Predicting Forex Currency Exchange Rate Using Machine Learning

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***Abstract*—This research seeks to investigate the potential of machine learning approaches for predicting foreign currency exchange rates by utilizing a complete set of technical and fundamental economic variables. Recognizing the complexity and the volatility of the foreign exchange market, our study aims to create a robust predictive model by incorporating modern machine learning algorithms. We aim to deal with the complexities of the foreign exchange market by discovering the most influential aspects through careful feature selection and building unique structures, then enhancing our model's performance through parameter optimization. The study intends to contribute to a more accurate understanding of the factors driving the forex market dynamics, ultimately yielding a reliable predictive model with potential applications for traders, investors, corporations, and policymakers.**

***Index Terms*—Forex market, Technical Analysis, Fundamental Analysis, LSTM, Deep neural network**

I. Introduction

Forex trading, also known as foreign exchange, stands as a cornerstone of global finance, where participants engage in the exchange of currencies, boasting a staggering daily volume exceeding $6 trillion. [19] As the largest and most the liquid financial market worldwide, it operates 24 hours a day, five days a week. The sheer scale of trading activities, coupled with its continuous nature, renders the forex market an ideal arena for the application of advanced computational techniques, particularly those stemming from the realm of Machine Learning (ML).

The forex market presents a rich tapestry of currency pairs, including but not limited to AUD/USD and EUR/GBP, which engenders diverse market structures contingent upon the unique combinations of currencies involved. Analysis within this domain traditionally hinges upon the examination of OHLC (Open, High, Low, Close) prices, furnishing comprehensive insights into price dynamics across distinct time intervals.

Within the ambit of predictive analytics, two overarching methodologies hold sway: Fundamental Analysis and Technical Analysis [20]. While the former examines macroeconomic factors, geopolitical events, and fiscal policies to identify underlying trends, the latter delves into historical price data and chart patterns to predict future price movements. The synthesis of these analytical frameworks seeks to provide insights into anticipated price fluctuations within specific currency pairs.

This research aims to answer key questions concerning the predictive capabilities of machine learning models within the forex market:

1) Can major trends in price fluctuations of a currency pair be predicted in advance?
2) Can the start point of that price fluctuation be predicted with acceptable accuracy?
3) Can the end point of that price fluctuation be predicted with acceptable accuracy?

Motivated by these inquiries, the research endeavors to design and evaluate multiple machine learning models, leveraging inputs derived from both technical and fundamental analyses. By comparing and assessing the efficacy of these models, the study aims to discern the most accurate predictive framework for predicting price movements within the Forex market.

In summary, this research seeks to bridge the domains of finance and machine learning, offering insights into the predictive capabilities of advanced computational methodologies within the dynamic landscape of forex trading. By clarifying the potential for leveraging ML techniques to predict price dynamics, the study endeavors to contribute to the ongoing discussion surrounding algorithmic trading strategies and financial forecasting methodologies.

II. Literature Review

A. Fundamental Analysis

Fundamental analysis entails a comprehensive examination of macroeconomic factors, including but not limited to interest rates, inflation rates, trade balances, and GDP growth rates, among others. In the realm of forecasting foreign exchange (Forex) currency exchange rates, fundamental indicators analysis plays a pivotal role in understanding and predicting market dynamics. Fundamental data (FD) serves as a critical indicator of a country's economic conditions, exerting a significant impact on currency prices upon its quarterly update and release. The relationship between these fundamental indicators and currency price movements highlight the intricate interplay between economic conditions and forex market trends. Various studies have underscored the significance of fundamental data updates, which are typically released quarterly, in influencing currency prices and market sentiment. However, challenges such as the FD releasing problem and unequal data changing frequency have prompted to exploration of innovative methodologies to enhance the accuracy and effectiveness of forex forecasting models. To address these challenges BERTFOREX,[1] is a novel approach integrating fundamental data and technical indicators (TI) using BERT. BERTFOREX applies BERT to FD to extract patterns over time, aggregates them as additional weights to TI, and extracts patterns across influencing days. The aggregated pattern is then fed into a neural network for forecasting. Results show BERTFOREX outperforms existing methods in signal correctness, sensitivity, specificity, precision, and negative predictive value, promising improved forex market forecasting accuracy.

Some research was carried out as an approach to event-driven business intelligence to address the complexities of contemporary markets, which are characterized by diverse and numerous price determinants and rapid shifts in market dynamics. While fundamental analysis traditionally focuses on the overall state of the economy, relying solely on this method may limit the quality of trading decisions. Therefore, traders often seek insights from various analyses to understand market conditions and price movements more comprehensively. Technical and fundamental indicators, [2] represented as time-series data are modeled using artificial neural networks (ANNs). Additionally, a knowledge base model is implemented to amalgamate signals generated by the time-series models. It leverages event-driven business intelligence to enhance trading decisions in dynamic market environments.

The impact of macroeconomic variables on stock price movements is extensively explored under the fundamental analysis. Researchers have diligently investigated how factors such as exchange rates, interest rates, industrial production, and inflation dynamics influence stock prices. It is widely acknowledged that governmental financial policies and broader macroeconomic events exert substantial influence on economic activities, including the stock market. This recognition has spurred numerous academic and practitioner inquiries into the dynamic relationship between stock returns and macroeconomic variables. One of the Studies delves into the intricate relationship between macroeconomic variables and stock prices in Ghana [3]. Spanning from 1991 to 2006, the research employs Johansen's multivariate cointegration test and innovation accounting methods to explore both long-run and short-run dynamics. The findings underscore a significant cointegration between macroeconomic indicators and stock prices, suggesting a lasting relationship. In the short term, fluctuations in inflation and exchange rates emerge as influential factors on stock price movements in Ghana, while in the long term, interest rates and inflation bear substantial significance. This work contributes to the extensive body of literature probing the interplay between macroeconomic conditions and stock market dynamics, shedding light on the nuanced dynamics within the Ghanaian financial landscape.

Further, researchers sought to enhance the accuracy of forecasting Forex rates by incorporating both financial factors and the simple moving average (SMA) technique. For example [4] using EUR/USD Forex rates they analyzed four distinct datasets: Forex rates alone, Forex rates with financial factors (Dollar Index, US Interest rate, Inflation rate, and real Gross Domestic Product), Forex rates with SMA, and finally, Forex rates with both financial factors and SMA. Through their research efforts, which included employing Multilayer Perceptron (MLP) and Linear Regression (LM) models for forecasting, they evaluated the performance using mean square error (MSE). The findings indicated a significant improvement in forecasting accuracy when incorporating financial factors and SMA into the Forex datasets. This suggests that the combination of the SMA technique and financial factors provides a more robust framework for predicting EUR/USD Forex rates, thereby aiding international businesses in making informed decisions amidst the inherent risks associated with Forex investments.

The emergence of advanced machine learning techniques, including natural language processing (NLP) models like BERT [1] (Bidirectional Encoder Representations from Transformers), has opened new avenues for incorporating and analyzing fundamental indicators in forex market forecasting. By harnessing the power of machine learning algorithms and big data analytics, researchers aim to uncover hidden patterns and signals within fundamental data sets, thereby improving the predictive capabilities of forex forecasting models and enabling more informed decision-making in currency trading and investment strategies.

B. Technical Analysis

Various technical analysis (TA) indicators are commonly used as features in Forex prediction algorithms. Both Machine Learning and traditional algorithms utilize TAs to predict price movements. [5] took the USD/JPY currency pair and trained six machine learning models to predict a binary classification for up and down price movements. Nine features were generated from the raw data based on Moving Averages(MA), Relative Strength Index(RSI), and Williams Percent Range(WR).

[6] derived a Support Vector Machine to predict future price trend directions, Seventy indicators were derived using technical analysis as features for the algorithm. The proposed model had an accuracy of 81% in forecasting future price movements. [7] proposed a method to combine historical price data and technical indicators and feed them into a neural network. [8] predicted future prices by using these popular technical indicators - Relative Strength Index (RSI), Commodity Channel Index (CCI), Moving Average Convergence Divergence (MACD), and Rate of Change (ROC).

[9] constructed a Convolutional Neural Network (CNN) model 'Fig. 1' to forecast monthly and weekly price trends. They chose technical indicators, exchange rates, and world indices as data features. The model achieved a 65% accuracy rate for monthly price trends and 60% accuracy for weekly price movements.[10] used moving averages (MA5), (MA10), and (MA20) line charts as input images to build a CNN to predict weekly price movements. More examples of these can be found in [11], [12], [13].

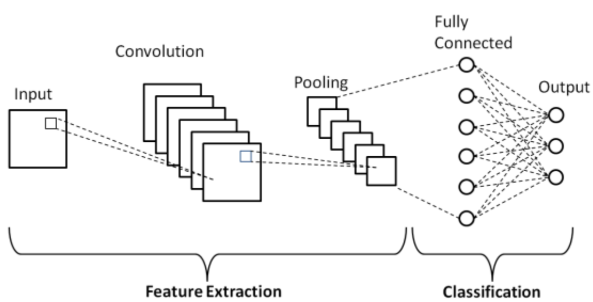

Fig. 1. CNN architecture

C. LSTM

Long short-term memory (LSTM) is better at learning temporal patterns in deep neural networks (DNNs) for time series data including text, signals, and market prices. Employing memory cells and gating mechanisms, Long Short-Term Memory (LSTM) networks effectively address the challenge of vanishing gradients encountered in traditional Recurrent Neural Networks (RNNs). LSTM architecture can be denoted as 'Fig. 2'.

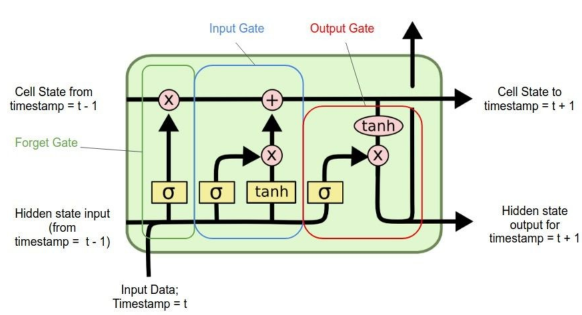

Fig. 2. LSTM architecture

[14]the study investigated the daily exchange rate of the Sri Lankan rupee (LKR) against the US dollar (USD). Employing Artificial Neural Networks (ANNs) and two variants of Recurrent Neural Networks (RNNs) – Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) – the researchers aim to predict forex rates. They utilize the rectified linear unit (ReLU) as the activation function and explore two optimizers: Adam and Stochastic Gradient Descent (SGD). The findings suggest that GRU with the Adam optimizer exhibits superior performance in terms of R2, RMSE, and MAE metrics, while LSTM performs better with the SGD optimizer in this specific study.

[15] introduced a novel hybrid model for Forex direction prediction, combining macroeconomic and technical indicators using LSTM models. The macroeconomic LSTM model incorporates financial factors like interest rates, inflation rates, and market indexes, akin to fundamental analysis. Meanwhile, the technical LSTM model leverages popular technical indicators such as moving averages, MACD, RSI, and others, reflecting a technical analysis approach. The hybrid model improves prediction accuracy by smartly combining the results of these two models and implementing decision rules to eliminate transactions with weaker confidence. Through empirical testing with recent real data, the study demonstrates the superior performance of the proposed hybrid model over the baseline models, offering a promising advancement in Forex prediction methodologies.

[16] introduced a novel feature fusion LSTM-CNN model, leveraging both temporal features from stock time series and image features from stock chart images. The proposed model first used an SC-CNN ((Stock Time Series LSTM) model to extract hidden patterns in stock chart images, then used an ST-LSTM (Stock Time Series LSTM) model to work on close prices and trading volumes. Kim and Kim's study found that candlestick charts outperformed bar charts, line charts, and filled-line charts in accurately predicting stock values. The study's lagged phenomenon was not addressed due to the use of only one stock price data. To improve performance, researchers suggest noise-canceling methods like autoencoder or wavelet transformation, along with macro variables and technical indicators, can be added. [17] had a deep multimodal reinforcement learning policy that uses CNN and LSTM for stock price prediction. The system generates charts from trading data and uses them as inputs for the CNN layer. The model uses a multi-modal structure, separating the input and hidden layers. The performance of the model was tested using daily data from the Korea KOSPI. The model performance was best in both bear and bull markets.

[18]the survey analyzed papers from the Digital Bibliography & Library Project database, categorizing them into deep learning methods like CNN, LSTM, DNN, RNN, Reinforcement Learning, and others. Results showed that recent models combining LSTM with DNN and reinforcement learning yielded great returns and performances.

III. Conclusion

Forex trading is a complex task. Only a small number of models trained to predict the forex market can achieve acceptable returns in the real market and they are highly valuable. Even such models fail to remain relevant over a long period as changes in the market dynamics often make most models are redundant.

Our project aims to improve the performance of the current models and push the field forward to introduce a model that can accurately predict foreign exchange currency pair trends in diverse, changing market conditions.

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