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A Survey on Forex Trading Prediction and Analysis Using Machine Learning Techniques

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Abstract -The Foreign Exchange (Forex) market is a global, decentralized financial market where currencies are traded in pairs. Predicting currency price movements is exceptionally challenging because exchange rates are influenced by dynamic, complex factors including macroeconomic indicators, central bank policies, market volatility, geopolitical events, and investor sentiment. Traditional technical analysis relies on indicators such as Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) to evaluate historical price trends and momentum. However, these individual indicators often produce conflicting or lagging signals under highly turbulent, non-stationary market conditions. Machine Learning (ML) and Deep Learning (DL) models offer robust data-driven alternatives by autonomously learning intricate linear and non-linear patterns from time-series historical data. This paper presents a comprehensive, structured survey of state-of-the-art machine learning and deep learning techniques applied to Forex market forecasting and algorithmic trading strategy development. It systematically reviews supervised learning paradigms including Support Vector Machines (SVM), Decision Trees, Random Forest (RF), and Artificial Neural Networks (ANN), alongside modern recurrent architectures designed specifically for temporal sequences, such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and hybrid GRU-LSTM frameworks. Furthermore, this study examines feature engineering protocols, technical indicator integration, model evaluation metrics (MAE, MSE, RMSE, Directional Accuracy, Sharpe Ratio), and time-series cross-validation schemes (such as walk-forward validation) necessary to prevent severe data leakage. Finally, key operational challenges—including non-stationarity, extreme market volatility, noise, overfitting, order execution latency, and realistic transaction costs (spreads, slippage, and overnight fees)—are analyzed, highlighting promising prospective research directions such as multi-task technical indicator prediction and explainable financial AI.

Keywords— Forex Market, Machine Learning, Technical Indicators, RSI, MACD, Moving Average, Random Forest, Support Vector Machines, LSTM, GRU, Hybrid Models, Currency Prediction, Financial Time-Series Forecasting.

I. INTRODUCTION

The Foreign Exchange market, widely known as Forex or FX, is the world's largest and most liquid financial market, operating 24 hours a day, five days a week across major global financial centers. With a daily trading volume exceeding $7.5 trillion, the Forex market enables global trade, international investment, and currency hedging. Currencies are always traded in pairs—such as Major pairs (EUR/USD, GBP/USD, USD/JPY), Minor pairs (EUR/GBP, GBP/JPY), and Exotic pairs (USD/INR, EUR/TRY). The exchange rate between two currencies reflects the relative strength, macroeconomic health, monetary policy divergence, inflation differential, and market confidence between two respective issuing jurisdictions.

Financial forecasting in Forex is notoriously challenging due to the inherent characteristics of financial time-series data. Forex price trajectories are non-stationary, non-linear, highly volatile, and heavily corrupted by high-frequency noise. Under the Efficient Market Hypothesis (EMH) proposed by Fama, currency markets in their weak or semi-strong forms assimilate all publicly available historical information, making simple linear prediction models insufficient for capturing persistent arbitrage opportunities or long-term trends. Furthermore, exogenous macroeconomic shocks—such as sudden central bank interest rate decisions, non-farm payroll announcements, geopolitical conflicts, and systemic banking crises—can trigger rapid structural breaks and regime shifts in currency dynamics.

Traditionally, Forex traders and quantitative analysts have relied on two primary paradigms for market forecasting: Fundamental Analysis and Technical Analysis. Fundamental analysis evaluates economic indicators, GDP growth rates, employment metrics, central bank balance sheets, and trade balances to ascertain a currency's intrinsic value. While fundamental analysis provides critical insight into long-term macro trends, it lacks the temporal granularity required for short-term, intraday, or swing trading. Conversely, Technical Analysis focuses exclusively on historical price and volume action, utilizing standardized indicators like Moving Averages (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) to identify recurring geometric chart patterns and momentum shifts. However, static rule-based technical indicators often generate contradictory signals in choppy or sideways market regimes, suffer from significant time lag, and fail to adapt dynamically when structural market conditions shift.

Over the past two decades, the rapid evolution of Artificial Intelligence (AI) and Machine Learning (ML) has fundamentally reshaped quantitative finance and financial engineering. Machine learning algorithms excel at identifying complex, high-dimensional non-linear relationships without requiring explicit parametric statistical assumptions. Researchers have progressively applied supervised algorithms—such as Support Vector Machines (SVM), Decision Trees, Random Forest (RF), and gradient boosted ensembles—alongside deep neural architectures like Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and hybrid network frameworks to model foreign exchange price movements. These learning algorithms ingest rich multidimensional feature sets containing historical Open-High-Low-Close (OHLC) prices, momentum indicators, sentiment scores, and macroeconomic metrics to generate

probabilistic predictions of price magnitudes or market directions.

This survey paper systematically examines contemporary machine learning and deep learning techniques utilized for Forex trading prediction and automated decision-making. The key contributions of this paper are organized as follows: (i) A comprehensive breakdown of core technical indicators used in feature engineering protocols; (ii) A detailed analytical review of traditional machine learning and deep temporal models applied to currency prediction; (iii) A structural comparative synthesis of key benchmark studies in recent literature; (iv) An rigorous examination of time-series evaluation metrics and validation methodologies to avoid severe data leakage; and (v) A critical discussion of existing research limitations, transaction cost realities, and promising future research paradigms.

II. REVIEW METHODOLOGY

To establish a comprehensive, high-quality, and structurally sound survey, a rigorous literature identification and screening protocol was adopted. The search strategy focused on major academic repositories and index databases, including IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, ACM Digital Library, and Google Scholar. The target publication window concentrated primarily on seminal and modern literature published between 2010 and 2026, capturing the evolution from traditional statistical time-series models to state-of-the-art hybrid deep learning architectures.

The primary search queries comprised combinations of Boolean terms and key descriptors: ("Forex Prediction" OR "Foreign Exchange Forecasting" OR "Currency Rate Trading") AND ("Machine Learning" OR "Support Vector Machines" OR "Random Forest" OR "Neural Networks" OR "LSTM" OR "GRU" OR "Deep Learning") AND ("Technical Indicators" OR "RSI" OR "MACD" OR "Time-Series Validation"). Initial candidate publications were filtered based on title, abstract relevance, mathematical rigor, explicit experimental design, and peer-reviewed status. Studies that lacked peer review, provided insufficient experimental detail, or omitted evaluation metrics were excluded from the final comparative syntheses.

The selected publications were categorized along five core analytical dimensions: (1) Target Currency Pairs (e.g., EUR/USD, GBP/USD, USD/JPY, AUD/USD); (2) Temporal Resolution and Data Granularity (e.g., 1-minute, 15-minute, 1-hour intraday bars, or daily closing prices); (3) Feature Engineering Schemes (OHLC raw prices, technical momentum indicators, sentiment attributes, or fundamental macroeconomic variables); (4) Model Architectures (Supervised classic ML vs. Recurrent/Hybrid Deep Learning); and (5) Performance Evaluation Criteria (Statistical prediction error metrics, Directional Accuracy, and empirical financial trading efficiency metrics such as Return on Investment and Sharpe Ratio).

III. FOREX MARKET ANALYSIS AND TECHNICAL INDICATORS

Technical analysis operates on the core principle that historical price movement reflects all known market information, public perception, and institutional positioning, and that price movements exhibit repeating statistical patterns over time. In algorithmic machine learning pipelines, technical indicators derived from raw Open, High, Low, Close (OHLC) and tick volume series serve as fundamental feature input transformations, converting raw price action into stationary momentum, trend-following, volatility, and volume indicators.

A. Moving Average (MA) and Trend Indicators

Moving averages smooth high-frequency price noise to isolate underlying market trend directions over specified temporal windows. The Simple Moving Average (SMA) calculates the unweighted arithmetic mean of price over N periods:

$$SMA_t = (1 / N) * \Sigma_{i=0}^{N-1} Price_{t-i} \quad (1)$$

To mitigate the lag inherent in equal-weighted SMAs, the Exponential Moving Average (EMA) applies exponentially decreasing weights to older observations, prioritizing recent price changes:

$$EMA_t = Price_t * \alpha + EMA_{t-1} * (1 - \alpha), \text{ where } \alpha = 2 / (N + 1) \quad (2)$$

Traders frequently analyze moving average crossovers—such as when a short-term EMA (e.g., 12-period) crosses above a long-term EMA (e.g., 26-period)—to detect bullish momentum initiation. In ML feature vectors, moving average ratios and distance-to-MA metrics enable models to normalize price scales across multi-year datasets.

B. Relative Strength Index (RSI)

The Relative Strength Index (RSI), developed by J. Welles Wilder, is a bounded momentum oscillator that measures the velocity and magnitude of recent directional price changes on a scale from 0 to 100. RSI is computed over a default lookback parameter of N=14 periods as follows:

$$RS = (\text{Average Gain over N periods}) / (\text{Average Loss over N periods}) \quad (3)$$

$$RSI = 100 - (100 / (1 + RS)) \quad (4)$$

Conventionally, an RSI value exceeding 70 indicates an overbought condition where price momentum may be overextended, whereas an RSI below 30 signifies an oversold condition. In machine learning models, raw RSI series, derivative changes in RSI (ΔRSI), and divergence between price highs and RSI highs provide crucial non-linear signals regarding impending market reversals.

C. Moving Average Convergence Divergence (MACD)

The Moving Average Convergence Divergence (MACD), developed by Gerald Appel, is a hybrid trend-following momentum indicator that illustrates the relationship between two exponential moving averages of a currency's price. The primary MACD Line is calculated by subtracting the 26-period EMA from the 12-period EMA:

$$MACD\ Line_t = EMA_{12}(Price_t) - EMA_{26}(Price_t) \quad (5)$$

A Signal Line, typically defined as a 9-period EMA of the MACD Line, is then plotted along with an indicator Histogram representing the difference between the MACD line and the Signal line:

$$Signal\ Line_t = EMA_{9}(MACD\ Line_t) \quad (6)$$

$$Histogram_t = MACD\ Line_t - Signal\ Line_t \quad (7)$$

Crossovers between the MACD Line and Signal Line, zero-line crossings, and histogram expansion/contraction dynamics serve as prominent continuous feature inputs for ML algorithms.

D. Bollinger Bands and Volatility Features

Bollinger Bands, created by John Bollinger, capture dynamic market volatility by constructing upper and lower envelope bands around an N-period SMA (typically 20 periods) at a distance of K standard deviations (typically K=2):

$$Upper\ Band_t = SMA_N(Price_t) + K * \sigma_N(Price_t) \quad (8)$$

$$Lower\ Band_t = SMA_N(Price_t) - K * \sigma_N(Price_t) \quad (9)$$

The percentage bandwidth (%B) and normalized band width metrics provide learning algorithms with standardized measures of market compression (squeeze) and expansion (breakout), allowing models to anticipate periods of elevated volatility.

IV. MACHINE LEARNING TECHNIQUES FOR FOREX PREDICTION

Machine Learning algorithms construct mathematical functions mapping input feature vectors $X_t = [x_{t-1}, x_{t-2}, ..., x_{t-k}]$ to a target output variable Y_{t+h} representing future price levels, directional movements, or optimal order executions.

A. Support Vector Machines (SVM and SVR)

Support Vector Machines (SVM) are robust supervised learning algorithms grounded in statistical learning theory and structural risk minimization principles. For binary market direction classification (UP vs. DOWN), SVM seeks an optimal hyperplane that maximizes the margin of separation between classes in a high-dimensional feature space. When handling non-linearly separable financial data, kernel functions—such as the Radial Basis Function (RBF) or Polynomial kernels—project feature vectors into higher-dimensional Hilbert spaces:

$$K(x_i, x_j) = exp(-\gamma ||x_i - x_j||^2) \quad (10)$$

In regression formulations (Support Vector Regression, SVR), an ε-insensitive loss function is introduced, ignoring errors within a specified tolerance zone around the predicted exchange rate. SVMs exhibit high resilience against overfitting in small to medium-sized financial datasets, though hyperparameter tuning (regularization parameter C, kernel coefficient γ) heavily governs predictive efficiency.

B. Random Forest (RF) and Ensemble Methods

Random Forest (RF) is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode classification or mean prediction of individual trees. Through bootstrap aggregation (bagging) and random feature subset selector protocols, RF significantly reduces prediction variance without increasing bias. RF offers distinct advantages for Forex forecasting: it inherently handles non-linear feature interactions, demonstrates immunity to monotonic feature scaling, and provides explicit Gini-impurity or permutation-based feature importance scores, enabling quantitative analysts to identify the most predictive technical indicators.

C. Artificial Neural Networks (ANN)

Multi-Layer Perceptrons (MLP) and classic feedforward Artificial Neural Networks (ANN) consist of an input layer, one or more hidden layers with non-linear activation functions (e.g., ReLU, Sigmoid, Tanh), and an output layer. ANNs act as universal function approximators capable of modeling complex continuous mappings between technical indicator feature vectors and target currency price changes. However, basic feedforward ANNs treat sequential inputs independently, failing to capture temporal memory or multi-period sequential dependencies inherent in time-series data.

D. Formulation: Regression vs. Classification Paradigms

Forex prediction systems are fundamentally formulated under two distinct algorithmic paradigms: (1) Regression Modeling: The system attempts to forecast precise scalar future exchange rate values $Y_{t+1} \in \mathbb{R}$. While exact numeric estimation is valuable, minute price fluctuations and market noise often severely degrade scalar accuracy. (2) Directional Classification: The continuous price change is discretized into discrete market signals $Y_{t+1} \in \{UP, DOWN, HOLD\}$. Classification formulations generally demonstrate superior statistical stability and align directly with rule-based algorithmic execution strategies.

V. DEEP LEARNING TECHNIQUES

Deep Learning frameworks represent an advanced class of machine learning models characterized by hierarchical representations. Recurrent Neural Networks (RNN) and specialized deep temporal architectures are specifically engineered to process continuous sequence data by maintaining internal hidden state memories across consecutive time steps.

A. Long Short-Term Memory (LSTM) Networks

Standard RNNs suffer from vanishing and exploding gradient problems when trained on long temporal sequences via backpropagation through time (BPTT). To overcome these limitations, Hochreiter and Schmidhuber introduced Long Short-Term Memory (LSTM) networks, which incorporate explicit memory cell states c_t and gating mechanisms to regulate information persistence across extended temporal horizons. An LSTM unit consists of three primary multiplicative gates:

$$Forget\ Gate: f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (11)$$

$$Input\ Gate: i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (12)$$

$$Candidate\ State: \tilde{c}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (13)$$

$$Cell\ State\ Update: c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (14)$$

$$Output\ Gate: o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (15)$$

$$Hidden\ Output\ State: h_t = o_t \odot tanh(c_t) \quad (16)$$

Through these selective gating mechanisms, LSTMs can retain long-term historical price dependencies (e.g., multi-day trend contexts) while filtering high-frequency noise.

B. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU), proposed by Cho et al., is a streamlined variant of the LSTM architecture that merges the cell state and hidden state into a single unified state vector h_t. GRU utilizes two primary gates: an Update Gate z_t (controlling how much past information is retained) and a Reset Gate r_t (controlling how past memory is combined with new input):

$$Update\ Gate: z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (17)$$

$$Reset\ Gate: r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (18)$$

$$Candidate\ Hidden\ State: \tilde{h}_t = tanh(W \cdot [r_t \odot h_{t-1}, x_t] + b) \quad (19)$$

$$Hidden\ Output\ State: h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (20)$$

Due to having fewer parameters than LSTM, GRU networks train significantly faster, demonstrate lower computational complexity, and reduce the risk of overfitting on smaller financial time-series samples.

C. Hybrid Deep Learning Architectures (GRU-LSTM & CNN-LSTM)

To leverage the complementary strengths of diverse deep learning topologies, contemporary research focuses on hybrid deep neural networks. For example, hybrid GRU-LSTM architectures pipeline sequential representations through stacked GRU layers for efficient initial temporal feature extraction, passing output states into deep LSTM layers to capture higher-order context. Similarly, CNN-LSTM models utilize 1D Convolutional layers to extract spatial local feature patterns across multiple parallel technical indicators, subsequently passing high-level feature maps to recurrent LSTM layers for multi-step temporal prediction.

VI. COMPARATIVE REVIEW OF SELECTED STUDIES

To provide a clear comparative evaluation of extant literature, key representative survey and experimental studies are synthesized in Table I below. The review highlights model variations, target datasets, feature configurations, and primary empirical findings.

Study	Technique / Models	Currency / Data	Input Features	Key Empirical Findings
Ayitey Junior et al. (2023) [1]	Systematic SLR & Meta-Analysis (60 studies)	Multi-pair Forex datasets (2010–2021)	OHLC, Technical Indicators, Macro Data	Identified LSTM and hybrid DL as dominant models; stressed critical necessity of standardized cross-validation.
Santuci et al. (2022) [2]	Random Forest vs. SVM Trading Strategies	EUR/USD, GBP/USD, USD/JPY (Daily)	RSI, MACD, MA Crossovers, Stochastic	RF achieved superior directional accuracy and profitability; feature importance confirmed RSI and MACD dominance.
Escudero et al. (2021) [3]	ARIMA, Elman RNN, LSTM Comparison	EUR/USD Exchange Rate (Intraday/Daily)	Historical Closing Prices	Deep LSTM significantly outperformed classical statistical ARIMA and linear Elman RNNs in non-linear regimes.
Islam & Hossain (2021) [4]	Hybrid GRU-LSTM vs. Standalone Models	EUR/USD, GBP/USD, USD/JPY, AUD/USD	OHLC, SMA, EMA, Technical Features	Hybrid GRU-LSTM achieved lowest RMSE/MAE across all pairs compared to standalone GRU, LSTM, and SMA models.

TABLE I. COMPARATIVE SUMMARY OF KEY FOREX PREDICTION LITERATURE

The empirical insights synthesized in Table I clearly demonstrate that model performance is highly contingent upon feature engineering quality, temporal resolution, and target currency dynamics. While traditional statistical models like ARIMA perform reasonably well under stationary, low-volatility regimes, deep neural sequence models (LSTM, GRU, and Hybrids) demonstrate statistically superior predictive power during highly volatile market transitions.

VII. EVALUATION METRICS AND VALIDATION

To rigorously quantify model accuracy and commercial viability, machine learning systems must be evaluated using standardized statistical error metrics, directional metrics, and financial backtesting metrics.

A. Statistical Regression Metrics

For continuous exchange rate regression, performance is quantified via error measures comparing predicted values $\hat{y}_t$ against ground-truth prices y_t over N sample evaluations:

$$MAE = (1 / N) * \Sigma_{t=1}^{N} |y_t - \hat{y}_t| \quad (21)$$

$$MSE = (1 / N) * \Sigma_{t=1}^{N} (y_t - \hat{y}_t)^2 \quad (22)$$

$$RMSE = \sqrt{(1 / N) * \Sigma_{t=1}^{N} (y_t - \hat{y}_t)^2} \quad (23)$$

$$MAPE = (100\% / N) * \Sigma_{t=1}^{N} |(y_t - \hat{y}_t) / y_t| \quad (24)$$

B. Directional and Classification Metrics

For classification tasks predicting directional movement $d_t = sign(y_t - y_{t-1})$, evaluation relies on confusion matrix derivatives:

$$Directional\ Accuracy\ (DA) = (1 / N) * \Sigma I(sign(y_t - y_{t-1}) == sign(\hat{y}_t - y_{t-1})) * 100\% \quad (25)$$

$$Precision = TP / (TP + FP),\ Recall = TP / (TP + FN),\ F1\text{-}Score = 2 * (P * R) / (P + R) \quad (26)$$

C. Time-Series Cross-Validation and Data Leakage Prevention

Standard K-fold cross-validation—which randomly partitions data samples into training and test splits—is fundamentally invalid for financial time-series analysis. Random splitting introduces severe Look-Ahead Bias and Data Leakage, where future price information inadvertently contaminates model training phases. To guarantee rigorous evaluation, time-series split routines must employ strictly chronological rolling-origin or Walk-Forward Validation structures:

In Walk-Forward Validation, a model is trained on an expanding or sliding historical window $[t_0, t_k]$, validated on $[t_{k+1}, t_{k+m}]$, and tested out-of-sample on unseen subsequent period $[t_{k+m}+1, t_{k+m}+p]$. The window then shifts forward sequentially, mirroring real-world automated execution environments.

VIII. RESEARCH CHALLENGES AND POSSIBLE RESEARCH GAP

Despite significant methodological advances in financial machine learning, key technical and practical obstacles hinder robust real-world deployment:

1. Non-Stationarity and Regime Shifts: Financial distributions continually evolve over time, causing trained model parameters to degrade rapidly as market regimes shift.

2. Extreme Signal-to-Noise Ratio: High-frequency Forex data contains immense stochastic noise, making deep neural networks highly prone to fitting noise rather than underlying signal patterns.

3. Realistic Transaction Costs & Slippage: Many high-accuracy models in published literature fail to achieve empirical trading profitability once bid-ask spreads, broker commissions, overnight swap fees, and execution slippage are accounted for.

4. The Black-Box Interpretability Problem: Deep neural architectures lack transparency, making it difficult for institutional risk managers to audit decision-making logic during unexpected market anomalies.

Identified Research Gap: Existing studies predominantly attempt direct end-to-end classification of price direction $Y_{t+1} \in \{UP, DOWN\}$. However, intermediate momentum transitions (such as anticipating RSI overbought reversals or MACD signal line crossovers prior to actual price turning points) remain under-explored. A promising research gap involves constructing Multi-Task Learning (MTL) networks designed to simultaneously forecast intermediate technical indicator trajectory shifts and final directional price outcomes.

IX. FUTURE SCOPE

Future research paradigms in Forex prediction are expected to advance along several impactful frontiers: (1) Explainable Artificial Intelligence (XAI): Incorporating SHAP (SHapley Additive exPlanations) and LIME frameworks to provide interpretable feature-attribution scores for every automated trade execution signal; (2) Deep Reinforcement Learning (DRL): Developing automated trading agents based on Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN) that dynamically optimize position sizing, stop-loss limits, and risk-adjusted returns directly from reward signals; (3) Multimodal Sentiment Integration: Combining temporal price features with natural language processing (NLP) models (e.g., FinBERT) to analyze central bank statements, financial news feeds, and social media sentiment in real time.

X. CONCLUSION

This paper presented a detailed, rigorous survey on machine learning and deep learning techniques applied to Forex trading prediction and analysis. It reviewed technical indicators (MA, RSI, MACD, Bollinger Bands), supervised learning algorithms (SVM, Random Forest, ANN), and advanced temporal architectures (LSTM, GRU, hybrid GRU-LSTM networks). The survey highlighted the critical necessity of proper chronological walk-forward validation to eliminate data leakage and emphasized the imperative of incorporating realistic transaction costs into quantitative backtests. By identifying key operational limitations and proposing novel multi-task technical indicator prediction paradigms, this study provides a solid foundation and clear roadmap for researchers and quantitative practitioners developing robust, automated FX trading intelligence systems.

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