Working Paper 2024.1.6.9
- Vol 1, No 6

KHẢO SÁT TOÀN DIỆN VỀ KỸ THUẬT HỌC SÂU VÀ HỌC MÁY TRONG DỰ ĐOÁN TỶ GIÁ HỐI ĐOÁI VÀ THỊ TRƯỜNG CHỨNG KHOÁN

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Tóm tắt

Trong những năm gần đây, sự giao thoa giữa kỹ thuật học máy với thị trường tài chính đã thu hút được sự chú ý đáng kể, đặc biệt là trong lĩnh vực dự đoán tỷ giá hối đoái và thị trường chứng khoán. Bài nghiên cứu này cung cấp cái nhìn tổng quan toàn diện về các phương pháp tiên tiến hiện nay, trong đó các vấn đề về tiền xử lý dữ liệu, những tiến bộ trong việc sử dụng học máy, trong đó mô hình học sâu đang được sự quan tâm rất lớn của cộng đồng để lập mô hình dự đoán trên thị trường tài chính vì có độ chính xác cao. Trong bài nghiên cứu, chúng tôi trình bày một số mô hình mạng thần kinh quan trọng như mạng thần kinh tích chập (CNNs), mạng thần kinh nhân tạo (ANNs), mạng thần kinh tái phát (RNNs) và các biến thể của chúng, bao gồm mạng bộ nhớ ngắn hạn (LSTM) và các đơn vị tái phát có kiểm soát (GRUs). Ngoài ra, chúng tôi còn thảo luận về các phương pháp tổng hợp và mô hình kết hợp học sâu với các phương pháp thống kê truyền thống. Thông qua phân tích so sánh các nghiên cứu thực nghiệm, chúng tôi nêu bật những điểm mạnh và hạn chế của các phương pháp tiếp cận khác nhau, làm sáng tỏ những thách thức như mô hình quá khớp, dữ liệu khuyết và sự kém hiệu quả của thị trường. Bài khảo sát này củng cố các tài liệu hiện có, cung cấp cho các nhà nghiên cứu, người thực hành và những người đam mê các hiểu biết có giá trị về xu hướng hiện tại và hướng đi tương lai trong lĩnh vực này, bao gồm việc tích hợp các nguồn dữ liệu thay thế, kỹ thuật học tăng cường và áp dụng các phương pháp Trí tuệ nhân tạo có thể giải thích để cải thiện khả năng diễn giải mô hình và quản lý rủi ro.

Từ khóa: Học sâu, Học máy, tỷ giá hối đoái, thị trường chứng khoán, dự báo.

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A COMPREHENSIVE SURVEY OF DEEP LEARNING AND MACHINE LEARNING FOR EXCHANGE RATE AND STOCK MARKET PREDICTION

Abstract

In recent years, the intersection of machine learning techniques with financial markets has garnered significant attention, particularly in the domain of exchange rate and stock market prediction. This survey paper provides a comprehensive overview of the current state-of-the-art methodologies, data preprocessing, and advancements in utilizing machine learning, especially deep learning for predictive modeling in financial markets with high accuracy. In this survey, we highlight key neural network architectures such as convolutional neural networks (CNNs), artificial neural networks (ANNs), recurrent neural networks (RNNs), and their variants, including long short-term memory (LSTM) networks, and gated recurrent units (GRUs). Additionally, we discuss ensemble methods and hybrid models that combine deep learning with traditional statistical approaches. Through a comparative analysis of empirical studies, we highlight the strengths and limitations of different approaches, shedding light on challenges such as overfitting, data sparsity, and market inefficiencies. This survey consolidates existing literature, providing researchers, practitioners, and enthusiasts with valuable insights into current trends and future directions in the field, including the integration of alternative data sources, reinforcement learning techniques, and the adoption of explainable AI methods for improved model interpretability and risk management.

Keywords: Deep Learning, Machine Learning, exchange rate, stock market, prediction.

1. Introduction

In today's digital era, advanced data and artificial intelligence are crucial for improving company productivity (Zougagha et al., 2021). Accurate forecasting influences short, medium, and long-term decisions, particularly in the financial sector, where trading securities, bonds, stocks, and foreign exchange can yield profits. This has spurred interest in financial time-series prediction among analysts, investors, and the public (Htun et al., 2023), leading researchers to focus on using artificial intelligence models like Machine Learning (ML) and Deep Learning (DL) for precise market analysis.

In recent years, ML algorithms have become pivotal for forecasting time series data, offering valuable insights across various fields. The unpredictable nature of data generation underscores the significance of time series prediction, where ML models excel in capturing underlying patterns (Qureshi et al., 2023). In financial and economic modeling, challenges such as nonlinearity, multicollinearity, and noise pose inherent issues. However, effectively addressing these challenges enhances the relevance of ML in prediction tasks, improving the accuracy of forecasts (Neghab et al., 2023).

Lately, deep learning (DL) methods have gained prominence, outperforming traditional machine learning (ML) in predictive accuracy, particularly in stock market forecasting. Many experts have utilized DL techniques, including convolutional neural networks (CNN), long short-term memory (LSTM), and hybrid algorithms, achieving consistently superior results compared to traditional approaches in financial time-series forecasting (Singh et al., 2022). While the standard LSTM model excels in multivariate time series forecasting, it lacks the ability to simultaneously analyze various influencing factors and their interactions. Addressing this limitation, the MF-LSTM model is proposed to simulate the impact of different information sources (Windsor et al., 2022).

DL techniques now surpass traditional ML methods in predictive accuracy, particularly in stock prediction. Experts widely employ DL, including ANN, CNN, LSTM, and hybrid algorithms, for superior results in financial time-series forecasting (Singh et al., 2022). Despite LSTM's effectiveness in multivariate forecasting, it struggles to analyze multiple factors concurrently. To address this, the MF-LSTM model is introduced to simulate diverse information sources (Windsor et al., 2022).

With the emergence of the new model, we have decided to focus our research on deep learning models. Our review identified a surge in deep learning applications for "financial time series forecasting" within the past five years. While older studies explored similar models like RNNs and Jordan-Elman networks, the term "deep learning" wasn't prevalent then. Therefore, we included these relevant works for comprehensiveness.

Our fundamental motivation in this paper was to come up with answers to the following research questions:

- Which DL models are mostly used for financial time series forecasting?
- How is the performance of DL models compared with traditional ML counterparts?
- What is the future direction for DL research for financial time series forecasting?

This effort aims to present one of the first comprehensive surveys on DL in "financial time series forecasting". Our analysis of developed models and applications aims to bridge this gap and empower researchers and developers to leverage DL effectively in their future work. We concentrate on evaluating papers that utilize ML or DL models. Our approach for identifying relevant papers follows the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). All collected papers are sourced from highly reliable websites, such as Springer, Elsevier, IEEE, ACM, DNB, and MDPi. The criteria used for selecting research papers are as follows: ("Exchange rate" or "foreign exchange") and ("Machine Learning" or "Deep Learning") and ("Predict" or "Forecast") and "Multimodal Fusion".

The rest of this paper is as follows. Section 2 shows the process involved in the method being suggested for a particular purpose or problem. Section 3 discusses performance criteria to evaluate the forecasting results. Section 4 lists the input features used in the study. Section 5 focuses on the challenges and future work of this survey. Section 6 presents the concluding remarks.

2. The procedure of the proposed method

No.	Study	Datasets	Tasks	Methods
		Springer		
1	Rama K. Malladi (2022)	Third-party	experiment	ML
2	Sang Il Lee et al. (2019)	Third-party	new model	DL
3	Hang (Robin) Luo et al. (2023)	Self-build	comparison	DL
4	Paravee Maneejuk et al. (2021)	Third-party	comparison	Hybrid
5	Janmenjoy Nayak et al. (2022)	Third-party	comparison	DL
6	Mohammad Zoynul Abedin et al. (2021)	Third-party	comparison	DL
7	Tinku Singh et al. (2022)	Self-build	comparison	DL
8	Edmure Windsor et al. (2022)	Self-build	comparison	DL
9	Yue Qiu et al. (2020)	Third-party	new model	Hybrid
10	Atharva Shah et al. (2022)	Third-party	new model	Hybrid
11	Jui-Sheng Chou et al. (2019)	Third-party	new model	ML
		Elsevier		
1	Klaudia Kaczmarczyk (2021)	Third-party	experiment	ML
2	Moiz Qureshi et al. (2023)	Third-party	comparison	ML
3	Smail Tigani et al. (2023)	Third-party	new model	DL
4	Siyuan Liu et al. (2023)	Third-party	new model	DL
5	Someswari Perla et al. (2023)	Third-party	new model	Hybrid
6	Pradeepta Kumar Sarangi et al. (2022)	Third-party	new model	Hybrid

No.	Study	Datasets	Tasks	Methods
7	M.S. Islama et al. (2021)	Third-party	new model	Hybrid
8	Pengfei Liu et al. (2023)	Third-party	new model	Hybrid
9	Dariusz Kobiela et al. (2022)	Third-party	comparison	Hybrid
		IEEE		
1	Ching-I Lee et al. (2019)	Third-party	comparison	DL
		ACM		
1	Ahmet Goncu (2022)	Third-party	comparison	ML
2	Alexander Jakob Dautel et al. (2020)	Third-party	comparison	DL
		DNB		
1	Davood Pirayesh Neghab et al. (2023)	Third-party	improvement	ML
		MDPi		
1	Pedro Escudero et al. (2021)	Third-party	comparison	DL
2	Ghahreman Abdoli et al. (2020)	Third-party	comparison	DL
3	Hualing Lin et al. (2020)	Third-party	new model	Hybrid
4	Fernando García et al. (2023)	Third-party	new model	Hybrid

Table 1: Datasets, Tasks, and Methods of the 28 current researchTable 1 provides a classification of 28 recent research papers based on the datasets utilized, tasks tackled, and the methods employed. Each paper is grouped under the respective publisher's name, with the publication year specified. The datasets are classified according to accessibility and origin. The addressed task in each research paper is categorized into proposing a new model, comparing existing models, improving an existing model, or conducting experimental analysis. Lastly, the methods applied are categorized into machine learning, deep learning, and hybrid methods.

2.1. Research data

We directed our attention towards structured-type inputs, which are primarily employed as features across various applications in the stock market. Three main categories of structured inputs are utilized in stock market forecasting:

i) Basic features encompass stock values such as OHLC data, with closing prices being the most prevalent information used to predict prices for the subsequent trading day.

ii) Technical indicators are derived from historical price series using mathematical formulas, aiding in the analysis of past price patterns and the prediction of future movements. Common technical indicators include the RSI, stochastic oscillator, and moving average convergence-divergence.

iii) Fundamental indicators encompass economic metrics ranging from macroeconomic factors (e.g., a country's overall economic condition) to microeconomic factors (e.g., company-specific information).

2.2. Predictive models

2.2.1. Machine learning

Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computers to perform tasks without being explicitly programmed for each step.

Logistic regression (LR) is a powerful supervised machine learning algorithm primarily used for binary classification tasks, where the target variable is categorical. The author conducted a comparison of several algorithms, including Random Forest, Naive Bayes, CatBoost, K-nearest neighbors (KNN), Logistic Regression (LR), and Support Vector Machine (SVM), using a backtesting simulator with data from the Warsaw Stock Exchange (WSE) (Klaudia Kaczmarczyk, 2021). The analysis revealed that LR yielded the best results, possibly because of limitations in the availability of suitable data for more complex algorithms.

Ridge regression, also known as Tikhonov regularization, is a regularization technique used in linear regression to prevent overfitting and improve the generalization performance of the model. After comparing the results of the linear regression, Ridge regression (RR), support vector regression (SVR), and decision tree regressor (DTR) for the 30, 60, 90, and 120 months, the author demonstrates that Ridge regression achieves the lowest standard deviation of the estimators' error (Ahmet Goncu, 2022). In Davood Pirayesh Neghab et al. (2023), the researchers assessed several forecasting models for predicting the CAD/USD exchange rate, classifying them into three main categories: linear (penalized) regression (LASSO - Least Absolute Shrinkage and Selection Operator and Ridge), tree-based models (ETR - Extra Trees Regressor, XGB - Extreme Gradient Boosting, and LGBM - Light Gradient-Boosting Machine), and deep learning (GRU). Results indicated that LASSO and LGBM excelled for short-term forecasts, while LGBM outperformed others for the 5-day horizon. Ridge showed superiority for 5-week predictions, with XGB emerging as the top performer for longer horizons, such as 10 periods ahead.

Support Vector Machines (SVMs) stand as a powerful and versatile class of supervised machine learning algorithms, renowned for their proficiency in classification and regression tasks. The author

Rama K. Malladi (2022) employed Linear Support Vector Machine (LSVM) as one of the top machine learning models for predicting crashes, alongside decision trees.

The Multi-layer Perceptron (MLP) is a type of ANN that consists of multiple layers of nodes, or neurons, arranged in a feedforward manner. Researchers proposed that the MLP model outperforms existing models, including the Extreme Learning Machine (ELM) model and classical time series models such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ES) models, in predicting the Real Exchange Rate (REER) dataset (Moiz Qureshi et al., 2023). This was evident in both scenarios where the data was split into testing sets of 40% and 20%.

2.2.2. Deep learning

Deep learning (DL) is a subset of machine learning that utilizes artificial neural networks with many layers (hence "deep") to learn from data. It aims to mimic the human brain's structure and function by creating complex neural networks capable of learning and making decisions like humans. Sang Il Lee and Seong Joon Yoo (2019) developed stock prediction models that combine information from the South Korean and US stock markets by using multimodal deep learning. The authors of Smail Tigani et al. (2023) present a currency market volatility estimator, which based on a deep neural network model combined with an Adam optimization algorithm for deep learning.

Recurrent Neural Network (RNN) is a type of ANN designed for processing sequential data and capturing patterns in sequences. However, the effectiveness of traditional RNNs can be hampered by the vanishing gradient problem, hindering their ability to learn long-term dependencies. Enter LSTM networks, a sophisticated extension of RNNs explicitly designed to address this limitation. LSTM networks introduce memory cells and intricate gating mechanisms, enabling them to retain and selectively update information over extended sequences. After evaluating various forecasting models, researchers concluded that RNNs and LSTM networks outperformed other deep learning models (such as Adaboost and RF) as well as the vector autoregressive (VAR) model in predicting bilateral exchange rate movements during the COVID-19 pandemic period (Hang (Robin) Luo et al., 2023). The authors of Pedro Escudero et al. (2019) conducted a comparison among three approaches - ARIMA models, Elman-type RNNs, and LSTM networks to forecast the EUR/USD exchange rate dataset. The findings reveal that while LSTM excelled in short-term forecasting accuracy, Elman-type RNNs demonstrated superior performance for long-term predictions. Similarly, the findings presented by Paravee Maneejuk et al. (2021) suggest that LSTM exhibited superior performance compared to both other deep learning models and traditional regression models when forecasting EUR/USD, GBP/USD, CAD/USD, and JPY/USD exchange rates. Additionally, the results presented in Alexander Jakob Dautel et al. (2020) suggest that RNN architectures such as LSTM and GRU neural networks exhibit superior forecasting performance compared to more traditional RNNs. Comparing the prediction accuracy of LSTM with the classical statistical model, the authors proposed that LSTM outperforms ARIMA in long-term prediction (Ghahreman Abdoli et al., 2020). In Janmenjoy Nayak et al. (2022), an LSTM-based deep learning approach is employed to forecast future stock market indices. The effectiveness of this method is evaluated by comparing it with various baseline methods such as RR, LR, LASSO, and Elastic Net. Results from the comparison demonstrate that the LSTM-based approach significantly outperforms the other methods.

The authors of Mohammad Zoynul Abedin et al. (2021) proposed an innovative ensemble deep learning technique called Bi-LSTM BR, which combines Bagging Ridge (BR) regression with Bi-directional Long Short-Term Memory (Bi-LSTM) neural networks as base regressors. Comparing its performance with traditional machine learning algorithms, the Bi-LSTM BR model demonstrated superior forecasting accuracy in terms of prediction error. In Tinku Singh et al. (2022) various deep learning models, including LSTM and its variants (vanilla, stacked, and bi-directional LSTM), as well as CNN and CNN-LSTM, were employed for time series forecasting. Among these models, B-LSTM emerged as the top performer for both Indian and US stocks. In Siyuan Liu et al. (2023), the authors propose a novel ensemble method, LASSO-BILSTM, which involves two steps: LASSO (least absolute shrinkage and selection operator) selects six highly correlated variables, and BILSTM utilizes them for forecasting. Comparative analysis with four other deep learning algorithms such as ELM, kernel extreme learning machine (KELM), LSTM, and SVR shows that LASSO-BILSTM achieves the best predictive performance overall.

The MF-LSTM model, introduced by the authors of Edmure Windsor et al. (2022), exhibited superior performance in both forecasting accuracy and error compared to existing models. They enhanced text analysis using BERT for sentiment from social media and uniquely incorporated both market indicators and investor sentiments. In Ching-I Lee et al. (2019), researchers focused on predicting future currency exchange rates for the Australian dollar (AUD) against the US dollar. They conducted a comparative study of the proposed attention-based LSTM with typical models, including ARIMA, SARIMA, SLP, and classical LSTM. Additionally, simple sentiment analysis using SnowNLP and keyword matching with "up/increase" in news articles enhances performance by 15%. The results demonstrated that the LSTM-attention model achieves the best performance.

2.2.3. Hybrid

One of the key trends in financial market prediction is the development of hybrid deep learning models that integrate multiple neural network architectures. These models combine the strengths of different algorithms to enhance prediction accuracy and robustness.

In Yue Qiu et al. (2020), it was reported that hybrid models achieve notably superior accuracy, mean squared error (MSE), and area under the ROC curve (AUC) compared to individual models. For instance, a study found that a hybrid RNN model surpassed other comparison models, boasting an average accuracy of 0.74, an MSE of 0.26, and an AUC of 0.74, showcasing its efficacy in timing the stock market. Multiple studies have corroborated these findings, observing promising results with hybrid models outperforming individual baseline models across the aforementioned metrics. For example, Atharva Shah et al. (2022) highlighted that the fusion of CNN with LSTM networks exhibited promising results in forecasting stock prices and currency exchange rates. Similarly, hybrid models integrating GRUs alongside LSTMs have demonstrated enhanced performance in predicting future trends in the forex market (M.S. Islama et al., 2021)

In Hang (Robin) Luo et al. (2023), GARCH (Generalized Autoregressive Conditional Heteroskedasticity) combined with GBDT (Gradient Boosting Decision Trees) exhibited the most accurate prediction performance for USD/CNY and USD/JPY using both 30- and 60-minute data intervals. Additionally, for forecasting GBP/USD using 60-minute data, GARCH + GBDT also outperformed other combinations, including GARCH + LSTM, GARCH + RNN, GARCH + AdaBoost, GARCH + RF, GARCH + LightGBM, as well as standalone GARCH and ARMA (Autoregressive Moving Average).

Hybrid models offer a promising approach to financial forecasting by leveraging the combined strengths of different machine learning algorithms. While various factors influence their effectiveness, they have demonstrated the potential to outperform individual models in certain scenarios.

3. Metrics of financial time series forecasting

Financial time series forecasting involves predicting future values of financial data like stock prices, exchange rates, or economic indicators. Evaluating the performance of these models is crucial, and several key metrics are used for this purpose.

Table 2: Financial Time Series Forecasting Evaluation Metrics

No.	Evaluation	Description
1	Mean Square Error (MSE)	Average of the squared difference between the predicted values and the actual values
2	Mean Absolute Percentage Error (MAPE)	Average of the percentage errors
3	Mean Absolute Error (MAE)	Average of the absolute difference between the predicted values and the actual values.
4	Root Mean Square Error (RMSE)	Measures for evaluating the quality of predictions.
5	Normalized Root Mean Square Error (NRMSE)	Relates the RMSE to the observed range of the variable.

Ultimately, a comprehensive evaluation approach that incorporates multiple metrics and considers the context of the forecasting problem is crucial for robust model assessment and informed decision-making in financial forecasting.

4. Empirical analysis and discussion

In this short survey, we have given a comprehensive review of how DL applications in the financial time series (FTS) have developed over recent years. We have explored the publicly available prediction corpora in English languages and presented a brief description in Figure 1. The methods approach (ML/DL, Hybrid) is presented in Figure 2 from 01/01/2019 to 31/12/2023.

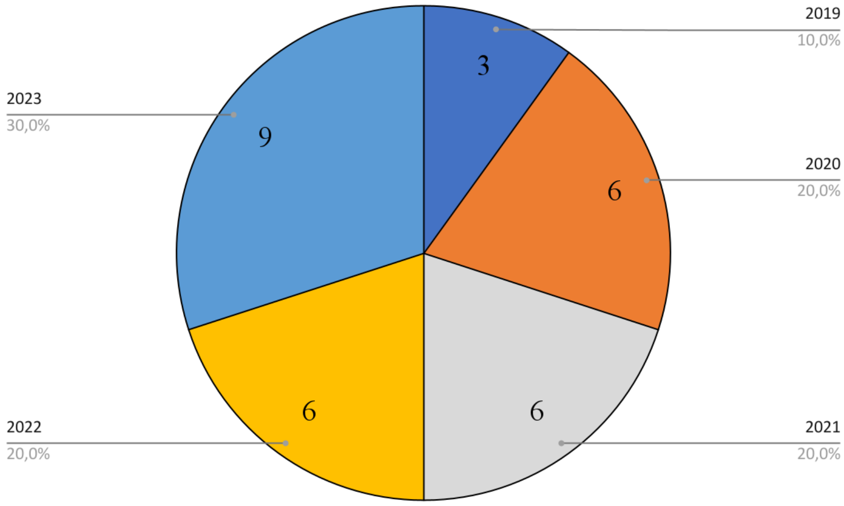

Figure 1: The number of collected research were published through years

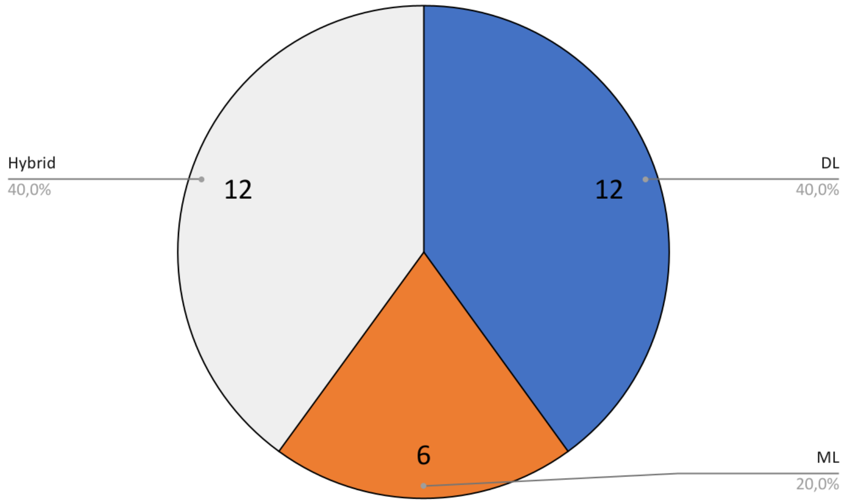

Figure 2: The number of collected research is classified in terms of methods approach

The forecasting of stock prices stands as the most extensively researched financial application. We noted a similar pattern in the utilization of deep learning techniques.

Table 3: Stock price forecasting using raw data, technical and fundamental indicators

	Art.	Dataset	Feature Set	Method	Performance Criteria
ML	Klaudia Kaczmarczyk (2021)	160 companies from the Polish Stock Exchange	Basic data, Technical indicators	RF, SVM, NB	Precision, Sharpe ratio

	Art.	Dataset	Feature Set	Method	Performance Criteria
DL	Dariusz Kobiela et al. (2022)	Share average prices of 10 companies in each sector (IT, Automotive, Financial, Logistics Clothing, Food, Energy, Healthcare, Entertainment & Media)	Basic data	ARIMA, LSTM	MSE, MAPE
	Ghahreman Abdoli et al. (2020)	Tehran Stock Exchange (TSE) intraday data	Basic data	LSTM ARIMA	MAPE, MSE, MAD, TS
	Janmenjoy Nayak et al. (2022)	The COVID-19 Indian confirmed, recovered and death data The Nifty50 data	Basic data, Coronavirus Statistics	Proposed LSTM-dropou, LSTM, LF, RR, LR, Elastic net regression	MAPE, MAE, RMSE, R-Square
	Tinku Singh et al. (2022)	NSE stocks, NASDAQ stocks	Basic data, Technical indicators	INC(U), LSTM (U), CNN-LSTM (U), INC, CNN, S-LSTM, B-LSTM, V-LSTM	MAE, RMSE, MAPE
Hybrid	Yue Qiu et al. (2020)	The five UCI datasets, 6 daily securities from SSE	Technical indicators	Hybrid RNN, SVM, KNN, NB, DT, LR, PCA-SVM, PCA-KNN, PCA-NB, PCA-DT, PCA-LR, LSTM and GRU.	Accuracy, MSE, RMSE, Recall, F1-score, AUC

Art.	Dataset	Feature Set	Method	Performance Criteria
Atharva Shah et al. (2022)	The daily closing price of the Nifty 50 stock market index. Technical indicators (strength, momentum, trend, and volatility indicators)	Basic data, Technical indicators	CNN-LSTM	R-Square, MAE, MAPE RMSE, F1-score, Accuracy

Survey categorizes stock prediction by ML, DL, hybrid methods. LSTM, hybrids prevalent (Table 3). Input mainly basic, technical. ML algorithms crucial for stock prediction, need hyperparameter tuning with current data for accuracy. Approaches used in univariate, multivariate time-series analysis with historical prices, technical indicators. After conducting experiments, the author concludes that among the various types of deep learning models, the Offline-Online methods yield better results with good evaluation (Tinku Singh et al., 2022). Recurrent neural networks excel in stock trend forecasting but lack research in market timing. Consequently, a new model called the hybrid RNN model is introduced for stock market timing, which integrates multiple layers of long short-term memory, multiple layers of gated recurrent unit, and one layer of Rectified Linear Unit (ReLU) with yielding competitive results: MSE 0.7406, RMSE 0.2592, AUC 0.7368. (Yue Qiu et al., 2020).

Rather than attempting to predict the price movement of individual stocks, many researchers opt to forecast the stock market index. Stock indices typically exhibit lower volatility compared to individual stocks, as they consist of multiple stocks from diverse sectors, offering a more comprehensive representation of the overall momentum and economic conditions.

Table 4: Forex forecasting using raw data, technical and fundamental indicators

	Art.	Dataset	Feature Set	Method	Performance Criteria
ML	Moiz Qureshi et al. (2023)	The daily stock exchange data from the State Bank of Pakistan.	Basic data	MLP ARIMA, ELM, ES	MSE, RMSE, MAE, MAPE

	Art.	Dataset	Feature Set	Method	Performance Criteria
	Ahmet Goncu (2022)	USD/TRY, FED Effective Funding Rates, Turkish Central Bank Real Effective Funding Rates, and the Money Supply in Turkey (M2).	Basic data, Fundamental indicators	The Ridge, Decision tree regression, SVR and linear regression.	MARE
	Davood Pirayesh Neghab et al. (2023)	CAD/USD exchange rate and the considered macroeconomic variables.	Basic data, Technical indicators, Fundamental indicators	LGBM, ETR, XGB, RIDGE, LASSO, GRU	NRMSE
DL	Edmure Windsor et al. (2022)	Gold Price, Silver Price, WTI crude oil price, Shanghai Securities Composite Shenzhen, Component, Dow Jones, S&P 500, NASDAQ, NYSE Indexes, China 10-year bond yield U.S. 10-year, Treasury bond yield Shibor O/N rate, FED fund rate, USD/CNY rate	Index data, Basic data, Technical indicators, Social media keywords (Twitter and Sina Weibo)	BERT-wwm, RoBERTa + ARIMA, SVR, BPNN, ELM, CNN, LSTM-single, LSTM-sentiment, LSTM-market, LSTM-all, MF-LSTM	R-Square, MAE, MSE, RMSE

Art.	Dataset	Feature Set	Method	Performance Criteria
Paravee Maneejuk et al. (2021)	JPY/USD, USD/GBP, EUR/USD, CHF/USD, CAD/USD.	Basic data	ARIMA, ANN, Elman RNN, LSTM, SVM	MAPE, RMSE, MAE, Theil U
Ching-I Lee et al. (2019)	AUD/USD	Basic data, Technical indicators	ARIMA, SARIMA, SLP, LSTM	RMSE, MAPE
Hang (Robin) Luo et al. (2023)	Exchange rate return (USD/JPY, GBP/USD, USD/CNY), COVID-19 confirmed cases, Benchmark interest rates (Fed Funds Rate, Overnight Rate of Japan, LIBOR, SHIBOR), Market sentiment (CBOE Market Volatility Index), Technical indicators (MACD, A/D, LWR, RSI, SMA, WMA, SD, SK, CCI, Momentum)	Basic data, Fundamental indicators, Technical indicators, Coronavirus Statistics	RNN, LSTM, RF, AdaBoost, VAR, GARCH+LSTM, GARCH+RNN, GARCH+Adaboost, GARCH+RF, GARCH+LightGBM, GARCH+GBDT, GARCH, ARMA	RMSE MAE MEDAE
Pengfei Liu et al. (2023)	Macroeconomic variables (FFER, EX, IM, CM2), Financial assets (The S&P 500 index), Sentimental index (UMCSI, GT, BI), other composite indicators	Index data, Basic data, Technical indicators	SVR, ELM, LSTM, BI LSTM, KELM	MAE, RMSE

	Art.	Dataset	Feature Set	Method	Performance Criteria
	Pedro Escudero et al. (2021)	EUR/USD	Basic Data	ARIMA, ELMAN, LSTM	MSE, RMSE, MAE, MdAE, MAPE, sMAPE, RMSPE, RMdSPE, MdAPE, SMdAPE
	Alexander Jakob Dautel et al. (2020)	EUR/USD, GBP/USD, JPY/USD, CHF/USD.	Basic data	GRU, LSTM, RNNs, FNN	Log loss, Acc, AUC.
	Mohammad Zoynul Abedin et al. (2021)	Confirmed COVID-19 cases and events. The exchange rates of some currencies (AUD, EUR, NZD, GBP, BRL, CNY, HKD, INR, KRW, MXN, ZAR, SGD, DKK, JPY, MYR, NOK, SEK, LKR, CHF, TWD, THB) against the USD.	Basic data, Coronavirus Statistics	RR, LR, RT, RF, SVR (Linear), SVR (RBF), SVR (Polynomial), LSTM, Bi-LSTM, Bagging ridge, Bi-LSTM bagging ridge	RMSE, MAE, MAPE
Hybrid	M.S. Islama et al. (2021)	EUR/USD, GBP/USD, USD/CAD, USD/CHF.	Basic data	GRU-LSTM hybrid	MSE, RMSE, MAE
	Fernando García et al. (2023)	EUR/USD, GBP/USD, JPY/USD, AUD/USD, NZD/USD.	Basic data	ARIMA, LSTM, ARIMA - LSTM	MAE, MAPE, RMSE

Art.	Dataset	Feature Set	Method	Performance Criteria
Pengfei Liu et al. (2023)	USD/RMB	Basic data	SVR, CNN, LSTM, GRU-LSTM, CNN-LSTM, CNN-LSTM-AM, CNN-STLSTM-AM	RMSE, MAE, R-Square,
Paravee Maneejuk et al. (2021)	CAN/USD daily exchange rate EUR/USD 4h closing price	Basic data	EMD, VMD, FFNN, ARMA, SW_LSSVR Sliding-window, MetaFA-LSSVR (SMOF system)	RMSE, MAE, MAPE, RSI, ROC
Someswari Perla et al. (2023)	MYR/USD, MXN/USD, EUR/JPY, EUR/GBP, EUR/HKD	Basic data, Technical indicators	DKRVFLN-AE	MAPE, MAE and RMSE

Literature reviews forex forecasting methods: RNN, LSTM, CNN, FNN, MLP, DKRVFLN-AE; popular choices include LSTM, RNN, and hybrids. Various input data sources, including technical indicators, index data, and social media news, impact market trends. ML methods like MLP, ELM, and classical models such as ARIMA and ES are studied for REER prediction. Real exchange rate data is critical in understanding market trends. Research combines AI and econometric modeling, achieving optimal forecasting of REER dynamics (Moiz Qureshi et al., 2023). Experiments comparing models show CNN-STLSTM-AM model outperforms, predicting USD/RMB exchange rate with high accuracy. A new STLSTM model enhances LSTM structure, improving predictive capability (Pengfei Liua et al., 2023).

Some researchers focus on predicting asset price direction, shifting from regression to classification, altering performance metrics. Despite this distinction, underlying approaches remain fundamentally similar; variation lies in output interpretation.

Table 5: Trend forecasting using raw data, technical and fundamental indicators

	Art.	Dataset	Feature Set	Method	Performance Criteria
ML	Rama K. Malladi (2022)	FRED-MD dataset	Fundamental indicators	LSTM	Accuracy
DL	Sang Il Lee et al. (2019)	OHLCV of KOSPI (KO), S&P 500, NASDAQ, Dow Jones indexes	Basic data	DNN	MSE, Hit ratio
	Smail Tigani et al. (2023)	Historical currency source: MetaTrader	Basic data, Technical indicators	DNN	MSE
Hybrid	Hualing Lin et al. (2020)	GBP/USD USD/AUD	Basic data	ARIMA, Bayesian, SVM, RNN, MRNN, LSTM, MLSTM, MLSTM–CEEMDAN.	MAPE, RMSE, MAE
	Someswari Perla et al. (2023)	MYR/USD, MXN/USD, EUR/JPY, EUR/GBP, EUR/HKD	Basic data, Technical indicators	DKRVFLN-AE	PCCA, Fm
	Pradeepta Kumar Sarangi et al. (2022)	INR/USD	Basic data	ANN, ANN-GA	RMSE

In literature, certain studies have utilized technical indicators, price data, and fundamental data across different time frames. Table 5 presents an overview of trend forecasting research employing these inputs. Furthermore, these studies are categorized into three subgroups: machine learning (ML), deep learning (DL), and hybrid approaches.

5. Limitations and future directions

Several limitations and areas for future research directions can be identified across the articles on machine learning and deep learning applications in financial markets.

Firstly, several studies (Sang Il Lee et al., 2019) and (Janmenjoy Nayak et al., 2022) have focused on predicting exchange rates or stock prices using historical data and technical indicators, but there is a growing recognition of the importance of incorporating fundamental indicators and external factors such as economic news and global sentiment. Future research could explore more sophisticated feature engineering techniques and sentiment analysis methods to enhance model performance.

Additionally, many studies have evaluated models based on standard performance metrics such as accuracy, MSE, and MAPE, but there is a need for additional research on the practical implementation and profitability of these models in real-world trading scenarios. This could involve backtesting strategies and incorporating transaction costs and market impact into model evaluation. (Smail Tigani et al., 2023)

Moreover, while deep learning models have shown promise in forecasting financial time series, there are challenges related to interpretability and explainability, which are crucial for gaining insights into model predictions and ensuring regulatory compliance. Future research could focus on developing transparent and interpretable deep learning architectures tailored to financial applications. (Dariusz Kobiela et al., 2022; Tinku Singh et al., 2022)

Overall, addressing these limitations and pursuing these future research directions could contribute to the advancement and practical deployment of machine learning models and deep learning models in financial markets. Returning to our initial research questions, here are our findings:

i) DL models, particularly RNN-based ones like LSTM, are widely used for financial time series forecasting. CNN and DMLP are also common for classification tasks with proper data preprocessing.

ii) DL models generally outperform traditional ML methods, although there are cases of comparable performance or even better performance by ML models in certain studies.

iii) The future of DL research in financial time series forecasting may involve hybrid models combining NLP, semantics, and text mining with time-series data.

6. Conclusion

In this comprehensive survey, we have provided an extensive exploration of the application of deep learning and machine learning techniques for the prediction of exchange rates and stock market movements. Through an analysis of existing literature and methodologies, several key insights have emerged. Firstly, deep learning and machine learning models have demonstrated remarkable potential in capturing complex patterns and dynamics inherent in financial data, thereby enabling more accurate predictions compared to traditional econometric models. Secondly, the efficacy of these computational techniques is contingent upon various factors, including the choice of model architecture, feature selection, data preprocessing, and hyperparameter tuning. Understanding the interplay of these factors is crucial for developing robust and reliable predictive models. Thirdly, while deep learning and machine learning offer promising avenues for forecasting exchange rates and stock prices, challenges such as data scarcity, model interpretability, and market volatility persist. Addressing these challenges requires interdisciplinary collaboration and innovative solutions.

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