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Classification of Exchange Rate Prediction Methods with a Focus on Deep Learning Techniques

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Abstract—**Currency exchange rate forecasting has always been one of the important issues for economic activists. In this context, the stationary, and non-linear behavior of this variable and random walk claim mentioned in some empirical studies have made forecasting as one of the challenges, and concerns in the field of economics. The present study briefly classifies various currency exchange rates forecasting models and methods, then focuses on five deep learning methods, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Reinforcement Learning (RL). For this purpose, the report of various studies on forecasting currency exchange rates using the above methods, with objectives, such as identifying the researchers in this field, the scope of studies, the scientific centers conducting studies, along with their geographical distribution, mixed methods used, studied currency pairs, forecasting periods, data frequency, evaluation criteria, obtained accuracy and features used for forecasting were studied. The study results will help future research in this field more effectively identify the research gaps with classified access to the previous studies, and define the topic and scope of future research to complete previous studies.**

Keywords: currency exchange rate forecasting, forex, machine learning, deep learning, time series

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I. INTRODUCTION

The currency exchange rate is one of the most important macroeconomic and financial variables in all countries. On the one hand, many economic theories and experiences are based on the assumption that the reflection of the economic activities of the two countries, and the state of macroeconomic variables, such as GDP, M2 money supply, inflation, and balance of payments are mirrored in the currency exchange rate. On the other hand, this rate can have significant effects on economic variables and decisions of economic actors. Therefore, monitoring and predicting this variable is very important both from the point of view of economic policymakers and economic agents. A significant obstacle in the prediction of economic variables is the unfavorable performance exhibited by economic models when forecasting currency exchange rates over various time horizons, including the short and long term. Considerable effort has been devoted by numerous researchers to unravel this perplexing issue. The puzzle of currency exchange rate forecasting goes back to the work of Meese and Rogoff [38], who showed that exchange rate fluctuation forecasting is

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very difficult using economic models, and the random walk model predicts exchange rates better than any economic model. This puzzle states that exchange rate changes are completely random, for which no rule and/or model can be considered. Since then, many studies have been conducted to find successful predictors of currency exchange rates, both statistically and economically, which are still ongoing. Thirty years after the design of this puzzle, Rossi [53] showed that the random walk model is still the best model of currency exchange rate forecasting, and thus raised this puzzle again [40]. Another path in the field of currency exchange rate forecasting claims that the past dynamics of exchange rate can predict its future values. By examining different exchange rates, Narayan [40] showed that 55-75% of changes in exchange rates can be predicted by past changes in the same variable. On the other hand, Iyke et al. [28] believed that often in literature, the effects of key issues such as the persistence of a specific condition in currency exchange rate forecasting are ignored. They showed that geopolitical risks can be effective in currency exchange rate forecasting.

This article presents a comprehensive overview of various methodologies, models, and techniques for forecasting exchange rates. Then, it continues with a detailed description of five deep learning methods selected for the study, highlighting their relevance and significance. Following this, the article provides a thorough review of previous research in this domain, drawing connections between past findings and the current state of knowledge in the field.

By offering an extensive presentation of existing approaches and their applications, the article aims to establish a solid foundation for understanding the complexities of exchange rate forecasting and the potential advancements that deep learning methods can bring to the field.

A. Motivation:

The forex market, being the largest financial market globally, has a substantial impact on global economies and financial systems. Accurate prediction of currency exchange rates is essential for various stakeholders, including investors, policymakers, and financial institutions. In recent years, deep learning has emerged as a powerful tool in forecasting financial trends, offering significant potential to improve prediction accuracy in forex markets. this article seeks to bridge the gap between artificial intelligence, deep learning, and forex market forecasting, fostering further research, innovation, and practical applications.

B. Summary of challenges in previous studies:

- Insufficient Depth in Individual Market Analysis: Previous studies often cover multiple financial domains, leading to a limited number of research papers focusing specifically on markets such as the foreign exchange (forex) market.
- Insufficient deep learning coverage: In reviews covering broad financial areas, the proportion of studies focusing on deep learning applications in the forex market is small.
- Limited studies on deep learning in forex: Even in studies specifically focusing on the forex market, deep learning is underrepresented.

These challenges collectively emphasize the necessity for more focused, comprehensive, and in-depth research on deep learning in the forex market, which the current paper aims to address.

C. The problem statement:

The problem statement of this article is centered around understanding the application of deep learning techniques in exchange rate prediction. It involves several key questions that the study aims to address:

- Evaluating the Utilization of Deep Learning Algorithms: The study seeks to identify which deep learning algorithms are most frequently used in exchange rate prediction. This involves examining various models to determine which ones have been preferred by researchers and why they are effective in this context.
- Data Selection: The study aims to explore what kinds of data are most suitable for training deep learning models in the context of exchange rate forecasting. This includes investigating the types of data inputs (e.g., historical prices, economic indicators).
- Forecasting Period and Data Frequency: The research aims to determine the length of the forecasting period (e.g., short-term, medium-term, long-term) and the frequency of data used (e.g., daily, weekly, monthly). Understanding these parameters is crucial because they influence the model's ability to make accurate predictions over different time horizons.
- Evaluation Criteria: The study intends to analyze the evaluation criteria that are used to assess the performance of deep learning models in exchange rate prediction. This includes understanding which metrics (e.g., Mean Squared Error, Mean Absolute Error, accuracy) are commonly used and how they vary across different models.
- Distribution and Range of Evaluation Criteria: The study will further investigate how these evaluation criteria are distributed across different methods. This involves examining whether certain criteria are more applicable to specific models or data sets and understanding the range of values these criteria can take, which could indicate the reliability or robustness of a model.

In summary, the problem statement focuses on systematically exploring the various factors that influence the effectiveness of deep learning models in exchange rate prediction. The goal is to provide a comprehensive understanding of the current state of research in this area, identifying the best practices, common challenges and potential gaps in the literature.

D. Contribution:

Our paper offers a unique approach by focusing on the recent application of deep learning techniques in the forex market. It aims to provide an in-depth analysis of this rapidly evolving field, given the increasing utilization of artificial intelligence in financial markets. By reviewing relevant studies, we can better understand the advantages, disadvantages, and obstacles of applying deep learning technology in this context, fostering further advancements and research opportunities. Our article contributes the following key aspects:

- In the present study, we classify various models and methods for exchange rate forecasting that are proposed by many scholars with a specific emphasis on the application of deep learning techniques in the forex market. For this purpose, we evaluate studies from various aspects such as identifying the researchers in this field, the scope of studies, the scientific centers conducting studies along with their geographical distribution, the hybrid methods they employed, the currency pairs under study the currency pairs under study, forecasting periods, data frequency, evaluation criteria, obtained accuracy and features used for forecasting.
- Comprehensive Review of Deep Learning Techniques: We present a thorough and up-to-date review of 5 deep learning techniques applied specifically to forex markets. This ensures that our analysis remains focused and relevant, providing valuable insights into current methodologies.
- Identification of Strengths and Weaknesses: We identify the advantages and disadvantages of utilizing deep learning methods in forex market prediction. This analysis is aimed at promoting further improvements and innovation in the field.
- Analysis of Research Gaps and Opportunities: We conduct an in-depth analysis of existing research, highlighting potential gaps and identifying opportunities for future studies in this rapidly evolving area of financial technology.
- Overview of Forecasting Methods: we provide a unique overview of various forecasting methods and models, offering an extensive perspective that is both innovative and has not been explored in other studies with comparable depth and breadth.

The rest of the article is structured as follows: Section 2 presents literature review including various approaches, models, and methods for currency exchange rate forecasting and an overview of the five deep-learning methods selected for this study. Section 3 consists of the research methodology, detailing the systematic approach undertaken to conduct this study. In section 4 we present study results and section 5 represents our discussion and conclusion.

II. LITERATURE REVIEW

A. Forecasting approaches

In general, forecasting approaches are divided into two fundamental and technical groups, each of which is divided into more categories. Figure 1 shows the classification of various currency exchange rate forecasting approaches and the related subsets. The fundamental approach posits that the exchange rate, as a dependent variable, is a function of the variables from which it is derived through their interaction. Indeed, the fundamental variables serve as the foundation for currency exchange rate variable, encompassing macroeconomic, political, and social factors, among others. The fundamental approach is classified into two economic and econometric models:

- Economic models are based on economic theories and in most cases, they introduce a specific and predetermined mathematical model to express the relationship between currency exchange rate and fundamental variables.
- Econometric models are developed based on economic theories, but for defining the type of relationships, they may not be completely subject to economic theory, but only use the variables recommended in the theory to build the model. These models have different types, and each type is selected according to the field of research and research objectives. For example, if the objective is to model the exchange rate in the dimensions of several countries and the international economy, so that the exchange rate of several different countries is modeled in the form of a single model, the Panel data model is an option [43], [53], [68], [71].

Unlike the fundamental approach, the technical approach does not consider the relationship between the exchange rate and other fundamental variables, and its objective is to extract relationships, and forecast the exchange rate based on experience. This approach is generally divided into four categories:

- The first category includes time series models. This method tries to get the best model that can explain the experimental reality by considering the dynamics of the studied variable and in some cases other explanatory variables as well as the dynamics of the shocks that have impact on the target variable [15], [43], [53], [62].
- The second category includes methods based on machine learning, which itself is divided into traditional machine learning and deep learning [1], [8], [24], [37], [44], [62].
- The third category includes methods that are not classified in the last two categories [33].
- The fourth category includes the mixed methods of time series models and machine learning methods[1] [18], [20], [24], [30], [57], [62].

Efficient market and random walk hypotheses are the basis of many technical methods of exchange rate estimation. However, if the market behaves like random walk, profitable traders and professionals who analyze the time series of the market using technical methods cannot benefit from predictability and/or inefficiency [17]. Therefore, if financial market experts with access to such information can consistently overcome reasonable predictions of market behavior, machine learning methods should be able to recognize the presence or absence of models in the market. This hypothesis is the basis of exchange rate estimation methods based on machine learning.

[1] Other methods that are gaining more attention and popularity are mixed methods based on DL, which are not covered in this article.

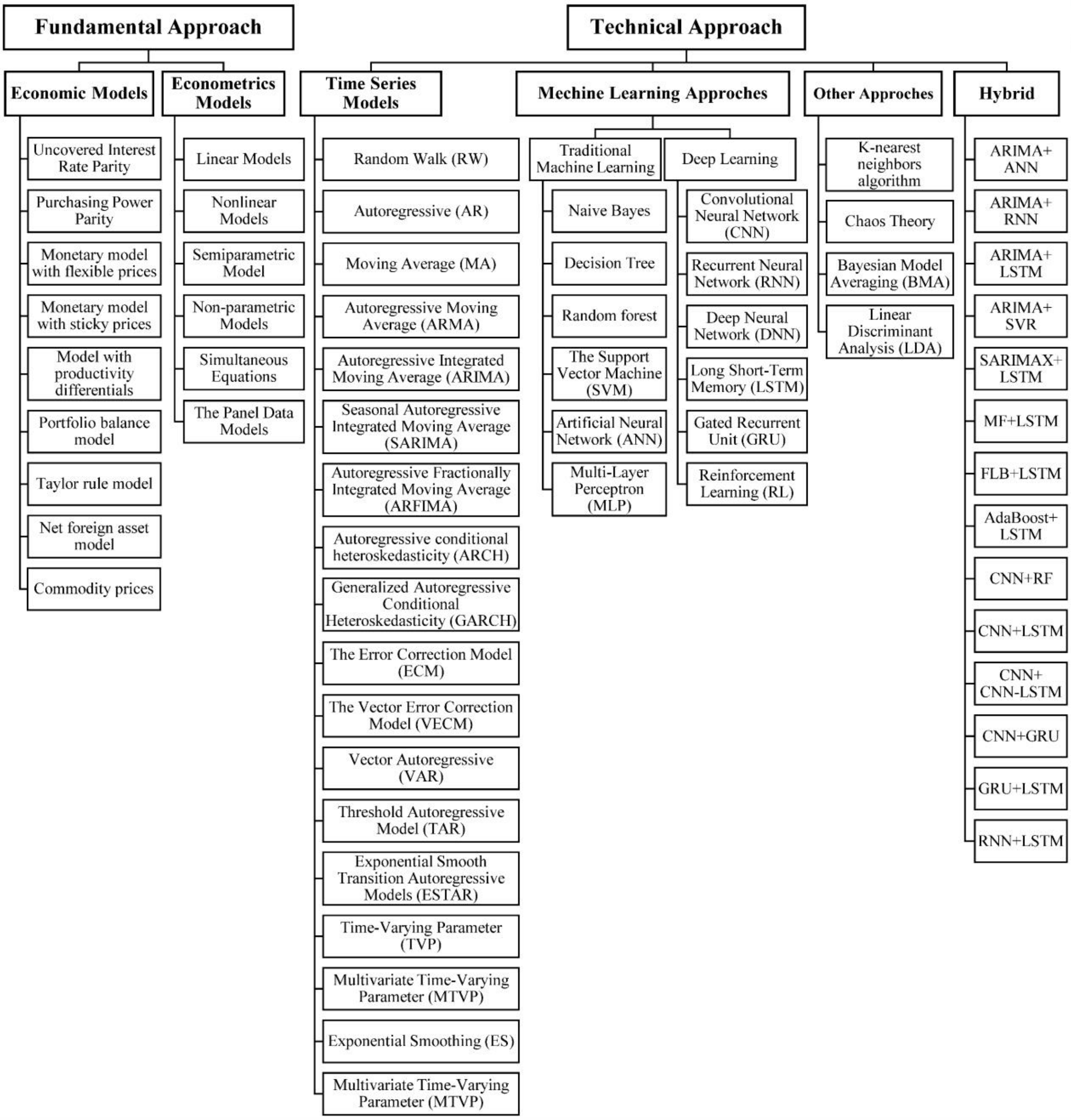

Figure 1. Different approaches, models, and methods for currency exchange rate forecasting

The use of neural networks for currency exchange rate forecasting has been a popular method for the past two decades, and the advances in deep learning computational techniques in the past five years have drawn more attention to neural networks [45]. In general, the types of exchange rate estimation methods, and models by a machine learning approach can be classified into two groups: "methods based on traditional machine learning" and "methods based on deep learning". Today, with the advance of computers and the development of artificial intelligence technologies, deep learning models are widely used for currency exchange rate forecasting in the forex market [26]. Deep learning applications were shown to outperform previous techniques in the area of financial forecasting in terms of accuracy and efficiency. Deep learning has the ability to characterize intricate effective factors, in contrast to conventional statistical and economic models [26].

B. Deep learning methods

Literature review shows that among various forecasting methods based on deep learning, in terms of their more successful results, some have been of more interest to researchers than others.

Furthermore, the focus of this study is on 5 of the most widely used deep learning methods for exchange rate forecasting, each of which will be briefly described below, and the research related to these methods will be reviewed by providing more details. The philosophy of focusing on deep learning methods in this article stems from the potential these techniques hold in accurately forecasting financial market trends. By doing so, deep learning methods can potentially offer more accurate and reliable predictions than traditional methods, thus providing invaluable insights to investors, policymakers, and other stakeholders in the financial markets. Incorporating deep learning techniques into a survey article on Forex prediction allows researchers to explore the cutting-edge approaches that are transforming the field. Furthermore, discussing the challenges and limitations of these deep learning methods can help researchers identify areas for improvement and inspire further innovations. By examining the successes and setbacks of deep learning in exchange rate prediction, the survey article can serve as a valuable resource for both researchers and practitioners looking to harness the power of AI in the financial domain.

CNN: CNNs make a family of models whose design was inspired by the way the visual cortex of the human brain works when recognizing objects [51]. A CNN is made up of a large number of artificial neurons that form a network like an artificial neural network (ANN). The difference between this network and the structure of fully connected neural networks, such as "sparse auto-encoder (SAE)" or "deep belief network (DBN)" is that in CNN, weights are shared between the neurons of each layer. This prevents the method from getting bogged down in high dimensions or limiting the results to local optima, as the network weight is significantly reduced [26]. This method is increasingly used in economic forecasts [51].

CNNs can achieve "end-to-end" learning, where the underlying feature representation of the original data is gradually transformed into higher-level features through multiple layers of feature transformation, and the processed data is then fed into a prediction function. The representation learned by CNNs can generate good features, avoiding the need for manual "feature engineering". While the evolution of CNN architectures has facilitated better feature representation, it has also led to challenges such as increased likelihood of overfitting and error rate increases in the training set as the networks become deeper and more complex. To address the shortcomings of these complex CNN models, various optimization techniques have been proposed, such as network pruning, knowledge distilling, and tensor decomposition [79]. After a period of limited interest in the 2000s, CNNs saw a major resurgence with the success of the AlexNet model in the 2012 ImageNet challenge, which marked a turning point in CNN performance. More recent research has focused on developing advanced CNN architectures and modules to improve the adaptability and transferability of them, beyond just enhancing recognition accuracy [13].

RNN: RNN is one of the deep learning methods used to simulate and predict sequential data. The main feature of RNN is to remember the previous information so that it can benefit from the past information to obtain the current information. This feature is very important to forecast in the forex market, because in this market, the fluctuations of consecutive times are usually correlated with each other. Despite the above feature, RNN cannot process well the dependencies between two times that are far away from each other and have long term relationships. This problem was first proposed by Hochreiter [25] and Bengio et al. [7] called it the "vanishing gradient problem". Based on this problem, if the length of a sequence increases, the propagation of information in the RNN will reduce [73]. This can make it difficult for RNNs to understand long-term data relationships. To address this issue, researchers have developed more sophisticated RNN designs, such as LSTM and GRUs, which are designed to handle long-term dependencies better [2].

LSTM: LSTM is a type of RNN whose architecture idea is to use self-looping to generate paths where the gradient can flow for long periods. Another important point is that the self-loop weight, rather than being fixed, can change based on the context [23]. This feature resolves the issue of the vanishing gradient problem. Based on empirical evidence, may effectively simulate non-linearity and correlation in time series. Because the time series in the forex market are correlated and the price behavior of currency pairs is non-linear, one purpose for this approach is to predict exchange rates. Optimization of LSTM model parameters is also crucial. Traditional optimizers like stochastic gradient descent can struggle with LSTM models, leading to slow training speeds and difficulty reaching high accuracy [5].

GRU: GRU was first proposed by Chung et al. [11] to solve the vanishing gradient problem, which is the same as a simple LSTM, with the difference that it has a forget gate and the number of its parameters is less than LSTM. The output gate is not defined for GRU, and it has two gates in total. It has different weights compared to LSTM. These differences make GRU calculations less than LSTM and thus the time required for data processing is reduced. The choice between GRU and LSTM depends on the specific use case and problem at hand, as both architectures have their advantages and disadvantages [56].

RL: A key element that distinguishes RL from other machine-learning methods is that it is based on the concept of learning by interaction [51]. This means that in RL, the model learns from interacting with an environment to maximize a reward function. In this type of learning, a specific action is determined in each situation. Then, the action execution results are used as new data to modify the new action according to the obtained results. Thus, the algorithm gains the ability to make decisions that maximize reward. For instance, in the forex market, trading transactions to buy or sell currency might be an action, while market data such as news, investor emotion, and fees can be a learning environment.

Traditional RL algorithms were mostly designed for tabular cases, which provide principled solutions to simple tasks but face difficulties when handling highly complex domains [80]. Recently, Deep RL (DRL) has gained significant attention. DRL combines the advantages of RL and deep learning, using a Deep Neural Network as the estimator to increase the scalability of RL. RL and DRL are suitable options for decision-making in complex dynamic environments with unknown and uncertain information, as they do not require complete knowledge of the system. RL methods are based on the Markov Decision Process, which is an effective mathematical tool for modeling the agents' interactions in a dynamic environment to achieve a long-term goal [74]. Despite the advancements, RL still faces challenges induced by the exploration-exploitation dilemma, where the agent needs to acquire sufficient interaction samples in environments with unknown dynamics, partial observability, sparse feedback, and high complexity of state and action spaces [80].

C. Review of previous similar studies

In a study, Nazareth and Reddy [41] examined the application of machine learning methods (traditional and deep) in financial markets (including the forex market) by reviewing 126 articles. The study results show that among different methods, deep learning methods are employed more in financial markets. However, these findings emphasize that the applications of DNN and RL are currently limited in financial fields, even though have increased over time. Furthermore, while the full extent of their potential is yet unknown, the use of hybrid models combining different deep-learning techniques has been more popular in recent years. Ayitey et al. [6] reviewed 60 studies on Forex market forecasting using ML models (traditional and deep). Based on the results, LSTM is among the most widely used methods and machine learning methods still have a lot of capacity to predict the price of currency pairs. Hu et al. [26] in a study reviewed 89 articles on the application of deep learning to predict the price of currency pairs in the forex market. Various types of deep learning methods, dependent variables, and input features were investigated and compared. The study results showed that few studies exploit mixed methods and also it seems that the use of deep learning in the forex market has increased exponentially in recent years. These findings suggest the following:

- Limited focus on specific markets: previous studies often cover multiple financial domains, which limits the number of papers dedicated to specific markets like the forex market.
- Insufficient deep learning coverage: in reviews covering broad financial areas, a small proportion of studies focus specifically on deep learning applications in the forex market. For example, only 7 out of 129 articles reviewed by nazareth and reddy [41] pertain to deep learning in the forex market.
- Limited studies on deep learning in forex: even in studies specifically about the forex market, deep learning is underrepresented. For instance, in ayitey et al. [6], only 26 out of 60 studies focus on deep learning models.
- Narrow review scope in previous research: Hu et al. [26] reviewed 89 articles on deep learning for predicting currency pairs, but only 5 studies were about the forex market, indicating a narrow scope in previous research.

These challenges highlight the need for more focused and comprehensive studies on deep learning in the forex market, as addressed in the current paper.

III. METHODOLOGY

The methodology of this study follows a systematic review approach based on the PRISMA standard, which ensures minimum evidence-based criteria for reporting in systematic reviews and meta-analyses. The methodology includes the following steps:

A. Article Collection: A.1. Relevant articles focusing on exchange rate forecasting using deep learning methods were collected. A.2. To capture both past and current research trends, a broad set of keywords was identified and used in the search process.

B. Database Selection: B.1. Unlike some previous studies that relied on a single source, this study utilized multiple databases, including Google Scholar, ScienceDirect, Springer, EBSCOhost, Taylor & Francis, and Sid.ir. B.2. This multi-source approach was adopted to ensure a comprehensive collection of relevant literature.

C. Search Strategy: C.1. An advanced search was conducted within the titles, keywords, and abstracts of articles published after 2015. C.2. The search included both Persian and English keywords related to deep learning techniques (e.g., LSTM, CNN, RNN, GRU, and RL) in combination with terms like "exchange rates", "currency pairs" and "forex."

D. Inclusion and Exclusion Criteria: D.1. Articles were screened for relevance, focusing on those that directly pertain to the application of deep learning in exchange rate forecasting. D.2. Irrelevant studies were excluded, ensuring that the final selection was highly focused on the research objectives.

E. Data Extraction: E.1. Key information from the selected articles was extracted, including the deep learning models used, the types of data employed, forecasting periods, data frequency, and evaluation criteria. E.2. This data was systematically organized to facilitate comparison and analysis.

F. Analysis and Synthesis: F.1. The extracted data was analyzed to identify common trends, advantages, and limitations of using deep learning methods in exchange rate prediction. F.2. Potential gaps in the literature were identified, providing a basis for recommendations for future research.

G. Reporting: G.1. The findings were reported according to the PRISMA guidelines, to ensure transparency and reproducibility. G.2. The results were synthesized to offer a comprehensive overview of the current state of research in this area, with a focus on deep learning applications in the forex market.

Regarding the pivotal role of the article collection section within the research methodology, a thorough explanation of the selection, collection, and filtering processes has been provided in the following:

Review of studies

Based on the objective of this article, articles related to the topic of exchange rate forecasting were collected with a focus on deep learning methods, and also, past and present study trends and keywords were identified. Our objective is to investigate the trend of research articles in the field of exchange rate forecasting by deep learning methods. In this regard, the articles published after 2015 in several databases were extracted. An (advanced) search of the article's titles, keywords, and abstract has been conducted for this reason. Enumerated values for the search filters are shown in Table 1.

Screening

Firstly, by going over the titles, we excluded the unrelated and repeated articles. Then, the abstracts of the articles were carefully read and the articles that had little relation to the subject were excluded. Furthermore, with an overview of the text of the articles, the articles that lacked the desired prediction model or methods or criteria for evaluating the results were excluded from the final list.

Text review

At this stage, the texts of the selected articles were carefully reviewed. The articles without the details of the model or the learning method were excluded from the list. Besides, articles that were not about exchange rates or forex currency pairs were excluded. After filtering this section, 44 articles remained. Figure 2 shows our process of searching and extracting articles.

Data extraction

At this stage, we extracted the data that address our research questions. The data include the model or algorithm used in the article, the target variable, the data used to estimate the exchange rate, the period, the frequency of the data, and the evaluation criteria of the forecasting method.

Quantitative review of the results

Table 2 shows the number of articles extracted under each title, and separately for journal and conference articles. The number of articles obtained from LSTM, CNN, LR, RNN, and GRU is 17, 12, 7, 5, and 3, respectively, and a total of 30 articles were published in scientific and research journals and 14 were conference articles. Figure 3 shows the distribution of articles in terms of the year of publication and the method used for exchange rate forecasting. According to the results, the largest number of articles have been published by all deep learning methods except for GRU in 2020. It seems that the trend of using deep learning methods for exchange rate forecasting has been upward since 2017, and reached its peak in 2020, then reduced in 2021 and slightly increased again in 2022. Given that the articles of 2023 have not been fully published, it is not possible to judge the number of articles of this year at this time. Figure 4 shows the distribution of different forecasting methods used in the extracted articles. As shown, LSTM has been the most frequent among others.

TABLE I. FILTERS USED IN THE PROCESS OF SEARCHING FOR ARTICLES

Filter	Defined range
Year of publication	Articles published since 2015
Type of document	Scientific research articles or conference articles
Language	Persian or English
Text available	Complete file available

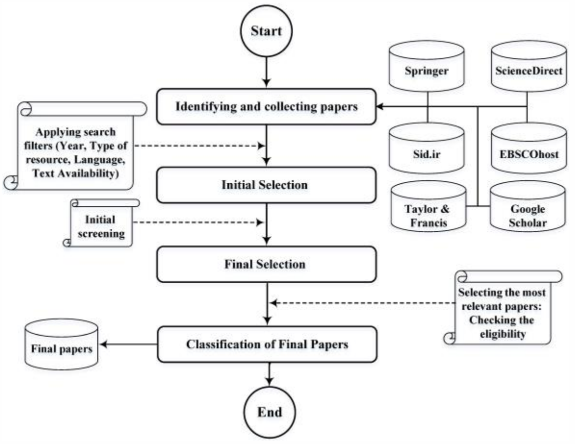

Figure 2. The process of searching and extracting articles

TABLE II. DISTRIBUTION OF ARTICLES IN TERMS OF FORECASTING METHOD AND TYPE OF ARTICLE

Method	Total Number	Number of Journal Articles	Number of Conference Articles
CNN	12	10	2
RNN	5	2	3
LSTM	17	10	7
GRU	3	3	0
RL	7	5	2

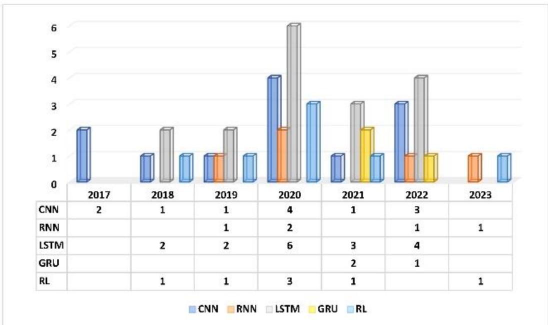

Figure 3. Distribution of articles in terms of publication year and currency exchange rate forecasting method

Criteria of classification

As previously stated, the primary goal of this study is to categorize deep learning approaches for currency exchange rate forecasting so that the findings may most effectively guide future research in this area. Therefore, selecting the appropriate criteria for classifying methods plays a crucial role in the effective use of the results for other researchers. For this purpose, while considering the classification criteria used in previous similar studies, other criteria were comprised so that researchers can utilize them in future studies. Table 3 lists the classification criteria and the reasons for the selection.

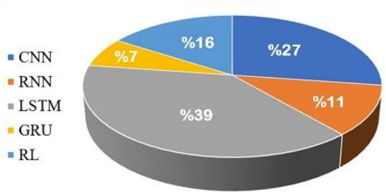

Figure 4. General distribution of forecasting methods in articles

TABLE III. LIST OF CLASSIFICATION CRITERIA AND THE NECESSITY OF THE SELECTION

No.	Criterion	Reason for selection
1	Deep learning algorithm	To find the most up-to-date and efficient methods for exchange rate forecasting with high accuracy
2	Training data set	To increase the accuracy of forecasting using ML methods, it is necessary to identify explanatory variables with high potential for improving forecasting. Moreover, extracting the duration and frequency of the used data is very important in this field.
3	data frequency	
4	Distribution of research centers	To identify the research directions of countries, and scientific synergy and use their previous research capacities and results
5	interest of researchers	
6	Target variable	Knowledge of scientific advances achieved for currency pair identification of the capacity to conduct new research and improve previous forecasts
7	Evaluation criteria	This review identifies the commonly used criteria for different forecasting methods, and obtains the frequency of different ranges for the selected criteria, which can be useful for future research.

IV. RESULTS

In the following, first, the results of studies and the criteria related to each of the deep learning methods are given, along with a brief description of each research, and then, the results of other criteria that are related to the general scope of research in the field of deep learning methods.

Results of the criteria related to the methods

- **CNN**

12 papers that used CNN for currency exchange rate forecasting in the forex market are showed in table 4. Liang et al. [34] used a combined ARIMA and CNN model and the crude oil WTI as an additional feature for forecasting China's "people's currency" renminbi (RMB) against the dollar. They concluded that using data filtering methods to decompose the target series into trend and noise (cycle) components can help improve forecasting. Panda et al. [46] showed that the combined model of CNN and RF provided more accurate forecasting than ARIMA, MLP, and linear regression models. Rostamian et al. [54] showed that the combined model of CNN and LSTM had higher prediction performance compared to SVM and random forest methods. Also, the feature of "DC" has improved the results. Moghaddam et al. [36] generated buy and sell signals by combining CNN with a hybrid CNN-LSTM model and exploiting moving average crossover as a feature. The result shows that this model performed better than the "relative strength index" (RSI) and "Bollinger bands", and CNN-bidirectional LSTM and PSR-LSTM. Pongsena et al. [47] by converting features into black-and-white images and using CNN reached accuracy of about 77%. Rahimi et al. [50] using the Sierpiński triangle found that CNN outperforms MC, ARIMA, ETS and ANN. Suchaimanacharoen et al. [59] proposed a type of RL model that has higher returns than the buy and hold strategy. Using CNN, Rassetiadi & Suharjito [52] showed that adding natural gas simultaneously with FTSE 100 to the model provided the best result. Tsai et al. [63] showed that simulating prices by GBM model then feeding these results and obvious trend into CNN, improves forecasting. Galeshchuk & Mukherjee [22] used MC, ARIMA, ETS, ANN, ANN, SVM, and CNN for currency pair forecasting in the forex market. The results of their study show that CNN performed much better than other models and methods. Liu et al. [35] proposed a CNN model that has higher accuracy in comparison with ANN, SVM, and GRU. Galeshchuk & Demazeau [21] proposed a CNN model that outperforms random walk, ARIMA and MLP.

- **RNN**

5 articles that used RNN for currency exchange rate forecasting in the forex market are briefly described below. Table 5 shows the reference number, author, year of publication, database, target variable, period, evaluation criteria, features used, and data frequency of these articles. Faru et al. [19] showed that while RNN-LSTM exhibited superior performance in certain currencies, LSTM delivered more precise forecasts in others. Singh et al. [58] introduced an RNN that performed significantly better than CNN-RNN. Using RNN, LSTM, BiLSTM and GRU, Qi et al. [48] showed that the event-based features made the investment strategy stronger, increased the forecasting accuracy, and reduced the risk. Dautel et al. [14] showed that RNN is more efficient than FNN, LSTM, and GRU. Shiao et al. [55] showed that RNN-LSTM has better performance than SVM in rate forecasting.

- **LSTM**

17 articles that used LSTM for currency exchange rate forecasting in the forex market are briefly described below. Table 6 shows the reference number, author, year of publication, database, target variable, period, evaluation criteria, features used, and data frequency of these articles. In an article, Windsor et al. [70] proposed a MS-LSTM that outperforms SVR, BPNN, ELM, CNN, and LSTM. Claveria et al. [12] showed that DFNN and LSTM performed better and CNN perform worse than the ARIMA model. Fallah et al. [16] in a study predicted the rate of the US dollar against Iranian rial using LSTM and GARCH. The study results showed that LSTM performed better than GARCH models, including GARCH, GJR-GARCH, IGARCH and SGARCH. Also, GJR-GARCH is more accurate for currency exchange rate forecasting than other GARCH models. Lee, J. S. et al. [32] showed that when the size of the training data is large, LSTM and CNN perform better than the ARIMA model, and vice versa. Wang et al. [67] proposed a CNN-TLSTN model that outperforms MLP, CNN, RNN, LSTM, and CNN-LSTM. Nemavhola et al. [42] showed that when MAE is used to compare the performance, ARIMA, SVR and LSTM have the best performance, and if the MSE performance is used as the basis, then LSTM, SVR and ARIMA provide higher performance in forecasting. Yilmaz et al. [73] proposed an ARIMA-LSTM that outperforms RW, ARIMA, ARFIMA, MLP, SVR, TAR, GRU, RNN, and LSTM. Cao et al. [9] introduced DC-LSTM, which processes market information and macroeconomic information with the LSTM method

and then uses the outputs of these two methods as input for another LSTM. This model outperforms the others in predicting currency exchange rates. Sun et al. [60] Proposed a LSTM-B by simulating the data set k times using the bootstrapping statistical method, and then made k LSTM networks. This model outperforms RW, ARMa, MLP, RBFNN, GRNN, ELMAN, WNN and ELM. Wijesinghe [69] proposed forex market currency pair forecasting using LSTM. The evaluation of the results shows that the proposed LSTM has performed better in forecasting compared to the EMA and ARIMA models. Aggarwal et al. [3] showed that LSTM has better forecasting performance than SRNN and GRU. Zahrah et al. [75] used LSTM for EUR/USD currency pair price forecasting in the forex market. They studied the effect of COVID-19 pandemic on the accuracy of LSTM. The results showed that the accuracy has reduced during the pandemic period, but still, during this period, LSTM can provide good accuracy for currency pair forecasting. Ahmed et al. [4] modified the LSTM loss function through the introduction of the FLF-LSTM that performed better than classical LSTM, RNN, ARIMA, and FB Prophet for currency exchange rate forecasting. Qu et al. [49] using OHLC price data along with 14 as features showed that LSTM compared with RNN has better performance for currency exchange rate forecasting. Lee, C. I. et al. [31] studied the performance of LSTM-attention, LSTM, ARIMA, SARIMA, and SLP for currency exchange rate forecasting. They extracted two different sentiment indicators using SnowNLP and the simple lexical method from the released news and then entered them as explanatory variables in the models. The results showed that adding sentiment indicators reduced the error by 15%. Also, LSTM-attention had the best performance for currency exchange rate forecasting. Zhang [77] proposed EMD-LSTM for foreign exchange rate forecasting. In this method, the time series of the exchange rate is first decomposed into Intrinsic Mode Functions (IMFs), and residual components by Empirical Mode Decomposition (EMD), then all the decomposed components, along with the residual are separately fed to the LSTM network to extract the forecast. The study results showed that the proposed method performed better than ANN and LSTM as well as the ARIMA model for the variable forecasting. Sun et al. [61] proposed AdaBoost-LSTM which performs better than LSTM, GRU, and Simple Moving Average (SMA).

- **GRU**

3 articles that used GRU for currency exchange rate forecasting in the forex market are shown in table 7 and briefly described below. Mabrouk et al. [36] introduced a combined CNN-GRU model for currency exchange rate forecasting in the forex market. CNN processes the variables in this model prior to passing the results to a GRU model, which uses them to generate buy and sell signals for the following trading day. The results showed that the strategy obtained from this method had better performance than SVR and LR. Islam and Hossain [27] proposed a combined GRU- LSTM model for forecasting the price of currency pairs. The study results showed that the proposed model performed better than LSTM, GRU, and Simple Moving Average. Yaraklou and Rabiei [72] used LSTM and GRU to forecast the dollar rate against the rial. The study results showed that GRU performed better for currency exchange rate forecasting.

- **RL**

7 articles that used RL to forecast exchange rates in the forex market are briefly described below and shown in table 8. Jamali et al. [29] first predicted the exchange rate using multiple regression and then extracted the best result by "Simulated Annealing" optimization algorithm. Next, the results were the inputs of trained RL, and finally, the output of the RL along with RSI was used to generate buy and sell signals. Tsantekidis et al. [65] proposed an RL approach in which teacher agents are first trained in different subsets of the RL space, whereby they diversify the policies they have learned. Then, the student agents are trained using the extracts of the teacher agents, leading to a better discovery of the solution space. The study results showed that this approach will improve the performance of the strategy. Zhang et al. [78] results showed that the performance of the strategy by RL and the Deep Q Network (DQN) algorithm was better than other approaches. Tsantekidis et al. [66] proposed a new RL on price sequences as rewards instead of profit and loss that improved the performance of conventional RL. Tsai et al. [64] used RL to design an investment strategy in the forex market. In this study, the Sure-Fire statistical arbitrage investment policy was used. Furthermore, the objective variables' time series were represented graphically through the use of a heat map and Gramian Angular Field (GAF). Furthermore, the proposed RL incorporated two distinct algorithms, namely "Proximal Policy Optimization" (PPO) and DQN, and compared their outcomes. The profitability of the business indicates that PPO outperformed DQN. Zarkias et al. [76] proposed a new RL in which the investor makes different investment decisions based on his forecast of the bullish or bearish state of the market. The study results showed that the proposed method is more profitable than the traditional method. Carapuco et al. [10] proposed a new RL for short-term trading in the forex market. This approach uses ReLU neurons in hidden layers and a Q learning algorithm. Thus, the market environment is simulated in a way that causes stable learning. The strategy resulting from this approach has brought good annual returns for currency.

Results of other criteria

This section presents the findings of 44 studies that were reviewed in this research, encompassing various dimensions. The information provided is valuable for researchers and future studies, as it outlines trends, models, and orientations in the domain of deep learning-based currency exchange rate forecasting.

TABLE IV. EXTRACTED ARTICLES ON THE USE OF CNN FOR CURRENCY EXCHANGE RATE FORECASTING

Auther(s)	Year	Journal /Database	Variables	Time Period	Performance Metric(s)	Feature(s)	Freq.	Ref. No.
Liang F, Zhang H, Fang Y.	2022	Journal of Organizational and End User Computing (JOEUC)	RMB/USD	Jan. 2015 to Oct. 2019	MAE = 0.0091, MAPE = 0.1295, RMSE = 0.0198, Theil-U = 0.0015, DAR = 0.9309	Currency Price	-	[34]
Panda MM, Panda SN, Pattnaik PK.	2022	International Journal of Advanced Computer Science and Applications	AUD/JPY NZD/USD GBP/JPY	Jan. 2001 to May. 2020	MAE = 0.1634, RMSE = 0.1942	OHLCV	Monthly	[46]
Rostamian A, O'Hara JG.	2022	Neural Computing and Applications	EUR/USD GBP/USD USD/CHF USD/CAD	Jan. to Aug. 2019	MAE = 0.0188, RMSE = 0.0248, R^2 = 0.972	OHLCV	-	[54]
Moghaddam AH, Momtazi S.	2021	Applied Soft Computing	EUR/USD	Mar. to Jul. 2020	Profit = 0.0217	OHLC	Monthly	[39]
Pongsena W, Ditsayabut P, Kerdprasop N, Kerdprasop K.	2020	International Journal of Machine Learning and Computing	EUR/USD	Jan. 2000 to Sep. 2018	ACC = 77.48	Currency Price & 15 Technical Indicators	Daily	[47]
Rahimi F, Mousavian Anaraki SA.	2020	Journal of Money and Economy	EUR/USD	Jan. 2019 to Feb. 2020	ACC = 70.28	Currency Price	-	[50]
Suchaimanacharoen A, Kasetkasem T, Marukatat S, Kumazawa I, Chavalit P.	2020	IEEE	EUR/USD	Jun. 2014 to Oct. 2018	Returns = 0.5222	Moving Average	30 Min.	[59]
Rassetiadi R, Suharjito S.	2019	Indonesian Journal of Electrical Engineering and Computer Science	EUR/USD	Jan. 2000 to Oct. 2018	MSE = 0.000589	OHLC, DAX, Dow, FTSE 100, NASDAQ, S&P500, Brent Oil, Copper, Gold, Natural Gas, Silver	-	[52]
Tsai YC, Chen JH, Wang JJ.	2018	Journal of Intelligent Systems	USD/JPY	2010 to 2011	ACC = 79.07	Currency Price		[63]
Galeshchuk S, Mukherjee S.	2017	Intelligent Systems in Accounting, Finance and Management	EUR/USD GBP/USD USD/JPY	2010 to 2015	ACC = 89.55	Close	Daily	[22]
Liu C, Hou W, Liu D.	2017	Neural Processing Letters	EUR/USD GBP/USD USD/JPY	Jan 2001 to Dec. 2015	MAPE = 0.006, MSE = 0.000104, R^2 = 0.996, DS = 0.9806, CEV = 0.9941	Currency Price	1 Hour / Daily	[35]
Galeshchuk S, Demazeau Y.	2017	IEEE	EUR/HUF USD/HUF	2000 to 2017	ACC = 73.2	Currency Price	Daily	[21]

TABLE V. EXTRACTED ARTICLES ON THE USE OF RNN FOR CURRENCY EXCHANGE RATE FORECASTING

Auther(s)	Year	Journal /Database	Variables	Time Period	Performance Metric(s)	Feature(s)	Freq.	Ref. No.
Faru SH, Waititu A, Nderu L.	2023	Journal of Data Analysis and Information Processing	GBP/USD CAD/CHF EUR/CAD USD/ZAR AUD/NZD	2022	MAE = 0.006473 MAPE = 0.0058 RMSE = 0.00076	Stochastic Oscillator, Bollinger Band, Relative Strength Index, Exponential Moving Average	-	[19]
Singh G, Sarangi PK, Rani L, Sharma K, Sinha S, Sahoo AK, Rath BP.	2022	IEEE	USD/INR	Sep. 2020 to Mar. 2022	MAPE = 0.0022	Currency Price	Daily	[58]
Qi L, Khushi M, Poon J.	2020	IEEE	GBP/USD EUR/GBP AUD/USD	Jan. 2005 to Sep. 2017	MAE = 0.00025 MAPE = 1.945 MSE = 0.00071 RMSE = 0.00026	Currency Price & 28 Technical Indicators	15 Min.	[48]
Dautel AJ, Härdle WK, Lessmann S, Seow HV.	2020	Digital Finance	EUR/USD GBP/USD USD/JPY USD/CHF	Jan. 1971 to Aug. 2017	ACC = 0.5019 AUC = 0.5003 Returns = 0.0406 Sharpe ratio = 0.024	The Time Series of Scaled Returns	Daily	[14]
Shiao YC, Chakraborty G, Chen SF, Li LH, Chen RC.	2019	IEEE	USD/JPY	Dec. 2017 to Oct. 2018	RMSE = 0.346	Close	5 Min.	[55]

TABLE VI. EXTRACTED ARTICLES IN THE FIELD OF USING LSTM FOR CURRENCY EXCHANGE RATE FORECASTING

Auther(s)	Year	Journal/Database	Variables	Time Period	Performance Metric(s)	Feature(s)	Freq.	Ref. No.
Windsor E, Cao W.	2022	Applied Intelligence	USD/CNY	Jan. 2015 to Apr. 2021	MAE = 0.129 MSE = 0.0004 RMSE =0.0161 R^2 = 0.9848	A Sentiment Indicator on Social Media Microblogs	Daily	[70]
Clavería González Ó, Monte Moreno E, Sorić P, Torra Porras S.	2022	SSRN	GBP/USD	Jan. 1971 to Jan. 2020	MAPE = 0.002 MSE = 1.966	Currency Price	Daily	[12]
Fallah R, Shirkund Z.	2022	Kankash Journal of management and accounting	USD/IRR	Oct. 2019 to Oct. 2021	RMSE = 0.002456	Currency Price	Daily	[16]

Lee JS, Yong YL, Hoo MH, Khor KC.	2022	Springer International Publishing	GBP/USD AUD/USD USD/JPY	Dec. 2007 to Mar. 2022	MAE = 0.003625	OHLC	Daily	[32]
Wang J, Wang X, Li J, Wang H.	2021	IEEE	USD/CNY	Jan. 2006 to Oct. 2020	MAPE = 0.2245 MSE = 0.00047 R^2 = 0.9894	Nasdaq Index, Dow Jones Industrial Average, Shanghai Composite Index, Hang Seng Index	Daily	[67]
Nemavhola A, Chibaya C, Ochara NM.	2021	IEEE	USD/ZAR	Jan. 2006 to Sep. 2020	MAE = 0.136 MSE = 0.0.0019	Date, Time, OHLCV	Daily	[42]
Yilmaz FM, Arabaci O.	2021	Computational Economics	GBP/USD AUD/USD CAD/USD	Jan. 1990 to Oct. 2019	MAE = 0.0153 SMSE = 0.0142	Currency Price	Monthly	[73]
Cao W, Zhu W, Wang W, Demazeau Y, Zhang C.	2020	IEEE Intelligent Systems	USD/CNY	Jan. 2009 to Apr. 2019	MAE = 1.0134 RMSE = 0.0179 ACC = 69.68	WTI Crude Oil Price, Gold Price, Shanghai Stock Exchange Composite Idx, Dow Jones Idx, Macro-Level Data, Chinese Money Supply Idx (M1 & M2), Chinese Consumer Index, Producer Price Index, Industrial Production Idx, Shibor 1-Week Rate (CHN), Federal Fund Rate (US), Chinese Inflation Rate, Trade Balance Idx, Payment Balance Idx, Chinese Economic Policy Uncertainty Idx, US Economic Policy Uncertainty Idx, Global Economic Policy Uncertainty Idx	3 Month	[9]
Sun S, Wang S, Wei Y.	2020	Advanced Engineering Informatics	EUR/USD GBP/USD USD/JPY USD/CNY	Jan. 1993 to Mar. 2019	RMSE = 0.0018	Currency Price	Daily	[60]
WIJESINGHE S.	2020	Instrumentation	GRB/USD USD/CAD AUS/CAD	Jan. 2011 to Dec 2018	MAE = 0.005267 MAPE = 0.4016 RMSE = 0.00686	GDP, Interest Rate, Inflation, Imports & Exports, Government Spending, Unemployment Rate	-	[69]
Aggarwal P, Sahani AK.	2020	IEEE	22 Currency Pair	2000 to 2019	MAE = 0.0475 MSE = 0.0004	Currency Price	-	[3]
Zahrah HH, Saâ S, Rismala R.	2020	International Journal on Information and Communication Technology	EUR/USD	May. 2010 to Oct. 2020	RMSE = 0.00135	OHLC	Daily	[75]
Ahmed S, Hassan SU, Aljohani NR, Nawaz R.	2020	Applied Soft Computing	EUR/USD	Jun. 2015 to Sep. 2018	MAE = 0.001529	OHLC	4 Hour	[4]
Qu Y, Zhao X.	2019	Journal of Physics	EUR/USD	Jun. 1993 to Mar. 2018	MAE = 57.54 RMSE = 75.17	OHLC, Short-Term, Medium-Term and Long-Term Moving Average (MA3) (MA20) (MA73), Exponential Smoothing with Moving Average (MACD), Boll, Bias, Relative Strength Index (RSI) And Other Data Sets Of 18 Dimensions	-	[49]
Lee CI, Chang CH, Hwang FN.	2019	IEEE	AUD/USD	Jan. 2016 to Mar. 2019	MAPE = 0.0052 RMSE = 0.0046	News Sentiment Index	-	[31]
Zhang B.	2018	Journal of Physics	USD/CNY EUR/CNY USD/EUR	Jan. 2000 to Apr. 2018	MAE = 0.001294 MSE = 0.000003 MAPE = 0.151	Currency Price	Daily	[77]
Sun S, Wei Y, Wang S.	2018	Computational Science	EUR/USD USD/CNY	Jan. 2015 to Dec. 2016	MAPE = 0.172 DS = 77.78	S&P 500 Index and Shanghai Composite Index	Daily	[61]

TABLE VII. EXTRACTED ARTICLES ON THE USE OF GRU FOR CURRENCY EXCHANGE RATE FORECASTING

Auther(s)	Year	Journal /Database	Variables	Time Period	Performance Metric(s)	Feature(s)	Freq.	Ref. No.
MABROUK N, CHIHAB M, HACHKAR Z, CHIHAB Y.	2022	International Journal of Advanced Computer Science and Applications	EUR/USD	Jan. 2014 to Jan. 2021	ACC=0.741	OHLCV+10 Technical Indicators	Daily	[36]
Islam MS, Hossain E.	2021	Soft Computing Letters	EUR/USD GBP/USD USD/CAD USD/CHF	Dec. 2018 to Jan 2019	MAE=0.00224 MSE=0.00001 RMSE=0.00301	Currency Price	Daily, Weekly, Monthly	[27]
Yaraklou M, Rabiei A.	2021	Computing Science Journal	USD/IRR	1993 to 2018	MAE=22.24±0.57 RMSE=34.48±1.2	Hour, Day, Week, Momentum, Average Price, Range, And OHLC	10 Min., 30 Min.	[72]

TABLE VIII. EXTRACTED ARTICLES ON THE USE OF RL FOR CURRENCY EXCHANGE RATE FORECASTING

Auther(s)	Year	Journal /Database	Variables	Time Period	Performance Metric(s)	Feature(s)	Freq.	Ref. No.
Jamali H, Chihab Y, García-Magariño I, Bencharef O.	2023	ISSN	EUR/USD	Oct. 2016 to Sep. 2020	Profit = 0.0232	OHLC+RSI	Daily	[29]

Tsantekidis A, Passalis N, Tefas A.	2021	Neural Networks	EUR/USD EUR/GBP GBP/JPY	2016 to 2018	Profit = 0.34±0.03	OHLC+Features represent the price range within a single candle in terms of its fraction to the close price of that candle	1 Hour	[65]
Zhang Z, Zohren S, Roberts S.	2020	The Journal of Financial Data Science	9 Different Forex contracts	2005 to 2019	Return = 0.528, DD = 0.553 SR = 0.546 Sortino = 0.955 MDD = 0.183 Calmar = 0.313 % +ve Ret. = 0.51 Ave. P to L=1.051	futures contracts prices	-	[78]
Tsantekidis A, Passalis N, Toufa AS, Saitas-Zarkias K, Chairistanidis S, Tefas A.	2020	IEEE Transactions on neural networks and learning systems	28 Currency Pair	2009 to Jun. 2018	Profit = .062 SR =1.525 MDD = 1.6	OHLC+the returns, the log returns and the distances of the current price to a moving average	-	[66]
Tsai YC, Wang CC, Szu FM, Wang KJ.	2020	Springer International Publishing	EUR/USD	Dec. 2018	Profit = 753 MDD = -5.18	Currency Price	4 Hour	[64]
Zarkias KS, Passalis N, Tsantekidis A, Tefas A.	2019	IEEE	EUR/USD	2007 to 2015	Profit = 0.27	Currency Price	4 Hour	[76]
Carapuço J, Neves R, Horta N.	2018	Applied Soft Computing	EUR/USD	2013	Profit = 109.1±17.8	Currency price, mean, maximum, standard deviation, minimum values for the different components of tick data: bid, ask prices, volumes	-	[10]

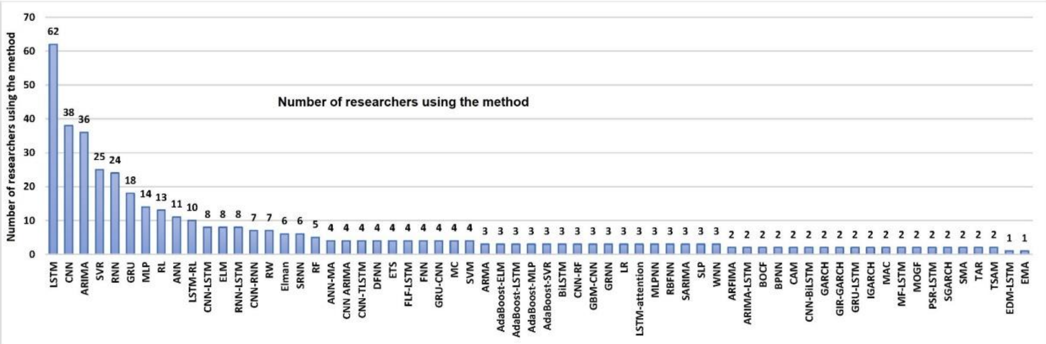

Figure 5. Number of researchers interested in various forecasting methods

Continent	Country	No. of Research Cent.
Europe	Australia	3
	Germany	3
	Spain	5
	France	4
	United Kingdom	6
	Sweden	1
	Greece	10
	Portugal	3
Asia	Bangladesh	2
	China	25
	Indonesia	5
	India	12
	Iran	8
	Japan	4
	Sri Lanka	1
	Malaysia	5
	Pakistan	2
	Thailand	8
	Turkey	2
	Taiwan	10
Africa	Kenya	3
	Morocco	7
	South Africa	1
Americas	United States	1

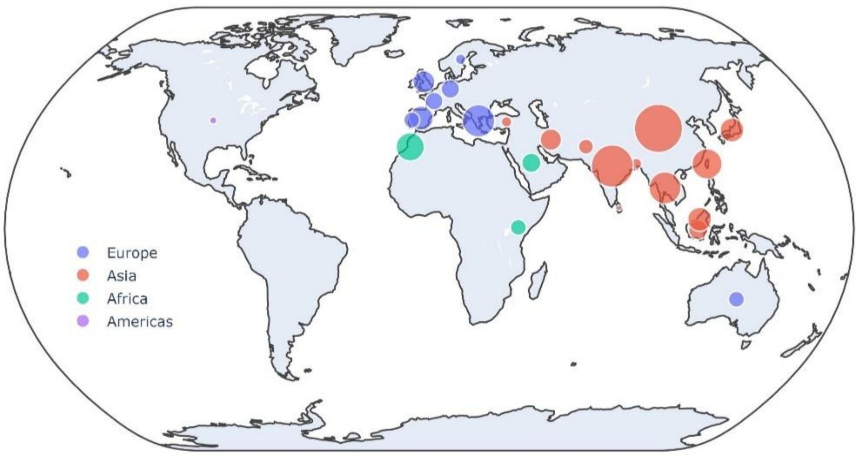

Figure 6. Geographical distribution of scientific centers related to the reviewed studies in this study

- **Forecasting methods**

Most of the 33 studies reviewed in this research, although the focus has been on using deep learning methods, have used the combined approach of methods as well as compared the results of different methods with each other. Hence, other diverse methods in addition to deep learning methods have been of interest to researchers. Figure 5 shows the research interest of the researchers in the above methods whose studies were reviewed in the scope of this research.

- **Research centers**

The studies reviewed in this research were conducted by researchers from different scientific, and research centers in countries from the three continents of Europe, Asia, and Africa. Figure 6 shows the geographical distribution of these centers, which somehow represents the focus and research orientation of scientific centers and researchers active in this field.

• **Currency pairs**

In the reviewed studies, a wide variety of currency pairs have been of interest to researchers. The literature review shows that EUR/USD currency pair forecast as the most common puts it in the position of the most prominent standard for determining exchange rate, followed by the USD/GBP currency pair. This shows that most studies have attempted to predict exchange rates between North America and Europe. The review of this study confirms the results of previous studies especially the results of Nazareth and Reddy [41]. Paying attention to the methods used for currency pair forecasting will provide good insight for future researchers to develop and improve the results of previous studies so that they can target a more appropriate and accurate scope for their research. This study shows that among the five deep learning methods, first, LSTM is the most widely used method to predict the most common currency pair (i.e. EUR/USD), and second, among five studied methods, in four methods, EUR/USD is the most common currency pair among researchers (Figure 7).

• **Evaluation methods**

In this section, we examine the methods of evaluating the results of extracted articles. This section is important from the point of view that it shows the common evaluation criteria in different methods. Therefore, researchers can select appropriate criteria for their future research. Furthermore, a closer examination has been given to a few of the most often evaluation criteria, as well as an examination of the many ranges that may be determined by that criterion. From this point of view, it is feasible to determine which field appears most often in the criteria, which may provide a more reliable foundation for assessing how well other research is performed. Table 9 reports the total number of evaluation criteria used along. As shown, a total of 21 criteria have been used for evaluation, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Accuracy (ACC) were the most frequently used by 17, 17 ,11 ,10 and 8 times, respectively.

Table 10 reports MAE, SMSE, and MAPE separately in different ranges. The results show that for MAE and SMSE, the range of 0.01-0.001 and 0.1-0.01 have been the most frequent with 7 and 5 reports, and also for MAPE the ranges of 0.001-0.01 and 0.1-1 have been the most frequent with 4 and 5 reports in the articles.

Table 11 reports MSE separately in different ranges. The results show that the ranges of 0.00001-0.0001 and 0.0001-0.001 have been the most frequent with 4 and 3 reports in the articles, respectively.

Table 12 reports ACC separately in different ranges. This measure reports the accuracy of results, and a higher value indicates higher accuracy (%). This is used for studies that attempt to predict DC and obtain the so-called classification of the future value of the variable. The results show that the range of 70-80% with 5 reports in the articles was more frequent.

TABLE IX. FREQUENCY OF EVALUATION METHODS IN ARTICLES

No.	Evaluation Criteria (EC)	Num.	Ref.
1	MAE	17	[9], [77], [49], [69], [70], [42], [3], [4], [73], [32], [34], [46], [54], [27], [72], [48], [19]
2	RMSE	17	[9], [49], [60], [69], [70], [75], [31], [73], [16], [34], [46], [54], [27], [72], [48], [55], [19]
3	MAPE	11	[77], [67], [61], [69], [12], [31], [34], [35], [48], [58], [19]
4	MSE	10	[77], [67], [70], [42], [3], [12], [52], [35], [72], [48]
5	ACC	8	[9], [22], [47], [50], [21], [63], [36], [14]
6	Profit	7	[39], [76], [29], [66], [10], [65], [64]
7	R2	4	[67], [70], [54], [35]
8	Returns	3	[59], [14], [78]
9	Sharpe Ratio	3	[14], [66], [78]
10	MDD%	3	[66], [78], [64]
11	DS%	2	[61], [35]
12	Sortino	1	[78]
13	DD	1	[78]
14	Calmar	1	[78]
15	%+ve Return	1	[78]
16	Ave. P to Ave. L	1	[78]
17	Theil-U	1	[34]
18	DAR	1	[34]
19	AUC	1	[34]
20	DA%	1	[34]
21	CEV	1	[34]

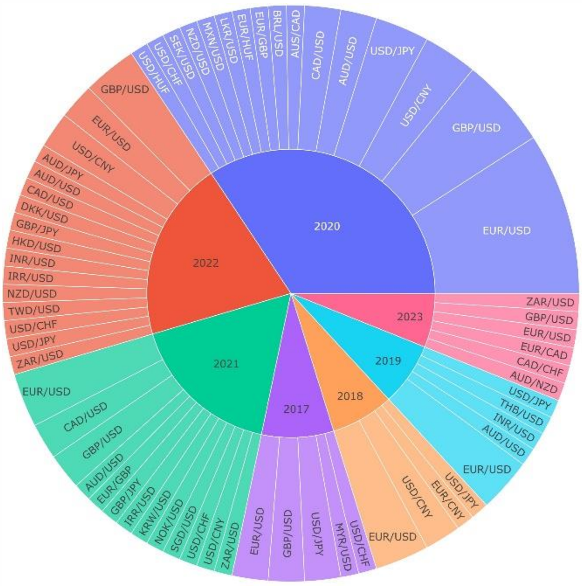

Figure 7. Variety of currency pairs and their forecasting methods

TABLE X. MAE, SMSE, AND MAPE RANGES IN ARTICLES

EC	Range	Num.	Ref.
MAE	< 0.001	1	[48]
	0.001-0.01	7	[77], [4], [72], [32], [69], [19], [34]
	0.01-0.1	5	[9], [70], [3], [73], [54]
	0.1-1	2	[42], [46]
	> 1	2	[49], [27]
SMSE	< 0.001	1	[48]
	0.001-0.01	7	[75], [60], [16], [72], [31], [69], [19]
	0.01-0.1	5	[9], [70], [34], [73], [54]
	0.1-1	2	[46], [55]
	> 1	2	[49], [27]
MAPE	0.001-0.01	4	[31], [58], [16], [35], [19]
	0.01-0.1	0	-
	0.1-1	5	[77], [67], [61], [69], [34]
	> 1	2	[12], [48]

TABLE XI. MSE RANGES IN ARTICLES

Range	Num.	Ref.
< 0.00001	1	[77]
0.00001-0.0001	4	[67], [70], [72], [35]
0.0001-0.001	2	[48], [52]
0.001-0.01	3	[42], [3], [12]

TABLE XII. ACC RANGES IN ARTICLES

Range	Num.	Ref.
%50-60	1	[14]
%60-70	1	[9]
%70-80	5	[47], [36], [50], [21], [63]
%80-90	1	[22]

V. CONCLUSION

In this study, we introduced different methods of currency exchange rate forecasting using deep learning methods. In this regard, we presented a comprehensive overview of fundamental and technical approaches including different models and methods. Next, we extracted and evaluated the articles using LSTM, CNN, RNN, GRU, and RL. At this stage, showing the distribution of articles from different aspects t, we examined various information about the articles and then extracted and interpreted, the evaluation criteria and scope of some widely used criteria. the results of which are as follows:

Forecasting method: Most of the articles were published by all deep learning methods except GRU in 2020. It seems that the trend of using deep learning methods for currency exchange rate forecasting has been upward since 2017 and reached a peak in 2020. Also, LSTM has been the most frequent among different methods.

Research center: The results showed that during the studied period, Asia and the scientific centers of China had the largest number of researchers and studies in this field, followed by India and Thailand, respectively. After Asia, Europe is the next.

Target variable: Among the currency pairs that were selected as the target variable, EUR/USD, GBP/USD, and JPY/USD were the most frequent. Also, among the five methods, in LSTM, CNN, RL and GRU, the EUR/USD currency pair has the most frequency in currency exchange rate forecasting.

Time-frequency: In terms of time-frequency, daily, minute (1, 5, 10, 15 and 30 minutes), hourly (1 and 4 hours), monthly, seasonal and weekly frequency with 19, 6, 5, 2, 1 and 1 cases were the most common. This finding showed that the long-term time horizon such as seasonal, weekly and monthly has been considered less and more attention was paid to shorter-term horizons.

Features: The features, such as final price (only), technical indicators, OHLC or OHLCV prices only, fundamental variables, market indicators, time, and sentiment indicators by 16, 8, 7, 3, 3, 2, and 2 were used, respectively. It seems that most researchers have used the price and trading variables for forecasting, and the tendency to use technical indicators was much more than the fundamental variables. Also, they believe that the price information, the target variable itself, and the technical criteria obtained from the market variables contain more information than the fundamental variables of the economy. An additional aspect that appears to have been overlooked is the sentiment index. It appears that there is considerable scope for future progress in the domain of artificial intelligence and linguistic and unstructured data interpretation, as evidenced by the expanding body of literature and substantial progress in this area.

Evaluation criteria: A total of 21 criteria were used for evaluation, of which MAE, RMSE, MAPE, MSE, and ACC were used the most in 17, 17, 11, 10, and 8 cases, respectively. The highest frequency for the range of MAE, RMSE, MAPE, MSE and ACC is 7 cases in the range of 0.01-0.1, 7 cases in the range of 0.001-0.01, 5 cases in the range of 0.1-1, 4 cases in the range of 0.00001-0.0001 and 5 cases in the range of 70-80%.

Focus on the analysis of time series: We found that most of the studies analyzed the time series of the target variables and less focused on the issue of classification of changes.

For future research in this domain, we recommend creating more sophisticated ensembles and hybrid models combining strengths of multiple deep learning methods, since hybrids tend to outperform single models, plus, incorporating more diverse economic and alternative data signals, as variables like news sentiment, fundamentals, technical indicators remain underutilized. Moreover, analyzing more currency pairs, especially those from emerging markets, to complement the predominant analysis of EUR/USD rates, establishing more rigorous evaluation frameworks to better compare model performance across studies, and also research production-grade operationalization challenges in integrating deep learning with existing forecasting systems are another prominent and promising area of future researches. In summary, future work should build on current deep learning advancements for exchange rates but tackle some of the open gaps highlighted above through more diverse and rigorous research.

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