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Deep Learning based Currency Trend Classification Trained on Technical Indicators based Generated Dataset

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Abstract

This research paper presents a deep learning-based predictive model for classifying currency trends using technical indicators. The model is trained on a dataset generated from three technical indicators: relative strength index (RSI), moving average convergence divergence (MACD), and stochastic. The dataset consists of historical currency data along with the corresponding values of the technical indicators. The deep learning model can accurately classify the trends of a given currency based on the importance of these indicators. The model's performance is evaluated using standard metrics, and the results demonstrate its effectiveness in classifying currency trends. The proposed model provides a valuable tool for traders and investors in the foreign exchange market by helping them make informed decisions about the direction of currency prices.

Keywords: Deep Learning; Algorithmic Trading; Predictive Analytics

1. Introduction

A multitude of researchers have developed mathematical models and algorithms for the purpose of price forecasting [1] or the classification of trends [2]. There were a few of them that made use of regression techniques, such as the linear discriminant algorithm [3]-[4]. This research makes use of technical indicators and the interpretations provided by a variety of deep learning models powered by artificial intelligence in order to determine the trading hours that are most likely to result in a profit. The study places a primary emphasis on the foreign currency market because it is a

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unique instance of financial markets; nonetheless, it is adaptable enough to incorporate additional elements, including stocks, commodities, and so on. A certain market index or currency symbol's volatility can be seen as a statistical representation of the variation in its return. The term ”volatility” refers to the rate at which prices change. You may figure this out by calculating the standard deviation or variance of the returns for the same market index or security. According to the information presented in [3], the bid-ask spread serves as a measure of variation. This spread is defined as the difference between the price when it was at its highest point and when it was at its lowest position for a given period of time. When there is a greater degree of volatility, the security risk is typically deemed to be higher. Several factors, including liquidity, interest rates, real estate, public opinion, and corporate capital, are among those that have the potential to affect volatility. The authors of the article [5] discuss how market liquidity providers might have an effect on volatility and stock returns. Additionally, the research that is published in the paper [7] explores the connection between fixed market share and volatility.

This paper extends the work published in [10] that deals with volatility estimation. Therefore, let's first recall the essential content of the previous work. This confirms that financial calendar anomalies have long been deeply studied and studied by financial experts. Much of the research on artificial intelligence also focuses on financial market stability as an application. Let's talk about the factors that affect asset prices. As introduced in [11], trading volume is a factor investors consider when predicting prices.

This is a measurement of the total number of shares that are traded within a certain financial instrument. For instance, the average daily trading volume on the New York Stock Exchange, sometimes known as the ”NYSE,” was 1.441 billion shares in 2002. Additionally, billions of dollars' worth of securities are traded each day among the approximately 2,800 companies that are listed on the NYSE.

The daily trading volume of a security may fluctuate on any given day depending on the amount of information published or otherwise known about the company. This information may be a press release or periodic earnings announcement from the company, or may be communications from third parties. As described in [14] , court rulings, social networks like Twitter, or publications by regulators that affect the company. The unusually high volume is due to investors' differing perceptions of valuations after considering new information. Researchers have a significant interest in analysing the trading volume that occurred in conjunction with the information release and the price movement that followed since it is possible to infer this information from the anomalous trading volume. It is essential for traders and investors to research the elements that contribute to the stability of each market, as well as the myriad of other factors that influence pricing, such as interest rates [6]-[12], employment levels, and political stability. Whatever it is, the disparity in wealth between those with the most and those with the least, which is referred to as the spread in this article, widens whenever prices are influenced by factors that are external and sometimes unknown.

This manuscript is organized as follows. The first section introduces related works. Furthermore, in the same section, we also discuss the most recent relevant research. The section demystifying the approach provides key definitions and preliminary interpretations of the different technical indicators used in this approach. The next section presents a proposed hybrid model for volatility clustering. This section discusses the use of mixture models in combination with density models. The test and discussion section presents the results obtained for several indicators and discusses the homogeneity between the results of financial experts' positions and approaches. Finally, the Conclusion recalls the main ideas and discusses their application to algorithmic trading, deep learning, and financial data analysis.

2. Technical Indicators Overview

2.1. MACD Indicator

Moving Average Convergence Divergence (MACD, sometimes pronounced ”Mac-Dee”) is a very popular indicator that is frequently employed in momentum and trend tracking systems. It is occasionally pronounced ”Mac-Dee.” In other words, the moving average convergence/divergence (MACD) is a lagging indicator that provides an indication of the overall price performance of a security. The MACD is a straightforward indicator that can be calculated with little effort despite its ominous sounding name. It combines the concepts derived from various indicators, specifically the exponential moving average (EMA) and the moving average crossover approach, into a single, straightforward value. In its most fundamental form, the EMA consists of two different signals. The most typical choices are 12 and

26 days for the fast and the slow options, respectively. These are computed on a daily basis by taking the slowest and the quickest values and subtracting them to determine the difference.

2.2. MACD Formal Definition

Moving Average Convergence Divergence (MACD, sometimes pronounced "Mac-Dee") is a very popular indicator and is often used in momentum and trend following systems. In other words, MACD is a lagging indicator that provides an indication of a security's overall price performance. Despite its intimidating name, the MACD is relatively easy to understand and calculate. It takes some ideas from other indicators namely EMA and moving average crossover strategy and combines them into one easy to use value. In its most basic form, there are two EMA signals. One is fast and one is slow (12 and 26 days are commonly chosen). These are calculated daily, subtracting the slowest from the fastest to find the difference. in pseudo code

- Fast EMA : $EMA\_fast[t] = (Price[t] - EMA\_fast[t-1]) * 2/(N\_fast + 1) + EMA\_fast[t-1]$
- Slow EMA :$EMA\_slow[t] = (Price[t] - EMA\_slow[t-1]) * 2/(N\_slow + 1) + EMA\_slow[t-1]$
- Subtract the two to get the MACD : $MACD[t] = EMA\_fast[t] - EMA\_slow[t]$

MACD is known as Moving Average Convergence Divergence. Converging and diverging are two EMAs. When the short-term and long-term EMA converge, they approach the same value, and the indicator moves to 0. Divergence is caused by the short-term EMA moving up and down, further increasing the distance between the two EMAs. There are other ways the terms convergence and divergence are used in this indicator. The easiest way to trade is to buy when MACD ¿ 0 and sell/short when MACD ¡ 0. 0 If positive, faster EMAs outperform long EMAs, and vice versa if negative. This setup is a basic exponential moving average crossover strategy.

2.3. RSI Indicator

We first need to understand the RSI indicator to write a program that uses the RSI. RSI stands for Relative Strength Index. This momentum indicator uses the magnitude of price changes to assess whether a security is overbought or oversold. If the RSI is above 70, the security is considered overbought, and if the value is below 30, the security is considered oversold. Overbought means that the bubble created by buying can quickly burst and drive prices down. However, as this approach is more conservative, we recommend placing sell orders only when the RSI crosses the overbought line. At the very least, when the RSI will reach its highest point. It is considered overbought when the RSI is above 70 and oversold when below 30. These traditional levels can also be adjusted as needed for security. For example, if a security repeatedly hits the overbought level of 70, you can change its level to 80. Note that during strong trends, the RSI can remain overbought or oversold for extended periods. The RSI often forms chart patterns that don't appear on basic price charts, such as B. Double highs, lows, and trend lines. Also, look for support or resistance on the RSI. During an uptrend or bull market, the RSI tends to stay in the 40-90 range, with the 40-50 range acting as support. During a downtrend or bear market, the RSI remains between 10 and 60, with the 50-60 zone acting as resistance. These ranges depend on the RSI setting and the strength of the underlying security or market trend. This divergence could indicate a price reversal if the underlying price shows new highs or lows that the RSI has not confirmed. A missed top swing occurred when the RSI fell below a previous low after making a higher low. A missed bottom swing occurred when the RSI created a higher low and then rose above its previous high.

2.4. RSI Formal Definition

The RSI is a fairly simple formula, but is difficult to explain without pages of examples. Refer to Wilder's book for additional calculation information. Let's consider $\bar{D}$ the average of upward price change and $\bar{U}$ average of downward price change. The basic formula is:

$$RSI = \frac{100\bar{U}/\bar{D}}{1 + \bar{U}/\bar{D}} \tag{1}$$

2.5. RSI Indicator

The stochastic oscillator is a momentum indicator that compares the defined closing price of an asset to its price range over a specified time period. This comparison is made using the stochastic oscillator. Adjusting the length of this period or computing a moving average of the data is two ways to lessen the oscillator's sensitivity to changes in the market. Utilising a constrained range of values between 0 and 100, it is used to provide trading signals for overbought and oversold conditions in the market.

2.6. RSI Formal Definition

Let's denote C, the most recent closing price, and L_{14}, the lowest price traded of the 14 previous trading sessions, and H_{14}, the highest price traded during the same 14 previous sessions. Let K be the current value of the stochastic indicator. In particular, K is sometimes called the fast probability index. The "slow" probability indicator is assumed to be a 3-period moving average of $D = K$. The general theory on which this indicator is based is that price closes near highs in up-trending markets and close near lows in down-trending markets. A transaction signal is generated when K crosses the 3-period moving average called D. The difference between slow and fast stochastic oscillators is that slow K includes 3 K deceleration periods that control the internal smoothing of K. Setting the smoothing period to 1 is equivalent to drawing a fast stochastic oscillator.

$$K = \frac{100(C - L_{14})}{H_{14} - L_{14}} \tag{2}$$

3. Data Analytics

3.1. Data Set Overview

The data comes streaming from some free web services or directly from a broker as in [20]. In our case, we have used the platform MetaTrader which is by default configured for download the data sets. For each financial instrument, the data contains the seven main elements, the date, and time of each observation as a first component. The open and close prices that are the prices in the beginning and the end of each time frame (one hour in the context of this approach). Then the high and low prices that represents the highest and lowest variations of the price between the beginning and the end of the time frame. Finally, volume that represents the invested amount of money in that time frame. In addition to pricing values, some technical indicators are computed and added to the dataset as columns such as MACD and RSI indicators.

3.2. Data Set Descriptive Statistics

This subsection focuses on the description of the input and output parameters. We compute mainly - for each parameter - the minimum observed value, the maximum, the mean and the standard deviation (S. D.). Table 1 describes the input data:

Table 1. FX Dataset Desctiptive Statistics

	Open	Close	MACD	RSI	Stochastic
Min	0.95	0.95	-0.0	16.81	1.23
Max	1.14	1.14	0.01	81.52	98.45
Mean	1.04	1.04	-0.0	48.89	47.61
S.D.	0.004	0.04	0.0	10.5	27.23

3.3. Pearson Correlation

Karl Pearson's correlation coefficient in Table 2 can be used to summarize the strength of the linear relationship between two data samples. Pearson's correlation coefficient is computed as the covariance of the two variables divided by the product of the standard deviations of each data sample. This is his covariance normalization between two variables to get an interpretable score. It is given formally with the equation :

$$C_{XY} = \frac{\sum_{i=1}^{n}(x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{X})^2}.\sqrt{\sum_{i=1}^{n}(y_i - \bar{Y})^2}} \tag{3}$$

In this case, $MACDSignalVSFinalSignal$ represents the correlation between the MACD decision based and the the final decision signal that we obtained combining all indicators while $RSISignalVSFinalSignal$ and $StochasticSignalVSFinalSignal$ represents the correlation between the final decision signal with the RSI based and Stochastic based one respectively. Using the equation 3 produces a Pearson's correlation coefficient and a p-value to test for lack of correlation. Using the mean and standard deviation in the calculation, we know that the two data samples should have a Gaussian or Gaussian-like distribution.

Table 2. MACD, RSI and Stochasic Signals Pearson Correlation with Final Signal

	Pearson Coefficient
MACD Signal VS Final Signal	0.533884
RSI Signal VS Final Signal	0.749148
Stochastic Signal VS Final Signal	0.589655

The correlation coefficient that was calculated as a consequence can be analyzed and evaluated to provide insight into the relationship. The coefficient returns a value between -1 and 1, representing the bounds of correlation, ranging from an entirely negative correlation to a wholly positive one. When referring to correlation, a value of 0 indicates that none exists. You are required to provide your interpretation of the value. Values with a correlation coefficient below -0.5 or above 0.5 are likely to have a substantial relationship.

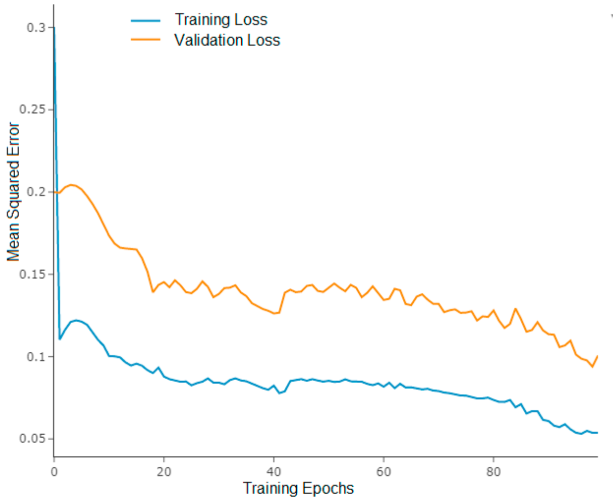
Still, values with a correlation coefficient below these levels have a less significant relationship. The p-value provides a rough estimate of the probability that an uncorrelated system can create datasets with Pearson correlations that are at least as extreme as those that were estimated from those datasets.

3.4. Deep Neural Network

The deep learning prediction model that was used to train the model that was proposed in this research was trained using a dataset of the currency exchange market that was gathered via open web services. During the training step, a supervised learning algorithm was utilised. Here, the model was trained to predict the trend of the currency exchange based on a set of input parameters, including RSI, Stochastic, and MACD. The model was then tested to see how accurately it predicted the trend. In our situation, we used TensorFlow, which is a software framework that was developed expressly with deep learning in mind to carry out the process of training the model.

The progression of the loss function during the training and validation phases of the model is depicted in the figure that can be found below. The loss function is a measurement of how effectively the model is able to predict the trend of the currency, and it is measured as the difference between the fade rate that was predicted and the actual fade rate. The blue line illustrates the training phase, while the orange line illustrates the validation phase of the process. As the training goes on, the loss function gets smaller, which shows that the model is getting better at making accurate predictions. The validation loss is an important metric for determining how effectively the model generalizes to data that has not been observed before.

Fig. 1. Deep Neural Network Training and Validation Loss Evolution



4. Conclusion

In this paper, we present a currency market volatility estimator. The proposed computational model is based on a deep neural network model combined with an Adam optimization algorithm for deep learning. The main goal of the proposed approach is to measure the probability of currency activity being in a particular region for each hour of the day. The proposed model has many applications in financial markets. On the one hand, implementations in platforms like Interactive Broker allow traders to predict symbol activity instantly. This means that the dealer can always choose a favorable symbol. On the other hand, the model can be implemented in trading robots to find enough volatility to execute a particular strategy. The analysis of real data supports this work. Transferring reports or data from one place to another takes too much time and energy, and it will cause high latency and energy issues. To handle these kinds of hazards, edge computing provides solutions. Also, the results confirm that the model has comparable accuracy and is close to the accuracy used by financial professionals. This approach uses a deep neural network model based on Adam's optimization method, an adaptive learning rate optimization algorithm designed specifically for training deep neural networks. The computational aspects of this method need to be deepened in future work. In terms of perspective, comparative studies in terms of computational complexity and accuracy between different sampling indicators such as MACD Moving Average convergence divergence. RSI Relative strength index and stochastic oscillator should be done. We set the upper and lower bounds of the profit zone in terms of percentages and conducted a study. The models in this document are implemented in real technical indicators built into the Interactive Broker platform. The favorable zone parameters are taken as the two inputs specified by the user according to the desired sensitivity. As some strategies require high volatility to be profitable, a separate study can be done to find the value of different trading styles from a perspective. We believe algorithmic trading powered by artificial intelligence is the future of financial markets. For this reason, future work will focus on the design of expert systems jobs. This joint distributed intelligence can create a kind of trading robot.

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Conflicts of Interest

I declare that I have no conflict of interest and no financial or other interest with any entity to disclose.

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