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Forex market forecasting using machine learning: Systematic Literature Review and meta-analysis

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Abstract

Background: When you make a forex transaction, you sell one currency and buy another. If the currency you buy increases against the currency you sell, you profit, and you do this through a broker as a retail trader on the internet using a platform known as meta trader. Only 2% of retail traders can successfully predict currency movement in the forex market, making it one of the most challenging tasks. Machine learning and its derivatives or hybrid models are becoming increasingly popular in market forecasting, which is a rapidly developing field.

Objective: While the research community has looked into the methodologies used by researchers to forecast the forex market, there is still a need to look into how machine learning and artificial intelligence approaches have been used to predict the forex market and whether there are any areas that can be improved to allow for better predictions. Our objective is to give an overview of machine learning models and their application in the FX market.

Method: This study provides a Systematic Literature Review (SLR) of machine learning algorithms for FX market forecasting. Our research looks at publications that were published between 2010 and 2021. A total of 60 papers are taken into consideration. We looked at them from two angles: I the design of the evaluation techniques, and (ii) a meta-analysis of the performance of machine learning models utilizing evaluation metrics thus far.

Results: The results of the analysis suggest that the most commonly utilized assessment metrics are MAE, RMSE, MAPE, and MSE, with EURUSD being the most traded pair on the planet. LSTM and Artificial Neural Network are the most commonly used machine learning algorithms for FX market prediction. The findings also point to many unresolved concerns and difficulties that the scientific community should address in the future.

Conclusion: Based on our findings, we believe that machine learning approaches in the area of currency prediction still have room for development. Researchers interested in creating more advanced strategies might use the open concerns raised in this work as input.

Keywords: Systematic Literature Review, Forex market, Machine learning, Meta-analysis

Introduction

The foreign exchange or forex market is the largest financial market in the world where currencies are bought and sold simultaneously. It is even larger than the stock market; According to the 2019 Triennial Central Bank Survey of FX and Over-the-Counter (OTC) derivatives markets, it has a daily volume of \$6.6 trillion [7]. It is a non-centralized market that operates 24 h a day except the weekend, which makes it unique from other financial markets. Because of its high volatility, nonlinearity, and irregularity, the forex market, unlike stocks, is one of the most complex markets [1]. The traits of Forex show differences compared to the stock, bond, and other financial markets. These differences make forex traders have more trading opportunities and advantages for profitable trades. Some of these advantages include no commissions, no middlemen, no fixed lot size, low transaction costs, high liquidity, almost instantaneous transactions, low margins/high leverage, 24-h operations, no insider trading, limited regulation, and online trading opportunities [73]. In the forex market, currency pairs are traded, with the base currency being the first listed currency and the quote currency being the second. Currency pairs compare the value of one currency to another (the base currency to the quote currency). When the prices depreciate, a quote currency is bought against the base currency, which leads to profit, and when the prices elevate, the base currency is bought against the quote currency [1]. Two main types of techniques are used to forecast future values for a typical financial time series, which are fundamental analysis and technical analysis. Fundamental analysis is a method of examining economic, social, and political issues that may influence currency prices in the forex market. In contrast, technical analysis involves using historical data price chart, which provides a roadmap for past price behavior. To forecast the future, a technical analyst looks to the past. Predicting the direction of a currency pair's movement is the most important choice in Forex. Predicting currency movement correctly can bring many benefits to traders and vice versa. In past and recent years, the research community has been highly active in predicting the forex market using machine-learning models. On one hand, many verifiable types of research have been conducted with the aim of understanding and predicting currency trends in the forex market using machine-learning models. According to Zhelev and Avresky [77], the cited literature in the field of deep learning is a basic foundation for solving the challenging problem of prediction of forex price. While the research community has spent a lot of time studying the methodologies used by researchers and practitioners in the context of predictive models in the forex market, there isn't much information on how to forecast currency pair movement in the forex market using machine-learning models and Meta-Analysis. To address this gap in knowledge, we conducted a Systematic Literature Review (SLR) on the use of machine learning (ML) techniques for forex market forecasting, with the goal of (i) understanding and summarizing current algorithms and models, and (ii) analyzing its evaluation metrics and open challenges to guide future research. Our SLR is to provide a complete examination of I machine learning as it has been considered in previous research, and (ii) the training processes used to train and assess machine learning algorithms. We also give a meta-analysis of the performance of the machine learning models that have been developed so far, as judged by their assessment criteria. In addition to examining the state of the art, we critically examined the approaches that have been applied thus far.

Research questions posed for our systematic literature review

Research Question	Motivation
1. For forecasting, what machine learning algorithm was used?	To look into the most up-to-date machine learning approaches for forecasting the FX market that has been considered so far
2. What dataset was used to train the model, the period and timeframe considered in the literature	In terms of machine learning algorithms, examine the machine learning parameters employed in previous studies. The answers to these questions will help practitioners and researchers figure out the best machine learning configuration for FX market forecasting: which training technique will produce the greatest forecasting results
3. Evaluation setup	
i. What types of validation techniques were exploited? ii. What evaluation measures were employed to get access to the prediction models?	
3. Performance Meta-Analysis: using evaluation metrics of the selected studies	Examine the approaches studied to (i) validate and (ii) assess the proposed forex market forecasting models

Related research

Our objective is to conduct a systematic literature review to comprehend and summarize studies on machine learning prediction models in the forex market. It's worth noting, however, that some secondary research on machine learning algorithms and deep learning has been proposed. [18, 27, 44, 54, 59].

According to Fletcher [18] when including advanced exogenous financial information to estimate daily FX carry basket returns, committees of discriminative techniques such as Support Vector Machines (SVM), Relevance Vector Machines (RVM), and Neural Networks) perform well.

Panda et al. [44] conducted a second SLR on Exchange Rate Prediction utilizing ANN and Deep Learning Methodologies, and offered novel approaches that were distinct according to them from 2000 to 2019, for predicted exchange rate projection the effects observed during the protected period within examined are displayed using newly proposed models such as Artificial Neural Network (ANN), Functional Link Artificial Neural Network (FLANN), Hidden Markov Model (HMM),

Support Vector Regression (SVR), an Auto-Regressive (AR) model. Some of the suggested novel neural network models for forecasting, on the other hand, took into account theoretical support and a methodical approach in model creation. This results in the transmission of new deep neural network models.

Islam et al. [27] conducted a SLR, which looked at recent advances in FOREX currency prediction using machine-learning algorithms. They utilized a keyword-based search approach to filter out popular and relevant research from papers published between 2017 and 2019. They also used a selection algorithm to decide which papers should be included in the review. They analyzed 39 research articles published on "Elsevier," "Springer," and "IEEE Xplore" that forecasted future FOREX prices within the specified time frame based on the selection criteria. According to their findings, in recent years, academics have been particularly interested in neural network models, pattern-based approaches, and optimization methodologies. Many deep learning algorithms, like the gated recurrent unit (GRU) and long short-term memory (LSTM), have been thoroughly investigated and show great promise in time series prediction.

Evaluating the Performance of Machine Learning Algorithms in Financial Market Forecasting was the subject of Ryll & Seidens [54] study, more than 150 related

publications on utilizing machine learning in financial market forecasting were reviewed in this study. They created a table across seven primary factors outlining the experiments done in the studies based on a thorough literature review. They provide a simple, standardized syntax for textually describing machine-learning algorithms by listing and classifying distinct algorithms. They conducted rank analyses to analyze the comparative performance of different algorithm classes based on performance criteria acquired from publications included in the survey. In financial market forecasting, machine-learning algorithms beat most classic stochastic methods, according to their findings. They also discovered evidence that recurrent neural networks outperform feed-forward neural networks and support vector machines on average, implying that there are exploitable temporal relationships in financial time series across asset classes and countries. The same is true when comparing the benefits of different machine learning architectures.

Sezer et al. [59] did a thorough evaluation of DL studies for financial time series forecasting implementations. Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), and Long-Short Term Memory (LSTM) were used to categorize the papers. Their findings show that, despite the fact that financial forecasting has a lengthy study history, overall interest in the DL community is increasing as a result of the use of new DL models, thus, there are numerous chances for researchers. They also attempted to predict the field's future by highlighting potential bottlenecks and opportunities in order to aid interested scholars.

Berradi et al. [6] suggested that giving the latest research of deep learning techniques applied to the financial market field can help investors to make an accurate decision. They gathered all the recent articles related to deep learning techniques applied to forecasting the financial market, which includes the stock market, stock index, commodity forecasting, and Forex. Their main goal was to find the most models used recently to solve the prediction problem using RNN, their characteristics, and their novelty. They gave all aspects that involve the process of forecasting beginning with preprocessing, the input features, the deep learning techniques, and the evaluation metrics employed. Their finding is that the hybrid model outperforms the traditional machine learning techniques, which leads to the conclusion that there is a very strong relationship between the combination of all the approaches and better prediction performance.

The goal of Henrique et al. [23] is to present methods for selecting the most important advances in machine learning applied to financial market prediction to present a review of the articles chosen, clarify the knowledge flow that the literature follows, and propose a classification for the articles. In addition, their study provides an overview of the best approaches for applying machine learning to financial time series forecasting as determined by the literature. The publications were then objectively assessed and categorized into the following categories: markets utilized as test data sources, predictive variables, predicted variables, methodologies or models, and performance metrics used in comparisons. In all, 57 papers from 1991 to 2017 were examined and categorized, spanning the specialist literature. Based on searches of connected article databases, no reviews employing such objective methodologies as main route analysis on the topic provided

here were discovered according to them. The most cited articles, those with the highest bibliometric coupling and co-citation frequencies, the most recently published articles, and those that are part of the primary path of the literature studied knowledge flow were all discussed in the study. It should be highlighted that they were objective and straightforward survey methodologies, independent of the researcher's expertise, that could be used not just for preliminary research but also as knowledge validation for seasoned experts. In addition, the prediction algorithms and key performance measures for each article were presented. In addition to using neural and SVM networks, the authors used data from the North American market extensively. Similarly, the majority of the forecasts are based on stock indexes. New suggested models will likely be compared to neural and SVM network benchmarks, using data from the North American market, as one of the probable findings regarding the categorization presented in the research. The examination of the behavior of forecasts in developing markets, such as those of the BRICS, as well as the application of novel models in financial market prediction, continues to provide research opportunities.

Kaushik [32] presents a comprehensive review of contemporary research on Machine Learning and Deep Learning for exchange rate forecasting, based on peer-reviewed publications and books. The paper examines how Machine Learning and Deep Learning algorithms vary in projecting exchange rates in the FOREX market. SVM, Deep learning approaches such as Feedforward Neural networks, and hybrid ensembles have superior prediction accuracy than standard time series models, according to research. Future research should be conducted to assess the performance of these models, according to the authors, however, no single forecasting model consistently stands out as the best when evaluated using different criteria and on different currency pairs, and decisions based on the models' predictions should be used with caution.

Regarding the publications mentioned above, it's worth noting that none of them focused specifically on machine-learning methods for the FX market from 2010 to 2021. Fletcher [18] concentrated on discriminative approaches (Support Vector Machines (SVM), Relevance Vector Machines (RVM), and Neural Networks) without examining other machine learning algorithms critically.

Islam et al. [27] took into account machine learning in the context of forex trading, highlighting Regression Methods, Optimization Techniques, SVM Method, Neural Network Chaos Theory, Pattern-based Methods, and Other Methods, but the period under consideration was from 2017 to 2019, but there has been a lot of work in this area over the last two decades. Panda et al. [44] concentrated on deep learning and hybrid techniques, as well as a few other machine learning algorithms, but the number of publications chosen was insufficient for the period under evaluation.

The research published by Sezer et al. [59] focused on deep learning research by looking at Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), and Long-Short Term Memory (LSTM): however, there are other deep learning models such as Radial Basis Function, Multi-layer Perceptron, and many more deep learning methods that have been used in forex market prediction that were not looked at by the article.

Contributions

The following are the contributions by this SLR:

1. We took a critical look at 60 primary articles or studies that present machine learning forecasting models in the forex market. Researchers can use them as a beginning stage to expand the knowledge on the topic.
2. We give a comprehensive summary of the primary studies found. This section is divided into three sections: (i) machine learning methodologies, (ii) evaluation strategies, and (iii) performance analysis of the presented models.
3. Based on our findings, we offer guidance and recommendations to help further research in the field.

Research methodology

In this study, a systematic literature review was employed as a research approach since it is a defined and methodical way of discovering, evaluating, and studying existing material in order to investigate a certain research issue or phenomenon Barbara [5].

We followed the SLR rules that were proposed by Barbara [5]. In addition, we incorporated the process of systematic reference inclusion, often known as "snowballing," as outlined by [71].

We adopted the SLR guidelines proposed by [71].

The following subsections describe the process followed.

Search strategy

A technique was proffered to retrieve all published articles/papers/literature associated with the topic. Our primary studies retrieval techniques involve search terms and phrase identification, databases to be searched, search and paper picking strategy adopted for the study.

Identifying search terms and phrases

To find the relevant search terms and phrases we followed five steps outlined by Barbara [5]:

- a. We found alternative spellings and/or synonyms for all major terms and phrases;
- b. We double-checked the keywords in any important paper;
- c. In cases where a database supports it, we employed Boolean operators for conjunction, such as the OR, AND operator for concatenation of major phrases and operator for concatenation of alternative spellings and synonyms. If necessary, we combined the search string into a summary form.

Results for a). To better tailor our search keywords, we first defined the population, intervention, and outcome. Specifically:

Results for b). The alternative spellings and synonyms identified are:

- Forex: (“forex “OR “foreign exchange”).
- Market: (“Market “OR “trading”).
- forecasting: (“forecasting” OR “predicting”)
- Machine Learning: (“machine learning” OR “supervised learning” OR “classification” OR “regression” OR “unsupervised learning”);

Results for c). We searched through the keywords in the relevant papers/articles and couldn't come up with any further spellings or synonyms to add to the list of terms to consider.

Results for d). The following search query was created using Boolean operators:

(“forex “OR “foreign exchange”) AND (“Market “OR “trading”) AND (“forecasting” OR “predicting”) AND Machine Learning: (“machine learning” OR “supervised learning” OR “classification” OR “regression” OR “unsupervised learning”);

Results for e). We also defined the short search string reported below, due to the IEEE Xplore digital library's search term limitation:

(“forex “OR “foreign exchange”) AND (“Market “OR “trading”) AND (“forecasting” OR “predicting”) AND Machine Learning: (“machine learning” OR “supervised learning” OR “classification” OR “regression” OR “unsupervised learning”);

Resources searched

In an SLR, selecting appropriate resources to search for germane material is critical. All available literature relevant to our study topics was selected and searched using the following resources:

- Google Scholar (<https://scholar.google.com>)
- IEEE Xplore digital library (<https://ieeexplore.ieee.org>)
- ScienceDirect (<https://www.sciencedirect.com>)
- Microsoft Academic (<https://academic.microsoft.com>)
- ACM digital library (<https://www.acm.org>)

Our decision to use these databases was based on our desire to collect as many publications as possible in order to adequately conduct our systematic literature review.

Because they contain a massive amount of literature related to our research questions, such as journal articles, conference proceedings, books, and other materials, the chosen sources or databases are recognized as one of the most representative for Forex market forecasting research and are used in many other SLRs.

Article selection process

Figures 1, 2 and 3 depicts the article selection procedure used in this study. The selection procedure is described in depth in the subsections that follow.

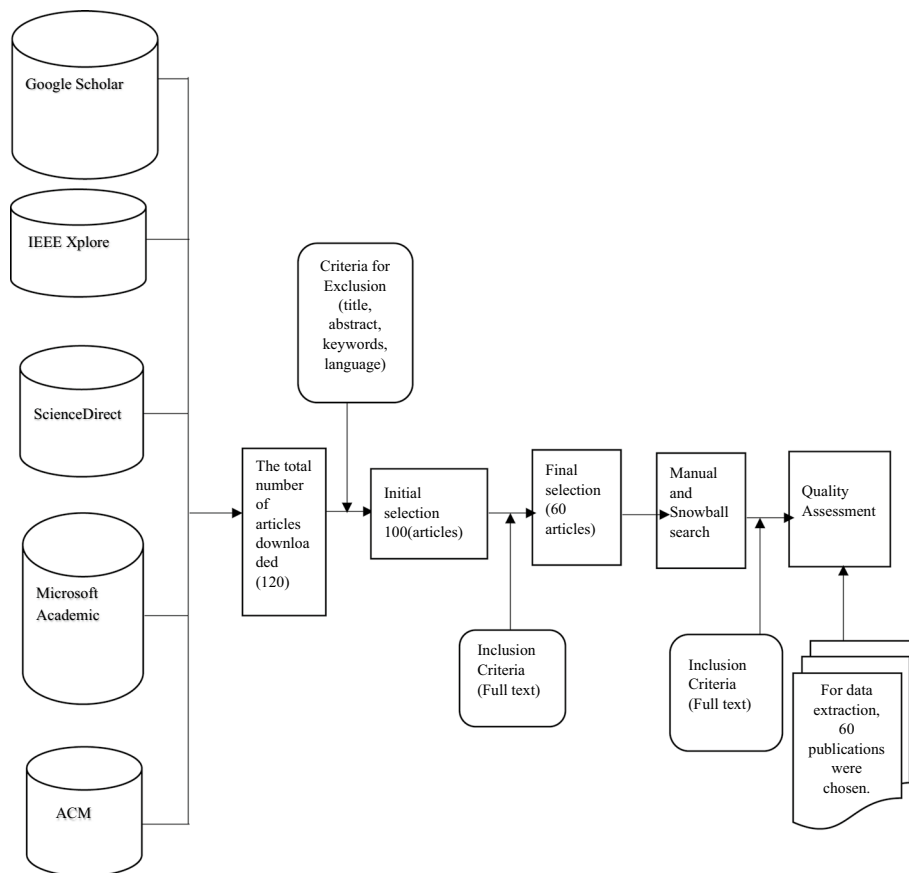


Fig. 1 Article selection process

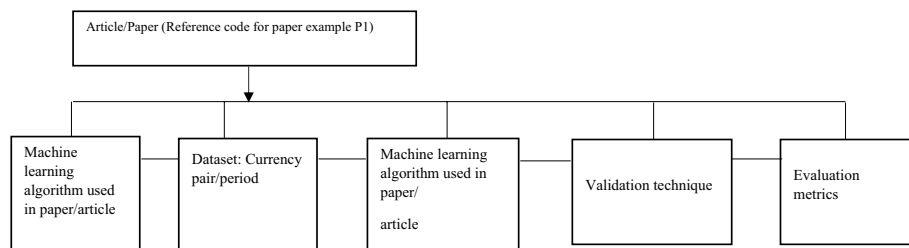


Fig. 2 Showing conceptual framework for data extraction from the primary studies

- a. We gathered the main research in the digital libraries specified in “[Resources searched](#)” section using the search strings given in “[Identifying search terms and phrases](#)” section. The search technique was restricted by a chronological range, therefore publications from 2010 to 2021 were examined. Table 1 second column displays the search results generated by the digital libraries: As you can see, we downloaded a total of 120 documents related to the query.
- b. We started by removing non-relevant publications from the complete list of retrieved sources using the exclusion criteria (detailed reported in “[Resources searched](#)” section). The exclusion criteria were applied after reading the title, abstract, and keywords of the 120 publications discovered. Table 1 shows data source and search



Fig. 3 VOSviewer (<http://www.vosviewer.com/>) was used to undertake a bibliographic coupling analysis. The number of references that are common across the publications evaluated is represented by the size and color of the nodes. The number of referenced references that two publications have in common is indicated by the link's strength

Table 1 Data source and search results

Resource name (Databases)	Total articles downloaded	Number of initial articles selected	Final selection
Google Scholar	120	100	60
IEEE Explorer			
ScienceDirect			
Microsoft Academic			
ACM			

results with 120 initial papers and 20 removed, leaving 100 for the second step of screening, which included the inclusion criteria. This approach yields our final search string, which consists of 60 articles (60 percent of the papers discovered in the previous stage).

Point c should be critically looked at.

- c. We employed a snowballing strategy to seek for possible missing papers [71]. The technique of identifying more sources using a paper’s reference list or citations is known as snowballing [71]. In our context, we employed both forward and backward snowballing: with the former, we included articles that were referred to in the initially

selected papers, and with the latter, we included publications that were referenced in the initially selected papers. We followed the same method as before, scanning the titles, abstracts, and keywords of the snowballed papers and applying the exclusion/inclusion criteria again: as a consequence, several publications were recognized as requiring further examination.

- d. Given a collection of 60 sources identified using search string and then supplemented with those collected via snowballing. As a result, 60 papers made it through all of the stages.
- e. We used the last filtering, i.e., the quality assessment step, after we had determined the set of final articles to evaluate in the SLR, to ensure that all of the final articles provided the data required to answer our research questions (see “[Evaluation of the study’s quality](#)” section). As a result of this phase, we were able to compile the final list of articles for our study. Until this point, all 60 sources found had passed the quality check. As a result, our SLR is based on 60 studies. “Extraction of data” section details the data extraction procedure. The next subsections include (i) inclusion/exclusion criteria, (ii) the procedure’s quality evaluation method, and (iii) the data extraction process.

Inclusion and exclusion criteria

An article has to meet the following criteria to be useful in answering our research questions.

A. Exclusion criteria: We omitted sources that satisfied the following limits from our research:

- Articles about predicting methods other than machine learning.
- Articles written in a language besides English.
- Articles that aren’t available in their whole.

B. Sources that complied with the following restrictions were considered for inclusion in our research:

- All the articles, written in English, report machine learning techniques for forex market forecasting;
- Articles that provide new strategies for improving the performance of existing machine learning algorithms for forecasting FX markets. It’s worth noting that we included a wide range of publications (for example, journal, conference, workshop, and short papers) in order to compile a comprehensive collection of relevant resources.

Evaluation of the study’s quality

After the final selection process, the quality of the publications was assessed. The legitimacy and completeness of the selected publications were assessed using the checklist below.

- Q1: Does the machine learner classifier have a well-defined definition?
- Q2: Can you tell me about the evaluation methodologies.

Consider the scenario in which research uses MAE, RMSE as an assessment statistic.

Extraction of data

We began extracting the data needed to address our study questions once we had chosen the final publications to be utilized for the SLR. We depended on the data in particular.

Table 2 shows the extraction form used in the selected publications, such as the machine learning algorithm.

Extraction of data form

Once we'd decided on the final papers for the SLR, we started extracting the data we'd need to answer our research questions. We used the data extraction form shown in Table 2 in particular. In addition to information on the specific aspects under examination, such as the machine learning approach employed in the selected publications, we have left aside a section for characterizing baseline models of the analyzed study. This made it easy to find a baseline model of prior research as well as future research direction.

Conceptual framework for data extraction

Result

In this part, we offer a brief description of the demographics of the articles that passed the inclusion/exclusion criteria and the quality evaluation before providing the findings of the SLR with regard to the examined research topics.

Characteristics of the population

The final list of relevant primary studies evaluated in this SLR is presented in Tables 3 and 4, with columns 'Year' and 'Book/Book Chapter/ Conf./Article/Thesis' indicating the year of publication and the periodicals in which the study was published. As can be

Table 2 Shows the descriptions for data extraction features

		Attribute description
Machine learning algorithm used		What type(s) of machine learning algorithms were employed in the research?
Dataset	Currency pair Period	What kind of data was utilized to train the model? EURUSD, for example What is the duration of the dataset? What period is under consideration? Eg. 1d,1H,4H,1 W,1 M etc
Validation techniques		What technique has been used to validate the model? E.g., k-fold cross-validation, the percentage split, etc
Evaluation metrics		What evaluation measures, such as Root Mean Square (RMS), Precision, Recall, F Measure, and AUC-ROC, were utilized to assess the model's accuracy?
Evaluation Metric Formulae		What is the formula for the evaluation metrics?
Baseline Model		What baseline model was used in the article?

Table 3 Shows the various primary studies and information's about them (The reviewed primary studies)

Author(s)	Year of Pub.	Book/Book Chapter/ Conf./Article/Thesis	Topic	Studies	Citations
Salman Ahmed, Saeed-Ul Hassan, Naif Radi Aljohani, Raheel Nawaz	2020	Elsevier	FLF-LSTM: A novel prediction system using Forex Loss Function	[P1]	[1]
Pradyot Ranjan Jena, Ritanjali Majhi, Babita Majhi	2015	Elsevier	Development and performance evaluation of a novel knowledge guided artificial neural network (KGANN) model for exchange rate prediction	[P2]	[28]
Juan Julián Cuéllar Abril	2019	IEEE	Currency Exchange Rate Prediction with Long Short-Term Memory Networks Based on Attention and News Sentiment Analysis	[P3]	[37]
Svitlana Galeshchuk and Sumitra Mukherjee	2017	SCITEPRESS – Science and Technology Publications, Lda.	Deep Learning for Predictions in Emerging Currency Markets	[P4]	[20]
Dadabada Pradeepkumar and Vadlamani Ravi	2014	Springer	FOREX Rate Prediction Using Chaos, Neural Network and Particle Swarm Optimization	[P5]	[45]
Michal DOBROVOLNY, Ivan SOUKAL, Kok Cheng LIM, Ali SELAMAT And Ondrej KREJCAR	2020	Hradec Economic days	Forecasting of FOREX Price Trend Using Recurrent Neural Network—Long Short-term Memory	[P6]	[14]
Amit R. Nagpure	2019	International Journal of Innovative Technology and Exploring Engineering (IJITEE)	Prediction of Multi-Currency Exchange Rates Using Deep Learning	[P7]	[39]
Md. Saiful Islam, Enam Hossain	2020	Elsevier	Foreign Exchange Currency Rate Prediction using a GRU-LSTM Hybrid Network	[P8]	[56]
João Carapuço, Rui Neves, Nuno Horta	2018	Applied Soft Computing Journal	Reinforcement learning applied to Forex trading	[P9]	[8]
Dadabada Pradeepkumar and Vadlamani Ravi	2017	Springer	FOREX Rate Prediction: A Hybrid Approach Using Chaos Theory and Multivariate Adaptive Regression Splines	[P10]	[58]
Christian González Rojas, Molly Herman	2018	Elsevier	Foreign Exchange Forecasting via Machine Learning	[P11]	[21]
Leslie C.O. Tiong, David C.L. Ngo, and Yunli Lee	2013	Researchgate	Forex Trading Prediction using Linear Regression Line, Artificial Neural Network and Dynamic Time Warping Algorithms	[P12]	[67]

Table 3 (continued)

Author(s)	Year of Pub.	Book/Book Chapter/ Conf./Article/Thesis	Topic	Studies	Citations
THEODOROS ZAFEIRIOU, DIMITRIS KALLES,	2013	International Journal on Artificial Intelligence Tools	short-term trend prediction of foreign exchange rates with a neural-network based ensemble of financial technical indicators	[P13]	[74]
Boning Zhang	2018	Journal of Physics	Foreign exchange rates forecasting with an EMDL-STM neural networks model	[P14]	[75]
Yaxin Qu1, Xue Zhao1	2019	Journal of Physics	Application of LSTM Neural Network in Forecasting Foreign Exchange Price	[P15]	[48]
Lina Ni, Yujie Li,Xiao Wang, Jinquan Zhang, Jiguo Yu, Chengming Qi	2018	Elsevier	Recurrent Neural Networks and ARIMA Models for Euro/Dollar Exchange Rate Forecasting	[P16]	[43]
V.V.Kondratenko1 and Yu. A Kuperin	2014	Researchgate	Using Recurrent Neural Networks To Forecasting of Forex	[P17]	[35]
Darko Vukovic	2013	Researchgate	Forex predicton with neural network: usd/eur currency pair	[P18]	[72]
Ling Qi, Matloob Khushi, Josiah Poon	2020	Elsevier	Event-Driven LSTM For Forex Price Prediction	[P19]	[47]
Alexander Jakob Dautel, Wolfgang Karl Härdle, Stefan Lessmann	2020	Springer	Forex exchange rate forecasting using deep recurrent neural networks	[P20]	[13]
Hsin-Yonn Seow					
Gunho Jung and Sun-Yong Choi	2021	Hindawi	Forecasting Foreign Exchange Volatility Using Deep Learning Autoencoder-LSTM Techniques	[P21]	[30]
Dinesh K. Sharma, H.S. Hota, Richa Handa	2017	Review of Business and Technology Research, Vol. 14, No. 1, 2017, ISSN 1941-9414	PREDICTION OF FOREIGN EXCHANGE RATE USING REGRESSION TECHNIQUES	[P22]	[61]
Deniz Can Yildirim, Ismail Hakki Toroslu and Ugo Fiore	2021	Springer	Forecasting directional movement of Forex data using LSTM with technical and macroeconomic indicators	[P23]	[73]
Thuy Nguyen Thi Thu, Vuong Dang Xuan	2018	IEEE	Using Support Vector Machine in FoRex Predicting	[P24]	[41]
Francesco Rundo	2019	MDPI Applied Sciences	Deep LSTM with Reinforcement Learning Layer for Financial Trend Prediction in FX High Frequency Trading Systems	[P25]	[52]

Table 3 (continued)

Author(s)	Year of Pub.	Book/Book Chapter/ Conf./Article/Thesis	Topic	Studies	Citations
AREEJ ABDULLAH BAASHER, MOHAMED WALEED FAKHR	2017	Researchgate	Forex trend classification using machine learning techniques	[P26]	[3]
Alexander Amo Baffour a, Jingchun Feng, Evans Kwesi Taylor,	2019	Elsevier	A hybrid artificial neural network-GJR modeling approach to forecasting currency exchange rate volatility	[P27]	[2]
Kiin Chinprasatsak, Nattee Niparnan, Attawith Sutsang	2018	Elsevier	ENMX: An elastic network model to predict the FOREX market evolution	[P28]	[9]
Smruti Rekha Das, Debahuti Mishra, Minakhi Rout	2017	ScienceDirect	A hybridized ELM-Jaya forecasting model for currency exchange prediction	[P29]	[12]
Mehreen Rehman,Gul Muhammad Khan, Sahibzada Ali Mahmud	2014	Elsevier	Foreign currency exchange rates prediction using CGP and Recurrent Neural Network	[P30]	[51]
Papongpat Taveeapiradeecharoen, Kosin Chamnongthai, (senior member, ieee), and Nattapol Aunsri	2019	IEEE	Bayesian Compressed Vector Autoregression for Financial Time-Series Analysis and Forecasting	[P31]	[64]
Mercedeh AmirAskari, Mohammad Bagher Menhaj	2016	IEEE	A modified fuzzy relational model approach to prediction of foreign exchange rates	[P32]	[25]
Nathan D'Lima, Shamsuddin S. Khan	2014	International Journal of Engineering Research & Technology (IJERT)	FOREX Rate Prediction using A Hybrid System	[P33]	[11]
Ahmad Bagheri, Hamed Mohammadi Peyhani, Mohsen Akbari	2014	Elsevier	Financial forecasting using ANFIS networks with Quantum-behaved 4 Particle Swarm Optimization	[P34]	[4]
LudmilaDymova,PavelSevastjanov*,KrzysztofKaczmarek	2016	Elsevier	A Forex trading expert system based on a new approach to the rule-base evidential reasoning	[P35]	[15]
Bernardo Jubert de Almeida, Rui Ferreira Neves,, Nuno Hortaa	2017	Applied Soft Computing	Combining Support Vector Machine with Genetic Algorithms to Optimize Investments in Forex Markets with High Leverage	[P36]	[29]
Milton Saulo Raimundo, Jun Okamoto Jr.	2018	IEEE	SVR-Wavelet Adaptive Model for Forecasting Financial Time Series	[P37]	[49]

Table 3 (continued)

Author(s)	Year of Pub.	Book/Book Chapter/ Conf./Article/Thesis	Topic	Studies	Citations
Pradeepta Kumar Sarangi, Muskaan Chawla, Pinaki Ghosh, Sunny Singh, P.K. Singh	2020	Elsevier	FOREX trend analysis using machine learning techniques: INR vs USD currency exchange rate using ANN-GA hybrid approach	[P38]	[36]
Yaroslav Vykylyuk1, Darko Vukovic2, Ana Jovanovic3	2013	ACTUAL PROBLEMS OF ECONOMICS #10((148)),2013	FOREX PREDICTION WITH NEURAL NETWORK: USD/EUR CURRENCY PAIR	[P39]	[69]
Kristina Sanjaya Putria*, Siana Halima	2020	International Journal of Industrial Optimization	Currency movement forecasting using time series analysis and long short-term memory	[P40]	[46]
ArashNegahdari Kia, Dr. SamanHaratizadeh and Dr. Hadizare	2013	Bonfring	Prediction of USD/JPY Exchange Rate Time Series Directional Status by KNN with Dynamic Time Warping AS Distance Function	[P41]	[34]
Shian-Chang Huang Pei-Ju Chuang a, Cheng-Feng Wub, Hluen-Jiun Lai a	2010	Elsevier	Chaos-based support vector regressions for exchange rate forecasting	[P42]	[24]
Pedro Escudero, William Alcocer and Jenny Paredes	2021	MDPI	Recurrent Neural Networks and ARIMA Models for Euro/Dollar Exchange Rate Forecasting	[P43]	[16]
Juszczuk Przemyslaw, Kozak Jan and Trynda Katarzyna	2016	Springer	Decision Trees on the Foreign Exchange Market	[P44]	[10]
Sitti Wetenriajeng Sidehabi, Indrabayu1, Sofyan Tandungan2	2016	IEEE	Statistical and Machine Learning Approach in Forex Prediction Based on Empirical Data	[P45]	[63]
Dadabada Pradeepkumar and Vadlalani Ravi	2017	Springer	FOREX Rate Prediction: A Hybrid Approach Using Chaos Theory and Multivariate Adaptive Regression Splines	[P46]	[58]
Gon_calo Abreu, Rui Neves, Nuno Horta	2018	Elsevier	Currency exchange prediction using machine learning, genetic algorithms and technical analysis	[P47]	[40]
Thuy Nguyen Thi Thu1, Vuong Dang Xuan	2018	International Journal of Engineering & Technology	Forex trading using supervised machine learning	[P48]	[42]
Theodoros Zafeiriou, Dimitris Kalles	2020	ACM	Intraday Ultra-Short-Term Forecasting of Foreign Exchange Rates using an Ensemble of Neural Networks based on Conventional Technical Indicators	[P49]	[58]

Table 3 (continued)

Author(s)	Year of Pub.	Book/Book Chapter/ Conf./Article/Thesis	Topic	Studies	Citations
Mihiran Rupasinghe, Malka N. Halgamage, Nguyen Tran Quoc Vinh	2019	IEEE	Forecasting Trading-Time-based Profit-Making Strategies in Forex Industry: Using Australian Forex Data	[P50]	[53]
Nima Shahbazi, Masoud M emarzadeh and Jarek Gryzi	2016	MATEC Web of Conferences 6, ICIEA 2016	Forex Market Prediction Using NARX Neural Network with Bagging	[P51]	[60]
Gene I. Sher	2012	ACM	Forex Trading Using Geometry Sensitive Neural Networks	[P52]	[62]
Leslie C.O. Tiong*, David C.L. Ngo, Yunli Lee	2016	Int. J. Computational Science and Engineering, Vol. 13, No. 4, 2016	Forex prediction engine: framework, modelling techniques and implementations	[P53]	[66]
Mustika Ulina, Ronsen Purba, Arwin Halim	2021	IEEE	Foreign Exchange Prediction using CEEMDAN and Improved FA-LSTM	[P54]	[68]
Wenyu Wei, Pengfei Li	2019	Proceedings of 2019 International Conference on Advanced Information Science and System	Multi-Channel LSTM with Different Time Scales for Foreign Exchange Rate Prediction	[P55]	[70]
AMAJURY HERNANDEZ-AGUILA1, MARIO GARCIA-VALDEZ 1, JUAN-JULIÁN MERELO-GUERVÓSZ, MANUEL CASTAÑÓN-PUGA 3, AND OSCAR CASTILLO LÓPEZ 1, (Senior Member, IEEE)	2021	IEEE	Using Fuzzy Inference Systems for the Creation of Forex Market Predictive Models	[P56]	[22]
Svitlana Galeshchuk, Sumitra Mukherjee	2017	Researchgate	Deep Networks for Predicting Direction of Change in Foreign Exchange Rates	[P57]	[19]
Yiqi Zhao, Matloob Khushi	2021	IEEE	Wavelet Denoised-ResNet CNN and LightGBM Method to Predict Forex Rate of Change	[P58]	[76]
Babu AS and Reddy SK	2015	Journal of Stock & Forex Trading	Exchange Rate Forecasting using ARIMA, Neural Network and Fuzzy Neuron	[P59]	[50]
Alireza Sadeghi, Amir Daneshvar, Mahdi Madanchi Zaj	2021	Elsevier	Combined ensemble multi-class SVM and fuzzy NSGA-II for trend forecasting and trading in Forex markets	[P60]	[55]

Table 4 Citation analysis of the primary studies on google scholar as at 16th October, 2021

Studies	Number of citations	Studies	Number of citations	Studies	Number of citations	Studies	Number of citations	Studies	Number of citations	Studies	Number of citations	Studies	Number of citations
P1	2	P11	3	P21	3	P31	8	P41	2	P51	10		
P2	25	P12	9	P22	6	P32	4	P42	113	P52	6		
P3	1	P13	10	P23	10	P33	NA	P43	NA	P53	3		
P4	9	P14	12	P24	10	P34	195	P44	5	P54	NA		
P5	15	P15	10	P25	21	P35	67	P45	13	P55	2		
P6	3	P16	NA	P26	25	P36	34	P46	7	P56	NA		
P7	7	P17	40	P27	21	P37	8	P47	10	P57	33		
P8	9	P18	1	P28	9	P38	NA	P48	3	P58	6		
P9	34	P19	5	P29	28	P39	23	P49	1	P59	49		
P10	7	P20	5	P30	48	P40	NA	P50	NA	P60	NA		

Table 5 Table showing machine learning algorithms use in the year 2022

Machine learning algorithm	Year of publication	ReferenceS
Support Vector Regression	2022	[33]
LSTM	2022	[31]
Gated Recurrent Neural Network and Convolutional Neural Network	2022	[38]

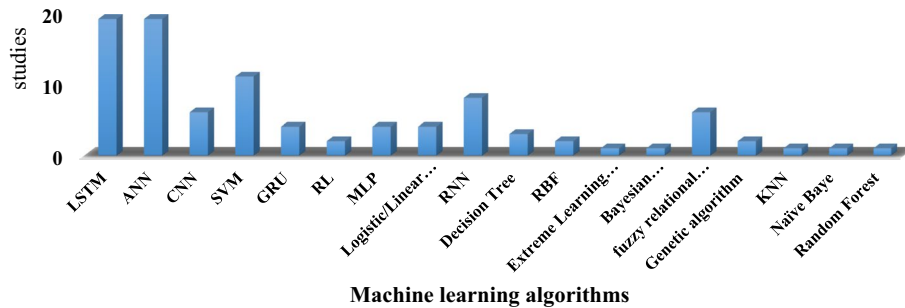


Fig. 4 Bar chart reporting the number of primary studies and the machine learning algorithm adopted in each

seen, all of the articles evaluated were published between 2010 and 2021; 80% of this primary research were published after 2014, perhaps indicating a developing tendency that is now establishing itself as a more established subject. In conclusion We determined that the application of machine learning techniques for FX market prediction still poses open difficulties based on the quantity and types of papers released by the research community.

RQ1—Algorithm for machine learning

The first research question of our SLR was connected to the machine learners utilized in the literature, as identified in the primary papers. We wanted to know I whose machine learning method was used, (ii) what deep learning (Neural Network and related algorithms) was used, and (iii) what additional machine learning strategies were used. The outcomes of our analyses are detailed in the subsections below.

Beyond the 60 primary considered from 2010 to 2021, some papers published in 2022 as shown in Table 5 used machine learning algorithms including the authors publication were also looked at but did not affect the analysis of the initial 60 papers.

RQ2.3 Machine Learning algorithms

Our investigation revealed that a wide range of machine learning methods were applied. The bar chart in Fig. 4 displays the algorithms utilized in the primary investigations, as well as their frequency of presence. The machine learning method, the primary research in which it was utilized, and the number of primary studies that employed it are all listed in Table 6. It’s worth noting that many or hybrid algorithms may have been utilized in single primary research.

Table 6 Showing machine learning models and studies that made use of it

Machine learning algorithms	Studies	Number of studies
LSTM	[P1], [P3], [P4], [P6], [P7], [P8], [P10], [P14], [P15], [P19], [P20], [P21], [P23], [P25], [P40], [P43], [P54], [P55], [P56]	19
ANN	[P2], [P5], [P7], [P9], [P10], [P11], [P12], [P13], [P18], [P27], [P28], [P39], [P45], [P46], [P51], [P52], [P53], [P57], [P59]	19
CNN	[P4], [P11], [P16], [P57], [P58]	6
SVM	[P7], [P24], [P26], [P36], [P37], [P42], [P45], [P48], [P50], [P57], [P60]	11
GRU	[P8], [P10], [P20], [P56]	4
RL	[P9], [P25]	2
MLP	[P10], [P26], [P33], [P56]	4
Logistic/Linear Regression, Regularized Logistic/Linear Regression, Gradient Boosting Classifier/Regression	[P11], [P12], [P22], [P53]	4
RNN	[P15], [P16], [P17], [P20], [P30], [P38], [P43], [P56]	8
Decision Tree	[P26], [P44], [P49]	3
RBF	[P26], [P50]	2
Bayesian Compressed Vector Autoregression	[P31]	1
fuzzy relational model	[P32], [P33], [P34], [P35], [P59], [P60]	6
Genetic algorithm	[P36], [P45]	2
KNN	[P41]	1
Naïve Baye	[P47]	1
Extreme Learning Machines (ELMs)	[P29]	1

LONG SHORT MEMORY NEURAL NETWORK (LSTM) as it is possible to these was investigated and used by 19 primary studies. A possible reason lies into the output of this type of models, which has shown a great performance and to properly analyze non-linear data, its ability to overcome the vanishing gradient problem pose by other neural networks.

ARTIFICIAL NEURAL NETWORK (ANN) as a deep learning model was also used by 19 primary studies indicating a growing trend in the use of it in the forex market prediction.

CONVOLUTIONAL NEURAL NETWORK is one of the deep learning algorithms that has not receive massive usage in the forex market, this model was use by 6 of our primary studies but can be further exploited in the foreign exchange market.

SUPPORT VECTOR MACHINE (SVA) was also used a number of times, 11 primary studies used this algorithm which is the third most used algorithm according to Figs. 4, 5, 6 and 7. This classifier, as previously described by Farhat [17] can attain very high performance.

GRU stands for GATED RECURRENT UNIT and is a type of RNN with a gating mechanism. Compared to LSTMs, GRUs do not contain an output gate [57], four primary studies exploited this algorithm for their work.

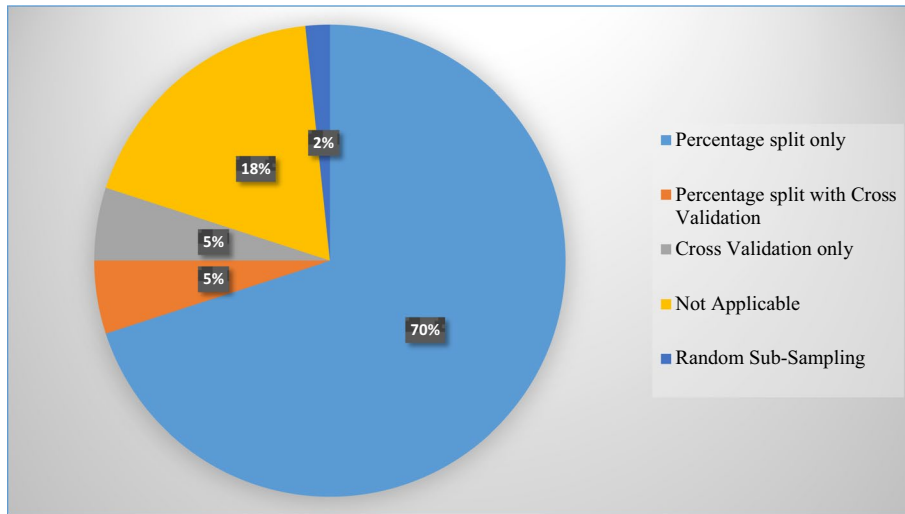


Fig. 5 Validation approaches used in primary investigations are depicted in a pie chart

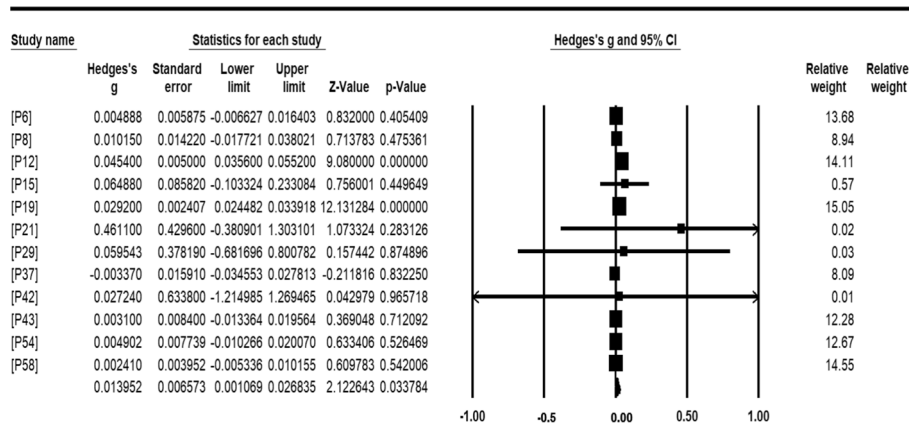


Fig. 6 Results of meta-analysis based on MAE as Hedge's g and RMSE as Standard error

Model	Effect size and 95% confidence interval						Test of null (2-Tail)		Heterogeneity				Tau-squared			
	Number Studies	Point estimate	Standard error	Variance	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed	12	0.021	0.002	0.000	0.018	0.025	12.464	0.000	78.174	11	0.000	95.929	0.000	0.000	0.000	0.017
Random	12	0.014	0.007	0.000	0.001	0.027	2.123	0.034								

Fig. 7 Results of meta-analysis based on MAE as Hedge's g and RMSE as Standard error

REINFORCEMENT LEARNING (RL) this algorithm has not been exploited much as only two of our primary studies made use of it showing more opportunity in the use of this algorithm in the forex market.

MULTILAYER PERCEPTRON (MLP) is a feedforward artificial neural network (ANN) with three layers of nodes: input, hidden layer, and output layer. Except for the

input nodes, each node in our selection is a neuron with a nonlinear activation function. Four key papers used this approach in their research.

LOGISTIC/LINEAR REGRESSION this machine learning algorithm was used by 4 of our primary studies, not popular in forex prediction.

RECURRENT NEURAL NETWORK Unlike traditional feedforward neural networks, RNNs have memory. Information fed into them persists, and the network can draw on this to make inferences. 8 papers from our primary studies used RNN for forex prediction.

DECISION TREE As may be seen, three key research studied Decision Trees. The output of these types of models, which consists of a rule describing the requirements for making a choice, could be one reason.

FUNCTION ON A RADIAL BASE NEURAL NETWORK (RBF) is a real-valued function whose value is solely determined by the distance between the input and a fixed point, such as the origin or another fixed point known as the center. This neural network was used by two of our key studies for their prediction models since any function that satisfies the property is a radial function.

EXTREME LEARNING MACHINES, BAYESIAN COMPRESSED VECTOR, K-NEAREST NEIGHBOR, NAÏVE BAYE AND RANDOM FOREST these are the least use algorithms according to our primary studies, from our studies we noticed that these algorithms were used in only one paper each showing the unpopularity in forex prediction.

FUZZY RELATIONAL MODEL was combined with other machine learning algorithms in predicting the forex market, 6 papers adopted this model in our primary studies.

The **GENETIC ALGORITHM** is a search heuristic based on Charles Darwin's natural selection hypothesis. This algorithm mimics the natural selection process, in which the most fit individuals are chosen for reproduction in order to create offspring for the following generation. It was combined with other machine learning models in predicting currency direction. 2 of our primary studies made use of this algorithm.

RQ2-dataset

Currency pairs are grouped into two thus the major and the minor, the major pairs are the four most heavily traded currency pairs in the forex (FX) market. The EUR/USD, USD/JPY, GBP/USD, and USD/CHF are the four major pairs at the moment. The EUR/USD is the most widely traded currency pair in the world, accounting for more than 20% of all forex transactions. The USD/JPY is a distant second, followed by the GBP/USD and, with a minor part of the global currency market, the USD/CHF. 75 percent of all forex trades are made on the big pairings. Minor currency pairs are ones which leave out the United States dollar, and they are normally less liquid. Examples include the euro and Swiss franc (EUR/CHF), Canadian dollar and Japanese yen (CAD/JPY), or pound sterling and Australian dollar (GBP/AUD etc).

Table 7 show the major currency pairs and corresponding primary papers/ articles that made use of dataset of them. From the table 42 papers made use of the EUR/USD currency pair and we can clearly say that according to our finding, it is the most traded and

Table 7 Major currency pairs and corresponding studies that used its dataset

Currency pairs (Major)	Studies [Papers that use dataset of the currency pair]
EUR/USD	[P1], [P4], [P6], [P7], [P8], [P9], [P10], [P12], [P13], [P14], [P15], [P16], [P18], [P19], [P20], [P23], [P24], [P25], [P27], [P28], [P29], [P34], [P35], [P36], [P38], [P42], [P43], [P44], [P46], [P47], [P48], [P49], [P50], [P51], [P52], [P53], [P54], [P55], [P56], [P57], [P60]
USD/JPY	[P4], [P5], [P7], [P10], [P20], [P28], [P34], [P41], [P49], [P50], [P56], [P57], [P58]
USD/GBP	[P4], [P5], [P7], [P8], [P10], [P16], [P19], [P20], [P25], [P28], [P34], [P35], [P42], [P44], [P49], [P50], [P51], [P54]
USD/CHF	[P7], [P8], [P10], [P16], [P20], [P27], [P32], [P34], [P35], [P56]

used currency pair. 18 papers made use of datasets of USD/GBP which is the next most traded pair after EUR/USD from our primary studies. USD/JPY came third as the next most used dataset from our study with 13 papers making use of its dataset. Last is USD/CHF dataset with 10 papers making use of it. From our study, we found out that some papers/articles made use of more than one dataset of the major currency pair. Some papers combined both minor and major pairs.

RQ3—evaluation setup

Our third research question revolves around the machine learning forecasting model evaluation strategies. It refers to:

- i. validation techniques,
- ii. evaluation metrics adopted, and
- iii. datasets exploited.

RQ3.1—validation techniques

70% of the pie chart which is made up of 42 primary studies used *percentage split only* as a validation technique which is the most used validation technique in the 60 primary studies. 3 of the primary studies made use of *percentage split and cross-validation* representing 5% of the total primary studies. Articles that used *cross-validation only* represent 5% of the total primary studies which is just 3 articles. Some primary studies were designed as systems that did not make use of any validation techniques and that took 18% of the primary studies representing 11 papers or studies, one validation technique.

that came up only is *Random sub-sampling* validation that is just 2% of the total primary studies. Papers that used percentage split divided the dataset into two parts (Training and Test dataset) with the large part for training with the other part for the test. K-Fold cross-validation was used with K being set to 10. In this approach, the technique divides the original data set into ten equal-sized subsets at random. One of the ten subsets is kept as a test set, while the other nine are utilized as training sets. The cross-validation is then done ten times, with each of the ten subsets serving as the test set exactly once [26].

Table 8 Evaluation metrics and corresponding primary studies

Evaluation Metrics	Studies
MAE	[P1], [P6], [P8], [P10], [P12], [P14], [P15], [P19], [P21], [P29], [P34], [P37], [P42], [P43], [P52], [P54], [P56], [P58]
MAPE	[P2], [P3], [P5], [P14], [P21], [P22], [P27], [P29], [P30], [P32], [P34], [P37], [P38], [P43], [P49], [P54]
RMSE	[P3], [P8], [P12], [P15], [P19], [P21], [P28], [P32], [P33], [P34], [P40], [P41], [P42], [P43], [P45], [P51], [P53], [P54], [P56], [P58]
MSE	[P5], [P6], [P7], [P8], [P14], [P17], [P19], [P21], [P27], [P29], [P32], [P38], [P42], [P43], [P48], [P49]
R-SQUARE	[P8], [P17]
AUC	[P20]
ACCURACY, PRECISION, RECALL, F1	[P23], [P24], [P25], [P47], [P57], [P60]
MAD	[P27]
PF	[P28]
Theil's U, ARV	[P29]
BCVAR-MS, MSFE, MAFE	[P31]
D-stat	[P33]
SEM	[P34]
Back Testing Base on sliding Window	[36]
ME, MPE, MASEP, AIC, BIC	[P37]
MdAE, SMAPE, RMSPE, RMDsPE, MdAE	[P43]
Confusion Matrix	[P44]

Table 8 shows evaluation metrics adopted by the primary studies, the most widely used are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Square Error (MSE). Studies [P20], [P27], [P28], [P29], [P31], [P33], [P34], [36], [P37], [P43], [P44] adopted evaluations metrics that didn't appear in any other primary paper aside them.

RQ4—meta-analysis of performance

The last research topic of our study was a statistical meta-analysis of machine learning algorithm performance in Forex market forecasting. A complete re-execution of the prediction models on a shared dataset with common assessment criteria would have been perfect for this sort of investigation, allowing them to be benchmarked. This, however, is not covered by a Systematic Literature Review; the purpose is to combine the findings of the major investigations. We looked at the effects of (i) the machine learning algorithm and (ii) the validation approach in this research. A statistical meta-analysis seeks to combine several studies to improve the estimates of impact sizes and clarify uncertainty when separate research disagrees. While individual studies are frequently insufficient to establish solid generalizable results, their combination may result in a lower random error and smaller confidence ranges. Meta-analyses have another significant flaw: they are unable to compensate for poor study design and bias in the individual research. If the studies are carried out and evaluated appropriately, the benefits vastly outweigh the minor drawbacks. We used the recommendations provided in the book to conduct the meta-analysis. In a meta-analysis, the first step is to calculate the result of interest and summary statistics from each of the individual studies. Not all prior research evaluated the performance of the presented models in the same way, as described in the evaluation

metrics. To have a common baseline, we utilized Mean Square Error, Root Mean Square Error, and other metrics that were used in most of the other sources. To make a fair comparison, we looked at all of the publications and the metrics used. Papers that evaluated the effectiveness of machine learning model prediction in terms of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and so on.

The analysis is based on twelve studies. The standardized difference in means (d) is the effect size index. The results of this analysis will be generalized to comparable studies. Therefore, the random-effects model was employed for the analysis. If we assume that the true effects are normally distributed (in d units), we can estimate the prediction interval. For all of the values in the primary studies, we utilized Comprehensive Meta-Analysis v3 to derive effect size estimates. It's worth mentioning that effect sizes must be normalized in order to be comparable across research. We used Hedges' g as the standardized measure of effect magnitude to achieve this goal. There are three main statistics recorded here which are the Q -value with its degrees and P -value, the I -square statistics, and finally Tau-square however these statistics don't tell us how much the effect size varies. In our case the Q -value is 78.174, the degree of freedom is 12 and P -value is 0.0. The next statistic recorded is I -square which is 85.929 in our analysis. Finally, the last statistic recorded is Tau-square which is the variance of true effects in our case Tau-squared is 0.017. The prediction interval tells how much the test size varies here we will report that the true effect size is 0.05 and 0.95. In our meta-analysis, the mean effect size using the Hedge's g is 0.013952 with the Mean Absolute Error of each selected study using the Hedges g value. A 0.5 effect size indicates that the treatment group's mean is half a standard deviation higher than the control group's mean, the effect sizes imply that the mean of the treatment group is half a standard deviation higher than the mean of the control group (Table 9).

Conclusion

The application of machine learning techniques for forex market forecasting was the subject of a systematic literature review in this research. It focused on three particular features of how prior research performed experiments on forex forecasting models, namely (i) which machine learning model was used, (ii) which sorts of assessment procedures were used, and (iii) what validation approaches were used. Our research was based on publications that were published between 2010 and 2021. We looked at 60 publications out of a total of 120 that proposed machine learning algorithms for FX market forecasting. Existing studies were examined, as well as unresolved topics that need to be addressed in a future study. The research shows that deep learning models like ANN, LSTM, MLP-Neural Networks, and Radial Basis Function are more suited for forecasting the forex market than other machine learning algorithms like KNN and Nave Baye. The results are encouraging. To make the research field more precise, we have offered a list of steps to take. As a result, we conclude that the conclusions on the use of percentage split are suspect, and that the dataset should be divided into three parts: training, test, and validation test. In this regard, we hope that our findings may serve as a springboard for further investigation.

Table 9 Shows the data extraction from each primary study

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Machine learning model	Period				
[P1]	Forex Loss Function (FLF) With Long Short-Term Memory	EURUSD	The H4 candles EURUSD data was collected from June 2015 to Sep 2018 using an MT4 tool	Percentage split (60–40)	Mean Absolute Error (MAE) of ARIMA, MAE of FLF-LSTM, MAE of FB Prophet	$MAE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y})$	Facebook Prophet
[P2]	Knowledge guided artificial neural network (KGANN)	conversion rates from 1US\$ to Pound and Rupees	NULL	Percentage split	MAPE	$MAPE(k) = \frac{\sum_{i=1}^k PE(m)}{M}$	LMS FLANN
[P3]	Long Short-Term Memory Networks	AUDUSD	January 1, 2016, to March 31, 2019	Percentage split	root mean square error (RMSE) and the mean absolute percentage error (MAPE),	$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y})^2 \right]^{\frac{1}{2}}$ $MAPE = \frac{1}{n} \sum_{i=1}^n \left \frac{Y_i - \hat{Y}}{Y_i} \right $	NOT AVAILABLE
[P4]	Deep Neural Network (LSTM, CNN)	(EUR/USD), (GBP/USD), (USD/JPY), (AZN/USD, AMD/USD, BYR/USD, MDL/USD, UAH/USD, GEL/USD)	2000 to 2015 (For each data set we train models for daily, monthly, and quarterly predictions)	Percentage split (80–10)	Mean Squared Error (MSE) and Mean Absolute Percentage Error	NA	ARIMA, ETS, NN (Single Layer (
[P5]	Chaos, Neural Network and Particle Swarm Optimization (Hybrid)	USD-JPY, USDGBP and USDEUR	The daily data of USD-JPY, USDGBP (1–1–1993 to 31–12-2013) and USD-EUR (3–1-200 to 31–12-2013)	Percentage split (80–10)	Mean Squared Error (MSE) and Mean Absolute Percentage Error	$MSE = \frac{\sum_{i=1}^k (y(t) - \hat{y}(t))^2}{k}$ $MAPE = \frac{100}{k} \sum_{i=1}^k \left \frac{y(t) - \hat{y}(t)}{y(t)} \right $	MLP, GRNN, GMDH and PSO
[P6]	Neural networks (NN) LSTM	EUR/USD	daily exchange rate data from 1.4.1971 until 9.5.2019	Percentage split (80–10)	Mean Square Error (MSE) and mean absolute error (MAE)	$MSE = \frac{\sum_{i=1}^k (y(t) - \hat{y}(t))^2}{k}$ $MAE = \sum_{i=1}^k \left \frac{y(t) - \hat{y}(t)}{y(t)} \right $	NULL

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P7]	Support Vector Regressor (SVR), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Neural Network with Hidden Layers	USD/EUR, USD/JPY, USD/GBP, USD/AUD, USD/CAD, USD/CHF, USD/CNY, USD/SEK, USD/NZD, USD/MXN and USD/INR	The data used to predict are daily data of the currency rate of the 1980s to December 2018 period	Percentage split (80–20)	Loss function: Mean Square Error, Optimizer: Adam The coefficient of determination ($MSE = \frac{\sum_{t=1}^k (y(t) - \hat{y}(t))^2}{k}$ $R^2 = 1 - \frac{\sum_{t=1}^k (y_i - \hat{f}_i)^2}{\sum_{t=1}^k (y_i - \bar{y})^2}$ $MAE = \frac{\sum_{t=1}^k y(t) - \hat{f}(t) }{k}$ $RMSE = \sqrt{\frac{\sum_{t=1}^k (y(t) - \hat{f}(t))^2}{k}}$	NULL
[P8]	GRU-LSTM	EUR/USD, GBP/USD, USD/CAD, and USD/CHF	January 1, 2017 to December 31, 2018 (10-min timeframe, and 30 min timeframe using the data from January 1, 2019 to June 30, 2020	Percentage split (80–20)	MSE, RMSE, MAE and R-square score,	$MSE = \frac{\sum_{t=1}^k (y(t) - \hat{y}(t))^2}{k}$ $MAE = \frac{\sum_{t=1}^k y(t) - \hat{y}(t) }{k}$ $R^2 = 1 - \frac{\sum_{t=1}^k (y_i - \hat{f}_i)^2}{\sum_{t=1}^k (y_i - \bar{y})^2}$	Standalone GRU model, a standalone LSTM model, and simple moving average (SMA)
[P9]	Reinforcement Learning (Neural networks with three hidden layers of ReLU neurons are trained as RL agents under the Q-learning algorithm)	EUR/USD	2010 to 2017	Percentage split (Rolling window)	NA	NA	NA
[P10]	Neural networks (MLP, RNN, GRU, and LSTM)	EUR/USD, USD/JPY, USD/CHF, GBP/USD, USD/CAD, and AUD/USD	GBP/USD (2000 to 2019)	K-Fold cross-validation 80–20	MAE	$MAE = \frac{\sum_{t=1}^k y(t) - \hat{y}(t) }{k}$	Random Forest, AdaBoost, XGBoost and Support vector machine

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P11]	Logistic/Linear Regression, Regularized Logistic/Linear Regression, Support Vector Machines/Regression (SVM/SVR), Gradient Boosting Classifier/Regression (GBC/GBR), Neural Networks (NN)	USDMXN	The dataset spans between the first week of January 2003 and the second week of November 2018	Percentage split (60–40)	NA	NA	NA
[P12]	Linear Regression Line, Artificial Neural Network and Dynamic Time Warping Algorithms	AUDUSD and EURUSD	from the beginning of 2012 until the end of 2012	Percentage split (70–30)	Mean Absolute Error (MAE) and Root Mean Square Error (RMSE)	$MAE = \sum_{t=1}^k \left \frac{y(t)-\hat{y}(t)}{y(t)} \right $ $RMSE = \sqrt{\frac{\sum_{t=1}^N \ y(t)-\hat{y}(t)\ ^2}{N}}$	NA
[P13]	Neural networks	USD/EUR	July 1, 2010 to March 23, 2011	NA	NA	NA	NA
[P14]	Empirical Mode Decomposition (EMD) and Long Short-Term Memory (LSTM)	USD/CNY, EUR/CNY, and USD/EUR	January 1, 2000 to April 17, 2018	Percentage split (94–6)	Mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE),	$MSE = \frac{\sum_{t=1}^k (y(t)-\hat{y}(t))^2}{k}$ $MAE = \sum_{t=1}^k \left \frac{y(t)-\hat{y}(t)}{y(t)} \right $ $MAPE = \frac{100}{k} \sum_{t=1}^k \left \frac{y(t)-\hat{y}(t)}{y(t)} \right $	ARIMA, ANN, LSTM
[P15]	LSTM, RNN	EUR/USD	June 1993 to March 2018	Percentage split (80–20)	RMSE and MAE	$RMSE = \sqrt{\frac{\sum_{t=1}^N \ y(t)-\hat{y}(t)\ ^2}{N}}$ $MAE = \sum_{t=1}^k \left \frac{y(t)-\hat{y}(t)}{y(t)} \right $	NA
[P16]	Hybrid (RNN AND CNN)	EURUSD, AUDUSD, XAUUSD, GBPJPY, EURJPY, GBPUSD, USDCHF, USDJPY, USDCAD	June 2008 to May 2018	Percentage split	NA	NA	LSTM or CNN deep neural network

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P17]	Recurrent Neural Networks	CHF EUR GBP JPY	22.07.1998 to 02.09.2001 Daily timeframe	NA	R squared Mean Squared Error	$R^2 = 1 - \frac{\sum_{i=1}^k (y_i - \hat{y}_i)^2}{\sum_{i=1}^k (y_i - \bar{y})^2}$	NA
[P18]	NEURAL NETWORK	USD / EUR	23.04.2012—04.05.2012	Percentage split (95–5)	NN1 NN2 NN3	NA	NA
[P19]	LSTM	GBP/USD, EUR/GBP, AUD/USD and CAD/CHF	15 min interval data from Jan 2005 to Sep 2017 for training and data from Oct 2017 to Sep 2020 for testing	Percentage split	Square error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE)	$MSE = \frac{\sum_{i=1}^k (y(t) - \hat{y}(t))^2}{k}$ $RMSE = \sqrt{\frac{\sum_{i=1}^k y(t) - \hat{y}(t) ^2}{N}}$ $MAE = \sum_{t=1}^k \left \frac{y(t) - \hat{y}(t)}{y(t)} \right $ $MAPE = \frac{100}{k} \sum_{t=1}^k \left \frac{y(t) - \hat{y}(t)}{y(t)} \right $	Simple recurrent neural network (RNN)
[P20]	Recurrent neural Networks (FNN SRNN LSTM GRU)	EUR/USD GBP/USD USD/JPY USD/CHF	January 4, 1971 until August 25, 2017	We divide each time series into study periods, scale the training data, and create input sequences and target variable values. Percentage split	Forecast Accuracy: logarithmic loss Predictive Accuracy (AUC)	NA	NA
[P21]	Long short-term memory (LSTM) and autoencoder models	currency-related volatility indices, namely, the BPVIX, JYVIX, and EUVIX	January of 2010 to December of 2019	K-fold cross-validation	MSE RMSE MAE MPE MAPE	NA	NA

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P22]	REGRESSION TECHNIQUES	INR/USD and INR/EUR	November 9th, 2016 to July 31st, 2017	Data is divided into two parts: training and testing (Percentage split). K-fold cross-validation technique is used for dynamic data partitioning to make the prediction more accurate	MAPE	$MAPE = \frac{\sum_{t=0}^n Y_{aj} - Y_{pj} }{n}$	NA
[P23]	Long short-term memory (LSTM)	EUR/USD	January 2013–January 2018	Percentage split (80–20)	accuracy	ProfitAccuracy = $\frac{\text{sumoftrue}}{\text{sumoffalse}}$	NA
[P24]	Support Vector Machine (SVM)	EUR/USD	01/01/2013 to 30/09/2016	cross-validation method	accuracy rates	NA	No_SVM
[P25]	Deep LSTM with Reinforcement Learning Layer	EUR/USD, GBP/USD, EUR/GBP	2004–2018	Percentage split (70–30)	accuracy	ROI = $\frac{100 * (\text{Gain} - \text{Investment})}{\text{Investment}}$ MD = $\frac{ \text{BalanceValley} - \text{BalancePeak} }{\text{BalancePeak}}$	Grid Trading System Trading System Threshold Strategy
[P26]	Bagging Trees, SVM, MLP, RBF	USD/YEN, USD/EGP, EURO/EGP and EURO/SAR	April 2003 to August 2010 excluding the weekends	Percentage split	NA	NA	NA
[P27]	artificial neural network	AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD	January 2001 to November 2013	NA	MSE, the MAD, and the MAPE measures	MSE = $\frac{1}{n} \sum_{t=1}^n (RV_t - \hat{\sigma}_t)^2$ MAPE = $\frac{1}{n} \sum_{t=1}^n \left(\frac{RV_t - \hat{\sigma}_t}{RV_t} \right)$ MAD = $\frac{1}{n} \sum_{t=1}^n RV_t - \hat{\sigma}_t $	Autoregressive conditional heteroskedasticity (GARCH), GJR, and Asymmetric Power Generalized Autoregressive Conditional Heteroskedasticity (APGARCH) models

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset	Currency pair	Period	Validation technique	Evaluation metrics	Formula	Baseline models
[P28]	Elastic Network Model (ENMX)	AUDCAD, AUDJPY, AUDNZD, AUDUSD, CADJPY, EURAUD, EURCAD, EURGBP, EURJPY, EURNZD, EURUSD, GBPAUD, GBPCAD, GBPJPY, GBPUSD, NZDCAD, NZDJPY, NZDUSD, USDCAD, USDJPY	AUDCAD, AUDJPY, AUDNZD, AUDUSD, CADJPY, EURAUD, EURCAD, EURGBP, EURJPY, EURNZD, EURUSD, GBPAUD, GBPCAD, GBPJPY, GBPUSD, NZDCAD, NZDJPY, NZDUSD, USDCAD, USDJPY	01.01.2015 (23:00 h) to 07.28.2017 (18:00 h),	NA	RMSE PF	$RMSE_c = \sqrt{\frac{1}{n} \sum_{i=1}^n \left\{ \hat{Y}_{i+H} - Y_{i+H} \right\}^2}$ $PF = \frac{\text{grossprofit}}{\text{grosslosses}}$	Simple random walk (RW) and vector autoregressive (VAR) model
[P29]	Extreme Learning Machines (ELMs) and the Jaya optimization technique	USD to INR, USD to EURO	USD to INR, USD to EURO	04/05/2000–03/06/2016 14/09/2001–03/06/2016	Percentage split	MSE MAPE MAE Theil's U ARV	$MSE = \frac{1}{n} \sum_{i=1}^n (A_i - P_i)^2$ $MAPE = \frac{\sum_{i=1}^N \left \frac{A_i - P_i}{A_i} \right }{N} \times 100$ $MAE = \frac{1}{N} \sum_{i=1}^N A_i - P_i $ $\text{Theil's } U = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (A_i - P_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n (A_i)^2} + \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i)^2}}$ $ARV = \frac{\sum_{i=1}^n (P_i - A_i)^2}{\sum_{i=1}^n (P_i - A_i)}$	NA
[P30]	Recurrent Cartesian Genetic Programming evolved Artificial Neural Network (RCGPANN)	Data of US currency obtained from Australian Reserve Bank, Japanese Yen, New Zealand Dollars, Canadian Dollars, Korean Won, and Indonesian Rupiah	Data of US currency obtained from Australian Reserve Bank, Japanese Yen, New Zealand Dollars, Canadian Dollars, Korean Won, and Indonesian Rupiah	500 days 1000 days from 1st February 2003	Percentage split	MAPE	$MAPE = \frac{1}{N} \sum_{i=1}^N \left(\frac{ L_i - L_A }{L_A} \right) \times 100$	NA

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset	Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period			
[P31]	Bayesian Compressed Vector Autoregression	AUD-JPY, CAD-CHF, CAD-JPY, EURDKK, EUR-MXN, and EUR-TRY	7th February 2018 through 2 August 2018	Percentage split (70–30)	NA	NA
[P32]	Modified fuzzy relational model (MFRM);	USDCHF	Jan.2012 to Dec. 2013	Percentage split (3.3–96.7)	MSE, MAPE, and RMSE	Multi-layer perceptrons, radial basis function neural networks and artificial fuzzy interface systems
			Daily time frame		$MSE = \frac{\sum_{t=1}^k (y(t) - \hat{y}(t))^2}{k}$ $MAPE = \frac{100}{k} \sum_{t=1}^k \left \frac{y(t) - \hat{y}(t)}{y(t)} \right $ $RMSE = \sqrt{\frac{\sum_{t=1}^k (y(t) - \hat{y}(t))^2}{k}}$	
[P33]	Multilayer Perception (MLP) and Adaptive Neuro-Fuzzy Inference System (ANFIS)	USDINR	23rd October 1993 to 23rd October 2014 (Daily period)	NA	Root Mean Square Error (RMSE) and D-stat (success of prediction in terms of direction)	NA
[P34]	Adaptive Network-based Fuzzy Inference System (ANFIS)	EUR/USD, GBP/USD, USD/JPY, USD/CHF	January 1, 2011, to February 28, 2014	Percentage split	Root Mean Squared Error (RMSE), the Standard Error of the Mean (SEM), the Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE)	NA
					$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Actual_i - Forecast_i)^2}$ $SEM = \frac{\sigma}{\sqrt{N}} = \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^N (X_i - \bar{X})^2}$ $MAPE = \left(\frac{1}{N} \sum_{i=1}^N \left \frac{Actual_i - Forecast_i}{Actual_i} \right \right) * 100$ $MAE = \frac{1}{N} \sum_{i=1}^N Actual_i - Forecast_i $	
[P35]	Synthesis of fuzzy logic and the Dempster-Shafer theory of evidence (SYSTEM)	EUR/USD, GBP/USD, EUR/CHF, USD/CHF	The quotations of currency pairs EUR/USD (timeframe: s1Hand4H), GBP/USD (30Mand4H), EUR/CHF(1H and4H) or azUSD/CHF (15Mand1H) from 01.11.2013t o 31.12.2014wer eused	NA	NA	NA

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P36]	Support Vector Machine with Genetic Algorithms	EUR/USD	1st of January of 2003 and 1st of January of 2015	Percentage split	The Backtesting approach is based on a Sliding Window	NA	Random Walk, B&H, S&H, and a Static GA approach
[P37]	Support Vector Regression (SVR)-Wavelet Adaptive Model	AUD-JPY, CHF-JPY, EUR-JPY, GBP-JPY and EUR-CHF	01/01/2003 to 12/30/2014, around 3000 values per series with intervals of 1 day, 1 h and 15 min	NA	Mean Error (ME), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), Auto-correlation of errors at lag 1 (ACF1), Akaike Information Criterion (AIC), Second-Order AIC (AICc) and Bayesian Information Criterion (BIC)	NA	ARIMA and ARFIMA Model
[P38]	Deep recurrent neural network (DRNN)-ARIMA	EUR/USD	data of EUR/USD between 2013 and 2015 were used to train the model and price data of EUR/USD between 2016 and 2017 were used to test and evaluate the model	Percentage split	MAPE, MSE	$MAPE = \left(\frac{100\%}{N} \sum_{i=1}^n \left \frac{A_i - F_i}{A_i} \right \right)$ $MSE = \frac{1}{N} \sum_{i=1}^N (A_i - F_i)^2$	NA

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P39]	NEURAL NETWORK	USD/EUR	23.04.2012–04.05.2012	Percentage split	NN1 NN2 NN3	NA	NA
[P40]	LSTM	EUR / USD	2014 to March 2020	Percentage split (80–20)	RMSE	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Actual_i - Predict_i)^2}$	ARIMA
[P41]	KNN with Dynamic Time Warping AS Distance Function	USD/JPY	Dec 4th of 1971 to Dec 24th of 2012	Percentage split (70–30)	RMSE	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2}$	Artificial Neural Network Multilayer Perceptron
[P42]	Chaos-based support vector regressions	(EUR/USD), (GBP/USD), (NZD/USD), (AUD/USD), (JPY/USD) and (RUB/USD)	January 3, 2005 to December 31, 2007, (daily timeframe)	Percentage split (80–20)	MSE, RMSE and MAE	$MSE = \frac{1}{N} \sum_{i=1}^N (r_i - t_i)^2$ $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (r_i - t_i)^2}$ $MAE = \frac{1}{N} \sum_{i=1}^N r_i - t_i $	SVR and BPNN
[P43]	Recurrent Neural Network (RNN) of the Elman type, and Long Short-Term Memory (LSTM)	EUR/USD	2 January 1998, to 31 December 2019 Daily prices	Percentage split	Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Median Absolute Error (MdAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), Root Mean Square Percentage Error (RMSPE), Root Median Square Percentage Error (RMDsPE), Median Absolute Percentage Error (MdAPE), and Symmetric (MdAPE), Mean Absolute Percentage Error (MAPE),	NA	NA

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P44]	Decision Trees (CART, C4.5)	EUR/USD GBP/USD USD/JPY	UNKNOWN	Random-sub sample	Confusion Matrix	NULL	CART, C4.5
[P45]	Support Vector Machine (SVM) and a hybrid form of Genetic Algorithm-Neural Network (GA-NN)		2007 to September 2012 Hourly data	Percentage split	RSME	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$	ASTAR model, SVM, and GANN
[P46]	Ensemble of Neural Networks based on Conventional Technical Indicators	EUR / USD	October 2018	NA	NA	NA	NA
[P47]	Naive Bayes Classifier	EUR/USD	January 1st, 2013 till March 9th, 2017 (hourly rate)	Percentage split and k-fold CV (80–20)	Accuracy, precision and recall	NA	NA
[P48]	Support Vector Machines	EUR/USD	01/01/2013 to 30/09/2016 Time frames of M1, M5, M15, H1, D1	Percentage split	MSE	$MSE = \frac{1}{N} \sum_{i=1}^N (r_i - t_i)^2$	NA
[P49]	Chaos Theory (Random Forest, Classification and regression tree) and Multivariate Adaptive Regression Splines	JPY/USD, GBP/USD, and EUR/USD	JPY/USD, GBP/USD are from January 1, 1993 to December 31, 2013 and EUR/USD from January 3, 2000 to December 31, 2013	Percentage split	MSE, MAPE	$MSE = \frac{\sum_{i=1}^N \epsilon_i^2}{N}$ $MAPE = \frac{100}{N} \sum_{i=1}^N \left \frac{\epsilon_i}{y_i} \right $	NA

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P50]	Support Vector Machine (SVM) with the Radial Basis Function (RBF) kernel and K-Means's clustering algorithms	EUR vs USD, GBP vs JPY, USD vs JPY, GBP vs USD and EUR vs JPY	NA	Percentage split	NA	NA	NA
[P51]	Nonlinear Autoregressive models with exogenous input (NARX) Neural Network with Bagging	GBPUSD and EURUSD	1 Hour time frame	Percentage split	RMSE	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - t_i)^2}$	NA
[P52]	Geometry Sensitive Neural Networks	EURUSD	2009–11–5–22:15 to 2009–11–20–10:15, using a 15-min time frame	Percentage split	NA	NA	NA
[P53]	linear regression line, artificial neural network (ANN), dynamic time warping (DTW)	AUDUSD and EURUSD	from 2012 and 2013	Percentage split	absolute error (MAE) and root mean square error (RMSE)	$MAE = \frac{1}{N} \sum_{i=1}^N r_i - t_i $ $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - t_i)^2}$	SVM, ANN, Statistic method
[P54]	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Improved Firefly Algorithm-Long Short-Term Memory (IFALSTM)	AUD/USD, EUR/USD, GBP/USD	from January 1, 2010 to December 30, 2019	Percentage split	Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2}$ $MAE = \frac{1}{N} \sum_{i=1}^N Y_i - \hat{Y}_i $ $MAPE = \frac{1}{N} \sum_{i=1}^N \frac{Y_i - \hat{Y}_i}{Y_i}$	LSTM, CEEMDAN-LSTM,

Table 9 (continued)

Studies	Machine learning model (Algorithm)	Dataset		Validation technique	Evaluation metrics	Formula	Baseline models
		Currency pair	Period				
[P55]	Multichannel-LSTM	EURUSD and EURAUD	30 min timeframe	Percentage split	Accuracy, F1, Precision, and Recall	NA	GRU, Simple RNN, and Single-Channel LSTM, Random Forest and SVM
[P56]	RNN, GRU, LSTM and MLP	EUR/USD, USD/JPY, USD/CHF, GBP/USD, USD/CAD and AUD/USD	from August 28th 2004 to May 18th 2020	Percentage split	RMSE MAE	NA	Random forest, AdaBoost, XGBoost and SVM
[P57]	ANN, ANNMA, SVM, and CNN	EUR/USD, GBP/USD, and JPY/USD	2010 to 2015 Daily time frame	Percentage split and Ten-fold cross-validation	Accuracy	NA	(ARIMA and ETS) MC (Majority Class)
[P58]	Wavelet Denoised-ResNet CNN and LightGBM	USD/JPY	2019-01-01 to 2020-06-10 5-min time frame	Percentage split (80-20)	MAE, RMSE	$MAE = \frac{1}{M} \sum_{i=1}^M x_i - y_i $ $RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^M (x_i - y_i)^2}$	NA
[P59]	ARIMA, Neural Network and Fuzzy Neuron	USD Vs INR GBP Vs INR EURO Vs INR YEN Vs INR	Daily RBI reference exchange rates from January 2010-April 2015	Percentage split	Accuracy Precision Recall	NA	ARIMA, Neural Network and Fuzzy Neuron
[P60]	SVM and fuzzy NSGA-II	EUR/USD	6-year timeframe from 2014 to 2019 Daily timeframe	Percentage split	Accuracy Precision Recall	$Accuracy = \frac{No_Correctly_Classified_Samples}{No_Test_Samples}$ $Precision_c = \frac{TruePositive_c}{TruePositive_c + FalsePositive_c}$ $Recall_c = \frac{TruePositive_c}{TruePositive_c + FalsePositive_c}$	SVM-GA

Abbreviations

MAE	Mean Absolute Error
MASE	Mean Absolute Scaled Error
MSFE	Mean square forecasting error
MAPE	Mean absolute percentage error
AIC	Akaike Information Criterion
SEM	Standard Error of the Mean
RMSE	Root Mean Square Error
BIC	Bayesian Information Criterion
ME	Mean Error
MSE	Mean Square Error
NN1	Neural Network 1
ARV	Average relative variance
R2	R-Square
NN2	Neural Network 2
MAFE	Mean absolute forecasting error
AUC	Area Under Curve
NN3	Neural Network 3
MPE	Mean Percentage Error
RBI	Reserve Bank of India
BCVAR-MS	Bayesian Compressed Vector Autoregression Mean Square
MAD	Mean absolute deviation
NA	Not applicable
ETS	Exponential smoothing
PF	Profit factor
ELM	Extreme Learning Machine
NSGA-II	Non dominated sorting genetic algorithm II
CGP	Cartesian Genetic Programming
ARIMA	Autoregressive integrated moving average
ReLU	Rectified linear unit
H1	One Hour Time frame
H4	Four Hour Time frame
1d	Daily Time frame

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Author contributions

MAJ searched through publication databases for the primary studies and also use inclusion and exclusion criteria to select the final studies for the research and assisted in performing the meta-analysis. PA played a supervisory role and assisted in designing data extraction form for retrieving interested information from the primary studies. OA analyzed and performed the bibliometric coupling for knowing the relationship that exists between the individual authors of each primary studies. CNB performed the meta-analysis of the twelve selected primary studies and reported the results. All authors read and approved the final manuscript.

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The authors declare that they have no competing interests.

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