SUPERVISED DECISION MAKING IN FOREX INVESTMENT USING ML AND DL CLASSIFICATION METHODS

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ISIK UNIVERSITY
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ABSTRACT

The suggested trading system offers an approach that takes into account the complexity and high trading volume of the foreign exchange (FX0) market. Its main objective is to address the challenges faced by traders in the GBP/JPY currency pair and assist them in making quick decisions. To achieve this, machine learning and deep learning techniques are integrated to propose a trading algorithm.

The proposed algorithm works by combining data from different time intervals. The Long Short-Term Memory (LSTM) model is used to predict indicator values, while the XGBoost classifier is employed to determine trading decisions. This method aims to adapt to rapidly changing patterns in the forex market and enables the detection of subtle changes in price dynamics through a sliding window training approach.

Experiments conducted have shown promising results for the suggested trading system. Positive outcomes have been obtained in terms of capital growth and prediction accuracy. However, since this method is highly risky and requires further development in terms of risk management, the inclusion of risk management techniques and algorithm optimization is targeted.

This study contributes to the improvement of trading strategies while bridging the gap between researchers and traders. It also demonstrates the potential of machine learning and deep learning techniques to enhance decision-making processes in financial markets.

This trading system offers traders a range of advantages. The utilization of machine learning and deep learning techniques enables rapid analysis of large amounts of data and decision-making capabilities. Additionally, by combining data from different time intervals, it becomes possible to evaluate long-term trends and short-term fluctuations more effectively.

In conclusion, the suggested trading system empowers traders to be competitive in the forex market and achieve better outcomes. Furthermore, it contributes to the increased utilization of machine learning and deep learning techniques in financial markets and encourages further research in the field.

Keywords: GBP/JPY Currency Pair, Machine Learning, Deep Learning, Long Short-Term Memory (LSTM), XGBoost Classifier

ML VE DL SINIFLANDIRMA YÖNTEMLERİ KULLANARAK FOREX YATIRIMLARINDA DENETİMLİ KARAR ALMA

ÖZET

Önerilen işlem sistemi, döviz (FX) piyasasının karmaşıklığını ve yüksek işlem hacmini dikkate alan bir yaklaşım sunmaktadır. Bu sistemin temel amacı, GBP/JPY döviz çifti için tüccarların karşılaştığı zorlukları ele almak ve hızlı kararlar alabilmelerine yardımcı olmaktır. Bu amaçla, makine öğrenimi ve derin öğrenme teknikleri entegre edilerek bir işlem algoritması önerilmektedir.

Önerilen algoritma, farklı zaman aralıklarındaki verileri birleştirerek çalışır. Uzun Kısa Vadeli Bellek (LSTM) modeli, gösterge değerlerini tahmin etmek için kullanılırken, XGBoost sınıflandırıcısı ise alım satım kararlarını belirlemek için kullanılır. Bu yöntem, kayar pencere eğitim yaklaşımıyla döviz piyasasındaki hızla değişen kalıplara uyum sağlamayı hedefler ve fiyat dinamiklerindeki ince değişiklikleri algılamayı mümkün kılar.

Gerçekleştirilen deneyler, önerilen işlem sisteminin umut verici sonuçlar gösterdiğini göstermektedir. Sermaye büyümesi ve tahmin doğruluğu açısından olumlu sonuçlar elde edilmiştir. Ancak, bu yöntem yüksek riskli olduğundan ve risk yönetimi açısından daha fazla geliştirme gerektirdiğinden, risk yönetimi tekniklerinin ve algoritma optimizasyonunun dahil edilmesi hedeflenmektedir.

Bu çalışma, araştırmacılar ve tüccarlar arasındaki boşluğu kapatırken işlem stratejilerinin geliştirilmesine katkıda bulunmaktadır. Ayrıca, finansal piyasalardaki karar verme süreçlerini iyileştirmek için makine öğrenimi ve derin öğrenme tekniklerinin potansiyelini göstermektedir.

Bu işlem sistemi, tüccarlara bir dizi avantaj sunar. Makine öğrenimi ve derin öğrenme tekniklerinin kullanımı, büyük miktarda veriyi hızlı analiz etme ve karar alma yeteneği sağlar. Ayrıca, farklı zaman aralıklarındaki verilerin birleştirilmesi sayesinde uzun vadeli trendleri ve kısa vadeli dalgalanmaları daha iyi değerlendirmek mümkün olur.

Sonuç olarak, önerilen işlem sistemi tüccarların döviz piyasasında rekabetçi olmasını ve daha iyi sonuçlar elde etmesini sağlar. Aynı zamanda, makine öğrenimi ve derin

öğrenme tekniklerinin finansal piyasalardaki kullanımının artmasına ve daha ileri araştırmaların yapılmasına katkıda bulunur.

Anahtar kelimeler: GBP/JPY Döviz çifti, Makine öğrenimi, Derin öğrenme, Uzun Kısa Vadeli Bellek (LSTM), XGBoost sınıflandırıcısı.

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Abdullah JIROUDI

To my family . . .

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LIST OF ABBREVIATIONS

FX: Foreign Exchange Market

LSTM: Long Short Term Memory

EA: Expert Advisor

RSI: Relative Strength Index

SMA: Simple Moving Average

GBP: Great Britain Pound

JPY: Japanese Yen

API: Application Programming Interface

MT5: Meta Trader 5

CHAPTER 1

1. INTRODUCTION

1.1 Background

The financial system has progressed substantially since its inception. It's been an exciting journey from barter trade to the current foreign currency market, or forex, full with innovations and significant turning moments. This introduction gives the reader a complete overview of the formation of the financial system, with a focus on the development of the currency market.

Commerce may be traced back to the ancient past, when individuals exchanged goods and services directly without the use of a conventional means of exchange, using a system known as barter. This method was popular in the ancient human civilizations of Mesopotamia, Egypt, and the Indus Valley about 6000 BCE (Bailey, 1995).

Money as a mechanism of exchange arose as a consequence of the limitations of barter. King Alyattes of Lydia (modern-day Turkey) developed the first known money about 600 BCE. Electrum coins, a naturally occurring gold and silver alloy, were used to foster trade in the region (Maurer, 2013).

The concept of banking initially emerged about 2000 BCE in ancient Mesopotamia, where temples provided a safe area to store wealth. Lenders and money changers were vital to the Roman Empire's economy, contributing to the development of contemporary banking practices. The Medici family established the first modern banks in Italy in the 14th century, and as a consequence, double-entry bookkeeping and bills of exchange evolved (Hunt and Murray, 2012).

The Dutch East India Company issued the first shares in 1602, laying the framework for modern stock markets. The Amsterdam Stock Exchange, today known as Euronext Amsterdam, created the market for buying and selling publicly traded company shares (Petram et al., 2011). The requirement for stable currency exchange rates drove the evolution of the forex market throughout time. The Gold Standard, which was implemented by a significant number of countries in the late nineteenth century, linked currencies to gold and provided stability in global trade. The system finally failed in the 1930s (Eichengreen, 2019) due to its inability to withstand the economic shocks of the first World War.

After World War II, the Bretton Woods Agreement, enacted in 1944, established a new monetary system. Most currencies were pegged to the US dollar, which had a set gold exchange rate. After the United States left the gold standard in 1971, a new foreign exchange market with floating exchange rates emerged (Bordo, 1993).

The Foreign Exchange Market, or Forex, is an international financial market where currencies are traded at predetermined exchange rates between buyers and sellers. This is the process that everyone from individuals to multinational corporations to national central banks use to change one currency into another. The daily trading volume in the Forex market was estimated in April 2013 at approximately 5.3 trillion dollars, according to the Bank for International Settlement (Hoang, 2013). When computerized trading platforms were developed in the 1980s, they revolutionized the forex market by facilitating faster transactions and increasing market accessibility. As retail forex trading grew and internet trading platforms emerged in the 1990s and 2000s, the market underwent major upheaval (Lyons et al., 2001). To trade FX, a trader must first open an account with a brokerage firm that offers forex trading services. While selecting a forex broker, one must consider topics like regulation, fees, spreads, trading platforms customer support as well as to check if the broker is regulated by a reputable agency, such as the CFTC (the US Commodities Futures Trading Commission) and the FCA (the UK Financial Conduct Authority). After choosing a broker, a trading account has to be opened. This stage often requires completing an online application form as well as supporting papers for identity verification.

Depending on the broker, you may be able to choose from many account types, such as standard, mini, or micro-accounts. The minimum initial deposit and trading amount for each account type varies.

Governments, banks, investors, and traders would not want to buy or sell currencies in an unexpected way. They would consider both short-term and long-term assessments and projections for the movements of their target currencies. They monitor a number of elements that influence market swings. They are seeking to “buy low” and “sell high.” An investor buys the currency that he or she feels will appreciate in value over time. Since the market is digital and prices vary instantaneously, a specific governmental action or change to any other influencing factor may cause the market to move dramatically. And for this reason various types of forex market analysis have developed, reflecting changes in technology, economic theories, and trading practices (Melvin and Norrbin, 2017). We will delve into the historical development of two main types of forex market analysis; technical and fundamental.

- Technical Analysis:

Technical analysis has its roots in the 17th century when Japanese rice traders used candlestick charting techniques to predict rice price movements (Nison, 2001). However, it was not until the 20th century that technical analysis gained significant traction in the Western world. In the 1920s and 1930s, Charles Dow, Ralph Nelson Elliott, and W.D. Gann developed some of the earliest technical theories, such as Dow Theory, Elliott Wave Theory, and Gann angles (Murphy, 1999a).

- Fundamental Analysis:

First proposed in their book "Security Analysis"(Lo and Hasanhodzic, 2010) published in 1934, basic analysis can be traced back to the early 20th century with the work of Benjamin Graham and David Dodd. Over time, these principles were adapted for the forex market, with traders examining macroeconomic factors that influence currency values (Rajendran et al., 2013).

With the development of computer science, machine learning, and deep learning appeared, and attempts to apply them to the forex market began. Researchers attempted to anticipate Forex using both classification and regression methods. They specified whether the price of the target currency would increase or decrease, which is known as “binary classification”. Another method is regression, in which they attempt to forecast the precise value of the currency in the future. In this study, we concentrate on binary classification by developing a unique hybrid model composed of XGBoost and LSTM models that predicts the movement of the pound sterling against the

Japanese yen currency for the next 30 minutes, utilizing sliding window and overlapping time frame techniques.

1.2 The Problem

The foreign exchange (FX) market is well-known for its complexity and magnitude, with daily trading volumes exceeding $6 trillion (Wooldridge, 2019). Currency values are affected by a broad variety of circumstances, including macroeconomic data, geopolitical developments, central bank activities, and market sentiment. The interconnection of this decentralized market adds another layer of complexity, since events in one place may affect currency exchange rates all around the globe. The huge quantity of produced data, including news, trading volume, and price quotes, makes data administration and analysis complex. To navigate the complexity of the forex market, traders are using big data and advanced analytics technologies such as machine learning algorithms, AI, and NLP. Traders may improve their chances of success in the intensely competitive and tough field of forex trading by making more informed decisions, monitoring several data sources, and using cutting-edge technologies.

In this study, we address two primary challenges faced by traders in the financial markets. The first challenge pertains to decision-making under high-pressure environments, where traders must navigate vast amounts of data, rapid price fluctuations, and psychological stress. This is particularly relevant for short-term traders who base their strategies on intra-day price movements.

The second challenge arises from the utilization of inappropriate data sources for analysis and decision-making. The foreign exchange market generates a plethora of data types, compounded by the vast array of technical indicators available to traders. Consequently, researchers have a broad scope for experimentation. However, some studies have employed data that may not be applicable in real-world trading situations, such as the use of future data, including closing prices. This practice results in research outcomes that may appear theoretically impressive, but lack practical significance and validity in real trading scenarios.

1.3 Aim of the Study

This study aims to integrate the fields of machine learning and deep learning in order to present a comprehensive and realistic trading system on the pound sterling currency in comparison to the Japanese yen that engages in direct trading on the forex market for three consecutive months. This study is presented as scientific research in addition to being a real system that functions as a trading robot and provides actual trading results directly from the market.

This study also aims to close the gap between theoretical scientific research and practical application of traders by suggesting ways to predict the movement of the future based on merging elements of the present with it.

CHAPTER 2

2. LITERATURE REVIEW

In this chapter, we will discuss various methods of prediction that are utilized in the foreign exchange market, factors that have an impact on the market, the application of machine learning in the financial sector, the scientific evaluation of the models that are utilized, and related studies that investigate the same problem.

2.1 Fundamental and Technical Analysis

Fundamental analysis and technical analysis are the two basic methods that investors and traders use to evaluate and forecast the performance of financial markets such as stocks and FX. Both approaches provide distinctive insights, and it is possible to use a combination of the two to obtain a deeper comprehension of the market.

An asset's intrinsic value is the primary focus of fundamental analysis, which determines this value by investigating the asset's underlying financial, economic, and qualitative characteristics. When it comes to equities, this includes factors like financial statements and ratios, as well as trends in the industry and management performance. While determining the value of a currency, various economic and political aspects are taken into account. They include interest rates, inflation rates, trade balances, and political stability. The purpose of fundamental analysis is to assess, given the present price of an asset on the market, whether or not the asset is now undervalued or overvalued.

On the other hand, technical analysis examines past price data in conjunction with volume information in order to uncover price trends and patterns that may serve as a predictor of future fluctuations. Technical analysts create forecasts based on the analysis of price charts and the application of a number of analytical techniques, including moving averages, trend lines, and technical indicators such as the relative strength index (RSI) and the moving average convergence-divergence (MACD). The underlying idea behind technical analysis is that past price patterns have a tendency to be repeated, and that these patterns may be utilized to make accurate predictions about how prices will behave in the future.

Investors and traders can obtain a more complete understanding of the market and be able to make decisions that are more in line with their interests by employing both fundamental analysis and technical analysis. In contrast to fundamental analysis, which reveals insights into the underlying worth of an asset and its long-term prospects, technical analysis gives a method for determining entry and exit points based on short-term price patterns and trends. The combination of the two tactics offers market players the potential to improve the efficiency of their risk management and investing strategies by optimizing their returns.

2.2 Factors Affecting the Forex Market

The foreign exchange market is subject to the effects of a wide range of factors, any one of which can contribute to shifts in exchange rates. The economic, political, and market-related aspects of these issues can be broken down into three basic categories. The following is a list of some of the most significant elements that influence the market for foreign exchange:

- Economic Factors:
    a. Interest rates: Central banks rely heavily on interest rates as a means of controlling inflation and promoting economic stability. Higher interest rates typically entice foreign investment, leading to a rise in the value of the domestic currency.

    b. Rates of inflation: Reduced inflation rates in a country might lead to an appreciation of that country's currency since the country's purchasing power increases in comparison to the purchasing power of other currencies.

c. Economic expansion and performance: Robust economic expansion and performance might entice foreign investment, which can then lead to an appreciation of the local currency

d. Balance of payments: A nation that has a positive balance of payments—that is, one in which exports are higher than imports—may see an appreciation in its currency as a result of an increase in demand for its goods and services.

e. Government spending, taxation, and the policies of a country's central bank can all have an effect on a nation's economic stability, which in turn can have an effect on the value of that nation's currency.

- Political factors:

a. Political stability: An environment that is free from political unrest is more likely to have favorable investment conditions, which can contribute to an increase in the value of the country's own currency.

b. Elections and other political events: Elections and other political events can induce uncertainty, which can have an effect on exchange rates since investors may shift their portfolios.

c. Events of a geopolitical nature: Wars, sanctions, and trade disputes can all have an impact on currency exchange rates because they hinder the flow of trade and investment between nations.

- Market-related factors:

a. Market sentiment: the perceptions of the market and level of risk appetite held by traders can have an effect on currency exchange rates. Both optimism and pessimism can influence the amount of demand for or opposition to a certain currency.

b. Speculation: The acts of currency traders, such as purchasing and selling currencies in anticipation of future price fluctuations, can have an effect on the exchange rates.

c. Factors of a technical nature: The decisions that traders make can be influenced by technical analysis, which is the study of previous price patterns and trends. This can have an effect on exchange rates.

d. Interventions by central banks: Central banks can adjust the value of their currency by intervening in the foreign exchange market.

e. Natural disasters: Unpredictable occurrences such as earthquakes, tsunamis, or hurricanes have the potential to influence the economic stability of a nation as well as the value of its currency.

These elements frequently interact with one another in convoluted ways, and market players regularly evaluate and respond to changes in these factors, which results in swings in the market for foreign exchange.

2.3 Machine Learning in Finance

The implementation of machine learning (ML) strategies in the financial industry has resulted in significant shifts in the business practices of various financial organizations, opening the door to methods of decision-making that are both more efficient and accurate (Henrique et al., 2019). It is possible for machine learning algorithms to learn from historical financial data in order to forecast future trends, identify hazards, and automate multiple activities; this can result in better accuracy and speed in financial operations (Sirignano and Cont, 2019). The algorithms that make up machine learning can acquire new knowledge from previously collected financial data.

The use of machine learning in the financial industry has produced a number of notable applications, one of which is algorithmic trading. Algorithms that learn through machine experience are able to examine vast quantities of historical data pertaining to the stock market in order to recognize patterns and trends, which can then be used to inform trading decisions (Ray, 2019). Automatic trading systems that are driven by machine learning have the ability to finish deals more quickly than human traders, which opens the door to the possibility of increased profitability (Cont, 2001).

In addition to its usage in algorithmic trading, machine learning has also found use in the fields of credit scoring and risk assessment. Conventional credit scoring algorithms rely on a set of predetermined features and have restricted access to data sources, both of which might result in estimations that are off (Webb et al., 2005). Algorithms that learn through machine learning are able to manage vast volumes of data that come from a number of sources, which enables more accurate forecasts of creditworthiness and risk level (Bengio et al., 2013). As a direct consequence of this, risk management has the potential to get better, and fewer people will fail on their loans (Hand and Henley, 1997).

The detection of fraudulent activity in the financial industry has been shown to benefit greatly from the application of machine learning. The rise in the number of financial transactions that are conducted online has coincided with an increase in the likelihood of individuals becoming victims of fraudulent activity (Fraga-Lamas and Fern´andez-Caram´es, 2019). The ability of machine learning algorithms to recognize unusual patterns and alert to the possible existence of fraudulent activity in real time is supporting financial institutions in the protection of their consumers and the mitigation of potential losses (Menshchikov et al., 2022).

The application of machine learning in banking presents a number of hurdles, despite the fact that its potential benefits are readily apparent. Because of the complexity of machine learning algorithms, it may be difficult to understand and describe how they operate, which raises questions about accountability and openness (Doshi-Velez and Kim, 2017). It is also important to ensure that the data used to train machine learning models is correct and representative because this might have a significant effect on the models' performance. (Wu et al., 2008).

To summarize, machine learning is having a profound impact on the financial sector by elevating levels of productivity, precision, and speed across a variety of financial operations. In order to maintain their position as market leaders, financial institutions will need to adopt machine learning (ML) and modify their operations in response to the continuously shifting environment (Brynjolfsson and McAfee, 2014). This is because there will be ongoing progress made in technological capabilities.

2.4 XGboost

Extreme Gradient Boosting (XGBoost) is a sophisticated and effective machine learning model that has grown in popularity due to its ability to provide great performance and scalability in a wide range of applications (Chen and Guestrin, 2016). Gradient boosting machines (GBMs) are tree-based ensemble learning systems that work by iteratively combining weak learners to create a strong learner (Friedman, 2001).

One of the key advantages of XGBoost is its capacity to deal with missing values. This capability makes it particularly useful for real-world applications, where data is frequently inadequate (Chen and Guestrin, 2015). XGBoost employs a sparsity-aware learning algorithm, allowing the model to learn the best strategy for dealing with missing values without human intervention (Lundberg and Lee, 2017). This removes the need for XGBoost users to do any manual work.

Another one of XGBoost's strengths is the regularization approach. These strategies help keep the model from overfitting the data and improve its generalizability (Schapire, 1990). XGBoost employs L1 (Lasso) and L2 (Ridge) regularization to control model complexity and reduces the risk of overfitting (Hastie et al., 2009). Ridge regularization is a very new development.

Furthermore, XGBoost was designed from the ground up to be computationally efficient, making it suitable for usage in large-scale applications (Li et al., 2014). It employs parallel and distributed computing to scale efficiently across a wide range of cores and computer nodes. Furthermore, because it supports out-of-core processing, XGBoost can manage datasets that are larger than the available RAM (Chen et al., 2015).

Classification, regression, and ranking are just a few of the many tasks where XGBoost has excelled. (Qian, 1999). It has been successfully adopted in a wide range of industries, including e-commerce, healthcare, and the financial sector (Kotsiantis et al., 2007). Because of its adaptability and effectiveness, it is widely used in both academic and commercial settings, and it has become a benchmark model for a substantial number of machine-learning competitions (Krizhevsky et al., 2017).

2.5 LSTM

An Efficient and Powerful Deep Learning Model for Sequential Data Long Short Term Memory

Recurrent neural networks (RNNs) with long short-term memories (LSTMs) were developed to address the limitations of traditional RNNs when it comes to learning long-range dependencies within sequential input.(Hochreiter and Schmidhuber, 1997). Natural language processing, speech recognition, and time-series prediction are just a few of the applications that have made LSTMs popular (Graves et al., 2013).

The incorporation of a memory cell capable of storing and updating information over long sequences is the most significant advancement brought forth by LSTM networks (Gers et al., 2000). This specific memory cell is built with gating mechanisms known as input, forget, and output gates (Cho et al., 2014b). These gates are in charge of managing the flow of data into, within, and out of the cell. Because of these gating mechanisms, LSTM networks can learn and recall long-term dependencies, which also assist alleviate the vanishing and exploding gradient problems that are common in ordinary RNNs (Bengio et al., 1994).

The Gated Recurrent Unit, sometimes known as the GRU, is a frequent LSTM variant. It simplifies the LSTM design by integrating into a single update gate the forget and input gates (Cho et al., 2014a). GRUs have been found to perform similarly to LSTMs in a range of tasks. As a result, while having fewer parameters and a lower level of computational complexity, they provide an enticing solution in certain scenarios (Chung et al., 2014).

The fact that LSTMs is applied in a wide range of applications has proven that they are competent in processing complex sequential data. LSTMs have been used in a range of natural language processing applications, including language modeling (Mikolov et al., 2010), machine translation (Sutskever et al., 2014), and sentiment analysis (Socher et al., 2013). In the realm of speech recognition, LSTMs have been integrated into end-to-end systems, yielding performance that is considered cutting-edge (Graves and Jaitly, 2014). LSTMs have also been used in the forecasting of time series in the finance industry and other fields (Selvin et al., 2017).

In conclusion, LSTM networks constitute a powerful and adaptable deep learning model capable of overcoming the challenges associated with sequential data. They have been a popular choice for a wide range of applications due to their ability to learn and recall long-term dependencies, and they remain a vital component of many cutting-edge artificial intelligence applications.

2.6 Related Studies

In this section, we will present studies in this field that aim to predict price direction, as well as the actual future price. As mentioned in the problem definition in the previous chapter, these values are termed as closing, high and low prices.

In the article of Thuy Nguyen Tih Thu and Vuong Dang Xuan (Thu and Xuan, 2018), the authors explore the application of supervised machine learning techniques to predict trends and make informed decisions in the foreign exchange (FoRex) market. Their objective is to enhance trading strategies and boost profitability by using machine learning algorithms that can learn from historical data and make improved decisions accordingly.

To achieve this goal, the researchers gathered a dataset consisting of daily exchange rates from 2010 to 2017, which includes the EUR/USD, GBP/USD, and USD/JPY currency pairs. The data was sourced from the Dukascopy Bank, a reliable financial service provider. The authors used a set of features to represent the data, including Open, High, Low, Close (OHLC) values, moving averages, and other technical indicators like Bollinger Bands, the Relative Strength Index, and the Moving Average Convergence Divergence. The study investigates different supervised machine learning models, including linear regression, support vector machines (SVM), and artificial neural networks (ANN), to identify the most effective model for predicting currency exchange rates. The authors perform a comparative analysis of these models using metrics like mean squared error, mean absolute error, and R-squared values to evaluate performance.

The results of the research show that the artificial neural network model outperforms both linear regression and support vector machines in terms of predictive accuracy. Additionally, the authors found that incorporating technical indicators as features in the models significantly improved their performance. This demonstrates the potential of supervised machine learning techniques to enhance FoRex trading strategies and overall performance, as these algorithms can adapt to changing market conditions and make better-informed decisions based on historical data.

In the article "Predicting stock and stock price index movement" by Jigar Patel, Sahil Shah, Priyank Thakkar, and Ketan Kotecha (Patel et al., 2015) the authors use historical data from the S&P BSE SENSEX (India), Dow Jones Industrial Average (USA), and FTSE 100 (UK) stock price indices, covering the period from January 1998 to August 2012. The data features include daily Open, High, Low, Close (OHLC) values, trading volume, and other technical indicators like the Rate of Change (ROC), the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD).

To ensure the reliability and accuracy of the prediction models, the researchers employ a trend deterministic data preparation (TDDP) method. This technique filters out noise and reduces the impact of random fluctuations in the data, enabling the machine learning algorithms to capture the underlying trends more effectively.

The study explores a variety of machine learning techniques, including Support Vector Machines (SVM), Naive Bayes Classifier (NBC), Artificial Neural Networks (ANN), and k-Nearest Neighbors (k-NN), to determine the most effective approach for predicting stock and stock price index movement. Authors use criteria including precision, recall, F1-score, and accuracy to assess these models' efficacy.

The results of the research show that the Support Vector Machines (SVM) model outperforms the other techniques in terms of prediction accuracy, particularly when combined with the trend deterministic data preparation method. This indicates that SVM is an effective tool for predicting stock and stock price index movement, and can help investors make better-informed decisions in the stock market.

In the paper of Sitti Wetenriajeng Sidehabi, Sofyan Tandungan (Sidehabi et al., 2016) the authors examine the use of statistical and machine learning methods for predicting trends in the foreign exchange (forex) market. The primary goal is to improve forex trading strategies and enhance profitability by developing accurate prediction models based on empirical data.

The study makes use of historical forex data from the Federal Reserve Bank of St. Louis, including daily exchange rates for the Euro to US Dollar, the British Pound to US Dollar, and the US Dollar to Japanese Yen. The data covers the period from January 2001 to December 2014. The authors use a set of features to represent the data, such as Open, High, Low, Close (OHLC) values, and many different technical indicators such as Bollinger Bands, the Relative Strength Index, and the Moving Average Convergence Divergence (MACD).

This research looks at the accuracy of forecasts made using several statistical and machine learning methods, such as the Autoregressive Integrated Moving Average (ARIMA), artificial neural networks (ANN), and support vector machines (SVM). Mean absolute percentage error, mean absolute error, and root mean squared error are some of the measures the authors use to evaluate the accuracy of these models against one another.

The study found that when comparing the predicted accuracy of several models, the Artificial Neural Networks (ANN) model was superior to both the ARIMA and SVM models. This highlights the possibility for improved forex trading tactics and overall performance using machine learning approaches, notably ANN.

In the article of El-Sherbiny, M. A., & Ibrahim, A. A. (2015) The authors used a two-step approach to predict the future direction of the EUR/USD exchange rate. In the first step, they used SMA to generate a signal that indicated whether the exchange rate was likely to go up or down. In the second step, they used financial factors to improve the accuracy of the SMA signal.

The authors used two different datasets in their study. The first dataset consisted of daily EUR/USD exchange rate data from January 1, 2000 to December 31, 2013. The second dataset consisted of daily data for three financial factors: interest rates, inflation, and economic growth.

The authors found that the SMA model with financial factors was able to predict the future direction of the EUR/USD exchange rate with an accuracy of 62.5%. This is significantly higher than the accuracy of the SMA model alone, which was only 50%. The results of this study suggest that the SMA model with financial factors is a useful tool for predicting the future direction of the EUR/USD exchange rate. The authors recommend that the model be used by traders and investors who are looking to make informed decisions about the EUR/USD exchange rate.

CHAPTER 3

3. APPROACH

The purpose of this chapter is to introduce the reader to the tools and methods that can be used to predict future currency movement in the Foreign Exchange (Forex) market. At first, the instruments employed in the study are introduced, followed by detailed accounts of their deployment. The next section provides an overview of datasets and data cleaning, preprocessing, and methods, before drawing a quick conclusion.

3.1 Tools

In general, we utilize common deep learning libraries and the Python programming language for our investigations. However, in this section, we will outline the specific tools employed in our research.

To conduct tests and develop predictive models, we rely on a range of tools. The Python programming language is our primary choice for constructing models. Additionally, we utilize historical data on specific currencies to assess their signals. Furthermore, we leverage other libraries that enable us to implement pre-built algorithms in various ways. A concise explanation of how each tool fulfills its role will be provided in the subsequent discussion.

MetaTrader 5:

MetaQuotes Software Corp. created the MetaTrader line of computerized trading platforms. Traders utilize these systems extensively, primarily in the foreign exchange market but also for dealing in contracts for difference (CFDs), stocks, and other financial products. MetaTrader 4 (MT4) and 5 are the two most popular versions of the trading platform (MT5).

Traders that use MetaTrader platforms have access to a wide range of features and tools, such as:

For in-depth market analysis, MetaTrader systems have sophisticated charting options over many timeframes. Technical indicators, trendlines, and other graphical objects can be used to analyze price action.

The built-in programming languages MQL4 for MetaTrader 4 and MQL5 for MetaTrader 5 allow traders to make their own unique technical indicators. These unique markers can be put to use for targeted analysis or to streamline laborious procedures.

Expert Advisors (EAs) are automated trading robots that traders can program on MetaTrader platforms and then use to make trades. These EAs assist traders automate their tactics and get rid of emotional decision-making because they are coded in MQL4 or MQL5, respectively, and execute trades based on predetermined trading strategies and market conditions.

MetaTrader's built-in Strategy Testers let traders put their EAs and algorithms through their paces on historical market data. Before putting their plans into action in the real market, traders can see how well they've performed utilizing this function.

In order to be abreast of the market and seize opportunities as they emerge, traders can set up alerts and notifications based on various market circumstances and events.

MetaTrader customers have access to the Market, a place to buy and sell trading robots, indicators, and other tools. You can also imitate the trades of experts by subscribing to their trading signals.

The MetaTrader platforms allow users to handle many trading accounts from a single terminal thanks to their multi-terminal functionality.

Because of their intuitive design, sophisticated charting capabilities, and compatibility with automated trading systems, traders frequently opt for the MetaTrader 4 and 5 platforms. These platforms provide a full set of resources for technical analysis, trade management, and the execution of algorithmic trading techniques, making them suitable for traders of all skill levels. MetaTrader was used to extract all the data used in the study, in addition to applying the proposed method, as direct entry to the market was made through this platform.

MQL 5:

MetaQuotes Language 5 (MQL5) is a high-level programming language designed for use with the MetaTrader 5 (MT5) trading platform. It is used largely for the development of trading robots, technical indicators, and scripts. MetaTrader 5, created by MetaQuotes Software Corp., is a popular and widely-used platform for trading foreign exchange (FX), equities, and other financial instruments.

MQL5 offers several significant features and advantages for traders and developers:

Object-oriented programming: MQL5 follows an object-oriented programming paradigm, which provides for improved code organization, reusability, and maintainability. This makes it easier for developers to construct and manage complicated trading algorithms and strategies.

Built-in functions: MQL5 contains a wide library of built-in functions for executing various trading operations, including as opening and closing orders, altering stop-loss and take-profit levels, and accessing market information.

Custom indicators and scripts: MQL5 enables users to generate custom technical indicators and scripts for evaluating financial markets and automating trading operations, allowing them to create their own trading tools adapted to their needs and tactics.

Expert Advisors (EAs): MQL5 allows developers to create Expert Advisors, which are automated trading robots capable of executing trades on behalf of the user depending on established strategies and market conditions. By automating their techniques, EAs assist traders cut out the time-consuming and potentially detrimental emotional component of trading.

Strategy Tester: MetaTrader 5 contains a built-in Strategy Tester that enables users to test and optimize their trading algorithms and EAs using historical market data. This helps traders analyze the performance of their techniques before employing them in actual trading.

Users can purchase and sell trading robots, indicators, and other tools on the MQL5 Market, which is supported by a vibrant community of traders and developers who share their knowledge and code on forums and blogs.

MQL5 is an essential tool for traders and developers who wish to design bespoke trading strategies, indicators, and automated trading systems for the MetaTrader 5 platform. Its robust capabilities and wide support from the community make it a popular choice among developers working in the field of algorithmic trading. This programming language was used to develop a trading robot whose mission is to communicate data between the trading platform and the Python program that contains the algorithm.

Google Colab:

Google Colab, sometimes known as Google Colaboratory, is a no-cost online environment for working on and running Jupyter Notebooks. It’s a great option for doing scientific computing, machine learning, and data science without having to download and install any additional software. Features such as pre-installed popular Python libraries like NumPy, Pandas, TensorFlow, and Keras, as well as free GPU support for rapid computing, real-time collaboration capabilities, connection with Google Drive for easy sharing and storing, and so on, are among the highlights. Google Colab is a popular platform among data scientists, researchers, and developers as a place to study, prototype, and collaborate on Python-based projects due to its user-friendliness, accessibility, and powerful computational capabilities. Google Colab was used to train the LSTM models used in the study.

3.2 Technical Indicators

A variety of built-in technical indicators are available on MetaTrader platforms, particularly MetaTrader 4 (MT4) and MetaTrader 5 (MT5), to assist traders in analyzing price movements and making wise trading decisions. Technical indicators help traders spot trends, patterns, and prospective trading opportunities by performing mathematical calculations based on historical price and volume data and visualizing the results on a chart. The selected technical indicators for this study, which are commonly used and available on MetaTrader platforms, are as follows:

Simple n-day Moving Average (SMA): This represents the average cost of an asset over a given time frame (n days). To determine it, tally up the asset's closing prices over a specified time period, and then divide by that number. The SMA is useful for spotting patterns since it flattens out daily price variations.

Weighted n-day Moving Average (WMA): The WMA is another method for determining the average price of an item over a given time frame, analogous to the SMA. However, WMA is more sensitive to recent price fluctuations since it gives more weight to more recent prices.

Momentum: The rate of price change is tracked by this indicator. By comparing the current closing price to a prior closing price, this method helps determine the strength of a trend and possible reversals.

Stochastic K%: A momentum oscillator, the Stochastic K% looks at how an asset's final price stacks up against its trading range over some period of time. It's useful for spotting when the market has become overbought or oversold.

Stochastic D%: This is a moving average of the Stochastic K% and provides a signal line to identify potential trend reversals.

Relative Strength Index (RSI): The Relative Strength Index (RSI) is a momentum oscillator that evaluates the rate of change in price. It can be used to spot overbought or oversold conditions and has a range of 0-100. An RSI calculation looks like this: RSI = 100 - (100 / (1 + RS)), where RS is the average gain/average loss over a given time frame.

Moving Average Convergence Divergence (MACD): The Moving Average Convergence Divergence (MACD) is a momentum indicator that helps traders follow price trends. It is useful for spotting potential trend reversals, and it is computed by deducting the longer-term moving average from the shorter-term one.

A/D (Accumulation/Distribution) Oscillator: This indicator evaluates the flow of capital into and out of an asset by considering both the asset's price and trading volume. It helps to identify buying and selling pressure in the market, as well as potential trend reversals.

CCI (Commodity Channel Index): The CCI is an example of a momentum oscillator that looks at how far asset prices are from the average. It's a useful tool for spotting reversals in trends and overbought/oversold circumstances in the market.

3.3 Datasets

This study has been applied to the sterling pound against the Japanese yen (GBP/JPY). Three types of data were extracted from the MetaTrader program. They will be explained in detail in this section. All data has been extracted in the form of Japanese candlesticks, which will be explained in detail for the purpose of clarity. The data was extracted from 2 different timeframes; one-hour timeframe and a 30-minute timeframe.

Table 3.1 Selected technical indicators & their formulas for this study.

Name of indicators	Formulas
Simple n-day Moving Average	$\frac{C_t + C_{t-1} + \cdots + C_{t-9}}{n}$
Weighted n-day Moving Average	$\frac{(10)C_t + (9)C_{t-1} + \cdots C_{t-9}}{n + (n-1) + \cdots + 1}$
Momentum	$C_t - C_{t-9}$
Stochastic K%	$\frac{C_t - LL_{t-(n-1)}}{HH_{t-(n-1)} - LL_{t-(n-1)}}$ x 100
Stochastic D%	$\frac{\sum_{i=0}^{n-1} k_{t-i}}{10}\%$
Relative Strength Index (RSI)	100 - $\frac{100}{1+(\sum_{i=0}^{n-1} UP_{t-i})/n)\ /\ (\sum_{i=0}^{n-1} DW_{t-i})/n}$
Moving Average Convergence Divergence (MACD)	$\mathrm{MACD}(n)_{t-1} + \frac{2}{n+1} \times \mathrm{DIFF}_t - \mathrm{MACD}(n)_{t-1})$
Larry William's R%	$\frac{H_n - C_1}{H_n - L_n} \times 100$
A/D (Accumulation/Distribution) Oscillator	$\frac{H_t - C_{t-1}}{H_t - L_t}$
CCI (Commodity Channel Index)	$\frac{M_t - SM_t}{0.015D_t}$

C_t can refer to both closing and opening price , L_t is the low price and H_t the high price at time t, $DIFF_t = EMA(12)_t - EMA(26)_t$, EMA is exponential moving average, $EMA(k)_t = EMA(k)_{t-1} + \alpha \times C_t - EMA(k)_{t-1}$, α is a smoothing factor which is equal to $\frac{2}{k+1}$, k is the time period of k-day exponential moving average, LL_t and HH_t implies lowest low and highest high in the last t days, respectively. $M_t = \frac{H_t + L_t + C_t}{3}$, $SM_t = \frac{(\sum_{i=1}^{n} M_{t-i+1})}{n}$, $D_t = \frac{(\sum_{i=1}^{n} | M_{t-i+1}) - SM_t |}{n}$, UP_t means upward price change while DW_t is the downward price change at time t. simple and weighted moving average n = 10.

3.3.1 Candlestick Charting

Candlestick charting is a popular kind of visual representation for technical analysis of stocks, currencies, and other tradable assets on the financial markets. Each "candle" on a candlestick chart represents the open, high, low, and close prices for a given time period. This type of charting has its roots in Japan, but it has gained widespread acceptance among traders and investors around the world.

The chart's candlesticks have two primary parts: the body and the wick (or shadow). The "body" of the candle depicts the range of prices from opening to closing, while the "wick" indicates the range of prices from high to low. The body is filled or colored (often green or white) to indicate a bullish phase when the closing price is greater than the opening price. In contrast, a bearish phase is indicated by a body that is empty or a different hue (usually red or black) when the closing price is lower than the opening price. By exhibiting patterns generated by the candlesticks, candlestick charts give important insights into market mood and probable price moves.

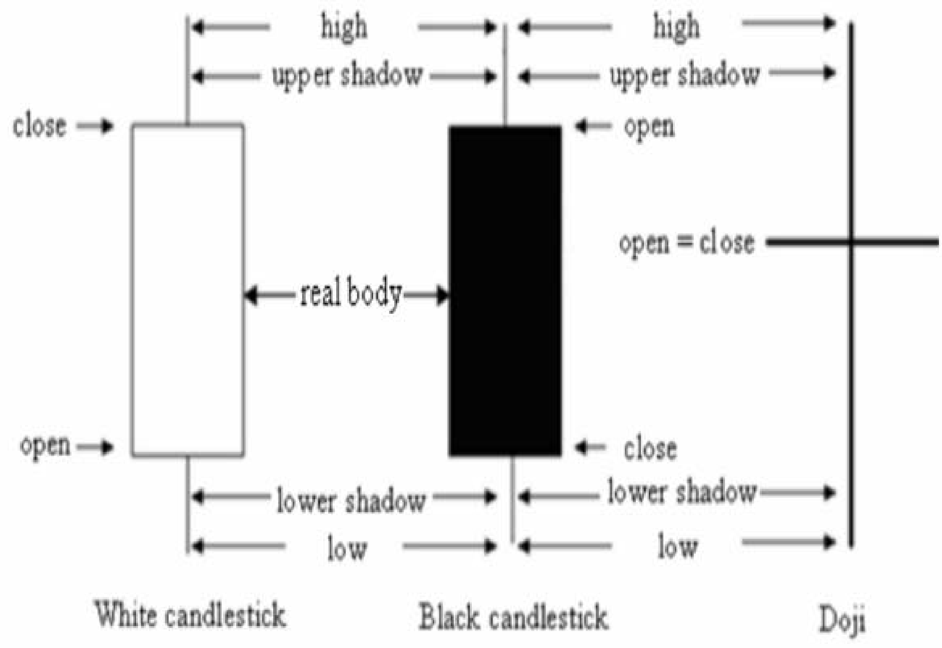

Figure 3.1 Candlestick construction

3.3.2 Dataset A: Forecasting

Initially, the goal of this dataset is to serve as a training set for an LSTM model, and using it, we want to improve our ability to predict the values of several different indicators. This dataset covers the period from 01/01/2022 to 29/07/2022 and consists of one-hour time frame candlesticks. It includes the Open, High, Low, and Close prices as features, as well as a TimeStamp and all the technical indicator values that were listed in Table 3.1. The closing price is used to calculate all technical indicator values in this dataset.

3.3.3 Dataset B: Support

This dataset works as a support for the primary dataset (Dataset C). We will explain more about that in the algorithm overview section. This dataset covers the period from 01/09/2022 to 30/11/2022 and consists of 30-minute time frame candlesticks. It only contains Open, High, Low, and Close prices.

3.3.4 Dataset C: Primary

This dataset covers the period from 01/09/2022 to 30/11/2022, but it consists of one-hour time frame candlesticks. It includes the Open price, TimeStamp, simple moving average, weighted moving average, momentum, moving average convergence divergence (MACD), relative strength index (RSI), and commodity channel index (CCI). The Open price is used to calculate all technical indicator values in this dataset.

Additionally, the results of predicted indicator values that have been generated from dataset A and dataset B values will be appended to this main dataset.

3.4 Pre-processing

Before delving into the methodology, it is crucial to carry out several pre-processing steps for each dataset identified in the previous section. This section will expound on these steps.

Dataset A: This dataset will be utilized to train an LSTM model to predict specific indicator values, as explained in the Indicators forecasting section. To achieve this objective, the dataset has been segmented into 3561 batches, with each batch comprising 39 data lines that correspond to the values of the indicator to be predicted.

Dataset B: This dataset has been labeled with the values of 1 and 0, 1 signifying a buying and 0 signifying a selling candlestick. The labels were derived by calculating the difference between the Open price and Close price, while upper and lower tails were calculated by subtracting the High price from the Close price and the Low price from the Open price, respectively, in instances where the label is 1. In instances where the label is 0, the High price is subtracted from the Open price and the Low price from the Close price to derive the upper and lower tails, respectively. Additionally, the candlestick size was calculated by determining the absolute value of the difference between the Open and Close prices.

Dataset C: Similarly to Dataset B, this dataset has been labeled with the values of 1 and 0. In addition, information has been appended from Dataset B, such as the upper and lower tails, candle size, and candlestick label. However, only information from the first 30 minutes has been included as Dataset C solely comprises hourly candlestick data. To represent technical indicators categorically, continuous values have been transformed into binary values of 1 and 0. Specifically, a value of 1 indicates an uptrend, while a value of 0 indicates a downtrend. This transformation is carried out by examining whether the value at time "t" is greater than the value at time "t − 1" and vice versa.

3.5 Algorithm Overview

This algorithm aims to determine the direction (0 or 1) of the hourly price candle, where 0 represents a sell position and 1 represents a buy position. In order to reach this goal, we will combine information from the hourly frame with the half-hour frame. In this section, we illustrate how the algorithm works over a 60-minute period candle price time line.

Firstly, at the opening moment of the hourly candle, we will predict the values of three indicators at the price candle's closing place in the future using the LSTM model. This model was previously trained using dataset A to predict the values of indicators at the closing places. The indicators are momentum, simple moving average, and RSI from Table 3.1. In this way, we will have an initial view of the direction of the price candle during the next hour.

After thirty minutes of the hour, a full candle in the lower timeframe (thirty minutes) will be formed. The data of this thirty-minute candle will be prepared as it was explained in the pre-processing section of the data, specifically the B dataset. In this way, now we have half of the complete trend completed from our primary goal, which is the hourly candle.

At the opening of the thirty-first minute, Dataset C starts to be created. The value of all indicators in Table 3.1 will be calculated using the open price of the one-hour candle price.

After that, we begin to append the whole Dataset B values into Dataset C, which has just been created. In this case, Dataset B values represent the first half-hour of the one-hour candle price.

Additionally, the forecasted values of the three mentioned indicators at the beginning will also be added to Dataset C, where these values represent the expected closing place for the price candle.

At the end, the whole Dataset C will be given to the pre-trained XGBoost model, and we will explain more about the following training techniques later in Section 3.7.

In conclusion, we are attempting to predict the direction of the second half-hour of a one-hour candlestick price by merging two perspectives. First, we predict the location of the closing through the predicted indicators from the upper timeframe (one-hour timeframe). Second, we use the real market data of the first half-hour from the lower timeframe (30-minute timeframe).

3.6 Forcasted Indicators

The Relative Strength Index (RSI), momentum, and simple moving average (SMA) are essential technical analysis tools in the MetaTrader platform for predicting market price movements. The RSI, a momentum oscillator, helps traders identify overbought or oversold conditions and potential trend reversals, offering valuable entry and exit points (Wilder, 1978). Momentum indicators measure the rate of change in prices, enabling traders to capture strong trends and identify weakening trends before they reverse (Murphy, 1999b). The SMA smoothens price data and allows traders to visualize the underlying trend by calculating the average price over a specified period, thus reducing the impact of short-term price fluctuations (Pring, 2002). When used in combination, these tools offer traders a comprehensive analysis of market conditions, helping them make informed decisions about potential trading opportunities. By leveraging the RSI, momentum, and SMA in the MetaTrader platform, traders can effectively predict market price movements, manage risk, and enhance their trading strategies.

Therefore, as previously indicated, our study involves the prediction of these three key indicators, which will be incorporated into our primary dataset. In this section, we will expound upon the selected indicators and their significance in aiding the prognostication of trend direction. The present section aims to explicate the layers of the LSTM model, along with a comprehensive analysis of the significant hyperparameters. Furthermore, the study endeavors to present the outcomes of the predictive model, accompanied by a thorough evaluation of the performance scores.

3.6.1 LSTM Structure

We employed an LSTM network to predict three selected indicator values. the same structure was employed to train all three models. Table 3.2 presents the layers utilized, with a ReLU activation function employed for all layers in conjunction with the 'adam' optimizer. The training epochs for all models were set at 100, with a validation split of 20%. The loss function utilized was Mean Squared Error. The primary challenge encountered was overfitting, which was addressed through the use of dropout layers and early stopping techniques. The batch size parameter was observed to exhibit two distinct values during the experimentation phase. Specifically, a value of 8 was utilized in the context of the Relative Strength Index (RSI), while a value of 16 was employed when considering the Momentum and Simple Moving Average indicators.

Table 3.2 LSTM Network's Structure Used In Forecasting

Layer	Type	Output shape	Number of parameters
1	LSTM	x,64	22016
2	Dropout	x,64	0
3	LSTM	x,60	30000
4	Dropout	x,60	0
5	LSTM	x,80	45120
6	Dropout	x,80	0
7	LSTM	120	96480
8	Dropout	120	0
9	Dense	1	121

3.6.2 Forecasting Results

The experimental duration spans a period of three consecutive months of live trading, commencing on September 1st, 2022, and concluding on November 30th, 2022. The test period for evaluating the efficiency of the LSTM models was selected as the duration between August 1st, 2022, and August 30th, 2022. The training dataset, as previously stated in the datasets section, consisted of data from January 1st, 2022, to July 29th, 2022. In order to evaluate the precision of the forecasting models, three distinct measurement techniques were employed as follows.

Regression models and other predictive algorithms are frequently measured using Mean Squared Error (MSE). In other words, it calculates the average squared deviation between the forecasted and observed values. The MSE is optimized in order to boost the model's precision. The definition of MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(P_i - Y_i)^2 \tag{3.1}$$

where n is the number of observations or data points, Pi is the predicted value for the i − th observation, Yi is the actual (true) value for the i − th observation, and the sum represents the sum of the squared differences across all observations.

A regression model's R-squared (R2, also written as r-squared) indicates what fraction of the total variance in the dependent variable can be attributed to the independent variables. In other words, a high R-squared value shows that the model is well-fitting and that the independent variables adequately explain the variation in the dependent variable.

R-squared can take on values between 0 and 1, with higher values suggesting that the model adequately explains the dependent variable's variation and lower values showing that less variance is explained by the model. An R-squared value of 1 indicates that all the observed variation in the dependent variable is fully captured by the model, whereas an R-squared value of 0 indicates that no variation is captured by the model.

To calculate R-squared, you can use the following formula:

$$R^2 = 1 - \frac{SSresidual}{SStotal} \tag{3.2}$$

where SS residual is the sum of squares of the residuals (the difference between the actual and predicted values) and SS total is the sum of squares of the total variance in the dependent variable.

Lastly, the method of visual matching, whereby the degree of congruence between the observed movement and the anticipated outcomes is assessed in relation to the initial values.

In Table 3.3, we can see the results of the mean squared error and R^2 for each indicator separately. In Graphs 3.2, 3.3, and 3.4, we can observe the visual matching results between the forecasted and original values.

Table 3.3 Accuracy of forecasted indicators values in terms of R-squared and MSE

Indicator Name	R-squared	Mean Squared Error
RSI	0.79	33.5
Momentum	0.75	0.22
Simple Moving Average	0.88	1.66

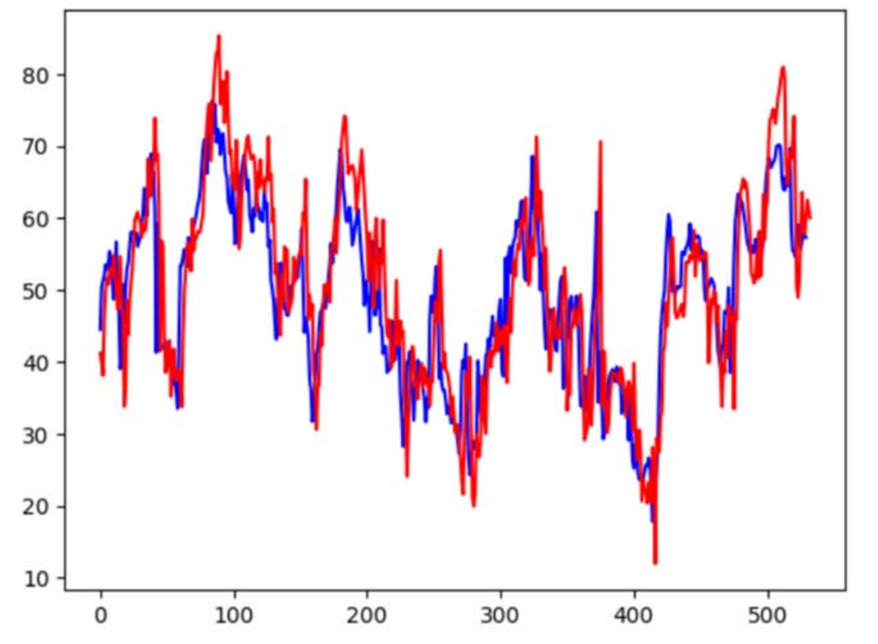

Figure 3.2 RSI Indicator Values Against Forecasted Values Among One Month

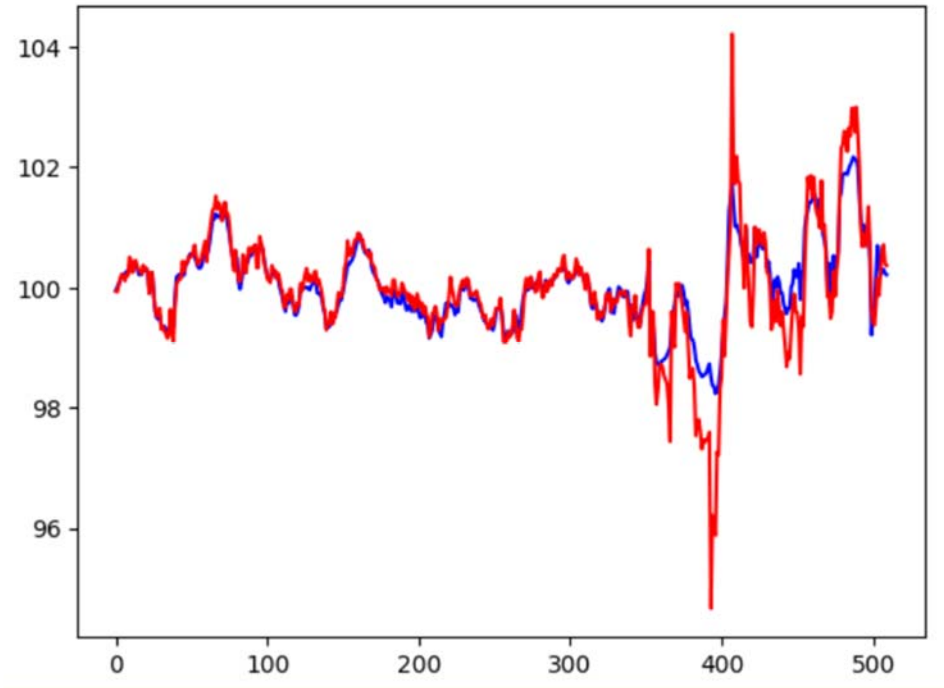

Figure 3.3 Momentum Indicator Values Against Forecasted Values Among One Month

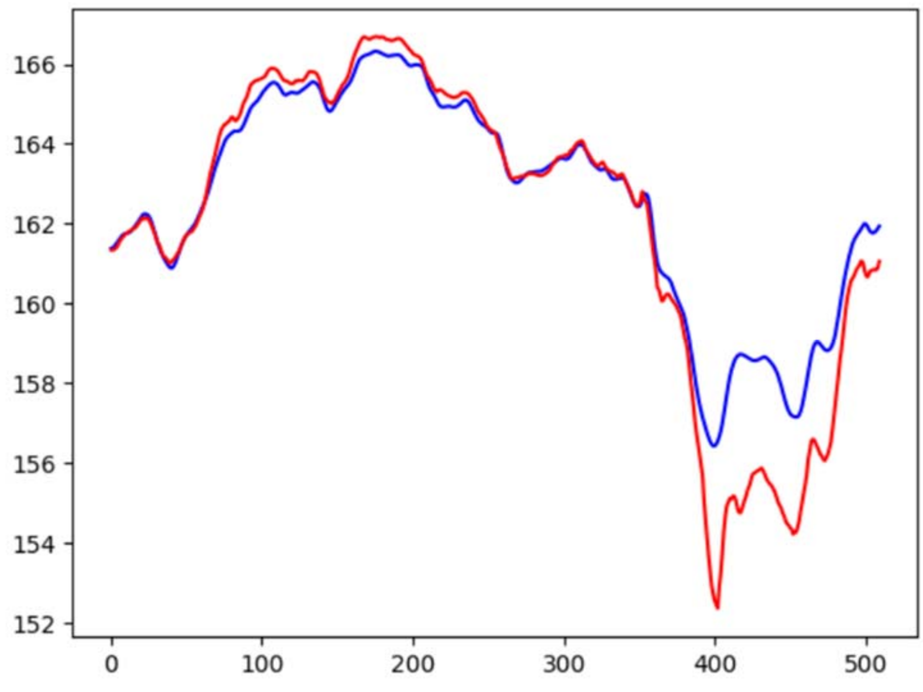

Figure 3.4 SMA Indicator Values Against Forecasted Values Among One Month

3.7 Sliding Window Training

In the subsequent section, we explicate the methodology employed to train the XGboost model on the primary dataset, with the objective of determining the optimal course of action, i.e., whether to buy or sell. This is preceded by a comprehensive exposition of the forecasting of indicator values, as detailed in the preceding section.

The forex market movement patterns are undergoing rapid transformations in recent years, driven by a confluence of factors such as technological advancements, geopolitical shifts, and evolving trading strategies (Eichengreen et al., 2020). The advent of high frequency trading and algorithmic systems has accelerated market movements, leading to higher volatility and more unpredictable patterns (Golub et al., 2021). Furthermore, emerging economies are playing a more significant role in forex markets, altering traditional currency relationships and contributing to the dynamic nature of these patterns (Prasad, 2021). Consequently, traders and investors need to constantly adapt to these evolving market conditions to remain competitive and exploit potential opportunities.

Due to this, it was unfeasible to depend on a singular model for the duration of the experiment, as its accuracy began to deteriorate after a mere 24-hour period following its deployment. The present study employed the sliding window approach as a means to address the aforementioned concern. In the initial phase of the experiment, the model was trained on a limited dataset of 35 records. Subsequently, the model was deployed for live trading and after 5 preliminary decisions, it was retrained on a fresh batch of 35 records. Notably, this time, the training batch consisted of 30 records from the previous training batch and 5 records from the original labels of the 5 predicted steps. This approach can be categorized as a “last in last out” training batch, with a fixed length of 35 data records. The employed methodology enables the detection of subtle variations in price dynamics, as the model undergoes retraining at every fifth step throughout the entire experimental duration.

CHAPTER 4

4. RESULTS

In this study we employ a live trading approach to evaluate the proposed algorithm. To accomplish our objective, we developed a trading Robot that operates through two distinct platforms, facilitating the execution of live trading positions based on buy/sell proposals of the method. The experimental period spanned from 2022 September 1st to end of November. This chapter aims to provide a comprehensive overview of the trading robot, as well as an analysis of the outcomes achieved at the conclusion of the experiment. The evaluation of the results is based on a rigorous and systematic approach, which will be explicated in detail.

4.1 Trading Robot

Explore the intriguing methodology employed in constructing a trading robot for this study, which seamlessly integrates the Meta Trader platform and cloud service for real-time analysis and execution of trades. Delve into the intricacies of data transmission, analysis, and decision-making using a Python codebase and the robust XGBoost model. Prepare to gain insights into the inner workings of this innovative trading system, which combines state-of-the-art technology and sophisticated algorithms to advance the field of automated trading. The tools utilized in this process have been expounded upon in Section 3.1. A graphical representation of the aforementioned cycle is provided in Figure 4.1.

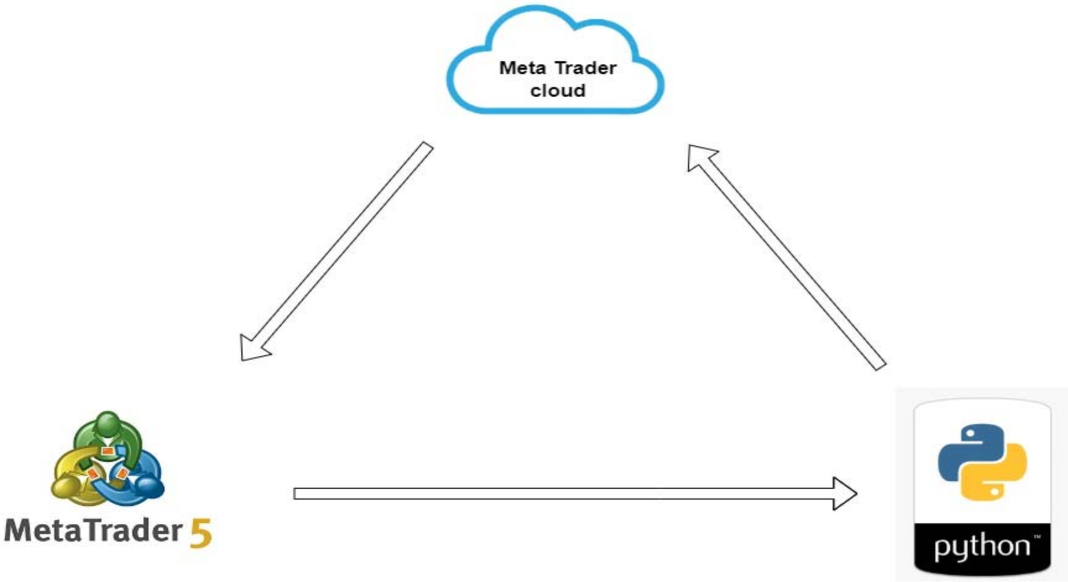

Figure 4.1 Trading Robot Life Cycle, Starting Point Is Metatrader 5

4.1.1 Trading Platform

MetaTrader 5 is a trading platform that operates using the MQL5 programming language. This platform provides developers with the opportunity to create "Expert Advisors" or, in other words, trading robots that trade automatically according to specific trading strategies. In this study, we have utilized this feature to develop a system that sends data via a socket library to a Python script containing the proposed algorithm.

At the first second of each hour, a sequence of data in JSON format is sent, which includes the last 39 candlestick data points and an identifier. The identifier serves as a unique ID to inform the Python script about the purpose of the data, which is to forecast the indicator values. At the beginning of the 30th minute of the same hour, another sequence of data is sent with a different identifier. This data contains information about the first 30 minutes of the same hour.

4.1.2 Python Platform

The platform operates on the same machine as the trading platform and connects to it using the previously mentioned socket. This platform functions as a receiver, processing data sequences sent from the socket. The program takes action based on the identifier: if it refers to LSTM, the data is channeled through the indicator forecasting pipeline, and the results are stored in a temporary variable. If the identifier refers to movement prediction, the data first undergoes pre-processing before the forecasted indicator values are appended. The data is then fed to the trained XGBoost model, and the predicted label is pushed to the MetaTrader cloud service.

If the identifier refers to updating the model, the incoming data goes through an updating pipeline. This process begins with pre-processing in order to append the data to the main file containing the previous 35 steps. Five data records are eliminated, and the new data is appended to the end of the file, following the “Last In, Last Out” principle mentioned earlier.

4.1.3 Meta Trader Cloud

The cloud functions as an API for the trading account. By utilizing the trading account credentials, we can access the account, execute position commands (buy/sell/close), adjust open positions, and apply comprehensive monitoring. This cloud service enables us to deploy the trading robot on any server, offering flexibility and adaptability for various hosting environments.

4.2 Measuring Criteria

As we mentioned earlier, this experiment was applied in the form of direct and live trading in the forex market for a period of three months in a row. Based on that, we had to choose certain criteria to evaluate the performance of the experiment outside the framework of theoretical evaluation. Four methods were chosen to evaluate the effectiveness of the method. We will explain the selected methods in this section.

PIP Gains: A pip in Forex is an acronym for “Percentage in Point” or “Price Interest Point.” It is the smallest price movement that can occur in the foreign exchange market and is used to measure the change in the value of currency pairs. A pip is typically equal to 0.0001 for most currency pairs quoted to four decimal places (except for pairs involving the Japanese Yen, where a pip is equal to 0.01).

In Forex trading, pips are used to express the change in the exchange rate between two currencies. For example, if the exchange rate for the EUR/USD currency pair moves from 1.1000 to 1.1005, it has moved by 5 pips. Traders use pips to calculate their profits and losses as well as to set stop-loss and take-profit levels.

Measuring the effectiveness of a strategy using pips:

When evaluating the effectiveness of a trading strategy, traders often use the number of pips gained or lost over a certain period. This measure is known as the strategy's pip performance. By comparing the total pips gained to the total pips lost, a trader can determine if the strategy is profitable or not. A positive pip performance indicates that the strategy is effective, while a negative performance suggests that the strategy might need adjustments or should be abandoned.

Change In Capital: The change in capital refers to the difference in the trader's account balance before and after implementing a trading strategy. It is another important metric used to measure the effectiveness of a trading strategy. The change in capital considers both realized and unrealized profits and losses from the trades executed using the strategy. It is usually expressed as a percentage of the initial account balance.

We should take in consideration that we select a standard lot size for this experiment whereas Lot size refers to the number of units of a currency pair being traded in a Forex transaction. In the Forex market, currencies are traded in standardized lot sizes, which represent the amount of the base currency being traded.

The most common lot sizes are:

One Standard Lot is equal to one hundred thousand of the base currency.

Mini Lot: Ten Thousand of the Base Currency

Third, the Micro Lot is defined as 1,000 of the Base Currency.

100 of the underlying currency constitutes a nano lot.

The lot size plays a crucial role in determining the value of a pip and, consequently, the potential profit or loss in a trade. The larger the lot size, the more significant the impact of each pip movement on the trader's account balance.

Relation between lot size and capital change: The lot size directly influences the change in capital because it determines the value of each pip movement. When a trader opens a position, the lot size multiplied by the pip movement results in the profit or loss incurred. Consequently, a larger lot size means that each pip movement has a greater impact on the trader's account balance, leading to a higher change in capital.

For example, suppose a trader opens a position with a standard lot (100, 000 units) of the GBP/JPY currency pair, and the position moves in their favor by 10 pips. With a standard lot, each pip is worth ¥1000. To convert the profit in yen to dollars, the trader would need to use the USD/JPY exchange rate. Let's say the USD/JPY rate is 110.00, meaning that ¥10, 000 would be equivalent to $90.91 (¥10, 000 / 110). If the same trade were executed with a micro lot (1, 000 units), each pip would be worth ¥10, resulting in a profit of ¥100, which is equivalent to $0.91 (¥100 / 110).

In MetaTrader, when you open a position, you can choose the lot size you want to trade. The platform will then automatically calculate the value per pip and display the potential profit or loss in your account's base currency (usually USD) as the trade moves in real-time. This allows you to easily monitor the change in capital for each trade and adjust your position size accordingly.

Therefore, the lot size is an essential factor when measuring the change in capital because it directly affects the account balance. Traders need to choose their lot sizes carefully, considering their risk tolerance, trading strategy, and account balance, to ensure that they can effectively manage the change in capital and maintain a sustainable trading approach.

To measure the effectiveness of a strategy using the change in capital, a trader can compare the percentage change in the account balance before and after the implementation of the strategy over a specific period. A positive change in capital indicates that the strategy is effective and has led to an increase in the account balance, while a negative change suggests that the strategy might not be profitable.

Max Drawdown: Another essential metric used to evaluate the effectiveness of a trading strategy, particularly from a risk management perspective. It measures the largest peak-to-trough decline in the value of a trading account, expressed as a percentage of the peak value. In other words, it represents the maximum loss an investor would have experienced if they had entered the market at the worst possible time and exited at the lowest point before a new peak was reached.

Max drawdown is crucial because it helps traders understand the potential risks associated with their trading strategy. A high max drawdown may indicate that the strategy carries significant risks, while a low max drawdown suggests that the strategy is more conservative and better at managing risk.

Accuracy of Correct Predictions: Percentage of the number of correct predictions over a period of one month

To effectively measure the performance of a trading strategy, traders should consider the combination of pip performance, change in capital, and max drawdown. Pip performance provides insights into the profitability of the strategy based on price movements, while the change in capital reflects the overall impact on the account balance. Max drawdown, on the other hand, highlights the potential risks and the worst-case scenario that the trader may face.

4.3 Results

Now that we are familiar with the criteria that were applied in determining how well the experiment was carried out, it is time to present the findings and have a conversation about them. The outcomes are presented in the following table 4.1, broken down into their respective months' sections.

Table 4.1 Experiment Results

Month	pips	Capital Change	Max drawdown	Percentage
September	98.63	+11.11%	63.65%	60%
October	147.19	+16.58%	41.48%	62%
November	78.52	+8.84%	14.44%	59%

The experiment was carried out on a demo account with an initial value of $ 10,000 and a fixed lot value at one (standard lot). After the end of the experiment, the account grew cumulatively over the three months to eventually become approximately $ 14098.

The proposed study shows very promising results as a full automated trading system, but at the same time, from a risk management perspective, it is considered a high-risk method. According to "The Handbook of Portfolio Mathematics,"(Vince, 2007) we consider a strategy high-risk when max drawdown exceeds 20%, as we can see in the September and October results, and therefore, as further work, we can apply multiple risk management techniques in order to make the method more coherent. As the aim of the study currently is to bridge the gap between researchers and traders, as we mentioned at the beginning.

we have re-implemented the experiments for some other researches.
in accordance with the methodology of this research, where we have converted.
the values of the indicators in the research (Patel et al., 2015) and (Kara et al., 2011) from the values of the indicators that were calculated using the closing prices to the values of the indicators that were calculated using the opening prices And, in the research, (Subasi et al., 2021) the closing prices were deleted from the training data set. In Table 4.2 we show a comparison in average accuracy of our results with theirs.

Author	methods	type of data	average accuracy
Subasi	comparison between 7 classifiers	Market prices + indicator values	48%
Patel	Naive-Bayes ANN SVM	indicator values	52%
Kara	ANN SVM	indicator values	47%
ours	LSTM + XGBoost	open price + indicator values	60%

Table 4.2: A comparison between the results of the proposed research compared to other research in the same field after re-implementation within the limits of the available data.

CHAPTER 5

5. CONCLUSION

This study aims to develop a comprehensive and realistic trading system for the GBP/JPY currency pair through deep learning techniques. The proposed method addressed two primary challenges in the financial markets; decision-making under high-pressure environments for traders and the utilization of appropriate data sources for analysis and decision-making for researchers. The developed algorithm combined information from different timeframes, predicted indicator values using the LSTM model, and employed the XGBoost classifier for the final buy or sell decision.

The sliding window training approach was utilized to train the XGBoost model, enabling the detection of subtle variations in price dynamics and addressing the rapidly changing patterns in the forex market. The experiment was conducted over three consecutive months, and the results demonstrated promising performance in terms of capital growth and prediction accuracy. However, the method was considered high-risk from a risk management perspective, as the maximum drawdown exceeded 20% in some cases.

This study represents a significant step in bridging the gap between researchers and traders, offering a practical and data-driven solution to navigate the complexity of the forex market. The proposed trading system showcased the potential for machine learning and deep learning techniques to enhance decision-making processes in the financial markets. Nonetheless, further work is required to refine the system by incorporating risk management techniques and optimizing the algorithm for improved performance and risk mitigation. By doing so, this research contributes to the advancement of trading strategies and the development of more robust, automated trading systems for the ever-evolving foreign exchange market.

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