Khan, Inzamam; Ahmed, Wajid Shakeel; Shad, Shafqat et al.

Article

Determine intraday trading currency's trend framework evidence from machine learning techniques

International journal of business intelligence research

International Journal of Business Intelligence Research
Volume 15 • Issue 1 • January-December 2024

Determine Intraday Trading Currency's Trend Framework Evidence From Machine Learning Techniques

Inzamam Khan
COMSATS University, Islamabad, Pakistan

Wajid Shakeel Ahmed
https://orcid.org/0000-0001-9003-2863
COMSATS University, Islamabad, Pakistan

Shafqat Shad
https://orcid.org/0000-0003-0339-1070
University of Montevallo, USA

Chandan Kumar
Iowa State University, USA

Muhammad Usman
Verizon Inc., USA

Milad Jasemi
University of Montevallo, USA

Khuarm Shafi
https://orcid.org/0000-0003-3416-4241
COMSATS University, Islamabad, Pakistan

ABSTRACT

The purpose of this study is to determine the intraday hourly trading trends of currencies using predictive modeling techniques. The study encompasses two distinct intraday time intervals of 30 minutes and 1 hour, analyzing currencies from 8 different countries. It incorporates the use of wavelets MODWT to identify trends and noise in intraday currency analysis. Three predictive models, namely Support Vector Regression, Recurrent Neural Network, and Long Short-Term Memory, are applied to relative time series data to predict intraday trading currency trends. The study reveals significant noise presence in three currencies based on MODWT analysis. Additionally, it demonstrates that deep learning techniques, such as LSTM, outperform traditional machine learning approaches in accurately predicting intraday currency trends. This study contributes substantially to the theoretical understanding of international finance and provides practical insights for real-time problem-solving in currency markets. Further, this research adds to the discourse on leveraging sophisticated analytical methods within the domain of business intelligence to enhance decision-making processes in organizations operating within dynamic and complex financial environments.

KEYWORDS

Currency's Trend Framework, Financial Decision Making, Intraday Trading, Machine Learning, MODWT

INTRODUCTION

In the finance literature, researchers have traditionally relied on conventional methods such as FIGARCH, ARFIMA, GARCH (1,1), and ARMA-GARCH for predicting high-frequency stock data and exchange rates (Chen et al., 2019; Guo & Li., 2019). As a result, there has been a shift from conventional to nonconventional machine and deep learning methods in recent years, driven by advancements in modern technologies and electronic data innovations. The surge in machine learning and artificial intelligence applications has attracted increasing interest from researchers seeking

DOI: 10.4018/IJBIR.346977

to predict market movements effectively, thereby mitigating losses and identifying opportunities (Fletcher et al., 2018).

Researchers have extensively employed machine learning methods for predicting currency market behavior, including long-short term memory (LSTM), artificial neural networks (ANN), and others (Fischer & Krauss., 2018). Hajiabotorabi et al. (2019) and Qin et al. (2017) utilized recurrent neural network (RNN) incorporating DWT for financial analysis, while Sharma & Sharma (2012) employed RNN for time series prediction. Demírel et al. (2020) utilized the support vector regression (SVR) machine learning model for prediction analysis, and Peng et al. (2018) employed SVR for volatility forecasting. Zeng and Khushi (2020) utilized RNNs for predicting financial market trends.

Forecasting foreign exchange rates remains an ongoing challenge for professionals, policymakers, and academics. Numerous studies have been dedicated to understanding the dynamics of exchange rates. One key conclusion drawn from these studies is that while macroeconomic fundamentals should inform theories about a country's currency purchasing power, they are less useful for predicting exchange rates (Bacchetta & Van. 2004, Bacchetta et al. 2009; Kim, .2003).

For investors and traders, the foreign exchange market (forex) market represents one of the most liquid and vast markets. Daily data production in the forex market is extensive, with price fluctuations influenced by various factors (Aguilar et al., 2017). Investors keenly monitor these factors to capitalize on buying low and selling high, aiming to profit from currency price fluctuations (Hansen & Lunde., 2011). As the forex market operates digitally, factors such as political actions or changes can rapidly influence market prices.

There exists a risk in foreign exchange rates known as forex risk or currency risk. This risk arises when financial transactions involve currency exchange, particularly in currencies other than a company's base currency (Urata & Kawai., 2000). A comparative study across markets for intraday multifrequency time series analysis is notably absent in the literature. This study aims to address this gap by evaluating the predictive performance of machine and deep learning models using two different frequency intervals of intraday data for eight liquid and volatile currencies over a 3-year period. Specifically, the study seeks to analyze the predictability power of these models and compare their outcomes based on accuracy indicators and statistical measures. Ultimately, the study aims to identify the best prediction model among machine and deep learning models, offering implications for trading strategies and investment-related policies for investors and practitioners (Vapnik et al., 1997). This study aims to propose the most effective prediction method for intraday time series analysis, providing valuable insights for researchers, the financial industry, and policymakers. Additionally, it offers practical suggestions for leveraging machine learning and deep learning methods in financial market prediction tasks.

Hence, this study endeavors to put forth the most effective prediction method for intraday time series analysis, offering suggestive implications that prove beneficial for refining trading strategies and making informed investment decisions across various sectors, including researchers, the financial industry, and policymakers. Furthermore, this research provides valuable insights into the utilization of machine learning and deep learning methods, offering practical recommendations for their application in the realm of financial market prediction tasks.

LITERATURE REVIEW AND CONCEPTUAL MODEL

The technique of machine learning or artificial intelligence extracts patterns by utilizing historical data, their work (Demirel et al., 2021) underscores the rising importance of Explainable

Artificial Intelligence (XAI) in navigating the opacity of advanced machine learning models. By offering a comprehensive literature review and taxonomy of interpretability techniques, it serves as a vital resource for researchers and practitioners. This contextualization enriches our study, emphasizing the significance of model transparency in critical domains like finance (Xiao et al., 2013). In the study of forecasting prices, machine learning techniques such as ANNs and support vector machines

(SVMs) were employed (Xiao et al., 2013). A machine learning study typically encompasses two key components: the selection of variables and models for prediction, followed by the optimization of the chosen model. Basic methods utilized in such studies include ANNs and SVMs (Xiao et al., 2013).

Jorion (2007) pioneered the application of wavelet methods in time series analysis, emphasizing their effectiveness in detecting real jumps and trends. These techniques, including discrete wavelet transforms (DWTs) and continuous wavelet transforms (CWTs), have since evolved, with the maximum overlap discrete wavelet transform (MODWT) addressing previous limitations (Jorion., 2007; Müller et al., 1997). Integrating these advancements into intraday currency trading trends can enhance the robustness of predictive modeling techniques, aligning with the broader narrative of leveraging cutting-edge methodologies for comprehensive trend identification and noise mitigation in financial analysis.

The research by Fischer & Krauss. (2018), demonstrating LSTM's effectiveness, and Cai . (2016), highlighting data filtering's significance, collectively illuminate the evolving landscape of predictive analytics in finance. These studies contribute to a broader discourse on enhancing forecasting accuracy and understanding market dynamics. Incorporating insights from these works into intraday currency trading trends research can not only enrich the predictive modeling approach but also contribute to advancing methodologies for improved performance in currency markets, thereby shaping the trajectory of predictive analytics in financial analysis.

Chong et al. (2017) investigated the application of deep learning networks in predicting stock market trends, highlighting their capacity to enhance prediction accuracy through the extraction of nuanced information from intraday stock data. Similarly, Tsai & Chiang. (2018) demonstrated the effectiveness of convolutional neural networks (CNNs) in developing trading strategies, emphasizing the broader utility of deep learning techniques in financial analysis and decision-making. These studies collectively underscore the growing adoption and efficacy of deep learning methodologies across various domains within finance, signaling a significant paradigm shift in predictive analytics and trading strategies.

Mohammadi et al. (2015) investigated exchange rate forecasting using machine learning techniques such as support vector regression (SVR), radial basis function (RBF), and LSTM, highlighting SVR's superior performance in predicting currency market movements. Their findings underscore the efficacy of machine learning in capturing complex patterns in currency markets, offering valuable insights for traders and investors alike.

Panda et al. (2020) conducted a systematic review on exchange rate prediction, affirming the efficacy of deep learning methodologies in improving prediction accuracy. Their comprehensive analysis consolidates the growing evidence supporting the adoption of deep learning techniques in currency forecasting, providing a valuable resource for researchers and practitioners in the field.

Dautel et al. (2020) and Yang et al. (2016) compared deep learning approaches for forex exchange rate forecasting, concluding that deep neural networks, particularly LSTM, outperform traditional methods. Their research highlights the transformative potential of deep learning in revolutionizing currency market analysis, paving the way for more accurate and reliable predictions in intraday trading scenarios.

Similarly, Fischer & Krauss (2018) and Kim & Won. (2018) advocated for LSTM's superiority in predicting financial market returns, especially in noisy financial time series data. Their findings underscore the robustness of LSTM models in handling the complexities of financial data, offering promising avenues for enhancing trading strategies and investment decision-making.

Niu et al. (2021) employed a nonconventional deep learning approach for financial time series forecasting, emphasizing the importance of accurate forecasting in investment decision-making. Their innovative methodology expands the repertoire of deep learning techniques available for financial analysis, offering new perspectives for optimizing trading performance and risk management strategies.

Meanwhile, Sun et al. (2020) utilized LSTM neural networks for exchange rate forecasting, demonstrating LSTM's effectiveness in enhancing forecasting accuracy and trading profitability. Their research reinforces the growing recognition of LSTM as a powerful tool for predicting currency movements, highlighting its potential to drive significant improvements in intraday trading strategies and market decision-making processes.

RESEARCH METHODOLOGY

The data for this study were sourced from Nasdaq Data Link Application Programming Interfaces (APIs), renowned for their flexible and efficient delivery of real-time exchange data and financial information. These APIs offer a suite of streaming and Representational State Transfer (REST) APIs, facilitating the seamless integration of real-time data from various sources and significantly reducing time to market for custom-designed applications. Nasdaq's market data APIs are highly scalable and robust, ensuring the reliable delivery of real-time exchange data essential for this study's intraday currency trend analysis.

The chosen setting of data duration and frequency duration, encompassing 1-hour and 30-minute intraday frequencies from January 2018 to December 2020, warrants justification to ensure its appropriateness for addressing the research question of the study.

Firstly, the selected duration of the data set, spanning 3 years from January 2018 to December 2020, provides a sufficiently extensive time frame to capture a diverse range of market conditions and fluctuations in currency prices. This duration allows for the inclusion of various economic events, geopolitical developments, and market dynamics that may influence currency exchange rates over time. By analyzing data over this period, the study can offer insights into the robustness and generalizability of the predictive models across different market environments and economic climates.

Secondly, the choice of intraday frequencies, specifically 1-hour and 30-minute intervals, is strategic in capturing both short-term and medium-term fluctuations in currency prices. The 1-hour frequency enables the examination of intraday patterns and trends, providing insights into short-term market behavior and price movements. On the other hand, the 30-minute frequency offers a more granular view of intraday fluctuations, allowing for the identification of finer nuances in currency price dynamics. By analyzing data at these two frequencies, the study can evaluate the performance of predictive models across varying levels of intraday granularity, thereby enhancing the comprehensiveness of the analysis.

Overall, the selected setting of data duration and frequency duration aligns with the research question of the study by providing a robust foundation for evaluating the predictive capabilities of machine and deep learning models in forecasting currency prices. The chosen timeframe and intraday frequencies enable the study to capture a diverse range of market conditions and fluctuations while offering insights into both short-term and medium-term currency price dynamics.

Before applying machine and deep learning models for currency price prediction, rigorous preprocessing steps were undertaken to ensure the quality and reliability of the data. The initial stage involved data acquisition, where raw currency price data for the selected eight currencies against the U.S. dollar were collected from reliable sources. Subsequently, the data underwent meticulous cleaning procedures to address various issues, such as missing values, outliers, and inconsistencies. Missing values were either imputed using appropriate methods or removed from the data set, depending on the extent of missingness and the impact on the analysis. Outliers, which could potentially skew the results, were identified and treated using robust techniques such as Winsorization or through manual inspection and validation. Inconsistencies in the data, such as discrepancies in formatting or erroneous entries, were rectified to ensure data integrity.

Following data cleaning, the preprocessed data were subjected to exploratory data analysis (EDA) to gain insights into the underlying patterns and distributions. This involved visualizing the data through descriptive statistics, histograms, and scatterplots to identify any trends, seasonality, or correlations between variables. Moreover, correlation analysis was conducted to assess the relationships between different currency pairs and detect any multicollinearity that could affect the predictive models.

Table 1. Overview of initial data exploration

Currencies	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
CHF	0.9701	0.9812	1.0223	0.8796	0.0322	–0.9499	2.9041	3966.087**
DKK	6.5083	6.5643	7.0121	5.9358	0.2439	–0.4612	2.2918	1482.443**
HKD	7.8091	7.8268	7.8499	7.7493	0.0400	–0.5292	1.5402	3563.291**
RUB	66.593	65.4784	82.0773	55.6618	5.5984	0.4343	2.6720	944.7942**
SEK	9.1169	9.1192	10.4490	7.8328	0.5118	–0.3166	2.5677	644.3605**
SGD	1.3640	1.3631	1.4642	1.3026	0.0266	0.3260	3.6683	955.7244**
TRY	5.8477	5.7827	8.5588	3.7222	1.1091	0.0278	2.6382	146.6345**
ZAR	14.782	14.5171	19.3075	11.5102	1.6678	0.3988	2.9402	701.3126**

Note. The table represents mean, median, maximum, minimum, standard deviation, skewness, kurtosis, and Jarque-Bera statistics. Skewness, kurtosis, and Jarque-Bera statistics CHF and DKK have negative values which are referred to as skewed data on the left. Whereas RUB, SGD, TRY, and ZAR are the positive valued skewness. Jarque-Bera is for the properness of the test that normally indicates normal distribution.

*** Confidence interval of *p* value @ 1% level.

** Confidence interval of *p* value @ 5% level.

* Confidence interval of *p* value @ 10% level.

Additionally, feature engineering techniques were applied to extract relevant features from the raw data, which could potentially enhance the predictive performance of the models. Furthermore, to address potential biases in the data and ensure the robustness of the predictive models, stratified sampling techniques were employed to partition the data into training, validation, and test sets. This helped to maintain the distributional properties of the data across different subsets, thereby minimizing the risk of overfitting and improving the generalization capability of the models.

Overall, the preprocessing phase played a crucial role in preparing the data for subsequent analysis, ensuring that the machine and deep learning models could effectively capture the underlying patterns and relationships in the currency price data. The transparency and rigor of the preprocessing steps enhance the reliability and replicability of the study findings, providing a solid foundation for the subsequent model application and evaluation.

Descriptive Statistics

Table 1 provides an overview of initial data exploration, incorporating central tendency measures alongside normality test statistics, specifically the Jarque-Bera (J-B) test. For data location measurement, skewness and kurtosis are interpreted to evaluate the concentration of observed values. Notably, in this data set, CHF, DKK, HKD, and SEK exhibit a negative trend compared to the rest, which demonstrates positive trends based on skewness.

Furthermore, the J-B test statistics are utilized to assess the normality of the data distributions. A lower J-B test value indicates a distribution closer to normal, while higher values suggest departures from normality. In this context, the examination of skewness and kurtosis, along with the J-B test results, aids in understanding the shape and symmetry of the data distributions. Notably, deviations from normality in certain currencies, such as CHF, DKK, HKD, and SEK, may have implications for subsequent modeling and analysis techniques, warranting further investigation into their underlying characteristics and potential drivers of observed trends.

Wavelet-MODWT

In this step, the MODWT is applied to each of the eight currencies in the 1-hour data set. The choice of MODWT for this study is deliberate, as it represents a more effective wavelet version capable of handling data of any length while capturing more information in each scale. By leveraging

Figure 1. CHF Original Series Versus MODWT

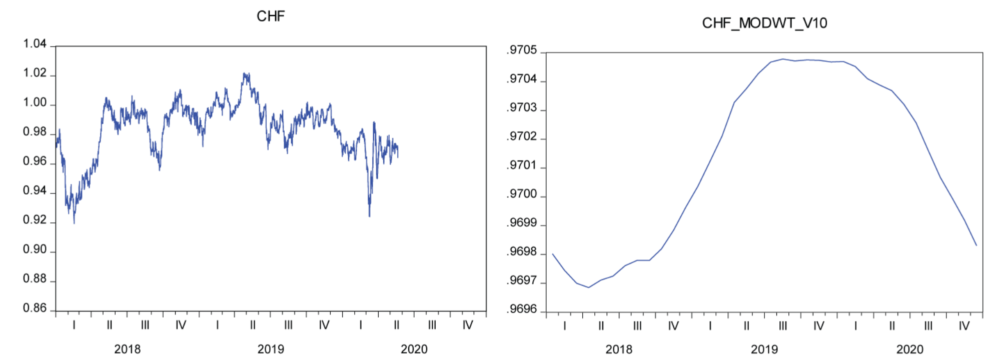
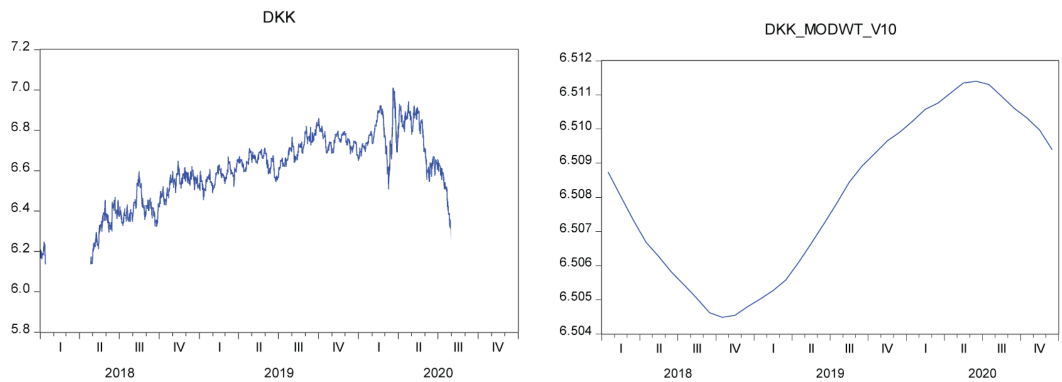


Figure 2. DKK Original Series Versus MODWT



MODWT, the study aims to extract meaningful insights from the currency data series, discerning underlying trends and patterns that may influence exchange rate dynamics.

The application of MODWT allows for a comprehensive analysis of currency price movements, enabling the identification of significant features and fluctuations across different scales and frequencies. Subsequently, the study presents graphical representations of each currency's original series juxtaposed with their corresponding MODWT series, providing visual insights into the decomposition process and highlighting notable trends and variations. This approach enhances the interpretability of the data and facilitates a deeper understanding of currency market dynamics, laying the groundwork for subsequent predictive modeling and analysis.

To investigate the trend of these currencies' prices, this study conducts wavelet MODWT analysis to address the trend in each currency price. Mentioned are the graphs of original series and series after applying wavelet MODWT analysis for the selected currencies, and every figure shows the original data series of a currency and its wavelet-analyzed series of currency against it. It is clear from the MODWT analysis of every currency that each currency contained a specific trend. Therefore, it is clear from the wavelet analysis that DKK and SGD were having down trends in their prices in the year 2018, and further in 2020, they reached a maximum point in their trend. RUB, TRY, and ZAR were observed to have fallen in their prices in 2019, as shown in the trend, and they reached a peak in 2020. For CHF and HKD, the trends show that their prices were on peak in 2019, and they started falling after it and reached a minimum in 2020, as shown in their respective trends.

Figure 3. HKD Original Series Versus MODWT

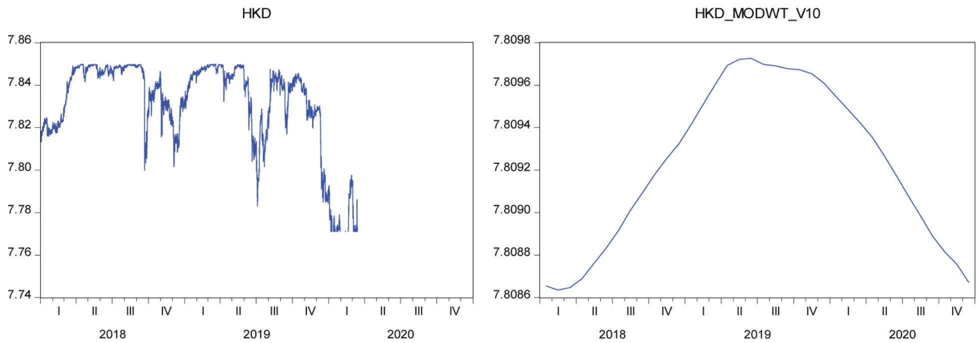
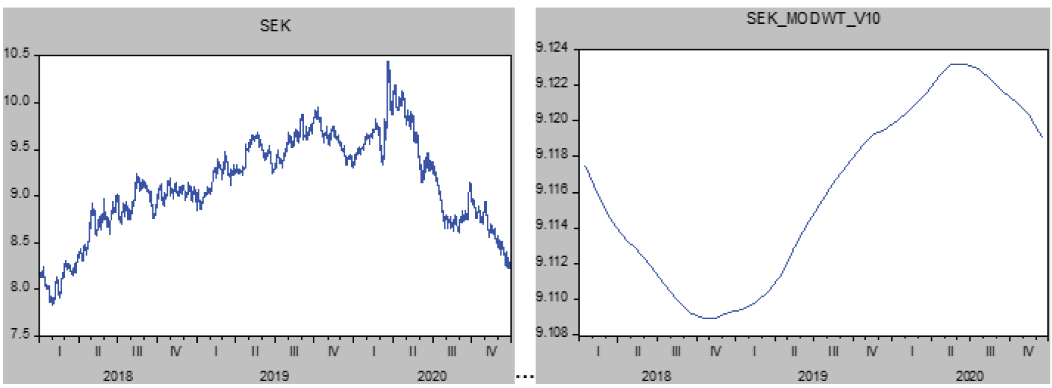


Figure 4. RUB Original Series Versus MODWT



The wavelet analysis shows that there were a lot of fluctuations in the prices of currencies. This study aims to investigate the future price of currencies by using highly effective machine and deep learning model techniques to predict the prices and to address the predictability power of machine

Figure 5. SEK Original Series Versus MODWT

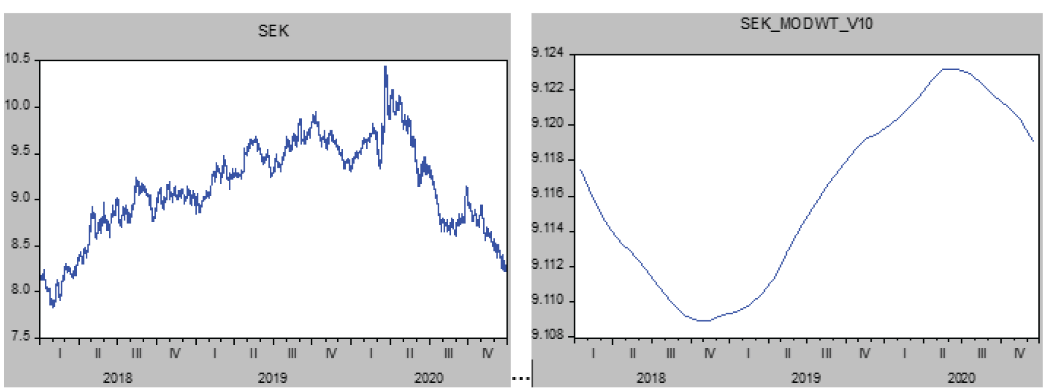


Figure 6. SGD Original Series Versus MODWT

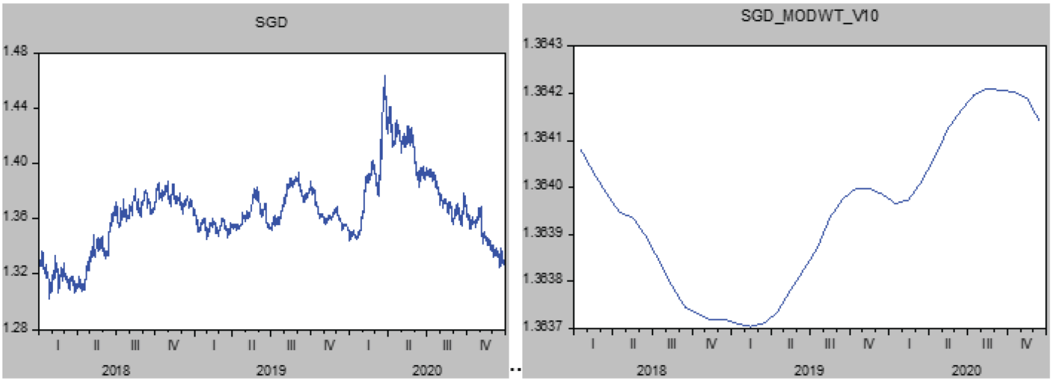


Figure 7. TRY Original Series Versus MODWT

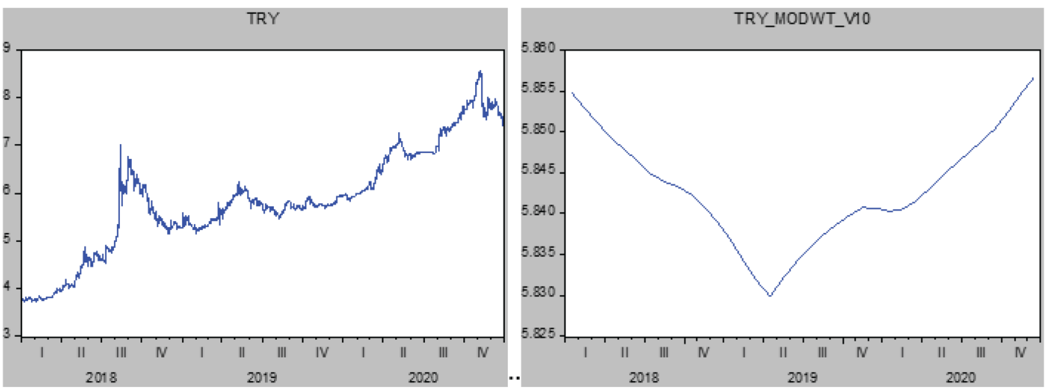


Figure 8. ZAR Original Series Versus MODWT

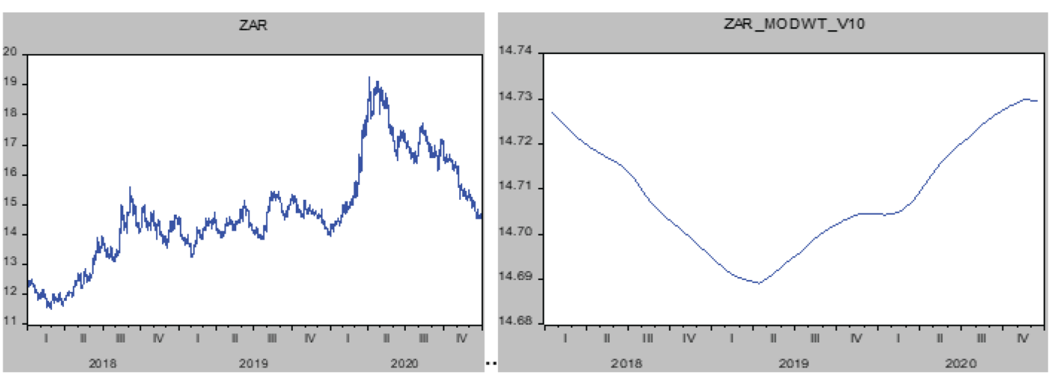


Table 2. Summary Comparison of Model Fitness for Multifrequency Intraday of Selective Exchange Rates Based on Accuracy Measures

Frequency time interval of 1 hour													
Currencies	**Volatility**	**MSE**			**MAE**			**RMSE**			**MAPE**		
		SVM	**RNN**	**LSTM**	**SVM**	**RNN**	**LSTM**	**SVM**	**RNN**	**LSTM**	**SVM**	**RNN**	**LSTM**
CHF	Low	**0.0010**	1.3838	1.3663	0.0267	0.0027	**0.0025**	0.0323	0.0037	**0.0036**	2.7953	0.2981	**0.2846**
DKK	Low	0.0584	**0.0003**	0.5868	0.2037	0.0136	**0.0056**	0.2417	0.0190	**0.0081**	3.1619	0.2034	**0.0866**
HKD	Low	**0.0016**	4.2866	5.6513	0.0367	0.0063	**0.0028**	0.0399	0.0065	**0.0029**	0.4707	0.0822	**0.0364**
RUB	High	30.817	**1.3382**	1.8300	4.3504	**0.9465**	1.0737	5.5513	1.8682	**1.3528**	6.4934	**1.2491**	1.4136
SEK	Low	0.2536	**0.0003**	0.0004	0.4131	**0.0117**	0.0165	0.5036	**0.0176**	0.0219	4.5842	**0.1255**	0.1787
SGD	Low	**0.0007**	9.4633	9.2496	0.0194	**0.0018**	**0.0018**	0.0263	**0.0030**	**0.0030**	1.4245	0.1328	**0.1280**
TRY	High	1.229	**0.0140**	0.0556	0.8427	**0.0832**	0.1910	1.1086	**0.1184**	0.2359	8.5444	**1.0879**	2.5361
ZAR	High	2.7662	0.0987	**0.0803**	1.2471	0.2091	**0.1940**	1.6631	0.3026	**0.2834**	8.5386	1.1807	**1.0976**
Frequency time interval of 30 minutes													
Currencies	**Volatility**	**MSE**			**MAE**			**RMSE**			**MAPE**		
		SVM	**RNN**	**LSTM**	**SVM**	**RNN**	**LSTM**	**SVM**	**RNN**	**LSTM**	**SVM**	**RNN**	**LSTM**
CHF	Low	**0.0010**	9.5267	1.9150	0.0267	0.0021	**0.0010**	0.0324	0.0030	**0.0013**	2.7938	0.2359	**0.1113**
DKK	Low	0.0598	6.9555	0.0001	0.2072	0.0063	0.0090	0.2445	0.0083	0.0112	3.2145	0.0956	0.1379
HKD	Low	0.0016	4.5207	1.9709	0.0368	0.0065	0.0042	0.0401	0.0067	0.0044	0.4721	0.0849	0.0548
RUB	High	31.751	1.0247	0.7011	4.4411	0.7838	0.6121	5.6348	1.0123	0.8373	6.6283	1.0302	0.8025
SEK	Low	0.2636	0.0009	0.0029	0.4221	0.0194	0.0385	0.5134	0.0305	0.0541	4.6821	0.2035	0.4009
SGD	Low	0.0007	8.8223	1.1765	0.0196	0.0017	0.0020	0.0266	0.0029	0.0034	1.4417	0.1228	0.1481
TRY	High	1.2511	0.0278	0.0224	0.8527	0.1247	0.1141	1.1185	0.1670	0.1496	15.711	1.6379	1.5035
ZAR	High	2.7939	0.1709	0.1905	1.2546	0.3179	0.3090	1.6715	0.4134	0.4365	8.5739	1.8145	1.7451

Note. Table 2 represents the summary statistics of best model for forecasting exercise based on the accuracy measures for intraday hourly currency trading. The table is divided into two parts – the first part shows the 1-hour volatility trend of selective currencies along with the best predicted learning models. The second part represents the 30-minute volatility trend of selective currencies with respective predicted learning models. Respective graphs and calculations have been omitted due to space issues. The respective volatility represents the Low = less volatile and High = more volatile; proposed supervised and unsupervised models are, that is, SVR = support vector regression, RNN = recurrent neural network, and LSTM = long-short term memory, and accuracy indicators are MSE = mean square error, RMSE = root mean square error, MAE = mean absolute error, and MAPE = mean absolute percentage error. The values in bold indicate the lowest error values from estimated models and thus considered to be the best among the others.

learning and deep learning models that which model among machine and deep learning performs well, by using selected accuracy indicators statistical based measures.

RESULTS AND DISCUSSION

This study embarked on a thorough exploration of historical currency data to gauge the predictive capabilities of various machine and deep learning models in forecasting currency prices. At its core, the primary objective was to uncover the inherent trends within the real data series of each currency, laying a solid foundation for comprehending the intricacies of exchange rate fluctuations over time. Leveraging wavelet MODWT analysis proved instrumental in this endeavor, providing a robust framework for unraveling the multifaceted dynamics underlying currency price movements.

The insights gleaned from the wavelet analysis offered a nuanced understanding of individual currency behaviors. Notably, currencies such as DKK, SEK, and SGD exhibited a pronounced downward trajectory in prices throughout 2018, culminating in their peak values in 2020. Conversely, currencies like RUB, TRY, and ZAR followed a contrasting pattern, experiencing a dip in prices during 2019 before surging to their peak levels in 2020. These observations underscore the fluid nature of currency markets and emphasize the importance of capturing these trends to enhance the accuracy of predictive modeling.

Transitioning from trend identification to predictive modeling, the study focused on employing advanced machine and deep learning models to forecast future currency prices. Central to this endeavor was the evaluation of these models' predictability power and subsequent comparison of their performance. To this end, a comprehensive suite of accuracy indicators, including mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), were meticulously applied. These metrics serve as robust benchmarks for assessing the accuracy and reliability of the forecasting models under scrutiny.

While LSTM's superior performance based on minimum error values in Table 2 is noteworthy, it is crucial to acknowledge that designating it as the outright winner solely on these metrics warranted careful consideration. Although LSTM consistently exhibited competitive performance across multiple measures, model selection and evaluation involved nuances that require attention. Therefore, additional analyses such as sensitivity analyses, cross-validation techniques, and scenario testing are warranted to strengthen the study's findings and provide a more comprehensive understanding. These approaches will illuminate LSTM's robustness and generalizability across diverse market conditions and timeframes, thereby enhancing the study's conclusions.

Transitioning seamlessly from identifying currency price trends to predictive modeling using advanced machine and deep learning techniques, the study rigorously evaluated these models' predictive power and compared their performance. A comprehensive set of accuracy indicators, including MSE, MAE, RMSE, and MAPE, is judiciously applied to assess the accuracy and reliability of the forecasting models under scrutiny. However, while LSTM consistently demonstrated competitive performance across multiple measures, the nuances of model selection and evaluation cannot be overlooked. Therefore, additional analyses, such as sensitivity analyses, cross-validation techniques, and scenario testing, are warranted to provide a more holistic understanding of LSTM's robustness and generalizability across diverse market conditions and timeframes, further strengthening the study's conclusions.

In conclusion, by exploring the nuanced dynamics of currency price trends, rigorously evaluating forecasting models using a diverse array of statistical measures, and advocating for further testing and validation, this study aimed to advance our understanding of currency market dynamics. Moreover, it seeks to empower investors and policymakers with actionable insights to inform more informed decision-making processes in the ever-evolving currency market landscape.

The second objective of the study was to analyze the predictability power of machine and deep learning best-estimated models for the intraday frequencies. The accuracy power of SVR, RNN, and LSTM in a 1-hour data set and their graphical visualization can be seen for each currency exchange rate prediction. The accuracy of these models was measured by accuracy indicator statistical-based measures such as MSE, MAE, RMSE, and MAPE, respectively, and the second question of this study was answered by identifying the results of these accuracy measures which show the predictability power of each model in each frequency of the time series. The resulting outcomes indicated that the performance of LSTM was best among other models for the task of prediction in intraday 1 hour and 30-minute frequencies of the time series.

The findings of this study aligned with existing literature, indicating that prediction performance can indeed be enhanced with the implementation of deep learning networks, as they possess the capability to extract additional information (Chong et al., 2017). Moreover, utilizing deep learning techniques has been shown to enhance accuracy and performance (Chatzis et al., 2018). Addressing the third research question, this study identified LSTM as outperforming other machine and deep learning models in predicting intraday frequencies of time series. Consequently, it recommends the utilization of LSTM for financial market prediction tasks involving intraday frequencies of time series, attributing its superior predictability power in handling larger-scale data series. These findings were consistent with existing literature, which highlights LSTM's ability to extract meaningful information and its superiority in financial time-series analysis (Yan & Ouyang., 2018; Sun et al., 2020).

On a broader scale, the foreign exchange market stands as one of the largest trading markets globally, facilitating currency trading to benefit individuals and economies alike. Serving as the backbone of international trade, the forex market holds significant importance, with every economy directly or indirectly influenced by foreign exchange rates. Researchers, practitioners, traders, and investment-related policymakers employ various techniques to predict these exchange rates. In recent times, advancements in technology, particularly in artificial intelligence and machine learning, have led to notable progress in these fields. Machine learning algorithms have proven to be increasingly effective in economics and finance, offering stakeholders in the currency market opportunities to forecast future investments, diversify risks, and identify investment-related opportunities.

This study undertook a comparative analysis of the most recommended machine and deep learning models, utilizing standard parameters such as batch size, epochs, neuron numbers, and activation functions for model tuning to discern currency trends. Based on empirical findings, the study advocates for the adoption of the LSTM deep learning algorithm by researchers, academicians, practitioners, and investors. Notably, LSTM excelled in extracting meaningful information from time series data, incorporating forget gates alongside input and output gates within its architecture, along with cell state regularization to determine the flow of information to subsequent levels. The study encourages stakeholders in the currency market to practically employ LSTM for financial market prediction tasks and investment-related policymaking, particularly in intraday scenarios, where LSTM demonstrated superior predictability power over larger-scale data series. This recommendation resonates with existing literature, which underscores LSTM's efficacy in handling financial time-series data. The study's findings further underscored LSTM's ability to minimize prediction errors in financial time series, particularly in extensive prediction tasks.

CONCLUSION AND IMPLICATIONS

The primary objective of the study was to determine the optimal prediction model among various machine and deep learning models for eight selected currencies, focusing on exchange rates. Firstly, wavelet-MODWT analysis was conducted to discern the genuine trends within each currency's original data series across both intraday frequencies of time series, namely 1 hour and 30 minutes. Subsequently, three models were chosen for comparative currency price prediction in the forex market. Informed by the literature review, the study selected the most recommended machine and deep learning models, including SVR, RNN, and LSTM.

After data preprocessing and environment selection, the predictive capabilities of these models were evaluated using historical data of eight currency prices, specifically exchange rates against the U.S. dollar, across two different intraday frequencies: 1 hour and 30 minutes. The data set spanned from January 1, 2018, to December 31, 2020, encompassing a period of 3 years. The empirical results of the tested models were compared, and the accuracy of these techniques was assessed using four statistical-based accuracy indicators: MSE, MAE, RMSE, and MAPE. These results demonstrated that deep learning LSTM outperformed other models in predicting currency prices, particularly exchange rates, with less error in intraday forecasting.

This study undertook a comparative analysis of the most recommended machine and deep learning models, utilizing standard parameters such as batch size, epochs, neuron numbers, and activation functions for model tuning to discern currency trends. Based on empirical findings, the study advocated for the adoption of the LSTM deep learning algorithm by researchers, academicians, practitioners, and investors. Notably, LSTM excelled in extracting meaningful information from time series data, incorporating forget gates alongside input and output gates within its architecture, along with cell state regularization to determine the flow of information to subsequent levels. The study encouraged stakeholders in the currency market to practically employ LSTM for financial market prediction tasks and investment-related policymaking, particularly in intraday scenarios, where LSTM demonstrates superior predictability power over larger-scale data series. This recommendation resonated with existing literature, which underscores LSTM's efficacy in handling financial time-series data. The study's findings further underscored LSTM's ability to minimize prediction errors in financial time series, particularly in extensive prediction tasks.

Our study's demonstration of LSTM's superior predictive performance highlighted the potential of deep learning techniques in enhancing financial forecasting accuracy, particularly in volatile and dynamic forex markets. Additionally, by showcasing the comparative performance of various prediction models, the research contributed to the advancement of predictive modeling methodologies in the domain of currency exchange rate prediction. These insights not only provide valuable guidance for financial practitioners seeking to improve their forecasting capabilities but also pave the way for further research exploration into the applicability and robustness of deep learning models across diverse financial data sets and market conditions.

Furthermore, our study's utilization of wavelet-MODWT analysis added another layer of depth to the research methodology, allowing for the identification of genuine trends within currency data series across different intraday frequencies. This analytical approach offered valuable insights into the underlying patterns and dynamics of currency exchange rate movements, facilitating more informed decision-making processes for traders, investors, and financial analysts. By integrating wavelet analysis with advanced prediction models such as LSTM, the study showcased a holistic and data-driven approach to currency forecasting that holds promise for improving decision outcomes and risk management strategies in the financial industry.

In conclusion, the findings of this study underscored the importance of leveraging advanced analytical techniques and machine learning models for accurate currency exchange rate prediction. Through a comprehensive evaluation of prediction models and methodologies, the research contributed to the advancement of financial forecasting practices and provides actionable insights for practitioners and researchers alike. By embracing deep learning approaches and incorporating sophisticated analytical tools like wavelet-MODWT analysis, financial professionals can enhance their predictive capabilities and navigate the complexities of the forex market with greater confidence and precision.

Future Work

For future work directions, this study suggests scholars use high-frequency data that include tick-by-tick observations of the time series and use more fast and updated computer machines. With the fastest computational capacities, high-frequency tick-by-tick data can be processed, and in that way, the results produced may be stronger. This study suggests using other machine and deep learning models and making hybrid models to predict exchange rates of more currencies with more updated tuning parameters in the high multiresolution frequency of time series.

CONFLICTS OF INTEREST

There are no conflicts of Interest.

FUNDING STATEMENT

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

PROCESS DATES

Received: This manuscript was initially received for consideration for the journal on 07/31/2023, revisions were received for the manuscript following the double-anonymized peer review on 05/09/2024, the manuscript was formally accepted on 04/24/2024, and the manuscript was finalized for publication on 05/09/2024

CORRESPONDING AUTHOR

Correspondence should be addressed to Shafqat Shad; sshad@montevallo.edu

REFERENCES

Aguilar, D., Batyrshin, I., & Pogrebnyak, O. (2017). A survey on computer science techniques in the FOREX market: Models and applications. *Research in Computing Science, 138*(1), 89–98. https://www.researchgate.net/publication/339206765_A_Survey_on_Computer_Science_Techniques_in_the_FOREX_Market_Models_and_Applications

Bacchetta, P., Mertens, E., & Van Wincoop, E. (2009). Predictability in financial markets: What do survey expectations tell us? *Journal of International Money and Finance*, *28*(3), 406–426. https://www.sciencedirect.com/science/article/abs/pii/S026156060800140X. 10.1016/j.jimonfin.2008.09.001

Bacchetta, P., & Van Wincoop, E. (2004). A scapegoat model of exchange-rate fluctuations. *The American Economic Review*, *94*(2), 114–118. https://www.nber.org/papers/w10245. 10.1257/0002828041301849

Cai, W. C. (2016). Empirical analysis of financial deterioration prediction of listed companies. *Accountability in Research*, (4), 31–38.

Chatzis, S. P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., & Vlachogiannakis, N. (2018). Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert Systems with Applications*, *112*, 353–371. https://www.sciencedirect.com/science/article/abs/pii/S0957417418303798. 10.1016/j.eswa.2018.06.032

Chen, X., Ghysels, E., & Wang, F. (2019). The HYBRID GARCH class of models, 53. https://www.researchgate.net/publication/228757859_The_HYBRID_GARCH_class_of_models

Chong, E., Han, C., & Park, F. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications*, *83*, 187–205. https://www.sciencedirect.com/science/article/abs/pii/S0957417417302750. 10.1016/j.eswa.2017.04.030

Dautel, A. J., Härdle, W. K., Lessmann, S., & Seow, H.-V. (2020). Forex exchange rate forecasting using deep recurrent neural networks. *Digital Finance*, *2*(1-2), 69–96. https://link.springer.com/article/10.1007/s42521-020-00019-x. 10.1007/s42521-020-00019-x

Demirel, U., Çam, H., & Ünlü, R. (2021). Predicting Stock Prices Using Machine Learning Methods and Deep Learning Algorithms: The Sample of the Istanbul Stock Exchange. *Gazi University Journal of Science*, *34*(1), 63–82. 10.35378/gujs.679103

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, *270*(2), 654–669. https://www.semanticscholar.org/paper/Deep-learning-with-long-short-term-memory-networks-Fischer-Krauss/701e59358fda0d865d7b26cd954a93a5ad20fd13. 10.1016/j.ejor.2017.11.054

Fletcher, T. (2018). *Machine learning for financial market prediction*. https://www.semanticscholar.org/paper/Machine-learning-for-financial-market-prediction-Fletcher/5a9b12f0e762095222425ea5da51229181947d81

Guo, Y., & Li, T. (2019). The empirical research of ARMA-GARCH models based on high-frequency data. *Journal of Physics: Conference Series*, *1325*(1), 012132. https://iopscience.iop.org/article/10.1088/1742-6596/1325/1/012132. 10.1088/1742-6596/1325/1/012132

Hajiabotorabi, Z., Kazemi, A., Samavati, F. F., & Ghaini, F. M. M. (2019). Improving DWT-RNN model via B-spline wavelet multiresolution to forecast a high-frequency time series. *Expert Systems with Applications*, *138*, 112842. https://www.sciencedirect.com/science/article/abs/pii/S0957417419305445. 10.1016/j.eswa.2019.112842

Hansen, P. R., & Lunde, A. (2011). Forecasting volatility using high-frequency data. In *The Oxford handbook of economic forecasting* (pp. 525–556). Oxford University Press., https://academic.oup.com/edited-volume/28323/chapter-abstract/215083228?redirectedFrom=fulltext&login=false

Jorion, P. (2007). *Bank trading risk and systemic risk. The risks of financial institutions*. National Bureau of Economic Research, Inc. https://www.nber.org/papers/w11037

Kim, H. Y., & Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. *Expert Systems with Applications*, *103*, 25–37. https://www.sciencedirect.com/science/article/abs/pii/S0957417418301416. 10.1016/j.eswa.2018.03.002

Kim, K. (2003). Financial time series forecasting using support vector machines. *Neurocomputing*, *55*(1–2), 307–319. https://www.sciencedirect.com/science/article/abs/pii/S0925231203003722. 10.1016/S0925-2312(03)00372-2

Mohammadi, K., Shamshirband, S., Anisi, M. H., Alam, K. A., & Petković, D. (2015). Support vector regression based prediction of global solar radiation on a horizontal surface. *Energy Conversion and Management*, *91*, 433–441. https://www.sciencedirect.com/science/article/abs/pii/S0196890414010449. 10.1016/j.enconman.2014.12.015

Müller, K.-R., Smola, A. J., Rätsch, G., Schölkopf, B., Kohlmorgen, J., & Vapnik, V. (1997). Predicting time series with support vector machines. In *Lecture notes in computer science* (999–1004). Springer Link. https://link.springer.com/chapter/10.1007/BFb0020283

Niu, Z., Zhong, G., & Yu, H. (2021). A review on the attention mechanism of deep learning. *Neurocomputing*, *452*, 48–62. https://www.sciencedirect.com/science/article/abs/pii/S092523122100477X. 10.1016/j.neucom.2021.03.091

Panda, M., Panda, S., & Pattnaik, P. K. (2020, February 7–15). *Exchange rate prediction using ANN and deep learning methodologies: A systematic review* [Conference session]. 2020 Indo-Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN) Rajpura, India. https://ieeexplore.ieee.org/document/9181351

Peng, Y., Albuquerque, P. H. M., Camboim de Sá, J. M., Padula, A. J. A., & Montenegro, M. R. (2018). The best of two worlds: Forecasting high-frequency volatility for cryptocurrencies and traditional currencies with support vector regression. *Expert Systems with Applications*, *97*, 177–192. https://www.sciencedirect.com/science/article/abs/pii/S0957417417308163. 10.1016/j.eswa.2017.12.004

Sharma, S. K., & Sharma, V. (2012). Time series prediction using KNN algorithms via Euclidian distance function: A case of foreign exchange rate prediction. *Asian Journal of Computer Science and Information Technology*, *2*(7). https://www.semanticscholar.org/paper/TIME-SERIES-PREDICTION-USING-KNN-ALGORITHMS-VIA-A-Sharma-Sharma/a1156a35b9190209ecb0bdc022df14431c0b164b

Sun, S., Wang, S., & Wei, Y. (2020). A new ensemble deep learning approach for exchange rates forecasting and trading. *Advanced Engineering Informatics*, *46*, 101160. https://www.sciencedirect.com/science/article/abs/pii/S1474034620301312. 10.1016/j.aei.2020.101160

Tsai, D.-M., & Chiang, C.-H. (2003). Automatic band selection for wavelet reconstruction in the application of defect detection. *Image and Vision Computing*, *21*(5), 413–431. https://www.sciencedirect.com/science/article/abs/pii/S0262885603000039. 10.1016/S0262-8856(03)00003-9

Urata, S., & Kawai, H. (2000). The determinants of the location of foreign direct investment by Japanese small and medium-sized enterprises. *Small Business Economics*, *8*(2), 79–103. https://link.springer.com/article/10.1023/A:1008173912813. 10.1023/A:1008173912813

Vapnik, V., Golowich, S. E., & Smola, A. J. (1997). Support vector method for function approximation, regression estimation and signal processing. *Advances in Neural Information Processing Systems,* 281–287. https://dl.acm.org/doi/10.5555/2998981.2999021

Xiao, Y., Xiao, J., Lu, F., & Wang, S. (2013). Ensemble ANNs-PSO-GA approach for day-ahead stock exchange prices forecasting. *Journal of Forecasting*, *7*, 272–290. https://link.springer.com/article/10.1080/18756891.2013.864472

Yan, H., & Ouyang, H. (2018). Financial time series prediction based on deep learning. *Wireless Personal Communications*, *102*(2), 683–700. https://link.springer.com/article/10.1007/s11277-017-5086-2. 10.1007/s11277-017-5086-2

Yang, Z., Yang, D., Dyer, C., He, X., Smola, A., & Hovy, E. (2016, June). *Hierarchical attention networks for document classification* [Conference session]. Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego, CA, USA. https://aclanthology.org/N16-1174

Zeng, Z., & Khushi, M. (2020, July 19–24). *Wavelet denoising and attention-based RNN-ARIMA model to predict forex price* [Conference session]. 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK. https://ieeexplore.ieee.org/document/9206832