97 (7)
NFLX	1.41 (6)	3.53 (2)	3.53 (1)	2.16 (3)	1.37 (7)	-0.74 (9)	1.58 (5)	0.05 (8)	1.96 (4)
NVDA	-0.14 (9)	2.66 (1)	1.49 (3)	0.9 (8)	2.09 (2)	1.2 (6)	1.06 (7)	1.29 (5)	1.32 (4)
OXY	-0.87 (9)	-0.28 (3)	-0.57 (6)	-0.8 (8)	-0.53 (5)	0.07 (2)	-0.7 (7)	1.26 (1)	-0.44 (4)
SQQQ	-0.55 (1)	-0.84 (6)	-1.03 (8)	-0.61 (3)	-0.84 (5)	-0.64 (4)	-0.6 (2)	-1 (7)	-1.11 (9)
TQQQ	1.04 (1)	0.53 (6)	-0.34 (9)	0.34 (7)	1 (2)	0.67 (4)	0.53 (5)	0.85 (3)	-0.16 (8)
TSLA	1.55 (9)	15.46 (1)	3.72 (6)	2.21 (8)	7.64 (3)	6.1 (4)	2.52 (7)	8.06 (2)	5.87 (5)
Avg. Sharpe ratio	0.61	**2.2**	0.53	0.51	1.36	0.84	0.41	1.39	0.77
Avg. Ranking	4.75	3.33	6.25	5.83	4	4.58	6.25	4.08	5.92

Table 10. Displays the Sharpe ratio values of each trading strategy for the year 2021. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	0.69 (4)	1.41 (1)	-0.46 (9)	0.41 (5)	1.32 (2)	0.11 (7)	-0.02 (8)	1.09 (3)	0.17 (6)
APA	2.65 (1)	0.43 (7)	1.08 (3)	1.89 (2)	1.02 (4)	0.94 (5)	0.05 (9)	0.35 (8)	0.75 (6)
DVN	2.39 (4)	1.92 (6)	4.12 (1)	2.57 (2)	2.56 (3)	0.8 (8)	2.09 (5)	0.79 (9)	1.91 (7)
GOOGL	2.16 (6)	3 (1)	2.82 (2)	2.6 (5)	2.74 (4)	1.33 (8)	2.79 (3)	0.49 (9)	1.48 (7)
MOS	1.04 (4)	0.98 (5)	0.66 (6)	0.23 (8)	1.05 (3)	1.07 (2)	1.63 (1)	-0.27 (9)	0.58 (7)
MRNA	1.73 (3)	1.83 (2)	-0.04 (8)	1.55 (6)	1.66 (4)	1.56 (5)	-0.46 (9)	2.65 (1)	0.95 (7)
NFLX	2.14 (1)	1.24 (2)	1.2 (3)	0.16 (8)	0.55 (6)	0.9 (4)	0.23 (7)	-0.63 (9)	0.57 (5)
NVDA	1.47 (6)	3 (4)	3.86 (1)	0.64 (8)	2.85 (5)	3.59 (2)	0.57 (9)	3.32 (3)	1.1 (7)
OXY	1.35 (3)	1.48 (2)	0.52 (8)	0.91 (4)	0.9 (5)	2.58 (1)	0.78 (6)	-0.45 (9)	0.55 (7)
SQQQ	-0.61 (3)	-1.23 (7)	-0.95 (5)	-0.13 (1)	-1.13 (6)	-0.43 (2)	-0.78 (4)	-1.33 (9)	-1.3 (8)
TQQQ	-0.36 (9)	1.82 (3)	3.15 (1)	0.34 (7)	1.76 (4)	2.39 (2)	0.59 (5)	0.27 (8)	0.58 (6)
TSLA	0.82 (4)	1 (3)	1.34 (1)	1.02 (2)	0.75 (5)	0.43 (7)	0 (9)	0.46 (6)	0.03 (8)
Avg. Sharpe ratio	1.29	1.41	**1.44**	1.02	1.34	1.27	0.62	0.56	0.61
Avg. Ranking	4	3.58	4	4.83	4.25	4.42	6.25	6.92	6.75

Table 11. Displays the Sharpe ratio values of each trading strategy for the year 2022. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	-0.65 (5)	-1.11 (8)	-1.05 (7)	0.27 (2)	-0.93 (6)	0.42 (1)	-0.16 (4)	-1.42 (9)	-0.08 (3)
APA	1.68 (2)	0.71 (7)	0.96 (5)	0.42 (9)	0.94 (6)	1.47 (4)	1.48 (3)	0.43 (8)	1.92 (1)
DVN	-0.38 (8)	1.57 (1)	0.53 (4)	-0.37 (7)	0.5 (6)	0.52 (5)	0.69 (3)	0.9 (2)	-0.62 (9)
GOOGL	-0.89 (5)	-0.97 (7)	-1.15 (8)	-0.65 (3)	-0.94 (6)	-0.17 (1)	-0.74 (4)	-1.44 (9)	-0.26 (2)
MOS	-0.08 (4)	-0.04 (3)	0.96 (1)	-0.28 (6)	0.21 (2)	-0.29 (8)	-0.28 (7)	-0.38 (9)	-0.23 (5)
MRNA	0.05 (3)	-0.54 (9)	-0.19 (6)	0.96 (1)	-0.31 (7)	-0.17 (5)	-0.49 (8)	0.03 (4)	0.12 (2)
NFLX	-0.47 (3)	-0.86 (9)	-0.67 (5)	-0.11 (1)	-0.77 (8)	-0.57 (4)	-0.24 (2)	-0.73 (7)	-0.68 (6)
NVDA	-1.3 (9)	0.25 (2)	-0.4 (4)	-0.75 (6)	-0.8 (7)	0.23 (3)	-0.47 (5)	-1.12 (8)	1.21 (1)
OXY	2.64 (2)	1.73 (4)	3.6 (1)	1.74 (3)	1.55 (5)	1.17 (7)	1.32 (6)	0.25 (8)	-0.15 (9)
SQQQ	2.75 (1)	0.73 (4)	1.12 (3)	0.43 (7)	0.69 (5)	1.36 (2)	0.23 (8)	-0.02 (9)	0.57 (6)
TQQQ	-0.57 (3)	-0.88 (8)	-0.32 (1)	-0.62 (5)	-0.81 (7)	-0.38 (2)	-0.8 (6)	-1.12 (9)	-0.61 (4)
TSLA	-0.93 (4)	-1.06 (8)	-0.34 (1)	-0.9 (3)	-0.99 (7)	-0.96 (6)	-1.2 (9)	-0.93 (5)	-0.69 (2)
Avg. Sharpe ratio	0.15	-0.04	**0.25**	0.01	-0.14	0.22	-0.06	-0.46	0.04
Avg. Ranking	4.08	5.83	3.83	4.42	6	4	5.42	7.25	4.17

In the context of a trading simulation, we conducted tests to examine the impact of increasing trading fees to 0.02% in order to enhance the fidelity of the experimental environment to real-world conditions. These fees were deducted from each buying and selling transaction. The outcomes are presented in tables 12, 13, 14, and 15.

Table 12 reveals that in the year 2020, subsequent to the imposition of trading fees, the BI-LSTM strategy exhibited the most promising performance, boasting an average Return on Investment (ROI) of 114.46% and an average ranking of 3.50. Additionally, the Buy and Hold strategy demonstrated a notable average ROI of 112.60%, accompanied by an average ranking of 3.58.

Table 13 demonstrates that in the year 2021, even after accounting for the trading fees, all strategies managed to outperform the market. Notably, the Buy and Hold strategy delivered the most substantial profitability with an average ROI of 64.69% and an average ranking of 3.33. Following closely was the MACD strategy, ranking second with an average ROI of 43.17% and an average ranking of 3.58. Lastly, the BiLSTM-CNN strategy secured the third position, exhibiting an average ROI of 30.51% and an average ranking of 4.67.

Table 14 highlights the outcomes observed in the year 2022, subsequent to the inclusion of trading fees. It became evident that solely the MACD and STO strategies prevailed over the market, with average ROIs of 11.27% and 1.57%, respectively. The corresponding average rankings were 3.08 and 3.50.

Table 15 presents the cumulative ROI of all three years, incorporating the impact of trading fees as depicted in tables 12, 13, and 14. It becomes apparent that, on average, all strategies yielded profitable results, except for the CNN-LSTM strategy. The Buy and Hold strategy emerged as the most lucrative, demonstrating an average ROI of 168.78% and an average ranking of 2.33. Following suit, the BiLSTM-CNN strategy secured the second position, with an average ROI of 131.99% and an average ranking of 3.67.

Table 12. Displays the ROI values, including fee transaction costs, of each trading strategy for the year 2020. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	61.17 (3)	67.66 (2)	16.49 (8)	30.22 (7)	88.32 (1)	-2.35 (9)	50.19 (4)	40.61 (6)	41.1 (5)
APA	-11.78 (5)	9.85 (4)	-64.47 (9)	-34.2 (6)	-44.7 (8)	46.05 (3)	-40.11 (7)	52.78 (1)	51.93 (2)
DVN	-35.87 (3)	-60.06 (8)	-83.39 (9)	-40.03 (4)	-40.04 (5)	35.63 (1)	-47.27 (6)	22.82 (2)	-51.26 (7)
GOOGL	23.5 (2)	11.85 (4)	-14.97 (9)	12.26 (3)	26.31 (1)	7.97 (5)	-1.73 (6)	-4.1 (7)	-4.52 (8)
MOS	-2.25 (7)	23.84 (2)	24 (1)	11.68 (5)	9.9 (6)	14.56 (4)	-5.48 (8)	17 (3)	-14.79 (9)
MRNA	66.16 (6)	333.57 (3)	-50.88 (9)	122.38 (5)	486.67 (1)	163.34 (4)	43.79 (8)	360.59 (2)	61.25 (7)
NFLX	-9.43 (7)	79.62 (1)	21.82 (5)	-20.22 (8)	67.12 (3)	-25.86 (9)	57.29 (4)	1.56 (6)	70.94 (2)
NVDA	-35.98 (9)	80.12 (2)	30.83 (7)	17.41 (8)	121.13 (1)	46.29 (6)	47.73 (5)	48.49 (4)	54.52 (3)
OXY	-71.48 (8)	-35.42 (3)	-55.87 (5)	-74.53 (9)	-60.66 (7)	5.8 (2)	-58.76 (6)	89.85 (1)	-42.03 (4)
SQQQ	-75.98 (6)	-90.97 (8)	-93.32 (9)	-72.7 (5)	-86.16 (7)	-47.33 (2)	-35.82 (1)	-68.56 (3)	-72.25 (4)
TQQQ	77.44 (2)	47.89 (4)	-42.34 (9)	28.17 (7)	105.54 (1)	46.93 (5)	45.71 (6)	54.09 (3)	-12.87 (8)
TSLA	39.48 (9)	905.62 (1)	174.22 (6)	111.9 (8)	677.81 (2)	401.65 (4)	158.06 (7)	496.22 (3)	299.84 (5)
Avg. ROI	2.08	114.46	-11.49	7.70	112.60	57.72	17.80	92.61	31.82
Avg. Ranking	5.58	3.50	7.17	6.25	3.58	4.50	5.67	3.42	5.33

Table 13. Displays the ROI values, including fee transaction costs, of each trading strategy for the year 2021. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	-2.28 (7)	15.12 (3)	-28.84 (9)	-15.25 (8)	55.1 (1)	3.17 (5)	-0.58 (6)	32.16 (2)	4.59 (4)
APA	87.87 (1)	7.83 (8)	26.23 (6)	87.03 (2)	63.81 (3)	38.87 (4)	2.44 (9)	14.93 (7)	26.76 (5)
DVN	58.09 (7)	78.75 (4)	98.37 (3)	106.96 (2)	141.79 (1)	30.94 (9)	76.1 (5)	31.71 (8)	67.95 (6)
GOOGL	8.55 (9)	60.11 (2)	37.7 (5)	57.87 (3)	67.52 (1)	21.56 (7)	45.48 (4)	9.17 (8)	21.91 (6)
MOS	35.88 (3)	29.4 (5)	7.6 (7)	-5.54 (8)	50.69 (2)	33.43 (4)	53.75 (1)	-8.87 (9)	17.76 (6)
MRNA	65.78 (4)	22.36 (7)	-39.4 (9)	43.67 (6)	135.43 (2)	79.03 (3)	-23.44 (8)	161.8 (1)	51.77 (5)
NFLX	-29.53 (6)	-57.03 (8)	-57.3 (9)	-33.12 (7)	17.84 (2)	21.07 (1)	4.72 (4)	-13.76 (5)	14.19 (3)
NVDA	9.95 (8)	116.89 (2)	48.02 (5)	-16.36 (9)	119.47 (1)	106.41 (3)	17.66 (7)	95.4 (4)	30.6 (6)
OXY	38.3 (5)	55.27 (2)	1.06 (8)	46 (4)	50.81 (3)	98.86 (1)	31.45 (6)	-18.2 (9)	19.5 (7)
SQQQ	-42.35 (4)	-66.22 (9)	-51.06 (6)	-21.84 (2)	-61.08 (8)	-16.53 (1)	-24.36 (3)	-52.88 (7)	-49.58 (5)
TQQQ	-31.28 (9)	86.26 (2)	77.1 (4)	-7.44 (8)	94.06 (1)	85.35 (3)	25.29 (5)	9.43 (7)	22.34 (6)
TSLA	-7.29 (9)	17.34 (4)	41.8 (1)	30.41 (3)	40.84 (2)	15.87 (5)	-0.13 (8)	15.72 (6)	1.31 (7)
Avg. ROI	15.97	30.51	13.44	22.70	64.69	43.17	17.37	23.05	19.09
Avg. Ranking	6.00	4.67	6.00	5.17	2.25	3.83	5.50	6.08	5.50

Table 14. Displays the ROI values, including fee transaction costs, of each trading strategy for the year 2022. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	-44.61 (5)	-67.65 (9)	-66.92 (8)	-8.57 (4)	-54.99 (7)	17.05 (1)	-7.21 (3)	-54.02 (6)	-3.47 (2)
APA	79.48 (1)	35.36 (6)	10.87 (9)	19.34 (7)	58.51 (5)	63.91 (4)	66.36 (3)	18.12 (8)	75.66 (2)
DVN	-26.41 (8)	74.35 (1)	2.67 (6)	-28.51 (9)	28.01 (3)	20.7 (5)	27 (4)	34.06 (2)	-20.41 (7)
GOOGL	-41.24 (8)	-39.35 (7)	-57.31 (9)	-38.82 (6)	-35.84 (5)	-4.48 (1)	-21.4 (3)	-35.16 (4)	-6.63 (2)
MOS	-17.37 (8)	-6.07 (3)	10.91 (2)	-22.63 (9)	12.47 (1)	-11.45 (5)	-12.31 (6)	-15.72 (7)	-9.23 (4)
MRNA	-34.26 (7)	-54.25 (9)	-42.96 (8)	0.65 (3)	-23 (5)	-8.43 (4)	-25.98 (6)	1.4 (2)	5.76 (1)
NFLX	-65.22 (7)	-66.53 (8)	-77.72 (9)	-61.47 (6)	-49.65 (5)	-26.83 (2)	-10.93 (1)	-31.14 (3)	-34.31 (4)
NVDA	-83.08 (9)	-25.48 (4)	-57.7 (7)	-62.84 (8)	-49.6 (6)	9.85 (2)	-21.6 (3)	-44.23 (5)	51.1 (1)
OXY	113.73 (1)	88.43 (4)	106.17 (2)	63.18 (5)	88.44 (3)	48.25 (7)	52.1 (6)	10.48 (8)	-5.67 (9)
SQQQ	106.43 (1)	61.51 (4)	55.75 (5)	25.82 (7)	62.78 (3)	92.28 (2)	11.8 (8)	-1.53 (9)	38 (6)
TQQQ	-50.6 (5)	-77.6 (9)	-36.23 (2)	-38.22 (4)	-76.04 (8)	-22.84 (1)	-62.06 (7)	-61.87 (6)	-38.13 (3)
TSLA	-72.34 (7)	-78.49 (9)	-58.79 (4)	-74.61 (8)	-63.44 (6)	-42.8 (3)	-62.02 (5)	-34.78 (2)	-33.84 (1)
Avg. ROI	-11.29	-12.98	-17.61	-18.89	-8.53	11.27	-5.52	-17.87	1.57
Avg. Ranking	5.58	6.08	5.92	6.33	4.75	3.08	4.58	5.17	3.50

Table 15. Displays the ROI values, including fee transaction costs, of each trading strategy for a total of 3 years. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	14.28 (7)	15.13 (6)	-79.28 (9)	6.39 (8)	88.43 (1)	17.87 (5)	42.4 (2)	18.75 (4)	42.22 (3)
APA	155.57 (1)	53.04 (7)	-27.36 (9)	72.18 (6)	77.62 (5)	148.83 (3)	28.69 (8)	85.83 (4)	154.35 (2)
DVN	-4.19 (9)	93.04 (2)	17.65 (7)	38.42 (6)	129.76 (1)	87.27 (4)	55.83 (5)	88.59 (3)	-3.72 (8)
GOOGL	-9.19 (7)	32.61 (2)	-34.57 (9)	31.31 (3)	57.99 (1)	25.05 (4)	22.35 (5)	-30.09 (8)	10.76 (6)
MOS	16.27 (6)	47.17 (2)	42.51 (3)	-16.49 (9)	73.06 (1)	36.54 (4)	35.96 (5)	-7.59 (8)	-6.26 (7)
MRNA	97.69 (7)	301.68 (3)	-133.25 (9)	166.69 (5)	599.1 (1)	233.94 (4)	-5.63 (8)	523.79 (2)	118.78 (6)
NFLX	-104.19 (7)	-43.95 (6)	-113.21 (8)	-114.82 (9)	35.31 (3)	-31.62 (4)	51.08 (1)	-43.34 (5)	50.82 (2)
NVDA	-109.12 (9)	171.54 (2)	21.15 (7)	-61.79 (8)	191 (1)	162.55 (3)	43.79 (6)	99.66 (5)	136.22 (4)
OXY	80.54 (4)	108.28 (2)	51.37 (6)	34.65 (7)	78.59 (5)	152.91 (1)	24.79 (8)	82.13 (3)	-28.2 (9)
SQQQ	-11.9 (2)	-95.68 (8)	-88.63 (7)	-68.73 (4)	-84.46 (6)	28.42 (1)	-48.38 (3)	-122.97 (9)	-83.83 (5)
TQQQ	-4.45 (7)	56.56 (3)	-1.46 (6)	-17.48 (8)	123.56 (1)	109.44 (2)	8.94 (4)	1.65 (5)	-28.66 (9)
TSLA	-40.15 (9)	844.48 (1)	157.23 (6)	67.7 (8)	655.21 (2)	374.72 (4)	95.91 (7)	477.16 (3)	267.31 (5)
Avg. ROI	6.76	131.99	-15.65	11.50	168.76	112.16	29.64	97.80	52.48
Avg. Ranking	6.25	3.67	7.17	6.75	2.33	3.25	5.17	4.92	5.50

Tables 16, 17, and 18 provide an overview of the Sharpe ratio values for the respective years, taking into account the impact of trading fees. These tables offer valuable insights into the risk-adjusted performance of different strategies.

In Table 16, the results illustrate the values of the Sharpe ratio in the year 2020, after incorporating trading fees. It is noteworthy that the Bi-LSTM strategy exhibited the highest average Sharpe ratio of 1.63, indicating a favorable risk-adjusted performance. Additionally, the average ranking for this strategy stood at 3.58. Subsequently, the SMA strategy and Buy and Hold approach obtained the second and third positions, respectively, with average Sharpe ratios of 1.39 and 1.36. The corresponding average rankings for these strategies were 4.08 and 4.00.

Moving on to Table 17, the data reflects the Sharpe ratio values for the year 2021. Remarkably, the Buy and Hold strategy showcased the highest average Sharpe ratio of 1.34, suggesting a relatively strong risk-adjusted performance. The average ranking for this strategy was 2.67. Following closely, the MACD strategy attained the second position with an average Sharpe ratio of 1.27, accompanied by an average ranking of 3.25.

Table 18 presents the Sharpe ratio values for the year 2022. Notably, the MACD strategy exhibited the highest average Sharpe ratio at 0.22, signifying a relatively favorable risk-adjusted performance within the given period. The corresponding average ranking for this strategy was 3.00. Additionally, the STO strategy secured the second position with an average Sharpe ratio of 0.04, and an average ranking of 3.33. It is important to highlight that the Buy and Hold strategy failed to outperform the stock market during this particular year.

Table 16. Displays the Sharpe ratio values, including fee transaction costs, of each trading strategy for the year 2020. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	1.93 (1)	1.12 (4)	0.28 (8)	0.5 (7)	1.39 (2)	-0.06 (9)	1.07 (5)	0.92 (6)	1.33 (3)
APA	-0.12 (5)	0.11 (4)	-0.64 (9)	-0.36 (6)	-0.36 (7)	0.53 (3)	-0.5 (8)	0.68 (1)	0.55 (2)
DVN	-0.33 (3)	-0.58 (7)	-0.93 (9)	-0.37 (4)	-0.37 (5)	0.46 (1)	-0.58 (6)	0.33 (2)	-0.65 (8)
GOOGL	0.63 (2)	0.34 (3)	-0.82 (9)	0.31 (4)	0.64 (1)	0.27 (5)	-0.05 (6)	-0.16 (8)	-0.13 (7)
MOS	-0.03 (7)	0.33 (3)	0.83 (1)	0.16 (5)	0.13 (6)	0.26 (4)	-0.1 (8)	0.35 (2)	-0.25 (9)
MRNA	0.93 (7)	2.97 (3)	-0.92 (9)	1.11 (5)	4.2 (1)	1.9 (4)	0.66 (8)	4.01 (2)	0.97 (6)
NFLX	-0.22 (7)	1.84 (2)	0.58 (5)	-0.54 (8)	1.37 (4)	-0.74 (9)	1.58 (3)	0.05 (6)	1.96 (1)
NVDA	-0.89 (9)	1.71 (2)	0.67 (7)	0.35 (8)	2.09 (1)	1.2 (5)	1.06 (6)	1.29 (4)	1.32 (3)
OXY	-0.96 (9)	-0.32 (3)	-0.69 (6)	-0.86 (8)	-0.53 (5)	0.07 (2)	-0.7 (7)	1.26 (1)	-0.44 (4)
SQQQ	-0.94 (4)	-0.95 (5)	-1.3 (9)	-0.99 (6)	-0.84 (3)	-0.64 (2)	-0.6 (1)	-1 (7)	-1.11 (8)
TQQQ	0.8 (3)	0.46 (6)	-0.54 (9)	0.27 (7)	1 (1)	0.67 (4)	0.52 (5)	0.85 (2)	-0.16 (8)
TSLA	0.85 (9)	12.59 (1)	2.55 (6)	1.65 (8)	7.63 (3)	6.1 (4)	2.52 (7)	8.06 (2)	5.87 (5)
Avg. Sharpe ratio	0.14	1.63	-0.08	0.10	1.36	0.84	0.41	1.39	0.77
Avg. Ranking	5.50	3.58	7.25	6.33	3.25	4.33	5.83	3.58	5.33

Table 17. Displays the Sharpe ratio values, including fee transaction costs, of each trading strategy for the year 2021. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	-0.07 (7)	0.43 (3)	-1.33 (9)	-0.45 (8)	1.32 (1)	0.11 (5)	-0.02 (6)	1.09 (2)	0.16 (4)
APA	1.89 (1)	0.14 (8)	0.6 (6)	1.5 (2)	1.02 (3)	0.94 (4)	0.05 (9)	0.35 (7)	0.75 (5)
DVN	1.6 (6)	1.57 (7)	2.95 (1)	2.06 (4)	2.56 (2)	0.8 (8)	2.09 (3)	0.79 (9)	1.91 (5)
GOOGL	0.42 (9)	2.51 (3)	1.69 (5)	2.39 (4)	2.73 (2)	1.33 (7)	2.78 (1)	0.49 (8)	1.48 (6)
MOS	0.79 (4)	0.67 (5)	0.19 (7)	-0.17 (8)	1.05 (3)	1.07 (2)	1.63 (1)	-0.27 (9)	0.58 (6)
MRNA	0.92 (5)	0.44 (7)	-0.7 (9)	0.66 (6)	1.66 (2)	1.56 (3)	-0.46 (8)	2.65 (1)	0.95 (4)
NFLX	-1.6 (7)	-2.29 (9)	-2.04 (8)	-1.06 (6)	0.55 (3)	0.9 (1)	0.23 (4)	-0.63 (5)	0.57 (2)
NVDA	0.27 (8)	2.82 (4)	1.44 (5)	-0.71 (9)	2.85 (3)	3.59 (1)	0.57 (7)	3.31 (2)	1.1 (6)
OXY	0.83 (4)	1.07 (2)	0.04 (8)	0.83 (5)	0.9 (3)	2.57 (1)	0.78 (6)	-0.45 (9)	0.55 (7)
SQQQ	-0.93 (4)	-1.34 (9)	-1.32 (7)	-0.7 (2)	-1.13 (5)	-0.43 (1)	-0.78 (3)	-1.33 (8)	-1.3 (6)
TQQQ	-0.91 (9)	1.64 (4)	1.9 (2)	-0.19 (8)	1.76 (3)	2.39 (1)	0.59 (5)	0.27 (7)	0.58 (6)
TSLA	-0.14 (9)	0.34 (6)	0.8 (1)	0.6 (3)	0.75 (2)	0.43 (5)	0 (8)	0.46 (4)	0.03 (7)
Avg. Sharpe ratio	0.26	0.67	0.35	0.40	1.34	1.27	0.62	0.56	0.61
Avg. Ranking	6.08	5.58	5.67	5.42	2.67	3.25	5.08	5.92	5.33

Table 18. Displays the Sharpe ratio values, including fee transaction costs, of each trading strategy for the year 2022. The bolded values indicate the highest ROI, considering all transaction costs, for each dataset (%).

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	-1.39 (7)	-1.25 (6)	-1.51 (9)	-0.26 (4)	-0.93 (5)	0.42 (1)	-0.16 (3)	-1.42 (8)	-0.08 (2)
APA	1.36 (4)	0.58 (6)	0.35 (8)	0.33 (9)	0.94 (5)	1.47 (3)	1.48 (2)	0.43 (7)	1.92 (1)
DVN	-0.88 (9)	1.37 (1)	0.06 (6)	-0.77 (8)	0.5 (5)	0.52 (4)	0.69 (3)	0.9 (2)	-0.62 (7)
GOOGL	-1.12 (6)	-1.1 (5)	-2.14 (9)	-1.16 (7)	-0.94 (4)	-0.17 (1)	-0.74 (3)	-1.44 (8)	-0.26 (2)
MOS	-0.32 (7)	-0.1 (3)	0.28 (1)	-0.68 (9)	0.21 (2)	-0.29 (6)	-0.28 (5)	-0.38 (8)	-0.23 (4)
MRNA	-0.68 (7)	-0.97 (9)	-0.93 (8)	0.01 (3)	-0.31 (5)	-0.17 (4)	-0.49 (6)	0.03 (2)	0.12 (1)
NFLX	-1.6 (9)	-1.05 (6)	-1.56 (8)	-1.36 (7)	-0.77 (5)	-0.57 (2)	-0.24 (1)	-0.73 (4)	-0.68 (3)
NVDA	-1.62 (9)	-0.5 (4)	-1.26 (7)	-1.43 (8)	-0.8 (5)	0.23 (2)	-0.47 (3)	-1.12 (6)	1.21 (1)
OXY	2.22 (2)	1.59 (3)	2.42 (1)	1.21 (6)	1.55 (4)	1.17 (7)	1.32 (5)	0.25 (8)	-0.15 (9)
SQQQ	1.99 (1)	0.69 (5)	0.77 (3)	0.3 (7)	0.69 (4)	1.36 (2)	0.23 (8)	-0.02 (9)	0.57 (6)
TQQQ	-0.66 (4)	-0.92 (8)	-0.56 (2)	-0.83 (7)	-0.81 (6)	-0.38 (1)	-0.8 (5)	-1.11 (9)	-0.61 (3)
TSLA	-1.75 (9)	-1.33 (7)	-1.33 (6)	-1.6 (8)	-0.99 (4)	-0.96 (3)	-1.2 (5)	-0.93 (2)	-0.69 (1)
Avg. Sharpe ratio	-0.37	-0.25	-0.45	-0.52	-0.14	0.22	-0.06	-0.46	0.04
Avg. Ranking	6.17	5.25	5.67	6.92	4.50	3.00	4.08	6.08	3.33

Tables 19, 20, 21, and 22 provide insights into the trading frequency of stock transactions over the course of three years. These tables highlight the number of trades, combining both buying and selling activities as a single event.

Table 19 presents the trading frequency in the year 2020. It is observed that the original strategy group exhibited a comparatively lower number of trades, in contrast to the Hybrid model group. Notably, the CNN-LSTM strategy emerged as the most active, averaging approximately 633.67 trades, followed by the CNN-BiLSTM strategy with an average of 506.75 trades. Among the original strategies, only the

MACD approach surpassed the 100-trade threshold, with an average frequency of 135.33 trades.

Moving on to Table 20, which represents the trading frequency in 2021, a similar pattern persists. The original strategy group once again displayed a relatively lower trading frequency compared to the Hybrid model group, as observed in the previous year. Notably, the CNN-LSTM and CNN-BiLSTM strategies maintained their dominance, averaging approximately 611.50 and 591.67 trades, respectively.

Table 21 reflects the trading frequency in 2022, revealing a consistent trend. The original strategy group continued to exhibit a lower trading frequency compared to the Hybrid model group, consistent with the observations in the preceding years. The CNN-LSTM and CNN-BiLSTM strategies remained the most active, with average trading frequencies of approximately 739.67 and 547.75 trades, respectively. Furthermore, the LSTM-CNN strategy experienced an increase in trading frequency, averaging approximately 518.17 trades.

Lastly, Table 22 presents the cumulative trading frequency over the three-year period. It is noteworthy that the CNN-LSTM strategy maintained the highest average trading frequency, totaling approximately 1984.83 trades. The CNN-BiLSTM strategy followed closely with an average of approximately 1646.17 trades. These findings shed light on the trading dynamics and highlight the prominence of these strategies in terms of transaction frequency.

Table 19. Displays the frequency of each trading strategy for the year 2020. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	587	209	508	182	1	148	32	49	22
APA	612	661	649	618	1	121	27	43	22
DVN	37	401	568	1	1	114	21	35	17
GOOGL	260	333	406	125	1	119	22	36	18
MOS	38	137	346	4	1	104	22	31	12
MRNA	643	206	454	308	1	144	25	42	14
NFLX	486	396	712	703	1	156	30	44	22
NVDA	825	685	707	566	1	149	31	44	25
OXY	769	213	758	704	1	131	30	39	17
SQQQ	767	502	790	671	1	145	31	38	25
TQQQ	502	173	840	204	1	153	29	37	25
TSLA	555	748	866	503	1	140	32	42	22
Avg. frequency	506.75	388.67	633.67	382.42	1.00	135.33	27.67	40.00	20.08

Table 20. Displays the frequency of each trading strategy for the year 2021. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	540	624	502	678	1	157	30	46	23
APA	736	548	624	506	1	123	25	38	20
DVN	685	394	745	499	1	136	31	45	25
GOOGL	655	185	423	86	1	113	25	42	20
MOS	307	398	606	489	1	115	21	38	17
MRNA	606	754	638	696	1	147	26	43	19
NFLX	483	615	620	275	1	125	26	44	16
NVDA	584	75	784	494	1	138	29	40	27
OXY	657	539	435	129	1	136	37	52	30
SQQQ	673	424	809	659	1	136	27	46	25
TQQQ	661	166	883	593	1	141	27	48	26
TSLA	513	356	269	227	1	147	31	49	21
Avg. frequency	591.67	423.17	611.50	444.25	1.00	134.50	27.92	44.25	22.42

Table 21. Displays the frequency of each trading strategy for the year 2022. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	782	402	903	460	1	132	31	49	25
APA	388	216	565	170	1	126	30	37	22
DVN	529	216	659	554	1	136	34	44	18
GOOGL	267	156	846	518	1	125	27	43	23
MOS	478	143	751	521	1	134	24	41	19
MRNA	719	519	672	566	1	149	32	38	21
NFLX	658	208	703	664	1	143	32	47	28
NVDA	574	638	845	724	1	138	31	45	30
OXY	365	152	852	569	1	151	34	49	21
SQQQ	695	84	561	303	1	113	25	39	21
TQQQ	400	418	710	466	1	114	25	38	21
TSLA	718	478	809	703	1	141	29	43	29
Avg. frequency	547.75	302.50	739.67	518.17	1.00	133.50	29.50	42.75	23.17

Table 22. Displays the frequency of each trading strategy for a total of 3 years. The bolded values indicate the highest ROI for each dataset (%)

STOCK	CNN-BiLSTM	BiLSTM-CNN	CNN-LSTM	LSTM-CNN	BH	MACD	RSI	SMA	STO
AMD	1909	1235	1913	1320	3	437	93	144	70
APA	1736	1425	1838	1294	3	370	82	118	64
DVN	1251	1011	1972	1054	3	386	86	124	60
GOOGL	1182	674	1675	729	3	357	74	121	61
MOS	823	678	1703	1014	3	353	67	110	48
MRNA	1968	1479	1764	1570	3	440	83	123	54
NFLX	1627	1219	2035	1642	3	424	88	135	66
NVDA	1983	1398	2336	1784	3	425	91	129	82
OXY	1791	904	2045	1402	3	418	101	140	68
SQQQ	2135	1010	2160	1633	3	394	83	123	71
TQQQ	1563	757	2433	1263	3	408	81	123	72
TSLA	1786	1582	1944	1433	3	428	92	134	72
Avg. frequency	1646.17	1114.33	1984.83	1344.83	3.00	403.33	85.08	127.00	65.67

Chapter 8

DISCUSSION

Based on the findings presented in Tables V, VI, and VII, it is evident that the mean Return on Investment (ROI) and Sharpe ratio for the years 2020 and 2021 is notably profitable, with a particular increase in the latter year. The upward trend in the prices of most technology stocks can be attributed to the COVID-19 pandemic situation, which has created a favorable financial outlook. The pandemic has resulted in an augmented demand for technology and digital services, leading to a rise in the stock prices of several technology companies, including those in healthcare, e-commerce, and software industries. Additionally, government stimulus packages and low-interest rates, aimed at stabilizing the economy, have furnished investors with increased liquidity, thereby further stimulating the stock market. These collective factors have facilitated the generation of substantial profits through Buy and Hold trading strategies, with technology stock prices continuing to ascend. Consequently, deep learning or traditional indicators-based trading strategies have demonstrated limited ability in outperforming the Buy and Hold strategy.

The experimental findings underscore the limited correlation between a model's favorable Mean Squared Error (MSE) and the subsequent attainment of a positive Return on Investment (ROI). To illustrate this point, we examine the case of MRNA stock during the year 2020. Notably, the CNN-LSTM model exhibited an MSE of 17.74 x 10^-2, whereas the BiLSTM-CNN model recorded an MSE of 92.76 x 10^-2, as outlined in Table 4. However, despite the superior MSE observed in the CNN-LSTM model, its associated ROI revealed an alarming -40.37% (Table 5), accompanied by a Sharpe ratio of -0.73 (Table 9). In stark contrast, the BiLSTM-CNN model, characterized by a relatively inferior MSE, demonstrated a noteworthy ROI of 355.18% (Table 5) and a Sharpe ratio of 3.16 (Table 9). These divergent outcomes indicate the limited predictive power of MSE as an isolated performance metric for ROI estimation. The salient insights are further elucidated through the analysis of Figures 13 and 14. Specifically, Figure 13 provides a simulated trading depiction of the CNN-LSTM model, whereas Figure 14 showcases the corresponding trading simulation of the BiLSTM-CNN model. A discernible trend emerges, with the BiLSTM-CNN model outperforming its CNN-LSTM counterpart in generating profits during the initial 50 data points. Within the visual representation of Figures 13 and 14, the presence of green and red points signifies the buy and sell positions, respectively. Furthermore, the second graph encapsulates the stock holding status, while the third graph depicts the portfolio value during the specified time interval.

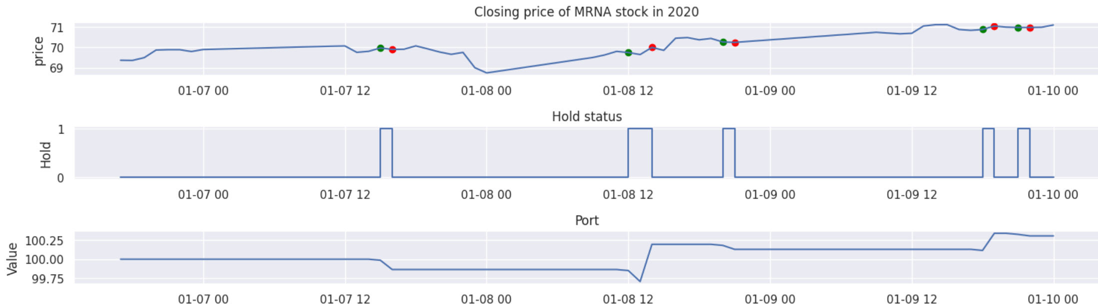

Figure 13. The simulation of trading outcomes from the CNN-LSTM model in the year 2020.

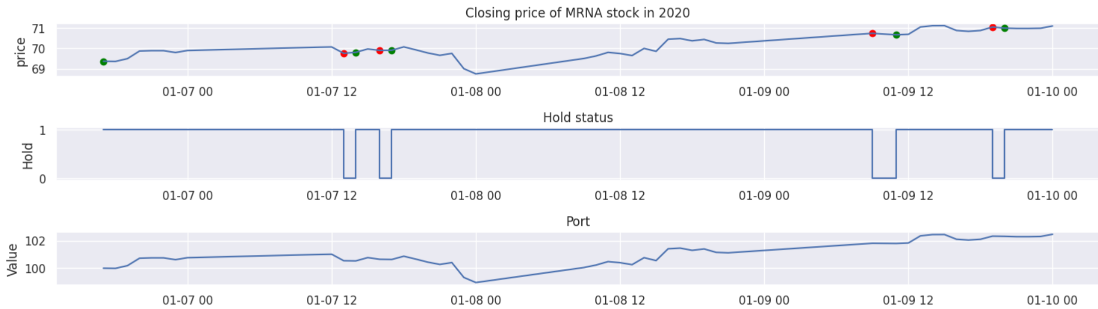

Figure 14. The simulation of trading outcomes from the BiLSTM-CNN model in the year 2020.

In the context of conducting experiments to evaluate the impact of increased trading fees, it has been observed that employing a Hybrid model for trading purposes yields noticeably inferior profitability compared to the original trading strategy. This disparity becomes evident when examining the trading frequencies presented in tables 19, 20, and 21, wherein the model's trading volume surpasses that of the conventional strategy by a significant margin for each respective year. Consequently, a substantial portion of funds is expended on trading fees, surpassing those associated with the original strategy to a considerable extent. Consequently, future endeavors in this domain may necessitate the development of trading strategies that incorporate models capable of effectively managing this aspect. For instance, one potential approach could involve fine-tuning the threshold values of the predictive model to ensure trades are executed only when there is a high degree of confidence in achieving profitable outcomes that outweigh the incurred fees.

The study highlights the potential of machine learning (ML) based trading strategies, particularly the BiLSTM-CNN model, to generate higher profits compared to traditional trading strategies when trading fees are not imposed. The results, as shown in the table, indicate that both the Buy and Hold strategy and the BiLSTM-CNN model delivered significant profits in 2020, with an average ROI of 112.62% and 149.74%, respectively, along with average Sharpe ratios of 1.36 and 2.2. In 2021, both strategies continued to generate profits. However, in 2022, both strategies incurred losses, with an ROI of -8.51% and -1.21% and average Sharpe ratios of -0.14 and -0.04, respectively. These findings suggest that the performance of the BiLSTM-CNN model aligns with that of the Buy and Hold strategy across all three years. While the Buy and Hold strategy may be profitable in certain years, ML-based models consistently demonstrate strong performance over multiple years, indicating their reliability and robustness. Moreover, ML-based strategies possess the ability to analyze large datasets and identify patterns that may be challenging for humans to detect, offering traders a competitive advantage in the market. The study further reveals that CNN-LSTM models were comparably profitable, exhibiting slightly higher overall average ROI and average Sharpe ratio when compared to conventional trading strategies, except for MACD in 2022. However, it is important to note that ML-based trading strategies do not always outperform traditional approaches. Nonetheless, in general, ML trading strategies exhibit an impressive overall performance compared to traditional strategies. Consequently, the study suggests that integrating ML-based trading strategies into investment portfolios could prove to be a promising approach for achieving higher returns.

Chapter 9

CONCLUSION

"Stocks" or equity securities provide public investment in a company, and their values can be influenced by various factors, including government policies, global trends, and investor sentiment. To predict stock prices, numerous models have been developed, such as the Convolutional Neural Networks and Recurrent Neural Networks like Long Short-Term Memory networks. Recent research has found the Bi-directional Long Short-Term Memory network architecture to be particularly effective in processing time series data and predicting stock prices.

This study proposes a new hybrid technique between CNN and BiLSTM for stock trading algorithms. An assessment was conducted to examine the effectiveness of this novel method in trading NASDAQ stocks from 2020 to 2022. Two primary evaluation measures, prediction error and trading performance, were considered. The experimental results demonstrate that the CNN-BiLSTM model outperforms other competing models. This is attributed to the model's ability to incorporate both CNN and BiLSTM components in an optimal sequence, which enables it to capture intricate relationships within the training data more effectively than alternative techniques.

REFERENCES

1. L. Yu, X.Z., and S. Wang, *Assessing Potentiality of Support Vector Machine Method in Crude Oil Price Forecasting. EURASIA Journal of Mathematics, Science and Technology Education, vol. 13, no. 12.* 2017.
2. Kaboudan, M.A., *Compumetric Forecasting of Crude Oil Prices.* . Proceedings of the IEEE Conference on Evolutionary Computation, ICEC, vol. 1, pp. 283-287, 2001.
3. Tsantekidis, A., et al., *Forecasting Stock Prices from the Limit Order Book Using Convolutional Neural Networks.* IEEE 19th Conference on Business Informatics (CBI). 2017. p. 7-12., 2017.
4. P. S. Sisodia, A.G., Y. Kumar and G. K. Ameta, *Stock Market Analysis and Prediction for Nifty50 using LSTM Deep Learning Approach.* 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), 2022, pp. 156-161, doi: 10.1109/ICIPTM54933. 2022.9754148., 2022.
5. Yang, C.e.a., *Deep Learning for Price Movement Prediction Using Convolutional Neural Network and Long Short-Term Memory.* 2020.
6. Wisaroot Lertthaweedech, P.K., and Boonserm Kijsirikul, *Effective Crude Oil Trading Techniques Using Long Short-Term Memory and Convolution Neural Networks. .* Journal of Advances in Information Technology, Vol. 13, No. 6, pp. 645-651, 2022.
7. *LSTM Cells.* Journal of Advances in Information Technology, Vol. 11, No. 1, pp. 1-9, February 2020. doi: 10.12720/jait.11.1.1-9.
8. Ibtissam Benchaji, S.D., and Bouabid El Ouahidi, *Credit Card*

Fraud Detection Model Based on LSTM Recurrent Neural Networks. Journal of Advances in Information Technology, Vol. 12, No. 2, pp. 113-118, May 2021. doi: 10.12720/jait.12.2.113-118.

9. Shanavas, D.M.a.A.R.M., *Novel Shared Input Based LSTM for Semantic Similarity Prediction.* Journal of Advances in Information Technology, Vol. 13, No. 4, pp. 387-392, August 2022.

10. Arry M. Syarif, A.A., S. Suprapto, and K. Hastuti, *Gamelan Melody Generation Using LSTM Networks Controlled by Composition Meter Rules and Special Notes.* Journal of Advances in Information Technology, Vol. 14, No. 1, pp. 26-38, February 2023., 2023.

11. M. A. Istiake Sunny, M.M.S.M.a.A.G.A., *Deep Learning-Based Stock Price Prediction Using LSTM and Bi-Directional LSTM Model.* 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES), Giza, Egypt, 2020, pp. 87-92, doi: 10.1109/NILES50944.2020.9257950.

12. M. Ibrahim, K.M.B.a.A.E.H., *Artificial intelligencebased approach for Univariate time-series Anomaly detection using Hybrid CNN-BiLSTM Model.* 2022 13th International Conference on Electrical Engineering (ICEENG), Cairo, Egypt, 2022, pp. 129-133, doi: 10.1109/ICEENG49683.2022.9781894.

13. Aggarwal, C.C., *Neural Networks and Deep Learning. 2018.*

14. Alzubaidi L, Z.J., Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, and F.M. Santamaría J, Al-Amidie M, Farhan L, *Review of deep learning: concepts, CNN architectures, challenges, applications, future directions.* J Big Data. 2021;8(1):53. doi: 10.1186/s40537-021-00444-8.

Epub 2021 Mar 31. PMID: 33816053; PMCID: PMC8010506. 2018.

15. Olah, C., Understanding LSTM Networks. 2021.

16. Graves, A., & Schmidhuber, J., *Framewise phoneme classification with bidirectional LSTM and other neural network architectures. Neural Networks.* 18(5-6), 602-610. doi: 10.1016/j.neunet.2005.06.042, 2005.

17. Modelling Radiological Language with Bidirectional Long Short-Term Memory Networks, C.e.a.

18. Institute, C., *Alternative Investment and Portfolio Management.* Vol. 6. 2020. 28.

19. Z. He, J.Z., H. -N. Dai and H. Wang, *Gold Price Forecast Based on LSTM-CNN Model.* 2019 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom /CyberSciTech), Fukuoka, Japan, 2019, pp. 1046-1053,doi: 10.1109/ DASC/PiCom/CBDCom/CyberSciTech.2019.00188.

20. Chen, C.-C.K., Yi-Chun & Huang, Chien-Hua & Chen, An-Pin., *WITHDRAWN: Applying market profile theory to forecast Taiwan index futures market. Expert Systems with Applications.* 41. 4617–4624. 10.1016/j.eswa.2013.08.093. , 2014.

21. Ganatra, A.K., Y.. (2010). *Spiking Back Propagation Multilayer Neural Network Design for Predicting Unpredictable Stock Market Prices with Time Series Analysis.* International Journal of Computer Theory and Engineering. 963-971. 10.7763/IJCTE.2010.V2.271.

22. Padial, D.L., Technical Analysis Library in Python. 2021.

23. Kumar, G., U.P. Singh, and S. Jain, *Hybrid evolutionary intelligent system and hybrid time series econometric model for stock price forecasting.* International Journal of Intelligent Systems, 2021. 36(9): p. 4902-4935., 2021.

24. Kumar, G., S. Jain, and U.P. Singh, *Stock Market Forecasting Using Computational Intelligence:.* A Survey. Archives of Computational Methods in Engineering, 2020. 28(3): p. 1069 -1101., 2020.

VITA

NAME	ภูริณัฐ พลศรี
DATE OF BIRTH	11 กันยายน 2539
PLACE OF BIRTH	กรุงเทพมหานคร, ประเทศไทย
INSTITUTIONS ATTENDED	วิศวกรรมศาสตรบัณฑิต วิศวกรรมไฟฟ้า จุฬาลงกรณ์มหาวิทยาลัย (พ.ศ. 2558 - 2561)