Original Research

Ranking Superior Technical Analysis Tools to Forecast Prices in the Forex Market Using Machine Learning

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Abstract

Accurately forecasting financial market prices is vital for corporate investment, especially given the inherent volatility, driving continuous research for higher accuracy and lower error rates in prediction. While forecasting often involves technical analysis using numerous market indicators, their abundance presents a challenge in selection. This research aimed to overcome this by identifying the most effective technical analysis indicators and comparing various machine learning (ML) methods for price trend prediction in the Forex market. Using daily data over 15 months for two major (EUR/USD, USD/JPY) and two minor (CAD/JPY, EUR/CHF) currency pairs, thirty common indicators were initially selected and then reduced to the top ten using the ReliefF feature selection method. These indicators were then modeled using six ML algorithms—Artificial Neural Networks, Decision Trees, Random Forests, Support Vector Machines, K-nearest Neighbors, Linear Regression, and Logistic Regression—implemented in MATLAB. The analysis concluded that the Artificial Neural Network (ANN) was the superior predictor, achieving the lowest MAPE and RMSE and providing the most accurate results among the tested methods. In conclusion, this study validates a two-step approach—combining ReliefF feature selection with an ANN—as a highly robust methodology for Forex price trend prediction. These findings underscore the practical value of advanced machine learning techniques in constructing more reliable automated trading strategies, offering a significant advantage over traditional technical analysis.

Keywords Forex; Price Prediction; Machine Learning; Technical Analysis; Feature Reduction

INTRODUCTION

Since the inception of financial markets, investors have consistently sought to forecast their future trajectories using various methods. The financial and economic literature presents diverse approaches to predicting investment returns, including technical analysis, fundamental analysis, classical time series forecasting, and intelligent techniques. Technical analysts, in particular, endeavor to forecast the returns of financial assets by identifying patterns and utilizing historical market data. Historically, users of this group believed that calculating the stock's intrinsic value should be based on historical price patterns and financial information [1]. However, recent research suggests that the factors influencing stock market fluctuations are highly complex and exhibit highly nonlinear and dynamic characteristics, increasing the difficulty and risk of investment.

Therefore, to enhance investor returns and mitigate investment risks, a more sophisticated analysis of the stock market is necessary [2]. Fundamental analysts view stock price movements as random walks and base their forecasts on the intrinsic or fundamental value of the stock. Time series analysis employs historical data and a linear combination of past values to predict future values. Classical forecasting methods assume that future prices follow a linear trend based on past values. This approach is known as simple and multiple economic regression [3]. Intelligent methods seek to identify linear and nonlinear patterns in market data to infer the underlying generating process. Consequently, numerous algorithms and software programs with varying complexities and structures have been proposed for this purpose over the years [4]. Furthermore, with extensive research conducted in recent decades, chart analysis has expanded significantly, encompassing diverse methodologies such as Elliott Wave, Fibonacci, and Andrews' Pitchfork, among others [3].

The primary motivation for individuals to invest in the stock market is profit generation, which necessitates accurate market information, stock price fluctuations, and the ability to forecast future trends. Consequently, investors require robust and reliable tools to predict stock prices [5]. Extensive research has been conducted in the realm of stock market analysis. There are two prevailing approaches to studying the stock market in the literature: The predominant and widespread approach to analyzing the stock market involves utilizing statistical analysis, financial theories, and domain knowledge. However, recent advancements have seen the integration of machine learning and artificial intelligence techniques, with most statistical analyses relying on quantitative data [2]. For instance, Arashim and Rounaghi [6] proposed using the ARIMA-GARCH model to analyze the daily stock index of the NASDAQ. Additionally, Al-Ani and Zubaidi employed the Kolmogorov-Smirnov, normality, and heteroscedasticity tests to validate the expected risk of the Iraqi stock market [7]. He et al. [8] employed OLS and quantile regression to investigate the relationship between investor sentiment and stock market volatility. Salman and Ali examined the impact of COVID-19 on the stock market using ordinary t-tests and non-parametric Mann-Whitney U tests. Given the widespread adoption of intelligent machine learning techniques across all disciplines, integrating these methods into stock price prediction has empowered traders to conduct their analyses without relying on other market analysts [9].

This research aims to develop a hybrid model combining technical analysis and machine learning to improve the accuracy of Forex market price trend prediction. By leveraging the strengths of both methodologies, this study seeks to outperform traditional investment strategies such as buy-and-hold and random selection. The proposed model is intended to provide traders with a more informed decision-making framework for executing buy or sell orders. Previous studies employing artificial intelligence methods have relied solely on a single machine learning technique for market analysis and price prediction. None of these studies has attempted to compare and rank technical analysis indicators. The novelty of the present research lies in the utilization of multiple AI methods to identify and select the most optimal and efficient technical analysis indicators for each currency pair price, thereby enabling more accurate and precise market forecasting and ranking of these indicators.

The rest of the paper is organized as follows. A literature review and study of previous work are discussed in Section 2. The research methodology and proposed model are described in detail in Section three. The analysis results are provided in Section 4. Section 5 is dedicated to conclusions and future study suggestions.

LITERATURE REVIEW AND PREVIOUS WORK

This section briefly reviews the literature and concepts involved in this research. In the end, the previous work is studied.

I. Forex Market

The foreign exchange (Forex) market is one of the world's largest financial markets, operating 24 hours a day, where participants trade various foreign currencies. As the most liquid market globally, trillions of dollars are exchanged daily within the Forex market. Unlike traditional exchanges, Forex is a decentralized electronic network comprising banks, brokers, institutions, and individual traders. The simplest definition of a foreign exchange transaction is converting one currency into another. Many of these exchanges facilitate corporations or governments' purchasing and selling of goods or services, tourist spending, and investments by individuals or firms in the currency's respective country. However, the primary motive behind most foreign exchange transactions is to profit from the price difference between the buying and selling rates, represented by the bid and ask prices. The global foreign exchange market involves a wide range of participants, including banks, large financial institutions, multinational corporations, traders, insurance companies, import-export firms, pension funds, speculators, and individuals who trade currencies such as the US dollar, euro, pound, yen, and others [10]. Currency pairs where one of the currencies is the US dollar are classified as major pairs, while those without the US dollar are termed minor or cross-currency pairs.

II. Machine Learning

Machine learning, a broad and widely used branch of artificial intelligence, studies algorithms and methods that enable computers and systems to learn from data and perform tasks. Learning is derived from observations or data and involves techniques for classifying data [11]. With machine learning and AI advancements, researchers have applied algorithms such as neural networks, support vector machines, and Bayesian models to predict stock market trends [2]. Research on financial market analysis using machine learning can be categorized into two main approaches: regression and classification. Regression analysis focuses on predicting future stock prices by training on large amounts of historical data, while classification involves categorizing data into different classes based on features [12].

III. Feature Reduction

A common challenge faced by many computer algorithms is their high computational cost. While advancements in high-speed computers and large storage capacities have somewhat mitigated this issue, the emergence of massive, high-dimensional datasets has underscored the persistent need for efficient dimensionality reduction algorithms [13]. Two primary approaches are used to tackle this issue:

Feature extraction: A new K-dimensional feature space is constructed as a combination of the original d dimensions [14].

Feature selection: A K-dimensional subset of the original d dimensions is selected to retain the most informative features while discarding the remaining (d-k) features [14]. Relief is one such feature selection method [15].

IV. Previous work

Miryazdi and Habibi-Lashkari focused on the Moving Average Convergence Divergence (MACD) indicator for four currency pairs: EUR/USD, GBP/USD, USD/CHF, and USD/JPY. They individually examined the effectiveness of the indicator based on the generated profit, using hourly market data from January 2001 to December 2010 [16]. Lale Sajjadi et al. [1] proposed an automated portfolio selection system, utilizing the Relative Strength Index (RSI) divergence as the primary tool alongside other technical analysis instruments. The empirical results from this study can be used to challenge classical finance assumptions. Dolou and Heidari's [3] study highlighted the significance of artificial neural networks (ANNs) among various financial market analysis methods. Given their unique characteristics, ANNs have emerged as a powerful tool for forecasting and analyzing stock market data. Numerous researchers have employed ANN models for predictive purposes. While these models have demonstrated promising results compared to other methods, they also exhibit certain limitations. One of the primary challenges in constructing ANNs is determining the optimal set of input variables, as this directly influences prediction accuracy. Another drawback of ANNs is the lack of a definitive method for determining the number of neurons in the hidden layer.

In their research, Sadeghi et al. [17] proposed a novel approach for Forex investment based on market trend prediction and trading rules grounded in fuzzy technical indicators. They employed a combination of a hybrid support vector machine (HSVM) algorithm for predicting and classifying the market into three classes (uptrend, downtrend, and no trend) and a genetic algorithm for optimizing the trading rules. In their research, Kurani et al. [18] reviewed risk management and stock price prediction using ANN and SVM algorithms. Ahmad et al. [19] employed a deep learning approach and a Forex-specific loss function to analyze the Forex market. Their findings revealed that this hybrid method significantly reduced the discrepancy between the actual and predicted values of Forex candlesticks. Furthermore, the proposed method demonstrated an approximately 11% decrease in mean absolute error compared to traditional deep learning techniques. Luciana et al. [20] identified news, economic data, and market sentiment as the most significant catalysts for Forex market movements. Market sentiment refers to the overall attitude of traders towards a specific Forex market. According to their findings, positive sentiment and expectations drive up Forex prices, while negative sentiment and news releases increase the inclination to sell. In their study, Farhangdoost et al. [21] compared the Iranian stock market with the global Forex market. Their findings indicate that the Iranian stock market is primarily influenced by domestic factors, with international events having a lesser impact. The analysis starts at the macroeconomic level and extends to the microeconomic level, although microeconomic variables more significantly influence it. The research concludes that psychology and capital management play a dominant role in the Forex market, and there is a high correlation between currency pairs, with the movement of one pair influencing others. In their research, Caporale and Plastun [22] delved into the fundamental flaws of technical analysis, arguing that, despite its widespread use among practitioners, from an academic standpoint, it can be viewed as little more than a form of financial alchemy. Specifically, the technique is plagued by subjectivity, questionable assumptions, unjustified algorithms, low profitability, data snooping, and insignificant and spurious statistical results.

Chen et al. [2] introduced a novel stock market analysis method rooted in evidence reasoning and hierarchical belief networks to support investment decisions such as buying, selling, and holding stocks in the Chinese market. Ayitey et al. [23] conducted a comprehensive review of various Forex market analysis methods in their literature review, focusing on evaluating and comparing machine learning techniques employed in research. Their analysis revealed that MAE, RMSE, MAPE, and MSE are the most commonly used evaluation metrics in this field, and the EUR/USD currency pair is the most frequently traded in the overall Forex market. Additionally, artificial neural networks are the most prevalent machine learning algorithms for Forex market forecasting. Chong and Sin [24] examined the efficiency of the Forex market based on reduced volatility analysis and demonstrated that large banks still possess the ability to manipulate the currency market. However, the net impact on exchange rates is estimated at only 20 to 30 pips. Ghanem et al. [25] investigated the predictability of technical analysis in the foreign exchange market using future returns. Focusing on trading timeframes of 1 to 7 days, their research introduced the 'optimal holding period' concept and examined the alignment between price movements and trading signals at different time intervals. The findings revealed that technical trading rules significantly predicted price movements in developed and emerging market currencies.

Additionally, simple moving average indicators demonstrated the most effective performance for emerging market currencies, while oscillator-based strategies were more successful in developed markets. Ikughur et al. [26] investigated the impacts of the stable and unstable Forex market on the inflation rate in Nigeria. They concluded that controlling the Forex market operation of dollars will significantly reduce the inflation rate in Nigeria. In their research, Wangchailert and Paireekreng [27] analyzed the accuracy of candlestick patterns in the Forex market technical analysis on eight currency pairs. They proposed a new pattern called the MInimal Difference in shadow for Directional Analytical Movement (MIDDAM). The experiments revealed the superiority of the proposed pattern. A summary of previous studies is presented in Table I.

TABLE I.
SUMMARY OF PREVIOUS WORK

Ref.	Statistical population	Method/Classifier	Efficiency (Accuracy)
[2]	China Stock Market	Analytic Hierarchy Process	Not addressed
[19]	Forex Market	Deep Learning and Forex Loss Function	Reduce AAE* by 11%
[23]	Forex Market	Review Study	Not addressed
[24]	Forex Market	Reduced Volatility analysis	Not addressed
[25]	Forex Market	Future Return Method	Not addressed
[27]	Forex Market	MIDDAM	Outperforming old patterns
[28]	South Korea	SVM	80%
[29]	Taiwan	SVR	Mean absolute error=1.31
[30]	Indian Stock Market	ANN, SVM, Random Forest, Naive Bayes	Not addressed
[31]	Tehran Stock Market	SVM, PSO, and Time Series	AAE = 0.053
[32]	Some Investment Companies	Bayesian and Levenberg-Marquardt neural network	88%
[33]	S&P 500 stock market	K-NN, RF, ANN, and SVM	Not addressed
[34]	14 Iranian Banks	SVM, k-NN, and Random Forest	91.84%
[35]	Forex Market	EmcSVM and NSGA	80.8% precision

*AAE: Average Absolute Error

A review of prior research indicates that the primary challenge in this field is identifying the appropriate predictive tool for price behavior. In this study, among 30 technical analysis methods, the most efficient tools were chosen using a feature selection method and subsequently ranked using a Decision Tree, Support Vector Machine (SVM), Artificial Neural Networks (ANN), k-nearest Neighbors (kNN), Linear Regression, Logistic Regression, Random Forest, Support Vector Regression (SVR), Naive Bayes, and Fuzzy Logic machine learning algorithms.

RESEARCH METHODOLOGY

I. Sample Data and Descriptive Analysis

Daily closing prices for the EUR/USD, USD/JPY, CAD/JPY, and EUR/CHF currency pairs in the Forex market over 48 months from February 7, 2021, to February 7, 2025, in a 15-minute timeframe were collected from https://forexsb.com/historical-forex-data as the research dataset. The primary statistics of the mentioned pairs are given in Table II.

TABLE II
THE STATISTICS OF THE UNDERSTUDIED CURRENCY PAIRS

Pair	Max. Price	Min. Price	Max. H – L*	Avg. H - L	Max O – C**	Avg. O - C

EUR/USD	1.226	0.953	0.016	0.0006	0.016	-2.1E-6
USD/JPY	161.9	104.4	4.235	0.1014	3.892	-4E-04
CAD/JPY	118.8	81.96	3.065	0.0884	2.826	-5E-04
EUR/CHF	1.115	0.920	0.020	0.0005	0.015	1.4E-6

** H-L: High – Low; ** O-C: Open - Close*

II. Technical Analysis Indicators and Feature Reduction

Considering the extensive range and variety of technical analysis methods and the limited scope of this study, in the first step, out of 94 indicators and their variants, 30 mainly used indicators were chosen for investigation in this research, listed in Table IV. Where C_t, O_t, H_t, L_t, V_t, O_n, Up_t, and Dn_t represent the closing price, the opening price, the highest price, the lowest price, the trading volume, the opening price on the t^{th} day, the increase in the method's output compared to the previous day, and the decrease in the method's output compared to the previous day respectively. The indicator type and the calculational relations presented in this table are adapted from docs.anychart.com and ncfe.org.in.

In the second step, the optimal lookback periods of the indicators are set up using the walk-forward approach by evaluating the performance of every strategy as follows.

Fourteen days is used for Accumulation/Distribution (CLV), Demarker, Parabolic SAR, Balance of Power (BOP), Average True Range (ATR), Bollinger Bands (BB), Average Directional Index (ADI), Relative Strength Index (RSI), Stochastic D%, Fast Stochastic D%, Williams R%, and True Strength Index (TSI); 10-day period for Simple Moving Average (SMA), Exp. Moving Average (EMA), Weighted Moving Average (WMA), and Money Flow Index (MFI); 20 days for On Balance Volume (OBV), Detrended price oscillator (DPO), and Keltner Channel (KCh); 35-day Ease of Momentum (EMV), 21-day Negative volume index (NVI); 28-day Commodity channel index (CCI) and Donchian Channel (DoCh); 26-day Moving average convergence/divergence (MACD); 25-day Aroon; 16-day Stochastic K%; 12-day Rate of Change (ROC); 13-week Smart Money Index (SMI); and 4-month Volume Price Trend (VPT).

The ReliefF feature selection method is applied in the third step to identify each pair's most effective technical analysis indicator. This method randomly selects a sample from the dataset at each iteration. The relevance of each feature is then updated based on the difference between the selected sample and its two nearest neighbors: one from the same class and the other from a different class. If a feature(actual price) of the chosen sample differs from the corresponding feature in the nearest neighbor of the same class (a hit), the weight of that feature is decreased. Conversely, if the same feature in the selected instance differs from the corresponding feature in the nearest neighbor of a different class (a miss), the weight of this feature is increased. Table III presents the results of the ReliefF feature selection technique applied to the EUR/USD currency pair. The calculated weights for the 30 methods employed in this study are obtained using MATLAB. Each technical analysis method is assigned a specific rank, indicating its relative importance in forecasting the price trend of this currency pair.

TABLE III
THE OBTAINED WEIGHTS AND RANKING OF INDICATORS USING THE RELIEFF METHOD

No.	Indicator	Weight	Rank	No.	Indicator	Weight	Rank
1	CLV	0.00287	29	16	Aroon	0.00360	23
2	EMV	0.00169	28	17	BOP	0.00712	15
3	OBV	0.00299	30	18	KCh	0.00014	24
4	VPT	-0.0020	17	19	DoCh	0.00543	25
5	NVI	0.00227	19	20	ATR	-0.0005	11
6	Demarker	0.00395	16	21	Bollinger Bands	-0.0046	6
7	CCI	-0.0032	20	22	ADI	0.00448	27
8	DPO	0.00027	14	23	RSI	0.00274	2
9	MACD	0.00273	4	24	MFI	0.00132	9
10	SMI	0.00067	18	25	Stochastic D%	0.00288	5
11	SMA	0.00266	26	26	Stochastic K%	9.72E-5	12
12	Parabolic SAR	0.00427	7	27	Fast Stochastic D%	-0.0033	13
13	VWAP	-0.0011	8	28	Williams R%	0.00682	3
14	EMA	0.00365	10	29	TSI	0.00356	21
15	WMA	0.00119	1	30	ROC	-0.0007	22

TABLE IV
TECHNICAL ANALYSIS INDICATORS EMPLOYED IN THIS RESEARCH

Indicator	Type	Calculation Formula
Accumulation/Distribution (CLV)	Volume	$CLV = ((Close - Low) - (High - Close)) / (High - Low)$
Ease of Momentum (EMV)	Volume	$EMV = ((High+Low)/2 - (PH + PL)/2) / ((Volume/Scale) / (High - Low)$
On Balance Volume (OBV)	Volume	$OBV_n = OBV_{n-1} \pm V_n$
Volume Price Trend (VPT)	Volume	$VPT = VPTprev + volume*((Close_{today}-Close_{prev})/Close_{prev})$
Negative Volume Index (NVI)	Volume	$NVI_i = NVI_{i-1} * Close_i/Close_{i-1}$ if $Volume_i < Vlume_{i-1}$ $NVI_i = NVI_{i-1}$ if $Volume_i \geq Vlume_{i-1}$
Demarker	Trend	$Demark_j = \frac{MAve_j(DeMax, N)}{MAve_j(DeMax, N) + MAve_j(DeMin, N)}$
Commodity Channel Index (CCI)	Trend	$CCI = (1/0.015)*((Pt-SNA(Pt))/MD(Pt))$ $Pt = (P_{high} + P_{low} + P_{close})/3$
Detrended Price Oscillator (DPO)	Trend	$DPO = SMA_n$ of $(\frac{n}{2} +1)$ periods ago
Moving Average Convergence/Divergence (MACD)	Trend	$MACDn = EMAn\text{-}12 - EMAn\text{-} 26$
Smart Money Index (SMI)	Trend	*SMItoday = SMIyesterday– opening gain or loss + last hour change*
Simple Moving Average (SMA)	Trend	$SMA_n = (C_1 + C_2 + \cdots C_n)/n$
Parabolic SAR	Trend	$SAR_{n+1} = SAR_n + \alpha(EP - SAR_n)$
Volume Weighted Average Price (VWAP)	Trend	VWAP = Σ(Price*Volume) / Σ(Volume)
Exp. Moving Average (EMA)	Trend	$Weighting\ Multiplier_n = (2/(n+1))$ $EMA_n = \left((C_t - EMA_{n-1}) * Weighting\ Multiplier_n\right) + EMA_{n-1}$
Weighted Moving Average (WMA)	Trend	$WMA_n = (C_1 + 2C_2 + \cdots + nC_n)/((n*(n-1))/2)$
Aroon	Trend	$AroonUp_t = 100*(25 - \sum_{i=1}^{25} Up_i)/25$ $AroonDown_t = 100*(25 - \sum_{i=1}^{25} Dn_i)/25$ $AroonIndicator_t = AroonUp_t - AroonDown_t$
Balance of Power (BOP)	Trend	$BOPt = (Ct - Ot) / (Ht - Lt)$
Keltner Channel (KCh)	Volatility	10-day simple moving average of typical price Typical price = (high + low + close)/3
Donchian Channel (DoCh)	Volatility	$Upper = HighestHigh(N)$ $Lower = LowestLow(N)$ $Middel = (Upper + Lower)/2$
Average True Range (ATR)	Volatility	$TR_t = \max\left(H_t - L_t : Abs(H_t - C_{t-1}) : ABS(L_t - C_{t-1})\right)$ $TR_t = \max(H_t : C_{t-1}) - min(L_t : C_{t-1})$ $ATR_t = (ATR_{t-1} * (n-1) + TR_t)/n$ $ATR_t = {(\sum_{i=1}^{n} TR_i)}/{n}$
Bollinger Bands (BB)	Volatility	$Middle\ Band_n = SMA_n$ $Lower\ band_n = SMA_n - (STDV_n * 2)$ $Upper\ band_n = SMA_n + (STDV_n * 2)$ $Bowlinger\ bands_n = (Upper\ band_n - Lower\ band_n)/Middle\ Band_n$
Average Directional Index (ADI)	Momentum	$+DI=(ATR\ Smoothed\ +DM)\times 100$ $-DI=(ATR\ Smoothed\ -DM)\times 100$ $DX=(\lvert +DI+-DI\rvert / \lvert +DI--DI \rvert)\times 100A$ $DX=14(Prior\ ADX\times 13)+Current\ ADX$
Relative Strength Index (RSI)	Momentum	$RSIt = 100 - (100/ 1+(\sum_{i=0}^{n-1} {U_{p_{t-i}}}/{n})/(\sum_{i=0}^{n-1} {D_{n_{t-i}}}/{n}))$
Money Flow Index (MFI)	Momentum	$Typical\ Price = (H_t + L_t + C_t)/3$ $Raw\ Money\ Flow_t = Typical\ Price * Vt$ $Money\ Flow\ Ratio_t =(Positive\ Money\ Flow14)/ (Negative\ Money\ Flow14)$ $Money\ Flow\ Index = 100 - 100/ (1 + Money\ Flow\ Ratio_t)$
Stochastic D%	Momentum	$StochasticD\%_n = (StochasticK\%_n + StochasticK\%_{n-1} + StochasticK\%_{n-2})/3$
Stochastic K%	Momentum	$StochasticK\%_n = ((C - L_n)/(H_n - L_n)) * 100$

Fast Stochastic D%	Momentum	$StochasticFastD\%_n = (StochasticD\%_n + StochasticD\%_{n-1} + StochasticD\%_{n-2})/3$
Williams R%	Momentum	$\text{WilliamsR}\%_t = (HighestH_t - C_t)/(HighestH_t - LowestL_t) * -100$
True Strength Index (TSI)	Momentum	*TSI = 100*(EMA(EMA(m,r),s)) / EMA((EMA(|m|,r),s))*
Rate of Change (ROC)	Momentum	*ROCt = [(Ct – Ct-n) / (Ct-n)]*

According to Table IV, the top ten technical analysis methods ranked in order of priority are distinguished as Weighted Moving Average, Relative Strength Index, Williams %R, Moving average convergence/divergence (MACD), Stochastic D%, Bollinger Bands, Parabolic SAR, Volume Weighted Average Price, and Exp. Moving Average. The bar histogram of calculated weights for EUR/USD, USD/JPY, CAD/JPY, and EUR/CHF is depicted in Figure 1. The indicator names and calculated weights are shown in horizontal and vertical axes.

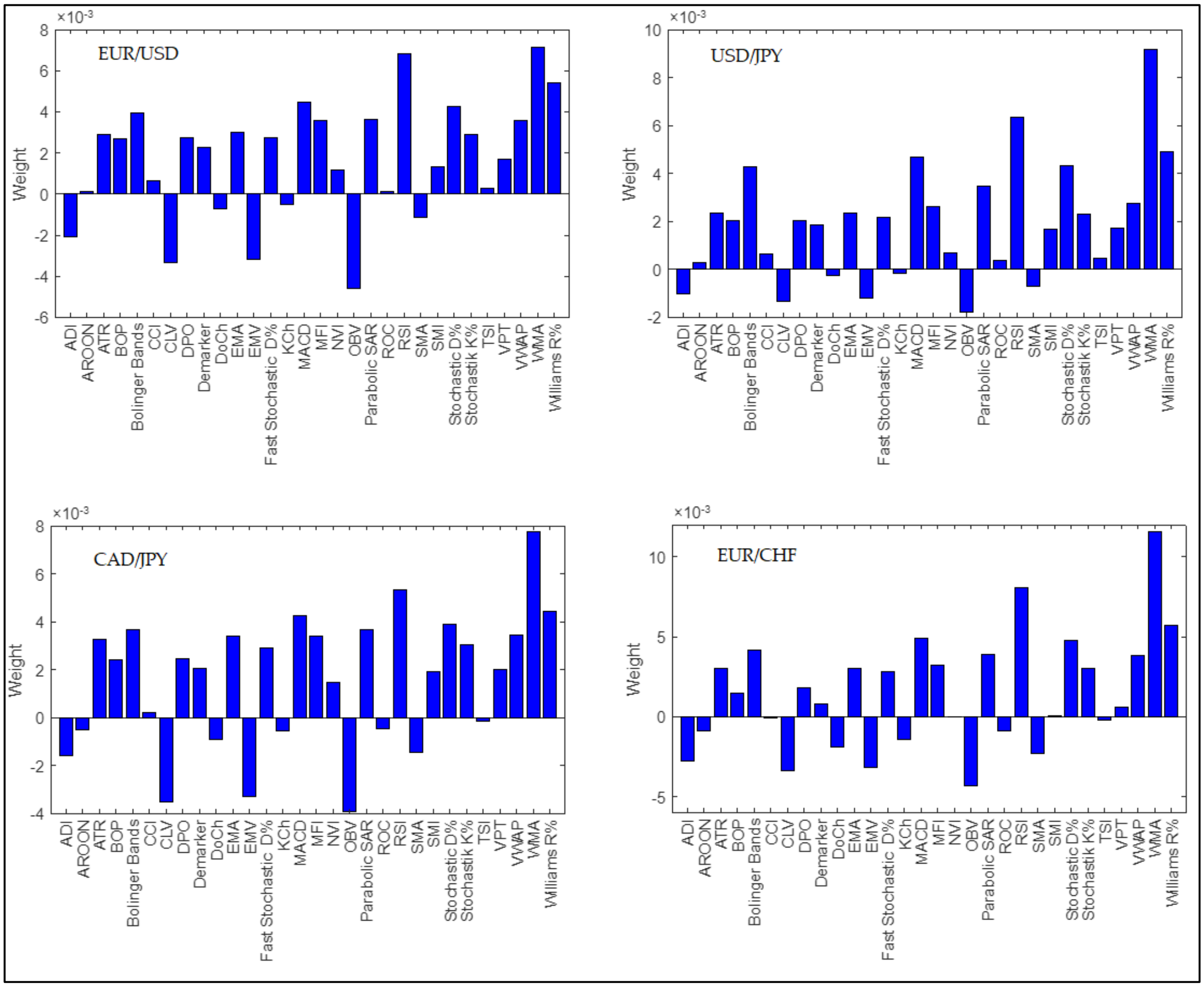

FIGURE 1
THE CALCULATED WEIGHTS FOR MAJOR/MINOR PAIRS USING THE RELIEFF METHOD

Considering the obtained weights, the top ten technical analysis indicators for other currency pairs are ranked and reported in Table V.

TABLE V
THE RANK OF THE TOP 10 INDICATORS OF CURRENCY PAIRS

Rank	USD/JPY	CAD/JPY	EUR/CHF
1	WMA	WMA	WMA
2	RSI	RSI	RSI
3	Williams R%	Williams R%	Williams R%
4	MACD	MACD	MACD
5	Stochastic D%	Stochastic D%	Stochastic D%
6	Bolinger Bands	Parabolic SAR	Bolinger Bands
7	Parabolic SAR	Bolinger Bands	VWAP
8	VWAP	MFI	Parabolic SAR
9	MFI	VWAP	MFI
10	EMA	EMA	Stochastic K%

According to Table V, the top 5 indicators are distinguished similarly for all understudy currency pairs. For USD/JPY and CAD/JPY pairs, the top 10 indicators are the same, with a slight difference in rank. The Stochastic k% indicator overtakes the EMA indicator for the EUR/CHF pair.

EMPIRICAL RESULTS

After identifying the most effective technical analysis indicators, ten well-known machine learning algorithms were implemented to predict the EUR/USD, USD/JPY, CAD/JPY, and EUR/CHF exchange rates based on the research data. Tables VI and VII compare the performance of these algorithms for major and minor currency pairs in terms of Root of Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE) criteria using equations (1) through (3), respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(A_i - P_i)^2}{n}} \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{(|A_i - P_i|)}{A_i} \times 100 \tag{2}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(A_i - P_i) \tag{3}$$

Where n, A_i, and P_i represent the size of the data set and the actual and predicted price of the currency pair, respectively.

TABLE VI
THE PERFORMANCE COMPARISON OF MACHINE LEARNING ALGORITHMS FOR MAJOR PAIRS

Algorithm	EUR/USD			USD/JPY		
	RMSE	MAPE	MBE	RMSE	MAPE	MBE
Decision Tree	0.002936	5.39%	0.001570	0.373588	4.15%	-0.158397
SVM	0.005363	1.79%	-0.017193	0.674004	2.51%	0.088970
Neural Networks	0.002068	1.71%	0.001015	0.116129	1.58%	-0.020529
k-NN	0.031378	2.73%	-0.002443	0.679816	5.34%	-0.162551
Linear Regression	0.01278	3.68%	0.001850	0.523543	7.16%	-0.158403
Logistic Regression	0.010269	2.60%	-0.006302	0.711331	10.26%	-0.155681
Random Forest	0.009209	3.60%	0.021129	0.502564	4.27%	-0.082006
SVR	0.004398	2.31%	0.004198	0.449028	3.56%	0.255783
Naive Bayes	0.00272	3.29%	0.004788	0.613045	2.80%	-0.106370
Fuzzy Logic	0.006864	2.80%	0.011700	0.394831	5.42%	0.173526

TABLE VII
THE PERFORMANCE COMPARISON OF MACHINE LEARNING ALGORITHMS FOR MINOR PAIRS

Algorithm	CAD/JPY			EUR/CHF		
	RMSE	MAPE	MBE	RMSE	MAPE	MBE
Decision Tree	0.018345	3.97%	-0.009423	0.213421	7.61%	-0.457382
SVM	0.011041	3.17%	0.001232	0.325427	3.54%	-0.210381
Neural Networks	0.004941	1.38%	-0.000775	0.074167	1.89%	-0.159580
k-NN	0.008709	2.46%	0.004379	0.401434	3.73%	0.305754
Linear Regression	0.008574	3.56%	0.003544	0.270195	5.66%	0.906018
Logistic Regression	0.011947	2.04%	0.012440	0.312469	2.84%	-0.190586
Random Forest	0.023061	1.49%	0.020114	0.444822	3.44%	-0.614429
SVR	0.027423	3.15%	0.040927	0.146035	1.48%	0.252759
Naive Bayes	0.025994	2.11%	0.002615	0.296342	4.28%	0.304006
Fuzzy Logic	0.051311	2.82%	0.002883	0.304187	8.83%	-0.448425

According to the evaluation analysis of Tables VI and VII, Neural Networks exhibited higher accuracy and smaller RMSE, MAPE, and MBE (except for SVR in EUR/CHF) than other algorithms. Hence, this research selected the ANN approach as the best forecasting method. Its details are described below.

The architecture of the proposed artificial neural network consists of an input layer, a hidden layer, and an output layer. The input layer in a neural network is responsible for receiving and representing input features from the external world. In the proposed architecture for price prediction in the Forex market, the input layer was designed to convey features related to technical analysis and market fluctuations to the neural network. The detailed structural specifications of this layer are as follows:

- Number of Neurons: The number of neurons in this layer must equal the number of input features. Each neuron corresponds to a specific feature of the input data. For instance, the number of neurons would be four if the input features include open price, close price, trading volume, and technical indicators.
- Input Type: Inputs can be continuous or discrete variables for the input layer. For instance, in technical analysis, open and closing prices are typically continuous, while technical patterns might be discrete (e.g., buy or sell signals).
- Input Feature Transformation: Input data must be transformed to enable the network to identify patterns and relationships within the data. Various transformations, such as normalization for scaling data, may be employed.
- Timeframes: In technical analysis, financial data is typically aggregated into specific time intervals (e.g., daily, weekly). Consequently, the input layer of a model should be designed to capture patterns within these temporal boundaries effectively.
- Feature Vectors: Each input data point can be represented as a feature vector, encapsulating various attributes. These feature vectors may include significant technical analysis indicators such as MACD, RSI, and Moving Averages.

The input layer in the proposed architecture is a multidimensional vector where each dimension corresponds to a specific feature derived from technical analysis data. This layer feeds crucial information related to the Forex market into the neural network, enabling it to learn and predict prices effectively. Accordingly, the technical inputs for the proposed network are the indicators listed in Table III. The price action inputs are detailed in Table VIII.

TABLE VIII
PRICE ACTION INPUTS OF THE PROPOSED ANN

Index/Feature	Description
Open Price	The opening price of a share at the beginning of the financial day

High Price	Highest share price during the day
Low Price	Lowest share price during the day
Close Price	Share price at the moment the financial market closes
Trading Volume	The volume of shares traded in the market
Price Changes	Percentage price changes over different periods

Combined with machine learning algorithms, these features train a model to predict prices in the Forex market. Each feature can be provided as an input to the machine learning network, allowing the model to identify hidden patterns in historical data and forecast future prices. The proposed neural network architecture is a deep feedforward type, with its parameters detailed in Table IX. The values of these parameters were determined through a trial-and-error approach, with the selection criterion being the achievement of the highest accuracy (lowest gradient of error). Each neuron in the input layer corresponds to an input feature, and the output of each neuron in the hidden layer is calculated based on input weights and an activation function. Subsequently, the output of the hidden layer is fed as input to the output layer, producing the final output. Notably, the topology of neurons in the hidden layers of the proposed neural network is fully connected, meaning every neuron in a layer is connected to all neurons in the subsequent layer. The training phases used 70% of the data, while the remaining 10% was used for validation, and 20% was used to test the network model.

TABLE IX
PROPOSED NEURAL NETWORK PARAMETERS

Parameter	Value
Number of hidden layers	2
Number of neurons in the input layer	6
Number of neurons in the first hidden layer	80
Number of neurons in the second hidden layer	120
1^{st} hidden layer activation function	Sigmoid
2^{nd} hidden layer activation function	elliotsig
Solver	sgdm
Gradient threshold value	1
Maximum Epoch	10
Iteration per Epoch	200

The proposed neural network architecture has two hidden layers, and the number of nodes in each layer has been tested in different scenarios on statistical samples to achieve the best performance. The results of these changes are given in Table X.

TABLE X
RESULTS OF ADJUSTING THE NUMBER OF NODES IN THE HIDDEN LAYERs

# of nodes in the first hidden layer	# of nodes in the second hidden layer	Gradient value	Computational time (seconds)
50	50	0.00092	25
50	70	0.0000883	37
60	90	0.0000729	56
70	100	0.00000269	78
80	120	0.00000009	102
100	150	0.00000005	138

As shown in Table X, as the number of nodes in the middle layers increases, the error gradient value decreases, and the quality of network training improves. This trend continues until the sixth row of the table. From this point on, increasing the number of nodes in the middle layers does not lead to a significant reduction in the error value and only increases the computational time. For this reason, the number of nodes in the first and second middle layers is set to 80 and 120, respectively. The convergence graph of MSE error reduction is plotted in Figure 2, and the final state of network training is plotted in Figure

3. According to this graph, convergence occurred at epoch 8, and in fact, more iterations did not lead to improvement and error reduction.

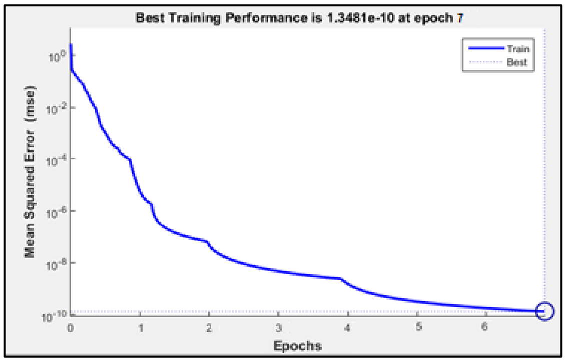

FIGURE 2
THE MSE ERROR CONVERGENCE DIAGRAM

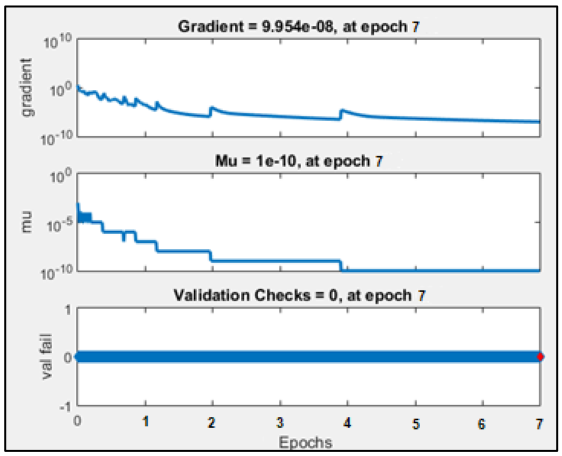

FIGURE. 3
THE FINAL STATE OF NETWORK TRAINING

The backpropagation method was employed to train the proposed neural network. This method involves calculating the error between the predicted and actual output and then propagating the error gradient from the output layer to the hidden layers. Subsequently, the weights are updated. This iterative process continues until the network achieves satisfactory accuracy and can generate reliable results for new data. The training process of the network is depicted in Figure 4.

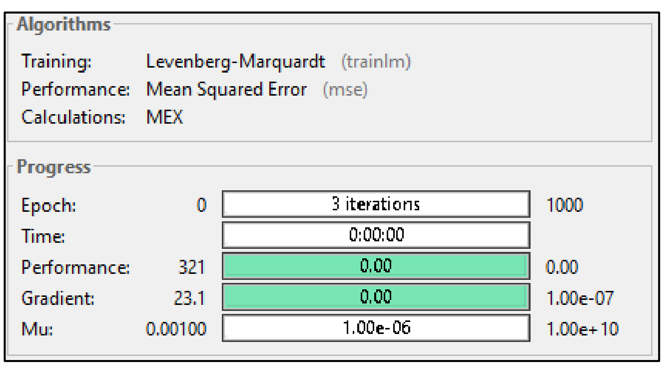

FIGURE 4
THE RESULTS OF THE PROPOSED NEURAL NETWORK TRAINING

The forecasted currency prices of EUR/USD, USD/JPN, CAD/JPY, and EUR/CHF are compared to the actual price during 115 days to validate the proposed ANN method. Figure 5 demonstrates the related comparison diagrams.

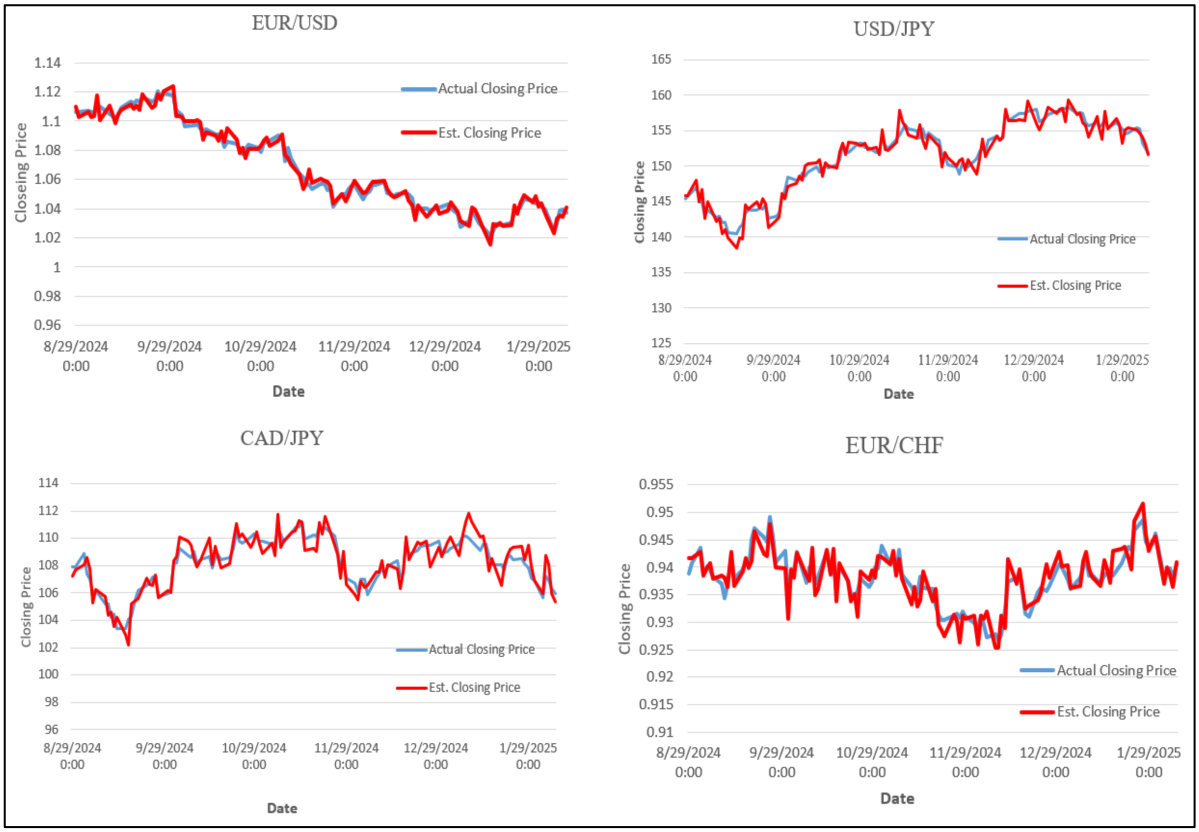

FIGURE 5
THE ACTUAL VS. PREDICTED PRICE DIAGRAM OF MAJOR/MINOR PAIRS USING THE PROPOSED ANN

The accuracy of forecasting the price can be measured using multiple criteria. Considering the ease of interpretation and intuitiveness, MAPE measurement is commonly used for this purpose [36]. According to the results reported in Tables VI and VII, the forecasting accuracy of the proposed method based on the MAPE criteria is obtained as 1.71%, 1.58%, 1.38%, and 1.89% for EUR/USD, USD/JPN, CAD/JPY, and EUR/CHF, respectively. The small MAPE measurement value indicates the proposed model's high accuracy.

CONCLUSIONS

This research investigated the technical analysis tools for forecasting price trends in the Forex market using machine learning algorithms. To this end, 30 technical analysis indicators were selected, and using the ReliefF feature reduction algorithm, these indicators were weighted and ranked, resulting in the selection of the top 10 efficient indicators. Subsequently, ten well-known machine learning algorithms for price prediction were evaluated based on the selected indicators. Comparative results demonstrated that neural networks outperformed other methods. Furthermore, the findings of this research indicate that artificial intelligence algorithms such as Random Forest, Support Vector Machines, and k-Nearest Neighbor exhibit superior performance compared to traditional technical analysis models, typically providing higher accuracy in forecasting price trends. Concurrently, neural networks have also shown promising potential for currency pair exchange rate prediction, particularly recurrent neural networks, which are capable of modeling more complex temporal dependencies. However, each model and algorithm possesses its strengths and weaknesses, and selecting an appropriate model should be tailored to the specific problem context and application requirements.

Additionally, developing hybrid models that leverage the combination of various algorithms can enhance prediction performance. Consequently, this research demonstrates that employing advanced artificial intelligence techniques and neural networks can improve price trend forecasting accuracy and efficiency. This finding holds particular significance for investors and decision-makers within the capital markets.
Based on the findings of this research and considering the advantages and limitations of the models employed, the following suggestions are proposed for future research in this area:

1. Evaluation of Hybrid Models: Investigating the potential of using hybrid models and combining various artificial intelligence algorithms and neural networks to enhance price trend prediction accuracy and performance.
2. Utilization of Larger and Multidimensional Datasets: Assessing the impact of using more extensive and diverse datasets, including economic, financial, and technical data, on the accuracy of price trend prediction.
3. Model Flexibility: Exploring the feasibility of employing models with adjustable and flexible structures to enhance the modeling of capital market behavior under varying conditions.
4. Neural Network Enhancement: Improving the architecture and structure of neural networks through advanced techniques such as transfer learning or attention mechanisms to enhance model accuracy and generalizability.
5. News Impact Assessment: Investigating the influence of economic and political news and events on price trends and the possibility of utilizing information related to these events in modeling.
6. Time-series Forecasting: Evaluating the feasibility of more accurate price trend forecasting for various time horizons, including short-term and long-term predictions.
7. Performance Evaluation in Varying Market Conditions: Assessing the performance of models under different market conditions, such as bull, bear, and sideways markets.
8. System Security and Trustworthiness: Evaluating the security and trustworthiness of price forecasting systems and proposing methods to enhance data security and prevent fraudulent activities.
9. Adaptability to Market Changes: Investigating methods to adapt forecasting models to market changes and unexpected events rapidly.
10. Impact of Emerging Technologies: Examining the impact of emerging technologies like blockchain, reinforcement learning, unsupervised learning, and reinforcement AI on the accuracy and efficiency of forecasting models.

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