Intraday Trading Strategy based on Gated Recurrent Unit and Convolutional Neural Network: Forecasting Daily Price Direction

Nabil MABROUK[1], Marouane CHIHAB[2]
Computer Sciences Laboratory
Ibn Toufail University
Kenitra, Morocco

Zakaria HACHKAR[3]
Fundamental and Applied Physics Laboratory
Cadi Ayyad University
Safi, Morocco

Younes CHIHAB[4]
Computer Sciences Laboratory
Ibn Toufail University
Kenitra, Morocco

***Abstract*—Forex or FX is the short form of the Foreign Exchange Market, it is known as the largest financial market in the world where Investors can buy a certain amount of currency and hold it on until the exchange rate moves, then sell it to make money. This operation is not easy as it looks; due to the forte fluctuation of this market, investors find it a risky area to trade. A successful strategy in Forex should reduce the rate of risks and increase the profitability of investment by considering economic and political factors and avoiding emotional investment. In this article, we propose a trading strategy based on machine learning algorithms to reduce the risks of trading on the forex market and increase benefits at the same time. For that, we use an algorithm that generates technical indicators and technical rules containing information that may explain the movement of the stock price, the generated data is fed to a machine-learning algorithm to learn and recognize price patterns. Our algorithm is the combination of two deep learning algorithms, Gated Recurrent Unit "GRU" and Convolutional Neural Network "CNN"; it aims to predict the next day signal (BUY, HOLD or SELL) The model performance is evaluated for USD/EUR by different metrics generally used for machine learning algorithms, another method used to evaluate the profitability by comparing the returns of the strategy and the returns of the market. The proposed system showed a good improvement in the prediction of the price.**

Keywords*—Forex; trading; machine learning; deep learning; random forest; technical indicators; technical rules; convolutional neural network; gated recurrent unit

I. Introduction

The price of a currency changes over time due to many macroeconomics and political factors. This price variation creates a rate of exchange; investors use it to make money by buying a certain amount of currency and holding it on until the exchange rate moves, then selling it. This type of market is called Foreign Exchange Market (FOREX or FX), and it is known as the largest financial market in the world [1], [2], [3], [4]. Because of geographical dispersion, the FX market is characterized by high liquidity, a large volume of trades, and continuous trades, as the market is open 24 hours a day [5]. Many national and international companies and financial institutions rely on exchange rate volatility for their benefits [3]; They are exposed to exchange rates risk, which poses a severe threat to international trade flows [6]. Traders, who represent over 90% of FX market volume, must be conscious and aware of the uncertainty since it significantly influences their investment decisions. However, we can notice the cyclical nature of the Forex market by using a large-scale analysis [7]. In the last few decades, the common research stream was on reducing the rate of risks and increasing the profitability of investment in the forex [8]; different types of analyses were employed, such as (i) technical analysis and (ii) fundamental analysis. According to [9], [10], both approaches are considered practical tools in forecasting the price movement.

(i) technical analysis has existed since [11], this method is based on the use of historical data such as prices, trading volumes, and other data to predict price trends that are expected to persist in the future [12], [11].

(ii) Fundamental analysis is a method for forecasting market trends and price movements based on analyzing a set of economic factors. These indicators include various activities related to the macroeconomic condition (e.g., government policies, bank policies, natural disasters, social stability, and economic trends) [13].

Investors always aim to get an idea of the future price's movement; this leads many researchers to propose different strategies to forecast the price movement by applying several techniques and methods. One of these methods is technical analysis, which is based on mathematical calculations of historical data, which may help investors in trading. [14] provided a remarkable literature that shows how to estimate the equity risk premium using technical indicators such as the moving-average rule, momentum rule, and volume-based indicators. Despite their widespread use among practitioners, technical indicators have received significantly less attention in the literature [15]. The technical indicators repose on past data (price and volume) to identify price patterns and trends believed to persist into the future [14]. Currently, many types of indicators may help in identifying trends. Many successful professional traders and academics have recommended that instead of depending on a single rule, they combine a variety of technical trading rules to increase the accuracy of their forecasting models [16], [17], [9], [18].

In this article, we propose a trading strategy based on technical indicators and machine learning especially deep learning. The goal is to forecast the next day's price direction, in each prediction the model is fed with specific sequence of observation as slid-window, the experiment was done on different slid-widows; firstly an algorithm generates technical indicators and target variable called signal (buy, hold, or sell); after that, the stage of features selection to reduce the high dimensionality and improve the performance of the model; prepare the dataset for the model using the sliding-window approach.

II. Related Work

Recently, new techniques of algorithm trading have come into existence; thanks to computer and technological progress [19], a lot of research has been established in several areas, especially algorithms and finance. However, most transactions are done electronically thanks to electronic markets, which helped collect a vast volume of data. Many studies suggested that the high evolution of global markets requires more and complex and developed techniques. Researchers have become interested in resolving electronic financial market problems using algorithms, especially machine learning algorithms, thanks to the enormous available volume of historical data. In the past, much research was carried on forecasting currency exchange rate, and several techniques and methodologies have been applied in this field. However, when it comes to successful trading strategies, fundamental analysis has gotten a lot of attention in this sector in the past; In this article, we are interested in machine learning and technical analysis, which is based on mathematical calculation and technical indicators.

The prediction of currency movements using technical indicators has been discovered firstly by [20] and [21]. According to Poole's viewpoint, currency exchange traders' expectations are shaped by the historical data of past price trends. Poole proved that based on specific rules, traders could make profits. According to these rules, traders can make a decision to buy or sell. Dooley & Schafar have worked on historical data from March 1975 to October 1975 trying to predict the next price direction based on seven different filter rules; they have proved that information about past exchange rate fluctuations is profitable when we use the correct filter rules. Traditional trading methods only use one approach [22]; on the other hand, algorithmic trading is a process in which a computer, rather than a human makes a specific investment. These methods can handle the complicated, non-linear, and dynamic properties of financial markets and the high frequency of data. Using appropriate non-linear approaches, such as neural networks, the suggested economic models could correctly anticipate future currency fluctuations for periods more extended than one year [23], [24].

Many studies proposed combining diverse approaches to improve regression and classification accuracy and performance [25]. Numerous researchers have applied machine learning to build trading strategies, among the machine learning algorithms, such as Random Forest (RF), support vector machine (SVM), Logistic regression (LR), Neural Network (NN). [25] have built numerous models using a bootstrap approach based on neural networks and combined the output of these models to forecast currency exchange rates. As a result, they found that their strategy significantly improved forecasting accuracy compared to the methodologies as mentioned earlier. A random forest algorithm has been introduced by [26], which made use of bagging to increase classification accuracy. [27] have described the random forest algorithm as the top-performing algorithm to predict stock price directions accurately. A small number of studies have been carried on forecasting currency exchange rate by using random forest algorithm; one of these studies was done by [28], they have used the random forest algorithm in forcasting currency exchange rates, and according to Them: random forest algorithm surpassed the SVM and Multiple Linear Regression methods predicting the Chinese Yuan correctly.

Intelligent machine learning systems played an important role and showed impressive performance in modeling and forecasting data, such as Bitcoin high-frequency price time series. [29] have employed three different sets of models of Artificial Intelligence systems in order to forecast high-frequency Bitcoin price time series, i.e., statistical machine learning approaches, algorithmic models, and finally, artificial neural network topologies. They have reported that the BRNN has exceptional forecasting accuracy as a result. Its convergence is unobstructed and very rapid; on the other side, artificial neural networks can imitate human decision-making thanks to the parallel processing features, even in the presence of underlying nonlinear input-output relationships in noisy signal environments. In the pre-market-efficiency era (i.e., pre- 1960s), several practitioners and researchers believed that predictable patterns in stock returns might lead to "abnormal" profits for trading techniques [30].

[31], have proposed a theoretical Multi-Agent System for stock market Speculation. They used four agents: the Metaheuristic Algorithm agent, technical indicators, Text Mining agent, and Fundamental Factor agent. The final decision is made based on combining the four agent's results. To forecast the future trend of the Forex market, [32] has applied deep neural network techniques. This study aims to help traders determine if there will be an uptrend or a downtrend, or a neutral trend in the future. The model performance is examined over various input data sizes and different window lengths. Besides, Different threshold values of exchange rate percentage change are tested to signal an uptrend or downtrend to find a good decision. The results show that deep neural networks can correctly predict market direction. Furthermore, according to the results, the model's accuracy is maintained throughout a range of input lengths and threshold values. Another approach was proposed by [33], to forecast the future price in the next week; the study showed impressive results to improve the prediction accuracy by using Random forest. Several recent research from other domains of application has demonstrated that the Long-Short Term Memory (LSTM), which is a type of deep learning that can be utilized to model time series, outperforms typical machine learning methods.[34] have developed a predictive model based on LSTM to forecast the next day's currency price. The results showed that the appropriate sequence input length for developing an accurate LSTM model should be between 9 and 12 periods. Also, training the model using data from a short period is preferable then training it with data from an extended period. Finally, re-training the model regularly with a new dataset can improve the model's accuracy. Also [35] used too LSTM to build their trading strategy, but instead of predicting the next day's currency price, they tried to forecast the next day's price direction, which facilitated the problem. However, their approach is based on feeding the model with two different datasets; the first is macroeconomic

data and the second is technical indicator data; their approach tries to combine two techniques in one hybrid model, the fundamental analysis and technical analysis. As a result, their proposed hybrid model had the best performance in terms of profit _accuracy for predictions in all periods. It reduced the number of transactions compared to the baseline models.

III. Our Proposition

A. Datasets

In this research, the dataset used is of the two most-traded currencies in the world: the United States Dollar (USD) and the Euro (EURO); the EUR/USD currency pair is the quotation of two currencies USD and EUR; when trading a currency pair, the first currency (base currency) is used to buy the second one (quote currency). The dataset covers the period, from January 01, 2014, until January 30, 2021. we have segregated the datasets into two parts, the first part is for training the model, and the second is for the test phase. However, to conserve the temporal order, we have segregated the dataset non-randomly because the collected data is a time-series dataset; it is sequential data obtained through repeated measurements over time, for example, hourly, daily, or weekly.

The goal of this work is to create a good strategy for day trading, and for that, we have used an OLHCV data, indexed on the timestamp one day; each row is a one-day observation of five variables: Open, High, Low, close, and Volume (OLHCV).

1) The Target Variable: In this article, we are trying to predict the next price direction, but the price feature in the collected dataset is a continuous variable. To formulate the problem as a classification problem, we created a new variable that indicates the decision as a signal (Buy Signal, Sell Signal, and Hold Signal). First, we determinate a positive number as a threshold called α. the goal is to compare this parameter with the log return. When the log return of the current day is inferior to -α, it indicates that it is an uptrend, so it is a SELL signal, and when the log return is superior to α , it indicates that's a downtrend, so it is a BUY signal; otherwise, it is a HOLD signal. However, in this case, the type of this variable is categorical; that is why We have converted this feature using one-hot encoding, so it can be provided to our algorithms and fit our model. The threshold (α): α is between 0 and 1. . Due to the forte fluctuation of the markets, there will always be a difference between the prices of the current and the next day. However, not each movement of the prices should be an uptrend or downtrend; the operation costs of buying or selling could be more expensive than the returns. To reduce the noise and identify the real trends, we compare the log-returns with a threshold called α to avoid the problem of unbalanced classes in the datasets, which happen in our case when α is too much low or too high. However, balancing the dataset artificially will affect the sequential datasets. We decided to run our algorithm using different thresholds starting from zero (which led us to a binary classification problem) to 0.001. when we go with a threshold higher than 0.001, we are stuck with unbalanced datasets

2) Technical Indicators: The collected dataset consists only of five features, Open, High, Low, close, and Volume (OLHCV). To add additional information to the original datasets, we created an algorithm that generates new features based on mathematical calculations, this type of feature is known as "technical indicators".

In general, technical analysts use technical indicators to understand and analyze the price movement in a specific market and avoid emotional investments. However, technical indicators give an idea of where the price might go next in a given market at a specific time.

In this research, we have used the most-used technical indicators:

- The Weighted Moving Average (WMA)
- The Exponential Moving Average (EMA)
- The simple moving average (SMA)
- The Relatively Strength Index (RSI)
- The average directional index (ADX)
- The Commodity Channel Index (CCI)
- The Rate-of-Change (ROC)
- The Bollinger Band (BB)
- The Moving Average Convergence Divergence (MACD)
- The Moving Polynomial trending

Technical analysts may get different results depending on the chosen parameters, even using the same technical indicators. So, to train our model with the best parameters of technical indicators, in our strategy, we generate each technical indicator on multiple periods, as shown in Table I. The goal is for our algorithm to identify the best subset of relevant characteristics predictors and determine the optimal combination of parameters (features).

TABLE I. Technical Indicators and their Parameters

Technical Indicators (TI)	Intervals for TI parameters
SMA	Period: [5, 30]
WMA	Period: [5, 100]
EMA	Period: [5, 100]
RSI	Period: [5, 30]
ADX	Period: [5, 30]
ROC	Period: [15, 30]
MACD	Period: Fast [15, 30] Period: Slow: [20, 35] Period: Signal: [5, 10]
CCI	Period: [5, 30]
BB	Period: [5, 30]

3) Simple Technical Trading Rules: In general, for technical analysts generating technical indicators is not enough to build a trading strategy; to reach their goal, they convert technical indicators into trading rules. in our research, to enrich our datasets and get the best results, we will use some simple trading rules such as:

- Simple Moving Average (10) Rule "SMA(10) signal"

$$\begin{cases} Buy, if PRICE_t > SMA(10)_t \& price_{t-1} < SMA(10)_{t-1} \\ Sell, if PRICE_t < SMA(10)_t \& price_{t-1} > SMA(10)_{t-1} \\ Hold, otherwise \end{cases}$$

- Simple Moving Average Crossover-Trading Rule "SMA Crossover Signal"

$$\begin{cases} BUY, if sma(10)_t > sma(50)_t \& sma(10)_{t-1} < sma(50)_{t-1} \\ SELL, if sma(10)_t < sma(50)_t \& sma(10)_{t-1} > sma(50)_{t-1} \\ HOLD, otherwise \end{cases}$$

- The Relative Strength Index Signal "RSI signal"

$$\begin{cases} Buy, if RSI < 30 \\ Sell, if RSI > 70 \\ Hold, otherwise \end{cases}$$

- the Average True Range rule "ATR signal"

$$\begin{cases} Buy, if price_{t-1} + ATR < Price_t \\ Sell, if price_{t-1} - ATR > Price_t \\ Hold, otherwise \end{cases}$$

B. Our Approach

1) Feature Selection: In machine learning, adding more features improves the accuracy of the model, but using a large number of features could lead to opposite effects due to noisy variables, this last reduce the model performance; The solution is to reduce the high dimensionality of the dataset by selecting the features that can add more information and contribute most to the prediction. The authors in [36] have specified the goal of features selection in three parts: improving the prediction speed, interpretation of predictors easily, and providing a better understanding of them, improving the prediction performance by eliminating the noisy features. The authors in [37], [38], [39] have categorized most existing feature selection algorithms into four main classes: similarity-based, information-theoretical-based, sparse-learning-based, and statistical-based methods. In our research, we used feature selection techniques to reduce the number of inputs from more than 150 variables to less than 30, we kept just the most important features.

2) Convolutional Neural Network: A convolutional neural network (CNN, or ConvNet) is a type of deep neural network; its name is taken from mathematical linear operation between matrixes called convolution. The connectivity patterns between its neurons are inspired by the organization of the animal visual cortex. The convolution technique allows for recognizing visual patterns in input data [40]. As with any Artificial Neural Network, CNN has Multiple layers, and the convolutional layer is the most important. Each convolutional layer looks for features by sliding several filters over the input matrix and comparing it piece by piece [41]. In [42], they specified the most important and beneficial aspect of a convolutional neural network in two parts: the first is solving complex tasks by reducing the number of parameters in ANN; the second is obtaining abstract features when going forward and deeper.

3) Gated Recurrent Unit: GRU is an abbreviation of Gated Recurrent Unit, and it is a Recurrent neural network unit, which is a type of deep neural network. GRU was proposed by [43] to have each recurrent unit record dependencies on multiple time scales in an adaptable way. In many machine-learning tasks, recurrent neural networks have lately shown promising results, especially when the input and/or output are of variable duration [44]. The GRU is known by its good performance in dealing with sequence learning tasks. When learning long-term dependencies, GRU overcomes the challenges of vanishing and explosion of gradients in traditional recurrent neural networks (RNNs).

4) Gated Recurrent Unit and Convolutional Neural Network Approach: In this article, our proposition to create a good trading strategy is based on combining two deep neural network approaches: the gated recurrent network and the convolutional neural network. As shown in Fig. 2, our model is composed of four layers:

- the first layer is the input layer; it takes a two-dimensional matrix as input; the number of rows is the same number of days to look back. Each row represents the observation of all variables on a specific day. The number of variables determines the number of columns; each column represents the values of a specific variable on the days to look back.

- the second layer is the convolutional layer, it is fed directly by the input layer; it looks for features by sliding multiple filters over the input matrix to recognize patterns.

- the third layer is the GRU layer; it is implemented on many-to-one architecture, as shown in Fig. 4 because the goal of our model is to predict the next day's price direction, not multiple days. This layer is added to deal with the sequential data nature.

- The last layer is the dense layers/output layer, reduce the number of features and get one decision (BUY, SELL or HOLD).

5) Sliding-Window Approach: The noisy part of the time-series datasets may negatively affect the RNN's memory, then the ability to learn patterns. To avoid this problem, we used the sliding-window approach, which consists of including previous time-steps as input. For example, a window of size four means it will take as input the current time-step and the previous three time-steps as shown in Fig. 5. Market forecasting, weather forecasting, and network traffic forecasting are all examples of this approach [45], [46], [47]. In our article, to choose the best window length, we experimented with our model on different windows length starting from 1 to 20. The results are shown in Table II

C. Our Investment Strategy

To develop an effective trading strategy, we must first determine the goal of our strategy, identify a personal risk profile, and finally evaluate the available time and resources.

Usually, in forex trading, the currency exchange rate is meager. This fact impacts the profitability of the investment when the invested amount of money is not so significant,

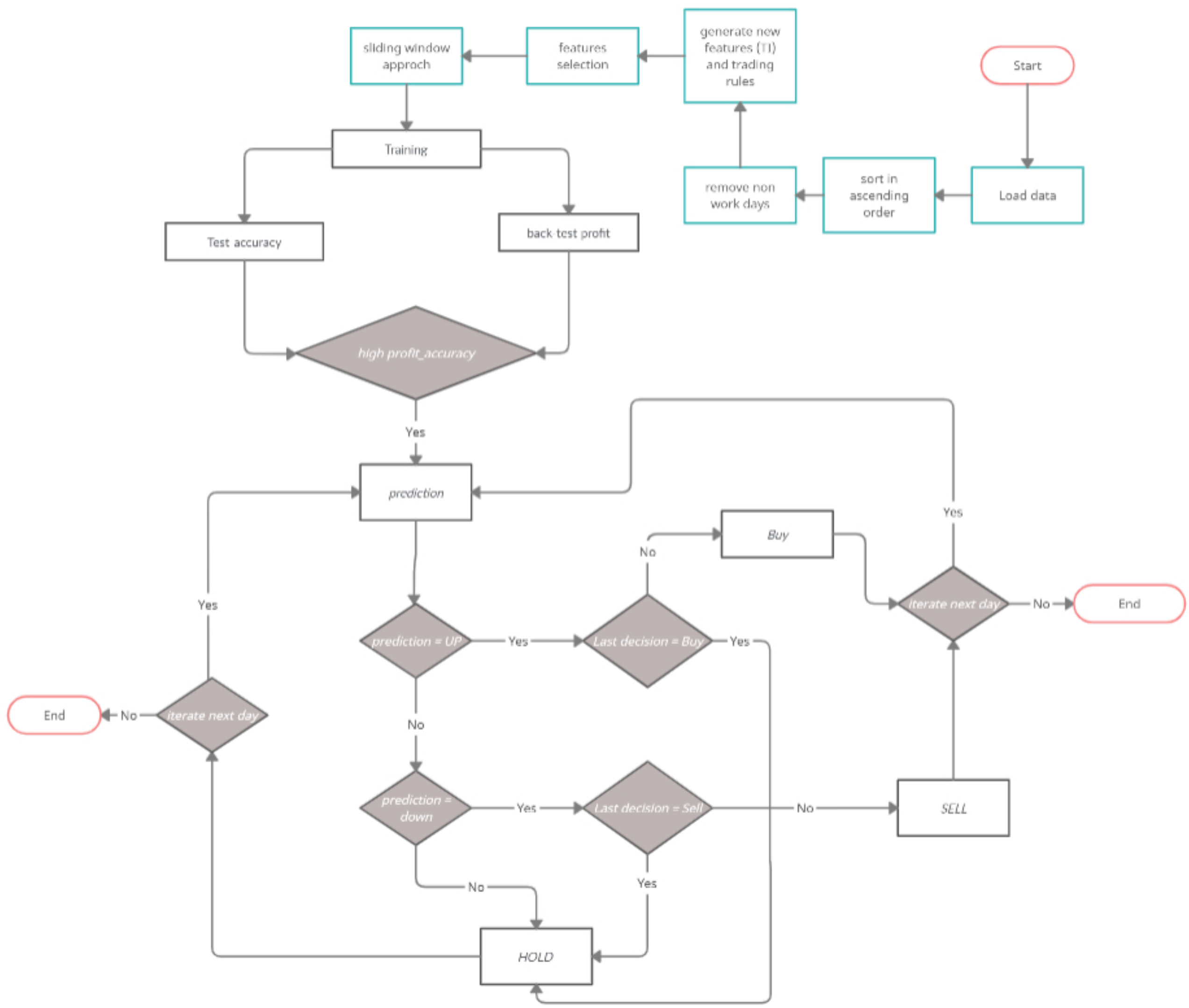

Fig. 1. Our Investment Strategy for Intraday Foreign Exchange.

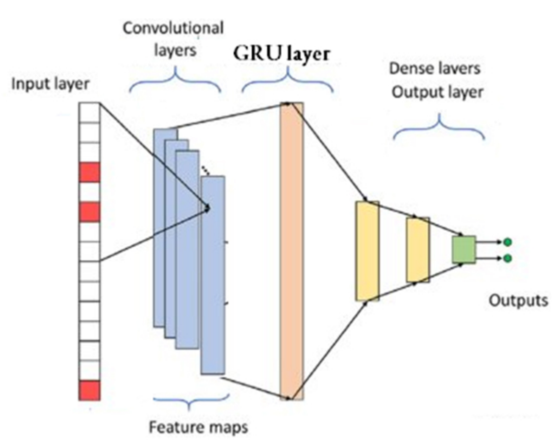

Fig. 2. GRU and CNN Approach.

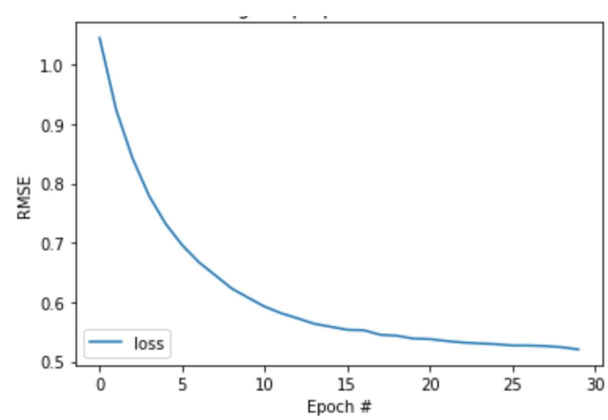

Fig. 3. Training Loss Per Epochs on Forex Dataset.

and the benefits could be lower than the transaction costs. However, in forex investments, a third intervening part called

TABLE II. MODEL ACCURACY BY WINDOW-SIZE VS THRESHOLD

Threshold \ window size [inputs]	1 [31x1]	2 [31x2]	3 [31x3]	4 [31x4]	5 [31x5]	6 [31x6]	10 [31x10]	15 [31x15]	20 [31x20]
0	0.635	0.686	0.704	0.704	0.726	0.713	0.741	0.739	0.693
0.0001	0.627	0.694	0.699	0.695	0.699	0.703	0.695	0.712	0.730
0.0002	0.582	0.683	0.684	0.695	0.7160	0.726	0.695	0.726	0.703
0.0003	0.603	0.669	0.688	0.683	0.709	0.718	0.711	0.696	0.709
0.0005	0.609	0.660	0.678	0.682	0.685	0.704	0.713	0.712	0.707
0.001	0.543	0.594	0.621	0.640	0.633	0.639	0.650	0.659	0.638

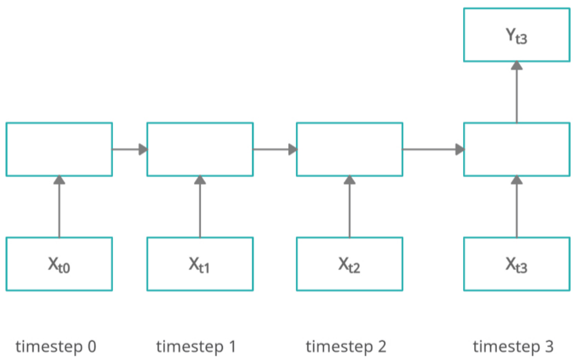

Fig. 4. Many-to-One GRU Architecture.

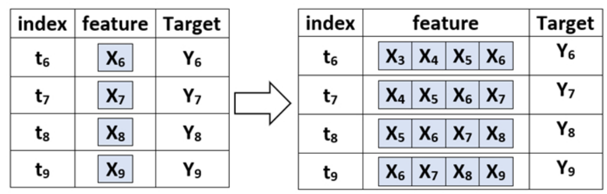

Fig. 5. Example of Sliding-Window Approach.

brokers proposes a technique called ”leverage” to resolve this issue; it is based on borrowing funds to purchase an asset. In our strategy, we used the leverage of 1:100, which is the equivalence of an investment of 1000$, and we can tread up to 100000$.

Our investment strategy is explained in Fig. 1; we buy only when the price is low, and we sell when the price is higher, which means that the machine learning model should predict the direction of trade in the future. For that, we have created an algorithm that compares the log return of the current day with the threshold α; if it is superior to α, we buy; if it is inferior to -α, we buy; otherwise, we HOLD. However, in this case, the type of this variable is categorical, and we converted it using one-hot encoding to be provided to our algorithms and fit our model.

IV. DISCUSSION AND RESULTS

Table II summarizes the overall results of our study; the experiments showed that, in general, the model reached a much higher accuracy in forecasting the next-day price direction, especially when the window length is between 6 and 10. We can notice a slight improvement in the accuracy when the window length goes larger until reaching 10 days; then, after this window length, it starts going down.

The experiment also was done on several thresholds, from 0 to 0.001. unlike the window length, each increment of threshold has a reverse influence on the accuracy, significantly when it surpasses 0.001. In this case, the model tends to predict a HOLD signal more than other signals due to the unbalanced dataset so that the accuracy could be more than 65%; the back-test showed that the profit_accuracy is lower than 40%. On average, the model showed its best results when the threshold was limited between 0 and 0.0002 and the window length was between 6 and 10. However, in forex trading, the machine learning metrics are not enough to evaluate the strategy's profitability; we used another back-test to evaluate it based on the log returns. After back-testing the results, we found a proportionality relation between the model accuracy and the profit_accuracy.

To improve the performance of our model in therm of accuracy and running time at the same time, we need to fine-tune the model with the best parameters and the optimal number of epochs to train our model. Figure 3 shows the training loss in each number of epochs; we notice that the plot of training loss decreases to the point of stability, which is 25. We can conclude that the optimal number of epochs to train our model is 25.

The proposed strategy may not be effective 100% due to the fort fluctuations of the market, and in some cases, the prediction could fail, because the market is related to the macroeconomic and political situation; in this case, we should take into consideration two parameters before taking a decision. The first one is the exchange rate: if the loss is too high, the algorithm stops investing until this value become positive. The second one is the number of successive fails. If the algorithm keeps failing in predicting the right price direction, then it should stop investing until it starts getting good results.

V. CONCLUSION

The proposed CNN-GRU model is a novel forecasting approach to forecast the daily price directions of USD/EUR.

It's based on technical analysis and deep learning algorithms. We used the original time series data to generate new features called technical indicators, and fed it to our model in a specific window; each timestep includes previous time steps as input. Our proposed approach allowed us to reduce the noisy part of the data and improve the trading results compared to samples algorithms such as SMV and logistic regression, which are impacted by the high-frequency fluctuation of the market and the noisy nature of time-series data. The experiments showed promising results in forecasting the daily price directions.

In the forex, many factors may impact the state of the market in different ways, making it too complex to develop the best trading strategy. In this study, we have proposed a trading strategy to trade the EUR/USD pair; this solution is developed and back-tested in a specific period, it may not stay helpful and profitable in the future. In this case, our proposed solution must be adapted to the current situation. Of course, previous success is no guarantee of future outcomes, but a strategy that has proven to be dependable in a variety of market situations may, continue to be so in the future.

REFERENCES

[1] O. DAVID and B. LEUSTEAN, "Forex and the liberalized financial market," vol. 71, Jan. 2009.

[2] M. Amiri, M. Zandieh, B. Vahdani, R. Soltani, and V. Roshanaei, "An integrated eigenvector–dea–topsis methodology for portfolio risk evaluation in the forex spot market," *Expert systems with applications*, vol. 37, no. 1, pp. 509–516, 2010.

[3] J. Kamruzzaman and R. Sarker, "Ann-based forecasting of foreign currency exchange rates," vol. 3, Jan. 2004.

[4] K. Tanamarttayarat, "The world's largest financial market: Forex," *Available at SSRN 3109245*, 2018.

[5] H. Law, S. Aghabozorgi, S. Lim, Y. Teh, and T. Herawan, "Processing of kuala lumpur stock exchange resident on hadoop mapreduce," in *Proceedings of the International Conference on Data Science (ICDATA)*. Proceedings of the International Conference on Data Science (ICDATA), 2014, p. 1.

[6] J. Yao and C. L. Tan, "A case study on using neural networks to perform technical forecasting of forex," *Neurocomputing*, vol. 34, p. 79–98, 2000.

[7] S. Borenstein, J. Bushnell, F. A. Wolak, and M. Zaragoza-Watkins, "Report of the market simulation group on competitive supply/demand balance in the california allowance market and the potential for market manipulation," *Energy Institute at Haas Working Paper*, vol. 251, 2014.

[8] M. R. E. Shazly and H. E. E. Shazly, "Comparing the forecasting performance of neural networks and forward exchange rates," *Journal of Multinational Financial Management*, vol. 7, pp. 345–356, 1997.

[9] J. J. Murphy, *Charting made easy*. John Wiley & Sons, 2012, vol. 149.

[10] R. J. Sweeney, *Foreign exchange markets*. Edward Elgar, 2005.

[11] A. Cowles, "Can stock market forecasters forecast?" *Econometrica*, vol. 1, p. 309, 1933.

[12] L. Menkhoff and M. P. Taylor, "The obstinate passion of foreign exchange professionals: technical analysis," *Journal of Economic Literature*, vol. 45, p. 936–972, 2007.

[13] M. R. Adariani, "Evaluation of the profitability of technical analysis for asian currencies in the forex spot market for short-term trading," *AU-GSB e-JOURNAL*, vol. 5, 2012.

[14] C. Neely, D. Rapach, J. Tu, and G. Zhou, "Forecasting the equity risk premium: The role of technical indicators," *Management Science*, vol. 60, Apr. 2011.

[15] J. D. Schwager, *Market Wizards*. New York Institute of Finance, 1989.

[16] K. Calhoun, "Forex volatility patterns," *TECHNICAL ANALYSIS OF STOCKS AND COMMODITIES-MAGAZINE EDITION-*, vol. 25, p. 22, 2007.

[17] C. Lento, N. Gradojevic, and C. S. Wright, "Investment information content in bollinger bands?" *Applied Financial Economics Letters*, vol. 3, p. 263–267, 2007.

[18] Z. Liu and D. Xiao, "An automated trading system with multi-indicator fusion based on ds evidence theory in forex market," in *2009 Sixth International Conference on Fuzzy Systems and Knowledge Discovery*, vol. 3. IEEE, 2009, pp. 239–243.

[19] R. Moscinski and D. Zakrzewska, *Building an Efficient Evolutionary Algorithm for Forex Market Predictions*. Springer, 2015.

[20] W. Poole, "Speculative prices as random walks: An analysis of ten time series of flexible exchange rates," *Southern Economic Journal*, vol. 33, pp. 468–478, 1967.

[21] M. P. Dooley and J. R. Shafer, "Analysis of short-run exchange rate behavior : March 1973 to november 1981," *Board of Governors of the Federal Reserve System*, 1975.

[22] G. Fusai and A. Roncoroni, *Implementing Models in Quantitative Finance: Methods and Cases*. Springer International Publishing, 2008.

[23] L. Kilian and M. P. Taylor, "Why is it so difficult to beat the random walk forecast of exchange rates?" *Journal of International Economics*, vol. 60, pp. 85–107, 2003, emperical Exchange Rate Models.

[24] M. Frömmel, *Portfolios and investments*. BoD–Books on Demand, 2013.

[25] H. He and X. Shen, "Bootstrap methods for foreign currency exchange rates prediction," in *2007 International Joint Conference on Neural Networks*. IEEE, 2007, pp. 1272–1277.

[26] L. Breiman, "Random forests," *Machine Learning*, vol. 45, pp. 5–32, 2001.

[27] M. Ballings, D. Van den Poel, N. Hespeels, and R. Gryp, "Evaluating multiple classifiers for stock price direction prediction," *Expert Systems with Applications*, vol. 42, pp. 7046–7056, 2015.

[28] W. Lv and R. Zhang, "A regression model on effective exchange rate of rmb based on random forest," in *2011 International Conference on E-Business and E-Government (ICEE)*. IEEE, 2011, pp. 1–3.

[29] S. Lahmiri and S. Bekiros, "Intelligent forecasting with machine learning trading systems in chaotic intraday bitcoin market," *Chaos, Solitons & Fractals*, vol. 133, p. 109641, 2020.

[30] J. Conrad and G. Kaul, "An anatomy of trading strategies," *The Review of Financial Studies*, vol. 11, p. 489–519, 1998.

[31] Y. Chihab, Z. Bousbaa, H. Jamali, and O. Bencharef, "An approach based on heterogeneous multiagent system for stock market speculation," *Journal of Theoretical and Applied Information Technology*, vol. 97, no. 3, pp. 835–845, 2019.

[32] H. Hassanpour, "Evaluation of deep neural network in directional prediction of forex market," 2020.

[33] Y. Chihab, Z. Bousbaa, M. Chihab, O. Bencharef, and S. Ziti, "Algo-trading strategy for intraweek foreign exchange speculation based on random forest and probit regression. applied computational intelligence and soft computing, p 2019," 2019.

[34] W. Pongsena, P. Sitsayabut, N. Kerdprasop, and K. Kerdprasop, "Development of a model for predicting the direction of daily price changes in the forex market using long short-term memory," *International Journal of Machine Learning and Computing*, vol. 11, pp. 61–67, Jan. 2021.

[35] D. C. Yıldırım, I. H. Toroslu, and U. Fiore, "Forecasting directional movement of forex data using lstm with technical and macroeconomic indicators," *Financial Innovation*, vol. 7, no. 1, pp. 1–36, 2021.

[36] G. Chandrashekar and F. Sahin, "A survey on feature selection methods," *Computers & Electrical Engineering*, vol. 40, no. 1, pp. 16–28, 2014, 40th-year commemorative issue.

[37] J. Li, K. Cheng, S. Wang, F. Morstatter, R. P. Trevino, J. Tang, and H. Liu, "Feature selection: A data perspective," *ACM Computing Surveys (CSUR)*, vol. 50, no. 6, pp. 1–45, 2017.

[38] J. Li and H. Liu, "Challenges of feature selection for big data analytics," *IEEE Intelligent Systems*, vol. 32, no. 2, pp. 9–15, 2017.

[39] Z. Kiala, O. Mutanga, J. Odindi, and K. Peerbhay, "Feature selection on sentinel-2 multispectral imagery for mapping a landscape infested by parthenium weed," *Remote Sensing*, vol. 11, no. 16, p. 1892, 2019.

[40] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[41] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[42] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *2017 International Conference on Engineering and Technology (ICET)*. Ieee, 2017, pp. 1–6.

[43] K. Cho, B. Van Merriënboer, D. Bahdanau, and Y. Bengio, "On the properties of neural machine translation: Encoder-decoder approaches," *arXiv preprint arXiv:1409.1259*, 2014.

[44] A. Graves, *Supervised Sequence Labelling with Recurrent Neural Networks*. Springer, 2012.

[45] S. Bengio, F. Fessant, and D. Collobert, "A connectionist system for medium-term horizon time series prediction," in *Proc. Intl. Workshop Application Neural Networks to Telecoms*. Proc. Intl. Workshop Application Neural Networks to Telecoms, 1995, p. 308–315.

[46] D. W. Patterson, K. H. Chan, and C. M. Tan, "Time series forecasting with neural nets: a comparative study," in *Proc. the international conference on neural network applictions to signal processing*. Proc. the international conference on neural network applictions to signal processing, 1993, p. 269–274.

[47] T. Edwards, D. S. W. Tansley, R. J. Frank, and N. Davey, "Traffic trends analysis using neural networks," in *Proceedings of the International Workshop on Applications of Neural Networks to Telecommuncations*, vol. 3. Proceedings of the International Workshop on Applications of Neural Networks to Telecommuncations, 1997, p. 157–164.