

Title:

Deep learning techniques for financial time series forecasting: A review of recent advancements: 2020-2022

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Abstract

Forecasting financial time series has long been a challenging problem that has attracted attention from both researchers and practitioners. Statistical and machine learning techniques have both been explored to develop effective forecasting models in the past few decades. With recent developments in deep learning models, financial time series forecasting models have advanced significantly, and these developments are often difficult to keep up with. Hence, we have conducted this literature review to provide a comprehensive assessment of recent research from 2020 to 2022 on deep learning models used to predict prices based on financial time series. Our review presents different data sources and neural network structures, as well as their implementation details. Our goals are to ensure that interested researchers remain up-to-date on recent developments in the field and facilitate the selection of baselines based on models used in prior studies. Additionally, we provide suggestions for future research based on the content in this review.

Keywords:

financial market; time series; forecasting; deep learning; model implementation; review

1. Introduction

The financial market is a vast concept that encompasses several markets, such as stock, commodity, cryptocurrency, and forex markets. Financial time series in financial markets are created by observing the price of an asset at regular intervals over a specific period of time (Green 2011). While financial time series from different markets may have varying value ranges, all financial time series are extremely stochastic and volatile. The time interval of the data points is used to classify financial time series into tick-level, minute, hourly, daily, weekly, monthly, etc. time series. Predicting the future price of a financial asset, which is known as financial time series forecasting (Hegazy et al. 2013), is essential for developing effective securities trading strategies that may yield substantial profits (Zhou et al. 2018). Trend prediction is another crucial forecasting task that aims to predict the future movement of an underlying asset. However, according to Sezer et al. (2020), the most widely studied forecasting task in financial markets is the price prediction of financial assets.

Various financial time series forecasting methods have been developed by researchers. Traditional statistical methods, such as the autoregressive integrated moving average (ARIMA) model, exponential smoothing (ES) model, and generalized autoregressive conditional heteroscedasticity (GARCH) model, are the most commonly used approaches for analyzing and forecasting financial market behavior (Lam 2004). In recent years, with the rapid increase in computational capacity and the availability of vast amounts of data from the internet, machine learning methods have emerged as superior techniques for forecasting tasks (Chen et al. 2020b; Nti et al. 2020; Tang et al. 2022). Several machine learning models, including random forests, support vector regression (SVR), and neural networks (NNs), have demonstrated exceptional accuracy in financial time series forecasting and have become increasingly popular in industry applications (Lu et al. 2009; Masini et al. 2023).

While machine learning algorithms are useful in forecasting tasks, more advanced methods, such as deep learning algorithms, have been more widely used for developing predictive models (Li and Bastos 2020). Among deep learning models, recurrent neural networks (RNNs), especially long short-term memory (LSTM) networks, and convolutional neural networks (CNNs) have proven to be powerful tools for financial time series forecasting (Durairaj and Mohan 2019; Nosratabadi et al. 2020; Sezer et al. 2020; Hu et al. 2021; Kumar et al. 2021; Lara-Benítez et al. 2021). Deep learning models have more complex structures than machine learning models, leading

to longer training time but more accurate and robust predictions (Alonso-Monsalve et al. 2020; Wang et al. 2022). The issue of model training time can be greatly alleviated by the parallel processing power offered by graphics processing units (GPUs) (Jiang 2021). In addition, high-level programming packages, such as TensorFlow and PyTorch, have made it easier to implement and test deep learning models, while features extracted from external data sources, such as online news and social media data, can be used to establish rich input feature sets for model training. As a result, interest in applying deep learning techniques to financial time series forecasting has increased among researchers.

Prior to our work, several review papers have been published on the development and application of machine learning and deep learning methods for predicting stock prices and other financial asset prices (Gandhmal and Kumar 2019; Bustos and Pomares-Quimbaya 2020; Nosratabadi et al. 2020; Nti et al. 2020; Sezer et al. 2020; Jiang 2021; Thakkar and Chaudhari 2021; Tang et al. 2022; Zhang et al. 2022a). Gandhmal and Kumar (2019) examined the effectiveness of various machine learning algorithms that appeared in the literature from 2010 to 2018, including artificial neural networks (ANNs), support vector machines (SVMs), K-means, and fuzzy-based techniques, for predicting stock market trends. They noted that additional soft computing methods were needed to improve the forecasting accuracy. In their review, Bustos and Pomares-Quimbaya (2020) categorized articles from 2014 to 2018 based on the modeling techniques employed and found that technical indicators were the most predictive data, with further improvement possible by analyzing social media topics.

Nti et al. (2020) conducted an extensive literature review on both fundamental and technical analysis techniques for stock market predictions from 2007 to 2018, with ANNs and SVMs being the most commonly used machine learning algorithms. Tang et al. (2022) conducted a survey on the use of machine learning models for forecasting financial time series from 2011-2021 and found that hybrid models combining several methods were used more widely than single models. However, they also noted that machine learning methods may not be the best approach for financial time series forecasting due to irregular market behaviors and sudden extreme events.

Furthermore, Sezer et al. (2020) analyzed deep learning implementations in studies from 2005 to 2019 based on intended asset classes and summarized different types of deep learning models. Nosratabadi et al. (2020) presented a comprehensive review on recent developments from 2016 to 2020 in machine and deep learning methods and their applications to economics, focusing on ensemble and hybrid models. In addition, Jiang (2021) presented an overview on recent progress with deep learning models for stock market forecasting from 2017 to 2019 and emphasized the importance of experimental reproducibility.

Moreover, Thakkar and Chaudhari (2021) examined fusion techniques applied in existing research for stock price and trend prediction from 2011 to 2020 and suggested potential fusion techniques that can be applied to financial markets. Zhang et al. (2022a) examined base models and fusion methods in ensembles from 1995 to 2021 and recommended integrating sentiment analysis and decision fusion techniques to enhance stock market predictions.

While most review papers focus on stock market predictions, it should be noted that the workflow for financial time series forecasting is similar across different markets, implying that review studies that consider only the application of forecasting methods in the stock market may be biased. Additionally, previous reviews mainly covered studies published prior to 2020, highlighting the need for an updated review that focuses on recent deep learning algorithms used for financial time series forecasting.

To address the above issues, we aim to present an updated review on recent advancements in deep learning for predicting prices based on financial time series, with a focus on developments in the last three years from 2020 to 2022. Specifically, we examine recent deep learning models used for price forecasting. By presenting the trends in deep learning model development for price forecasting over the past three years, we hope to assist researchers and practitioners in remaining updated on recent developments in the field. Furthermore, we focus on model implementation to assist readers in selecting baselines for their own research. This review also suggests potential research directions for future studies on financial time series forecasting.

To accomplish this goal, this review is divided into several sections. Section 2 presents an overview of the reviewed literature, while Section 3 discusses the raw datasets used for model training and evaluation. In Section 4, we summarize the most common deep learning models that have been used for price forecasting. Section 5 reports the implementation details of these models, and Section 6 proposes some potential areas for future research. Finally, the conclusions of this study are presented in Section 7.

2. Overview

In this section, we present an overview of the papers that we review in this study. All of the papers were obtained from Scopus and Web of Science databases using keywords such as deep learning and financial time series forecasting. We included a total of 62 journal papers and 12 conference papers in our analysis. Table 1 presents the major journal rankings, and the most relevant journals include IEEE Access, Expert Systems with

Applications, Neural Computing and Applications, and Energy. Additionally, some of the reviewed papers were presented at international conferences.

Table 1. Major journal rankings.

Journal	Number of papers
IEEE Access	8
Expert Systems with Applications	5
Neural Computing and Applications	4
Energy	3
Applied Soft Computing	2
Complexity	2
Computational Intelligence and Neuroscience	2
Electronics	2
Soft Computing	2
Others (one article from each journal)	32

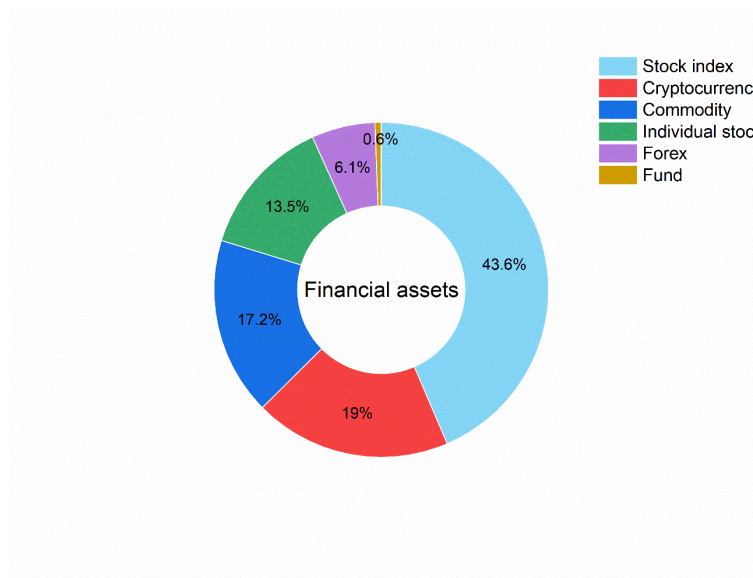


Figure 1. Different types of financial assets as forecasting targets.

The primary focus of most included studies was to predict the closing price of various financial assets based on a particular frequency. For the forex market, the forecasting target was the exchange rate of different currencies. Figure 1 outlines the different types of financial assets that were used as forecasting targets in the reviewed studies. It is worth noting that stock indices were the most common forecasting target, with approximately 40% of studies focusing on this target, followed by cryptocurrency. However, forecasting for funds has not received much attention. These results reflect the fact that stock market-related predictions attract more attention from researchers than other types of financial time series forecasting.

3. Raw data

Further, we conducted analysis on various types of financial assets used as forecasting targets. Table 2 presents the stock indices commonly used as forecasting targets in previous studies, with researchers often selecting indices from stock exchanges in the United States and China, such as the Standard & Poor's 500 Index (S&P 500) and Shanghai Stock Exchange Composite (SSE). Table 3 outlines the commodities frequently used as forecasting targets, with crude oil and gold being the most commonly predicted commodities. In the area of cryptocurrency forecasting, as shown in Table 4, Bitcoin (BTC) and Ether (ETH) are the two most commonly predicted cryptocurrencies. Additionally, we have observed that a limited number of studies have focused on forex rate forecasting, as indicated in Table 5. Overall, the preferences of researchers highlight that financial time series forecasting remains an intriguing and challenging research topic. The benchmark datasets chosen by most papers are suitable for evaluating forecasting models.

Table 2. Types of stock indices in the surveyed literature.

Stock Index Price	Articles
S&P 500	Qiu et al. (2020); Song et al. (2021); Yu and Yan (2020); Chen et al. (2020a); Kumar et al. (2022a); Iqbal et al. (2021); Durairaj and Mohan (2021, 2022); Wang et al. (2021b); Liu and Long (2020); Althelaya et al. (2021); Deng et al. (2022); Yujun et al. (2021); Rezaei et al. (2021)
SSE	Song et al. (2021); Chen et al. (2020a, 2021); Lu et al. (2020); Niu et al. (2020b); Durairaj and Mohan (2021, 2022); Wang et al. (2021b); Shu and Gao (2020); Deng et al. (2022); Xuan et al. (2020)
DJIA	Tang et al. (2021); Qiu et al. (2020); Yu and Yan (2020); Chen et al. (2020a); Niu et al. (2020b); Liu and Long (2020); Rezaei et al. (2021)
HSI	Qiu et al. (2020); Yu and Yan (2020); Kanwal et al. (2022); Niu et al. (2020a); Huang et al. (2021); Deng et al. (2022); Yujun et al. (2021)
DAX	Kanwal et al. (2022); Wang et al. (2021b); Yujun et al. (2021); Rezaei et al. (2021)
CSI300	Zhou et al. (2022); Yu and Yan (2020); Chen et al. (2021); Wang et al. (2020)
Nifty 50	Kumar et al. (2022a); Durairaj and Mohan (2021, 2022)
SZSE	Wang et al. (2021a, b); Yujun et al. (2021)
FTSE	Niu et al. (2020a); Huang et al. (2021)
IXIC	Chen et al. (2020a); Niu et al. (2020a)
KOSPI	Song et al. (2020, 2021)
VIX	Huang et al. (2021); Yujun et al. (2021)
Nikkei225	Yu and Yan (2020); Rezaei et al. (2021)
Sensex	Kumar et al. (2022a)
ASX	Yujun et al. (2021)
ChiNext	Yu and Yan (2020)
Russell 2000	Chen et al. (2020a)
KOSDAQ	Song et al. (2020)
KSE	Omar et al. (2022)
TASI	Malibari et al. (2021)
SSE Fund Index	Niu et al. (2020b)

Table 3. Types of commodities in the surveyed literature.

Commodity Price	Articles
Crude oil	Wang and Wang (2020, 2021a, b); Yang et al. (2020); Boubaker et al. (2022); Durairaj and Mohan (2021, 2022); Liu and Huang (2021); Huang et al. (2021); Lin and Sun (2020)
Gold	Zhang et al. (2022b); Livieris et al. (2020b); Durairaj and Mohan (2021, 2022); Lin et al. (2022)
Soya Beans	Li et al. (2020); Durairaj and Mohan (2021, 2022)
Natural Gas	Wang and Wang (2021a); Livieris et al. (2020a)
Silver	Lin et al. (2022)
Platinum	Lin et al. (2022)
Palladium	Lin et al. (2022)
Electricity	Li and Becker (2021)
Heating Oil	Wang and Wang (2021a)
Gasolin	Yang et al. (2020)
Coal	Yang et al. (2020)
Energy Futures Index	Li and Wang (2020)

Table 4. Types of cryptocurrencies in the surveyed literature.

Cryptocurrency	Articles
Bitcoin	Tripathi and Sharma (2022); Livieris et al. (2021, 2022); Dixon and London (2021); Zhang et al. (2021, 2022b); Kang et al. (2022); Nasirtafreshi (2022); Guo et al. (2021); Yin et al. (2022)
Ether	Livieris et al. (2021, 2022); Kang et al. (2022); Nasirtafreshi (2022); Zhang et al. (2021); Yin et al. (2022)
Litecoin	Livieris et al. (2022); Nasirtafreshi (2022); Zhang et al. (2021); Yin et al. (2022); Patel et al. (2020)
Ripple	Livieris et al. (2021, 2022); Kang et al. (2022); Zhang et al. (2021)
Bitcoin Cash	Nasirtafreshi (2022); Zhang et al. (2021)
Monero	Patel et al. (2020)
Dash Coin	Yin et al. (2022)
EOS	Zhang et al. (2021)
CCi 30	Livieris et al. (2022)

Table 5. Types of forex rates in the surveyed literature.

Forex Rate	Articles
INR/USD	Durairaj and Mohan (2021, 2022)
JPY/USD	Durairaj and Mohan (2021, 2022)
SGD/USD	Durairaj and Mohan (2021, 2022)
EUR/USD	Vuong et al. (2022)
USD/CAD	Huang et al. (2021)
USD/CNY	Huang et al. (2021)
USD/JPY	Huang et al. (2021)

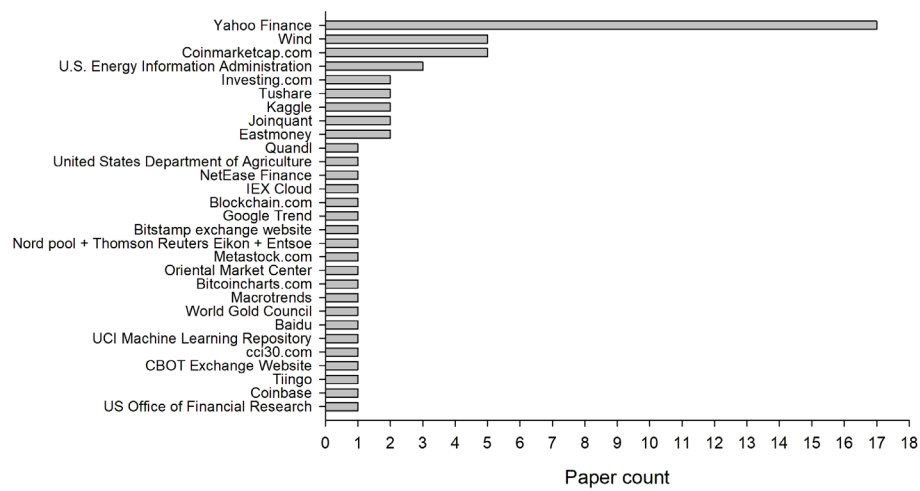


Figure 2. The source of raw data.

Figure 2 illustrates the primary sources of raw data for financial time series. Yahoo Finance is the most widely used source, offering an accessible database that can be queried and downloaded. Additionally, sources such as Wind, Tushare, and Joinquant were specifically designed for retrieving financial market data from China. Moreover, specific sources are available for obtaining data from various financial markets, such as the U.S. Energy Information Administration for energy market data and the World Gold Council for gold price data.

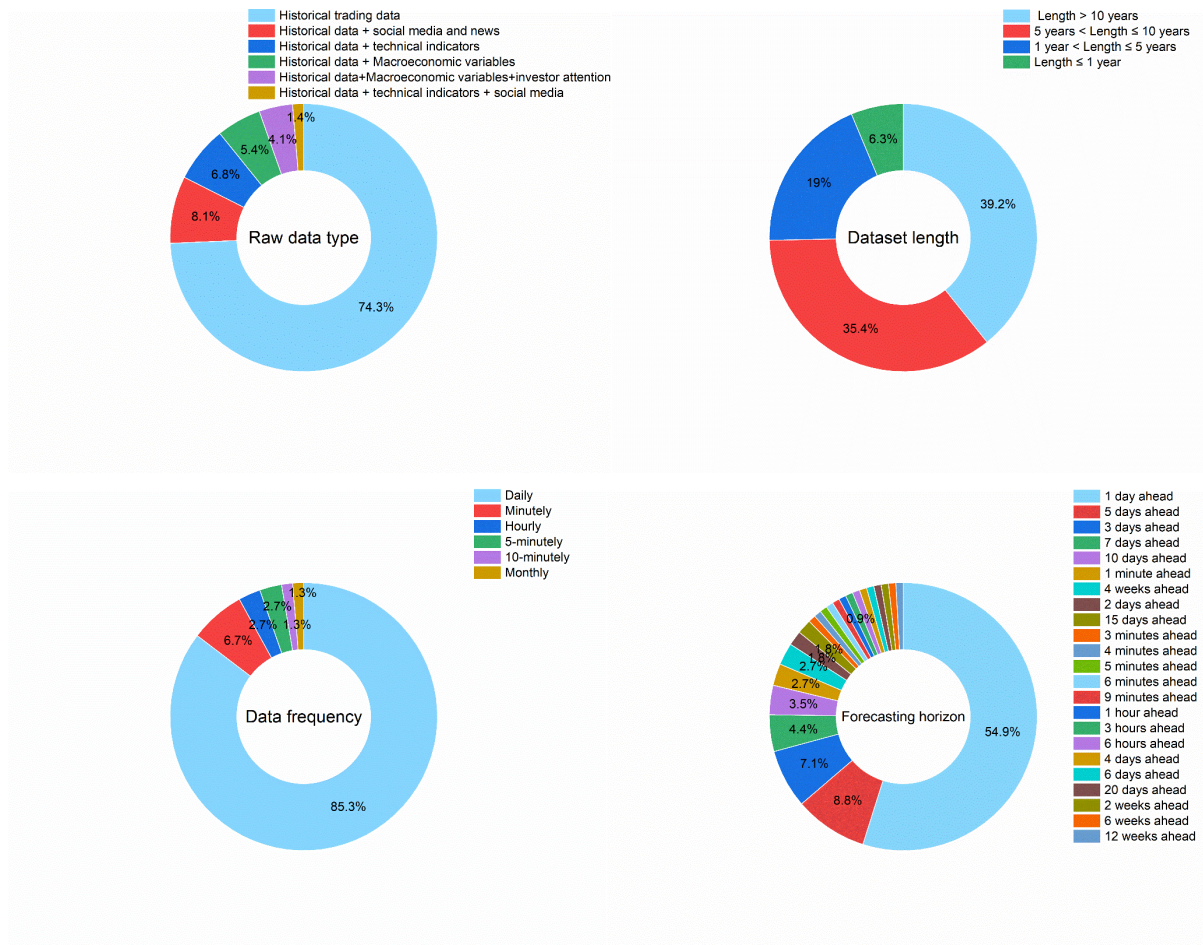


Figure 3. Characteristics of raw datasets.

Figure 3 summarizes the statistics of the relevant raw datasets, including the data type, length, and frequency. Most studies included in this review utilized daily historical trading data as their raw data, indicating the easy accessibility and reliability of this type of data for research purposes. However, essential features can be extracted from more complex data, such as the combination of historical data and social media, improving the accuracy of the forecasting model. For deep learning models, a larger raw dataset containing more than 5 years of data is typically necessary to ensure sufficient model training, as indicated in Figure 3. Additionally, while most studies have focused on one-step-ahead forecasting, a few studies have explored multistep-ahead forecasting, which can help decision-makers make informed decisions by providing a clearer picture of future trends, thereby maximizing opportunities while minimizing risks.

4. Prediction models

In a forecasting task, machine learning or deep learning algorithms act as mapping functions that map input features to actual prices. To train the model, the prices of an asset are typically used as labels. For example, if the closing price of the asset at time t is predicted, the data at the previous L time points and other technical indicators are used as input features. These features include technical indicators calculated based on historical trading data and/or sentiment features extracted from news and social media.

This section focuses on forecasting models, which are categorized based on the deep learning algorithm used in their construction. We classified the deep learning models into standard, hybrid, and ensemble categories, along with several variants. While these deep learning models may be complex, they are built based on basic deep learning algorithms such as deep neural networks (DNNs), RNNs, and CNNs. For a more in-depth understanding of deep learning models, we recommend referring to Goodfellow, Bengio, and Courville (2016). The abbreviations used to refer to the deep learning methods are provided in the Appendix.

4.1. Standard model

The standard model is a forecasting model based on a single deep learning algorithm or one of its variants. Researchers proposed this type of model to maximize the potential of a single deep learning algorithm. Table 6 presents a list of standard models and their variants.

Table 6. List of standard models and their variants.

Articles	Input attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Tripathi and Sharma (2022)	Multivariate sequences (Historical data + fundamental indicators + TI)	1, 3, 5, 7 days	DNN	LSTM, BiLSTM	RMSE, MAE, MAPE
Livieris et al. (2022)	Univariate sequences	1 day	Dropout weight-constrained RNN	SVR, LSTM, BiLSTM, CNN, KNN, Linear Regression	RMSE, MAE
Dixon and London (2021)	Multivariate sequences (Historical data)	4 minutes	AlphaRNN	LSTM, RNN, GRU	MSE
Wang and Wang (2021a)	Univariate sequences	1 day	DBGRUNN	SVR, LSTM, ERNN, GRU, DBGRUNN, RIF-GRUNN	RMSE, MAE, SMAPE, TIC, R^2
Chou et al. (2021)	Multivariate sequences (Historical data + sentiment index + event features)	1 day	LSTM-AM	LSTM	RMSE, MAE, MAPE, R^2
Yang et al. (2020)	Multivariate sequences (Historical data)	1 day	LSTMRT	LSTM, SVR, BPNN, EEMD-	RMSE, MAE, MAPE, SMAPE, TIC

Articles	Input attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Patil et al. (2020)	Multiple sequences	3, 6, 9 minutes	Graph CNN	LSTM, VMD-LSTM ARIMA, Graph Based Linear model	RMSE, MAE, MAPE
Zhou et al. (2022)	Multivariate sequences (Historical data)	1, 3, 5 days	A-SFM	LSTM	MSE

One of the most basic deep learning models is the DNN, which has multiple hidden layers, in contrast to the more primitive ANN, which has only one hidden layer. Tripathi and Sharma (2022) found that DNNs outperformed LSTM and CNN-LSTM models in predicting BTC exchange prices by using technical indicators as inputs. On the other hand, RNNs differ from DNNs in that their connections between nodes are formed in a cycle based on a temporal sequence, enabling RNNs to be used to display temporal dynamic behaviors. Livieris et al. (2022) developed a dropout weight-constrained RNN model that used dropout techniques to improve the forecasting accuracy for major cryptocurrency prices. Dixon and London (2021) proposed AlphaRNN, a general class of exponentially smoothed RNNs with fewer layers and parameters than gated recurrent units (GRUs) and LSTMs, for modeling nonstationary dynamical systems in industrial applications.

However, RNN architectures are negatively impacted by vanishing gradients, with some weight gradients shrinking or enlarging excessively as the network progresses. To address this issue, researchers designed LSTM networks with recurrent gates called forget gates to replace the hidden layer. The LSTMRT model, a novel LSTM network developed by Yang et al. (2020), incorporates a random time effective function into the LSTM model and outperforms decomposition ensembles. Chou et al. (2021) proposed an LSTM model that incorporates investor sentiment and an attention mechanism; this model was the most accurate model for predicting the closing price of Apple in 2020.

The use of GRU neural networks, which have fewer parameters than LSTMs and utilize forget gates, has also been explored in financial time series forecasting. Wang and Wang (2021a) applied the random inheritance formula (RIF) with a deep bidirectional gated recurrent unit neural network (DBGRUNN) to predict commodity prices and found that this model outperformed six other models, including SVMs, GRUs, Elman recurrent neural networks (ERNNs), LSTMs, and RIF-GRUNNs. In addition to DNNs and RNNs, CNNs have been used to forecast one-dimensional financial time series because of their feature extraction and pattern recognition abilities in image classification. Patil et al. (2020) constructed graphs and fed them into a CNN to predict stock prices based on the spatiotemporal relationship between companies and their stock prices, and this graph-based model outperformed single linear and traditional statistical models. Furthermore, standard models such as the attention

state-frequency memory neural network (A-SFM) are capable of identifying hidden states and frequencies in financial time series data, providing excellent stock price predictions (Zhou et al. 2022).

4.2. Hybrid models

Researchers have also proposed hybrid models that combine deep learning algorithms with other computational methods, such as data processing techniques, or other deep learning algorithms. This hybrid approach generates an input feature set with more intrinsic information about the forecasting target, which can then be fed into the predictive model to obtain more accurate predictions. The hybrid models can be classified into five categories and are presented in Table 7.

Table 7. List of hybrid models.

Article	Input attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
<i>Denoising method + Deep learning algorithm:</i>					
Tang et al. (2021)	Multiple sequences	1, 3, 6 hours	WT-LSTM, SSA-LSTM	LSTM, RNN	RMSE, MAE, MAPE, SDAPE
Qiu et al. (2020)	Multivariate sequences (Historical data)	1 day	WT-LSTM-AM	LSTM, WT-LSTM, GRU	MSE, RMSE, MAE, R ²
Zhang et al. (2022b)	Univariate sequences	5 days	WT-LSTM-P	LSTM	MSE, RMSE, MAPE, R ²
Ji et al. (2021)	Multivariate sequences (Historical data + TI + sentiment index)	1 day	Doc-WT-LSTM	LSTM, RNN, ARIMA	RMSE, MAE, R ²
Song et al. (2021)	Univariate sequences	1 day	P-FTD-LSTM	LSTM, RNN, P-FTD-RNN, GRU, P-FTD-GRU	RMSE, MAE, MAPE
Bukhari et al. (2020)	Multivariate sequences	1 day	ARFIMA-LSTM	GRNN, ARIMA, ARFIMA	RMSE, MAE, MAPE
Omar et al. (2022)	Univariate sequences	1 day	AR-DNN	ARIMA, AR-RF	RMSE, MAE, MAPE, R ²
<i>Feature extraction and/or feature selection + Deep learning algorithm:</i>					
Yu and Yan (2020)	Univariate sequences	1 day	PSR-Stacked BiLSTM	SVR, MLP, ARIMA	RMSE, MAPE, Correlation coefficient
Jin et al. (2020)	Multivariate sequences (Historical data + sentiment index + event features)	1 day	S-EMD-LSTM-AM	LSTM, LSTM-AM, Random Forest	RMSE, MAE, MAPE, R ²
Boubaker et al. (2022)	Multivariate sequences (Historical data + TI)	4 weeks	CP-ADARNN	LSTM, GRU, ARIMA, Random Forest, Random walk, Lasso, ENet, Ridge	RMSE, MAE, Information coefficient, R ²

Article	Input attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Chen et al. (2020a)	Multivariate sequences (Historical data + TI)	1, 2, 3, 4, 5 days	PCA-MLP-BiLSTM	SVR, LSTM, MLP, CNN, MLP-BiLSTM	MSE, MAE, EVS, MSLE, MedAE, R ²
Li et al. (2020)	Multivariate sequences (Historical data + fundamental indicators + TI)	1 day	DP-MAELS: VAE + GRU + AR	SVM-VAR, LSTM, CNN, RNN, ARIMA	MAPE, TIC, Correlation coefficient, RSE
Chen and Zhou (2021)	Multivariate sequences (Historical data + TI)	1 day	GA-LSTM	PCA-SVR, LSTM, DA-RNN, Random Forest	MSE
Vuong et al. (2022)	Multivariate sequences (Historical data + TI)	5 minutes	XGBoost-LSTM	ARIMA	MSE, MAE, RMSE
Song et al. (2020)	Multivariate sequences (Historical data)	1 day	BIRCH-LSTM	LSTM, RNN	RMSE, MAE, MAPE
<i>Hyperparameter tuning method + Deep learning algorithm:</i>					
Kumar et al. (2022a)	Multivariate sequences (Historical data + TI)	1 day, 1, 2, 4, 6, 12 weeks	Adaptive PSO-LSTM	LSTM, PSO-LSTM, GA-LSTM, ENN	MSE, RMSE, SMAPE, TIC, MAAPE
Kumar et al. (2022b)	Multivariate sequences (Historical data + TI + sentiment index)	1 day	ABC-LSTM	LSTM, DE-LSTM, GA-LSTM	RMSE, MAPE
<i>Combination of two or more deep learning algorithms:</i>					
Livieris et al. (2020b)	Univariate sequences	1 day	CNN-LSTM	SVR, FFNN, LSTM	RMSE, MAE
Lu et al. (2020)	Multivariate sequences (Historical data + TI)	1 day	CNN-LSTM	LSTM, MLP, CNN, RNN, CNN-RNN	RMSE, MAE, R ²
Livieris et al. (2020a)	Univariate sequences	1 day	CNN-LSTM	SVR, ANN, DTR	RMSE, MAE
Aldhyani and Alzahrani (2022)	Univariate sequences	1 day	CNN-LSTM	LSTM	MSE, RMSE, NRMSE, R ²
Wang et al. (2021a)	Univariate sequences	1 day	CNN-BiLSTM	LSTM, BiLSTM, MLP, RNN, CNN-LSTM, CNN-BiLSTM	RMSE, MAE, R ²
Zheng (2021)	Multivariate sequences (Historical data + TI)	1 day	CNN-BiLSTM-AM	LSTM, ARIMA, DNN	MSE, MAPE, R ²
Chen et al. (2021)	Multivariate sequences (Historical data)	1 day	CNN-BiLSTM-ECA	LSTM, BiLSTM, BiLSTM-ECA, CNN, CNN-LSTM, CNN-LSTM-ECA, CNN-BiLSTM	MSE, RMSE, MAE

Article	Input attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Jaiswal and Singh (2022)	Multiple sequences (Historical data)	1 day	CNN-GRU	CNN-RNN, CNN-LSTM	RMSE, R ²
Kang et al. (2022)	Univariate sequences	1 minute	CNN-GRU	LSTM, BiLSTM, RNN, CNN-LSTM, ARIMA, Prophet, XGBoost	RMSE
Nasirtafreshi (2022)	Univariate sequences	1 days	RNN-LSTM	SVR, LSTM, MLP, CNN, GRU, LSTM-GRU, ARIMA, XGBoost, Random Forest, GRU-CNN	RMSE, MAE, MAPE, R ²
Guo et al. (2021)	Multivariate sequences (Historical data + sentiment index + event features)	1 day	MRC-LSTM	LSTM, MLP, CNN, CNN-LSTM	RMSE, MAE, MAPE, R ²
Ko and Chang (2021)	Multivariate sequences (Historical data + sentiment index + event features)	1 day	BERT+LSTM	LSTM	RMSE
Niu et al. (2020b)	Multivariate sequences (Historical data + TI)	1 day	ConvLSTM-LSTM-GRU	MLP, ARIMA, GPR, WNN, ConvLSTM-LSTM, ConvLSTM-GRU, ConvLSTM-LSTM-GRU	RMSE, MAE, MAPE, TIC, MdAPE
Wang et al. (2020)	Multivariate sequences (Historical data + sentiment index + event features)	1 day	ConvLSTM-ConvLSTM	SVR, LSTM, LSTM+Attention, Linear Regression, ConvLSTM-AM, Seq2Seq	MSE, TIC, Directional symmetry
Kanwal et al. (2022)	Univariate sequences	1 day	BiCuDNNLSTM-1dCNN	LSTM, LSTM-CNN, LSTM-DNN, CuDNNLSTM	RMSE, MAE
Zhang et al. (2021)	Multiple sequences	1 day	Weighted & Attentive Memory Channels Regression: GRU+CNN	SVR, LSTM, MLP, CNN, GRU, LSTM-CNN, ARIMA, XGBoost, Random Forest, GRU+CNN	RMSE, MAE, MAPE, R ²
Other types: Li and Becker (2021)	Multivariate sequences (Historical data + TI)	1 hour	Autoencoder: LSTM-LSTM	NARMAX, CNN-LSTM, Convolutional layer-LSTM	RMSE, MAE, MAPE, SMAPE
Choudhury et al. (2020)	Multivariate sequences (Historical data + TI)	1 minute	Autoencoder (LSTM-LSTM)	Prophet	RMSE, MAPE, R ²

Article	Input attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Iqbal et al. (2021)	Multivariate sequences (Historical data)	1 day	Autoencoder: ConvLSTM-LSTM	LSTM, ConvLSTM	MSE, RMSE, MAE, MAPE
Malibari et al. (2021)	Multivariate sequences (Historical data)	1 day	Transformer	NA	MSE, RMSE, MAE, MAPE
Staffini (2022)	Multivariate sequences (Historical data + TI)	1, 5 days	DCGANs: (CNN-BiLSTM-RNN) - (CNN)	LSTM, GAN, Random Forest, ARIMAX-SVR	RMSE, MAE, MAPE
Li et al. (2021)	Multivariate sequences (Historical data + TI)	1 minute	GGM-GAN (LSTM-CNN)	LSTM, GGM-LSTM, GAN	RRMSE
Yin et al. (2022)	Multiple sequences	1, 2, 3, 5, 6, 7 days	Graph Neural Network: LSTM-CNN Blocks	LSTM	RMSE, MAE, MAPE
Durairaj and Mohan (2022)	Multiple sequences	1 day	Chaos-CNN-PR	CNN, Chaos-CNN, ARIMA, Prophet, Random Forest, Chaos-Random Forest, CART, Chaos-CART	MSE, MAPE, D-stat, TIC
Durairaj and Mohan (2021)	Multiple sequences	1 day	Chaos+LSTM+PR	LSTM, Chaos+LSTM, ARIMA, Prophet	MSE, TIC, D-Stat
Li and Wang (2020)	Univariate sequences	1 day	ST-GRU	LSTM, BPNN, EEMD-SVR, GRU, WNN, WNNRT	RMSE, MAE, SMAPE, TIC, Directional symmetry, Correct uptrend, Correct downtrend, Correlation coefficient, MCCS
Paquet and Soleymani (2022)	Multivariate sequences (Historical data)	1, 5, 10, 15, 20 days	Deep quantum neural network	ARIMA, DNN	RMSV

The first type of hybrid model combines a denoising method and a deep learning algorithm, such as the use of data denoising techniques to reduce noise in financial time series. Combining denoising methods with LSTM models has proven to be effective for developing forecasting models. Attention-based LSTM models with wavelet transforms have been found to have higher accuracy than commonly used neural network models (Qiu et al. 2020). Statistical methods are also useful for denoising and modeling data by using residuals as time series trends. Hybrid models, such as the ARFIMA-LSTM and autoregressive deep neural network (AR-DNN) models,

outperformed traditional models in forecasting stock markets (Bukhari et al. 2020; Omar et al. 2022). Additionally, the phase-space reconstruction (PSR) method has been combined with stacked bidirectional long short-term memory (BiLSTM) networks for nonlinear stock index analysis (Yu and Yan 2020).

The second type of hybrid model combines feature extraction and/or feature selection methods with deep learning algorithms. Ji et al. (2021) used doc2vec to convert text content into a sentiment index, which was added to the input features of a wavelet transform long short-term memory (WT-LSTM) model. Jin et al. (2020) used empirical mode decomposition (EMD) to decompose the closing price into a set of sequences, and the price trend was combined with the sentiment index to create the input for an LSTM network. Boubaker et al. (2022) developed the change point-adaptive recurrent neural network (CP-ADARNN), which uses change points to construct a generalized RNN model for predicting crude oil market time series. Chen et al. (2020a) used principal component analysis (PCA) to reduce 31 candidate features to ten features and applied multilayer perceptron (MLP) and BiLSTM models to predict stock prices. Vuong et al. (2022) combined extreme gradient boosting (XGBoost) and an LSTM network to develop an improved stock price forecasting system, in which important features were selected and redundant features were discarded based on high-dimensional time series data. These approaches reduced the computational complexity while improving the predictive accuracy.

The third type of hybrid model combines hyperparameter tuning methods with deep learning algorithms. Kumar et al. (2022a) proposed an adaptive particle swarm optimization long short-term memory (PSO-LSTM) hybrid approach that uses an adaptive PSO technique to automatically determine the initial input weights, recurrent weights, and biases of the LSTM networks. Kumar et al. (2022b) integrated artificial bee colonies (ABCs) with an LSTM network to develop a hybrid model to perform hyperparameter tuning. ABC is an effective and adaptable optimization algorithm for solving global optimization problems with continuous parameters.

The fourth type of hybrid model combines two or more deep learning algorithms. One commonly used approach is to combine a CNN and an LSTM (CNN-LSTM), with the CNN serving as an automatic feature extraction component and the LSTM capturing the temporal dependencies among the multidimensional features extracted by the CNN (Livieris et al. 2020a, b; Lu et al. 2020; Aldhyani and Alzahrani 2022). The combination of a CNN and BiLSTM can also improve performance (Chen et al. 2021; Wang et al. 2021a; Zheng 2021). Similarly, other deep learning algorithms, such as GRUs, can be combined with LSTM models (Jaiswal and Singh 2022; Kang et al. 2022). Nasirtafreshi (2022) proposed an RNN-LSTM model to predict cryptocurrency prices, while Guo et al. (2021) developed a hybrid method that combines a multiscale residual block and an LSTM network to forecast Bitcoin prices. Researchers have also proposed a hybrid model containing convolutional

LSTM, LSTM, and GRU models (Niu et al. 2020b) and a hybrid model combining convolutional LSTM components with a self-attention layer to forecast financial derivatives and stock prices (Wang et al. 2020). Kanwal et al. (2022) developed a hybrid model called BiCuDNNLSTM-1dCNN, which achieved enhanced accuracy in stock price prediction.

Other types of forecasting models include those with novel architectures that have been proposed in recent years. Choudhury et al. (2020) proposed an autoencoder hybrid architecture using LSTM architectures as both the encoder and decoder. In addition, Li and Becker (2021) proposed an LSTM-LSTM encoder-decoder model for electricity market prediction, while Iqbal et al. (2021) proposed an autoencoder architecture in which the encoder was a convolutional LSTM. Furthermore, Malibari et al. (2021) proposed a transformer-based formalization model for stock price prediction. Generative adversarial networks (GANs) have also been used in financial time series forecasting. Li et al. (2021) developed a novel Gaussian graph model-generative adversarial network (GGM-GAN) based on the concept of a sparse partial correlation graph. Yin et al. (2022) proposed a graph neural network (GNN) for forecasting cryptocurrency and financial stress indices by using LSTMs and graph convolution networks (GCNs) to obtain temporal and spatial features, respectively. Moreover, Paquet and Soleymani (2022) developed a quantum leap system consisting of an encoder, a deep quantum network, and a conventional network. Finally, deep learning algorithms have been combined with chaos theory (Duraiaraj and Mohan 2021, 2022) and the stochastic time intensity function (Li and Wang 2020).

4.3. Ensemble models

Researchers have found that combining multiple models is often more effective than using a single model for financial time series forecasting (Bishop and Nasrabadi 2006). This combination of multiple models, which are known as ensemble models, involves a series of parallel base models that produce one optimal predictive model. The ensemble models proposed by the researchers in the included studies can be roughly categorized into two types: traditional ensembles and decomposition ensembles. Table 8 presents a list of these ensemble models.

Table 8. List of ensemble models.

Article	Input Attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
<i>Traditional ensemble models:</i>					
Patel et al. (2020)	Univariate sequences	1, 3, 7 days	LSTM+GRU	LSTM	MSE, RMSE, MAE
Livieris et al. (2021)	Univariate sequences	1 day	Multiple-input deep neural	CNN-LSTM	RMSE, MAE, R ²

Article	Input Attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Wang et al. (2021b)	Multiple sequences	1, 3, 5, 7, 10, 15 days	network (MICDL) BiLSTM+BiGRU	BiLSTM, BPNN, GRU, Random Forest	RMSE, MAE, MAPE
Lu and Peng (2021)	Multivariate sequences (Historical data + TI)	1 day	MLP+LSTM+GRU+RNN	LSTM MLP, RNN, GRU	MSE, MAE, MAPE, R^2
Yang et al. (2022)	Multivariate sequences (Historical data + TI)	1 day	CNN+(GRU+FC)	CNN, GRU, GRU-AM, Ensemble: (CNN+GRU)	RMSE, MAE, MAPE, R^2
Liu and Huang (2021)	Multivariate sequences (Historical data + sentiment index + event features)	1 day	ARIMA+(ARIMA-GARCH)+LSTM	SVR, LSTM, ARIMA, ARIMA-GARCH	RMSE, MAPE, D-stat
Chong et al. (2020)	Multivariate sequences (Historical data)	1 day	CNN+LSTM+ConvLSTM	CNN, RNN, Random Forest	RMSE
<i>Decomposition-ensemble models:</i>					
Niu et al. (2020a)	Univariate sequences	1 day	VMD-LSTM	LSTM, CNN, BPNN, ELM, EMD-BPNN, EMD-ELM, EMD-CNN, EMD-LSTM, VMD-BPNN, VMD-ELM, VMD-CNN	RMSE, MAE, MAPE
Guo et al. (2022)	Multivariate sequences (Historical data + TI)	1 day	EEMD-Cluster-SVR-PSO-LSTM	LSTM, PSO-LSTM, BPNN, ELM, EEMD-PSO-LSTM, EEMD-SVR	MSE, RMSE, MAE, D-stat
Huang et al. (2021)	Univariate sequences	1 day	VMD-LSTM	SVR, FFNN, LSTM, ELM, EMD-SVR, EMD-Lahmiri, EMD-RKELM, EMD-SVNN, VMD-Lahmiri, VMD-SVNN, VMD-SVR, ARIMA, ARMA, SVNN	RMSE, MAE, MAPE
Wang and Wang (2021b)	Univariate sequences	1 day	WPD-SW-LSTM	SVR, LSTM, BPNN, WPD-BPNN, WPD-LSTM	RMSE, MAE, MAPE, SMAPE, TIC
Lin et al. (2022)	Univariate sequences	1, 5, 10 days	MEEMD-LSTM	SVR, LSTM, MLP, EEMD-SVR, EEMD-LSTM, EEMD-MLP, MEEMD-SVR, MEEMD-MLP	RMSE, MAE, MAPE, SMAPE
Liu and Long (2020)	Univariate sequences	1 day	EWT-dLSTM-PSO-ORELM	LSTM, PSO-LSTM, PSO-LSTM-ORELM, PSO-LSTM-RELM, PSO-LSTM-ELM, BPNN, EWT-PSO-LSTM	RMSE, MAE, MAPE, SMAPE, TIC

Article	Input Attributes	Prediction horizon	Proposed model	Baselines	Performance metrics
Althelaya et al. (2021)	Univariate sequences	1 day, 1 month	EWT-Stacked LSTM	Stacked LSTM	RMSE, MAE, MAPE, R^2
Lin and Sun (2020)	Univariate sequences	1 day	CEEMDAN-Stacked GRU	LSSVR, LSTM, EEMD-Stacked GRU, EEMD-GRU, EEMD-LSTM, EEMD-LSSVR, EEMD-ANN, CEEMDAN-Stacked GRU, CEEMDAN-GRU, CEEMDAN-LSTM, CEEMDAN-LSSVR, CEEMDAN-ANN, ANN, GRU, Staked GRU, ARIMA, Naïve	RMSE, MAPE
Wang and Wang (2020)	Univariate sequences	3 days	EMD-SW-GRU	EEMD-SW-GRU, EMD-BPNN, EMD-SVR, EMD-GRU	RMSE, MAPE, SMAPE, TIC
Shu and Gao (2020)	Univariate sequences	1 day	EMD-CNN-LSTM	SVR, LSTM, CNN-LSTM, EMD-LSTM, EMD-SVR; Persistence model	RMSE, MAE
Deng et al. (2022)	Multivariate sequences (Historical data)	1, 3, 5, 10 days	MEMD-LSTM	LSTM, BPNN, EMD-LSTM, ARIMA	RMSE, MAPE, Directional symmetry
Xuan et al. (2020)	Univariate sequences	1 day	EMD-LSTM-CSI	SVR, LSTM, LSTM-AM, EMD-LSTM, EMD-LSTM-AM	RMSE, MAE, MAPE
Yujun et al. (2021)	Univariate sequences	1 day	VMD-LSTM	SVR, BARDR, RFR, KNR	RMSE, MAE, R^2
Rezaei et al. (2021)	Univariate sequences	1 day	CEEMD-CNN-LSTM	LSTM, CNN-LSTM, EMD-LSTM, EMD-CNN-LSTM, CEEMD-LSTM	RMSE, MAE, MAPE

Ensemble models have been found to be more effective for financial time series forecasting than single models alone. Traditional ensembles combine a series of parallel base models to produce one optimal predictive model. Each base model is independent, and their predictions are combined using meta-learning or a simple average. Researchers aim to increase the diversity of the base models to compensate for the weaknesses of the different models and obtain a collective prediction (Chong et al. 2020; Patel et al. 2020; Liu and Huang 2021; Lu and Peng 2021; Wang et al. 2021b; Yang et al. 2022). In recent years, decomposition ensembles have attracted more attention from researchers (Zhang et al. 2022a). In a decomposition ensemble, the original time series is decomposed into spectra using signal decomposition techniques such as EMD, ensemble empirical mode decomposition (EEMD), multivariate ensemble empirical mode decomposition (MEMD), and complete ensemble empirical mode decomposition (CEEMD), and each spectrum is fed into an independent deep learning model for training. The predictions obtained based on each spectrum are then combined to generate the final prediction of

the response variable. State-of-the-art decomposition ensembles include CEEMD-CNN-LSTM (Rezaei et al. 2021), MEMD-LSTM (Deng et al. 2022), and EEMD-Cluster-SVR-PSO-LSTM (Guo et al. 2022).

5. Model implementation and evaluation

The implementation of a model involves several crucial aspects, including model training, hyperparameter tuning, model regularization, and the coding and hardware environments. For model evaluation, appropriate performance metrics and statistical tests should be considered. In this section, we discuss each of these aspects in detail.

5.1. Model training

Initializing the structure of a forecasting model is insufficient to start using the model for forecasting. In addition to the structure, the trainable parameters of the model, such as the weights of the hidden layers in a deep neural network, are crucial components. These parameters are incrementally adjusted through model training to determine their optimal values. To achieve this, the dataset is usually split into a training set and a test set. During the training phase, the forecasting model's cost (or loss) is calculated by comparing the prediction values to the ground truth labels in the training set using the cost function (or loss function). The deep learning model's parameters are updated using techniques such as gradient descent to minimize the cost (or loss). During the testing phase, the predictions based on the test set are compared with the actual prices to evaluate the model's performance on the benchmark dataset.

Moreover, the model parameters are treated as the input to the loss function, and the loss value is the output. However, due to the multidimensionality of the input, visualizing the loss function in three dimensions is impossible. In a simple scenario in which the number of parameters is two, a plot of the loss function resembles an irregular surface with hills, valleys, and saddles. The task of model training is similar to searching this surface to identify the point at the lowest position, which represents the optimal values of the parameters.

Two factors determine the outcome of the search: the search approach, including the optimizer and learning rate used during training, which determines how the parameters are modified, and the selected surface shape or loss function. The included studies adopted various optimizers and loss functions for model training, as shown in Tables 9-10, respectively. Adaptive moment estimation optimization (Adam) was the most commonly used optimizer, followed by RMSprop and stochastic gradient descent (SGD). Researchers have also used variants

of Adam, such as Adamax, AdamW, and NAdam. For the loss function, the mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) were the most frequently selected by researchers, with mean absolute percentage error (MAPE) and binary cross entropy (BCE) also being viable options. There is no standard approach to selecting the learning rate, and researchers often rely on experience or use hyperparameter tuning methods to determine the optimal parameter values.

Table 9. List of optimizers.

Optimizer	Articles
Adam	Livieris et al. (2020a, b, 2022); Lu et al. (2020); Durairaj and Mohan (2021, 2022); Patel et al. (2020); Lin et al. (2022); Wang et al. (2021a); Ji et al. (2021); Kumar et al. (2022a); Lu and Peng (2021); Kanwal et al. (2022); Lin and Sun (2020); Kang et al. (2022); Li and Becker (2021); Niu et al. (2020b); Choudhury et al. (2020); Dixon and London (2021); Liu and Huang (2021); Zhang et al. (2021); Boubaker et al. (2022); Song et al. (2020, 2021); Shu and Gao (2020); Bukhari et al. (2020); Guo et al. (2021); Deng et al. (2022); Tang et al. (2021); Xuan et al. (2020); Chong et al. (2020); Chen and Zhou (2021); Chen et al. (2021); Staffini (2022); Vuong et al. (2022)
RMSprop	Yin et al. (2022); Aldhyani and Alzahrani (2022); Tripathi and Sharma (2022); Zhou et al. (2022)
SGD	Kang et al. (2022); Li et al. (2021)
Adamax	Kang et al. (2022)
AdamW	Malibari et al. (2021)
NAdam	Wang et al. (2020)

Table 10. List of loss functions.

Loss function	Articles
MSE	Livieris et al. (2020a, b); Durairaj and Mohan (2022); Jaiswal and Singh (2022); Guo et al. (2022); Kumar et al. (2022a); Lu and Peng (2021); Lin and Sun (2020); Li and Becker (2021); Choudhury et al. (2020); Zhang et al. (2021); Boubaker et al. (2022); Song et al. (2020, 2021); Chen et al. (2020a, 2021); Tripathi and Sharma (2022); Guo et al. (2021); Malibari et al. (2021); Tang et al. (2021); Chen and Zhou (2021); Yu and Yan (2020); Zhou et al. (2022)
RMSE	Wang and Wang (2021a, b); Yang et al. (2022); Kang et al. (2022); Kumar et al. (2022b)
MAE	Lu et al. (2020); Wang et al. (2021a); Kanwal et al. (2022); Shu and Gao (2020)
MAPE	Zhang et al. (2022a)
BCE	Staffini (2022)

5.2. Regularization for deep learning

The primary goal of a deep learning project is to create a model that can effectively predict outcomes based on new and unseen data. However, deep learning models are often complex and have a tendency to overfit the training data, leading to poor performance for test data. To address this issue, model regularization can be applied to restrain the complexity of the model and achieve the optimal balance between the bias and variance. As shown in Table 11, several regularization methods can be used, such as adding a dropout layer or a penalty term to the loss function. Regularization techniques can also be applied to the data, such as batch normalization (Jin et al. 2020;

Guo et al. 2021; Livieris et al. 2021). Other methods include RIF (Wang and Wang 2021a) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (Niu et al. 2020b). These techniques can effectively prevent overfitting and improve the generalizability of deep learning models.

Table 11. List of regularization methods.

Regularization method	Articles
Dropout	Patel et al. (2020); Livieris et al. (2021, 2022); Ji et al. (2021); Liu and Long (2020); Kanwal et al. (2022); Niu et al. (2020b); Choudhury et al. (2020); Zheng (2021); Aldhyani and Alzahrani (2022); Kumar et al. (2022b); Deng et al. (2022); Chong et al. (2020); Chen and Zhou (2021); Staffini (2022); Yu and Yan (2020)
Lasso regression (L1)	Li and Becker (2021); Niu et al. (2020b); Dixon and London (2021); Zhang et al. (2021)
Ridge regression (L2)	Li et al. (2021); Zhang et al. (2021); Tripathi and Sharma (2022)
Batch normalization	Livieris et al. (2021); Guo et al. (2021); Jin et al. (2020)
CEEMDAN	Niu et al. (2020b)
Random inheritance formula	Wang and Wang (2021a)

5.3. Hyperparameter tuning

Hyperparameters are parameters that cannot be estimated by the model during training, such as the number of layers in a neural network, the filter number in a CNN, or the learning rate value. These hyperparameters can significantly impact the performance of a forecasting model for a specific dataset. Therefore, hyperparameter tuning approaches aim to identify the best set of hyperparameters for the forecasting model. It should be noted that the optimal hyperparameters for a model can vary depending on the dataset.

Table 12 presents various hyperparameter tuning methods that have been used to obtain the optimal architecture of a forecasting model. One simple and commonly used method is grid search, which involves exhaustively testing the model for all possible combinations of hyperparameters within predefined ranges. However, as the number of hyperparameters increases, the number of required trials increases exponentially, making this approach computationally expensive. Additionally, due to the discrete nature of grid search, this approach may not identify the optimal hyperparameter values.

Table 12. List of hyperparameter tuning methods.

Hyperparameter tuning method	Article list
Grid search	Livieris et al. (2022); Lin and Sun (2020); Kang et al. (2022); Niu et al. (2020b); Song et al. (2021); Shu and Gao (2020)
PSO	Guo et al. (2022); Kumar et al. (2022a); Liu and Long (2020)
GA	Huang et al. (2021)
Random search	Kanwal et al. (2022)
Bayesian optimization	Tripathi and Sharma (2022)
Trial and error	Chen et al. (2020a)

Hyperparameter tuning method	Article list
Hyperas7	Choudhury et al. (2020)
ABC	Kumar et al. (2022b)
Cuckoo search	Wang et al. (2021b)
OATM	Deng et al. (2022)

Alternative hyperparameter tuning methods have been developed to address these issues, such as random search (Kanwal et al. 2022), Bayesian optimization (Tripathi and Sharma 2022), PSO (Liu and Long 2020; Guo et al. 2022; Kumar et al. 2022a), ABC (Kumar et al. 2022b), and genetic algorithms (GAs) (Huang et al. 2021). Random search involves randomly selecting hyperparameters and testing the model, while Bayesian optimization, PSO, ABC, and GA use optimization algorithms to search for the best hyperparameters. Among these methods, random search can serve as a baseline for comparison models using different hyperparameter tuning methods.

Other less common hyperparameter tuning methods applied in the reviewed studies include manual search (Chen et al., 2020a), the Hyperas package (Choudhury et al. 2020), Cuckoo search (Wang et al. 2021b), and the orthogonal array tuning method (OATM) based on the Taguchi experimental design (Deng et al. 2022). These methods have been used to improve prediction performance and optimize deep learning models for specific datasets.

5.4. Experimental environment

In this subsection, we examine the experimental environment, including programming language and hardware. Table 13 provides a summary of the coding languages used in the included studies. Although the choice of programming language has little effect on the forecasting results, there is a trend showing that Python is the most popular language for deep learning model implementation. The high-level API Keras plays an important role in this task, followed by TensorFlow, which is a free and open-source software library for machine learning and artificial intelligence.

Table 13. List of coding languages.

Coding languages	Articles
Python	Durairaj and Mohan (2021, 2022); Wang et al. (2021b); Liu and Huang (2021); Chen et al. (2020a, 2021); Li et al. (2020); Jin et al. (2020); Staffini (2022)
Keras	Livieris et al. (2020a); Kanwal et al. (2022); Choudhury et al. (2020); Vuong et al. (2022)
Keras (TensorFlow)	Jaiswal and Singh (2022); Zhang et al. (2021, 2022b); Wang et al. (2021a); Althelaya et al. (2021); Lin and Sun (2020); Deng et al. (2022)
Keras (Theano)	Livieris et al. (2020b)
TensorFlow	Wang and Wang (2020); Dixon and London (2021); Shu and Gao (2020); Qiu et al. (2020); Kumar et al. (2022b); Tripathi and Sharma (2022); Malibari et al. (2021); Tang et al. (2021)
PyTorch	Lu and Peng (2021); Boubaker et al. (2022); Guo et al. (2021)

Coding languages	Articles
MATLAB	Livieris et al. (2022); Kumar et al. (2022a); Boubaker et al. (2022)
R	Durairaj and Mohan (2021, 2022); Omar et al. (2022)

Table 14 presents the hardware environments used by researchers in the included studies. Most studies used only central processing units (CPUs) for code execution, indicating that computational resources are still expensive for most researchers. However, the capacity of CPUs to run deep learning code is insufficient compared to that of GPUs or tensor processing units (TPUs), thereby limiting the efficiency of model training and testing. One solution to this challenge is to use cloud computing, as reported by Kanwal et al. (2022).

Table 14. List of hardware environments.

Hardware environments	Articles
CPU	Livieris et al. (2020a, b); Lu et al. (2020); Jaiswal and Singh (2022); Kumar et al. (2022a, b); Lu and Peng (2021); Shu and Gao (2020); Aldhyani and Alzahrani (2022); Durairaj and Mohan (2021); Jin et al. (2020); Staffini (2022)
GPU	Wang et al. (2021a); Lin and Sun (2020); Boubaker et al. (2022); Chen et al. (2020a); Tripathi and Sharma (2022); Li et al. (2020)
Cloud	Kanwal et al. (2022)

5.5. Performance metrics

Several performance metrics have been proposed to evaluate the regression results produced by the proposed model against the ground truth values. The included studies employed various metrics, as illustrated in Figure 4. The most commonly used metrics include the RMSE, MAE, MAPE, and coefficient of determination (R^2), followed by the MSE, Theil inequality coefficient (TIC), and symmetric mean absolute percentage error (SMAPE), which are also popular metrics. The formulas used to calculate the top performance metrics are presented in Table 15, where n denotes the size of the test set, \hat{y}_i denotes the predicted result, and y_i denotes the actual stock index value.

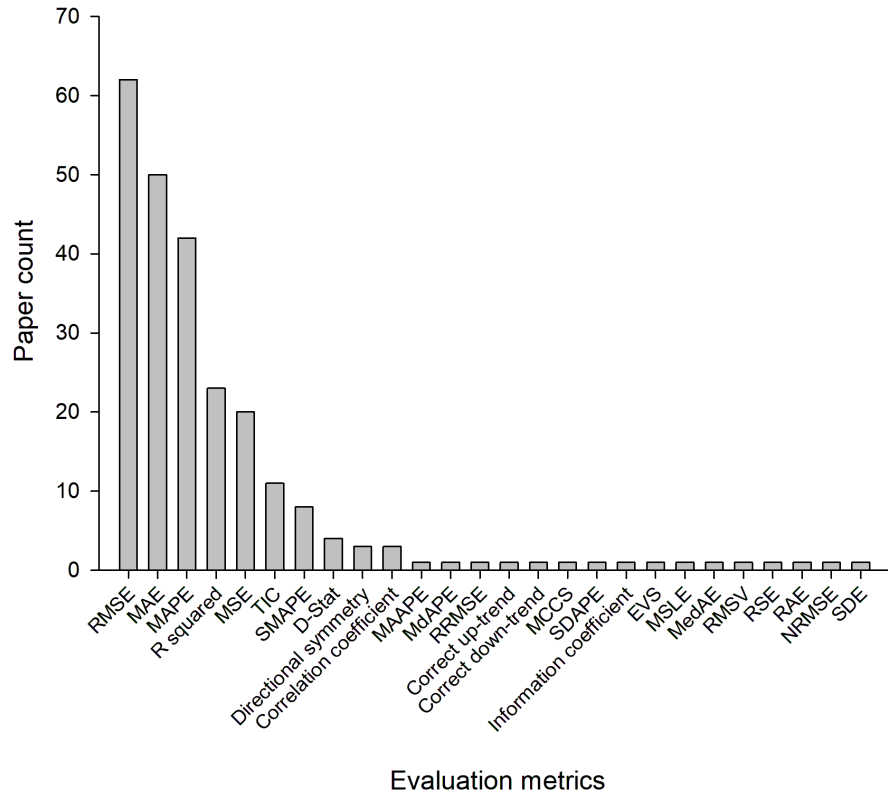


Figure 4. Types of performance metrics.

Table 15. Formulas to calculate different performance metrics.

Performance metrics	Formula
RMSE	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$
MAE	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $
MAPE (%)	$MAPE (\%) = \frac{100}{n} \sum_{i=1}^n \left \frac{y_i - \hat{y}_i}{y_i} \right $
R ²	$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n \left(y_i - \frac{1}{n} \sum_{i=1}^n y_i \right)^2}$
MSE	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$
TIC	$TIC = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2} + \sqrt{\frac{1}{n} \sum_{i=1}^n \hat{y}_i^2}}$
SMAPE (%)	$SMAPE (\%) = \frac{100}{n} \sum_{i=1}^n \frac{ y_i - \hat{y}_i }{(y_i + \hat{y}_i)/2}$

5.6. Statistical tests for model comparisons

Although statistical tests are not necessary to report research results in machine learning or deep learning, some researchers perform statistical tests to demonstrate the superiority of the proposed model over baseline models. These statistical tests are based on the comparison of two or more resulting distributions and are primarily used to determine which model provides the best fit for the data. Table 16 outlines the statistical tests employed by the researchers in the included studies. The paired t test is a common method for comparing two distributions of results (Ji et al. 2021); however, this test is reliable only when the distributions are normally distributed. A more general comparison method is the Wilcoxon rank-sum test (Mann–Whitney Wilcoxon test), which does not assume that the results are normally distributed (Li and Wang 2020; Yang et al. 2020; Paquet and Soleymani 2022).

Table 16. List of statistical tests.

Statistical test	Articles
Diebold-Mariano	Lin and Sun (2020); Li and Becker (2021); Liu and Huang (2021); Deng et al. (2022); Staffini (2022)
Friedman Aligned Ranking	Livieris et al. (2021, 2022); Yang et al. (2020)
Wilcoxon rank sum test (Mann–Whitney Wilcoxon test)	Li and Wang (2020); Yang et al. (2020); Paquet and Soleymani (2022)
Ljung-Box Q test	Livieris et al. (2020a)
Independent t tests	Staffini (2022)
Paired T test	Ji et al. (2021)
Z test	Wang et al. (2021b)
Dickey-Fuller test	Dixon and London (2021)
Finner test	Livieris et al. (2021, 2022)
Autocorrelation function	Livieris et al. (2020a)

6. Future directions

The no-free-lunch theorem demonstrates that no single deep learning algorithm is universally superior to other deep learning algorithms for every possible problem (Wolpert 2002). Given the volatile and stochastic nature of financial time series, it is improbable that one deep learning model can provide satisfactory predictions in all scenarios. Therefore, the development of more advanced deep learning models for financial markets is essential. In this section, we discuss several possible future research directions.

6.1. New modeling scheme for the decomposition ensemble

According to the analysis by Zhang et al. (2022a), the popularity of decomposition ensembles has increased since 2015. However, there are limitations to using this type of forecasting model. Most existing decomposition-

ensemble models based on time-frequency decomposition adopt a one-time decomposition for the whole price series. As a result, the decomposed components used to train the base models are derived from both in-sample and out-of-sample data, which may expose future characteristics and lead to higher forecasting accuracy (Zhang et al. 2015; Wu et al. 2022). Moreover, the use of other decomposition methods, including variational mode decomposition (VMD) and multidecomposition, has been ineffective for addressing this problem. Additionally, it has been reported that the EEMD-based decomposition ensemble modeling paradigm cannot be used to reliably predict crude oil futures prices (Xu and Niu 2022). Therefore, researchers should review the effectiveness of similar models and develop new schemes for decomposition ensemble modeling.

6.2. Novel Algorithms

Developing novel algorithms or neural architectures is a promising direction for establishing more advanced forecasting models. However, creating a novel deep learning algorithm is a challenging task. Alternatively, researchers can combine different algorithms to create novel hybrid neural architectures. Section 4 highlights that a significant number of forecasting models are based on hybrid neural architectures or combinations of different deep learning algorithms. Another approach is to develop ensembles of base models using novel algorithms such as the jump-diffusion algorithm, GAN, GNN, and capsule network (CapsNet).

6.3. Integrating predictive models into high-frequency trading

Deep learning models have the potential to provide traders with a more accurate and nuanced understanding of market behavior, allowing traders to analyze large amounts of data and identify complex patterns. This is especially valuable in high-frequency trading, in which even small improvements in the predictive accuracy can lead to significant gains. By utilizing deep learning models for financial time series forecasting, traders can gain a competitive edge over traders who rely on more traditional methods. However, despite advancements in deep learning techniques for financial forecasting, integrating these techniques into real-time trading situations remains challenging due to factors such as the models' complexity, the difficulty of training models with sufficient data, and the need to adapt models to changing market conditions. Therefore, additional research and development are necessary to effectively integrate these models into high-frequency trading systems.

7. Conclusion

The increasing use of deep learning models for financial time series forecasting prompted us to conduct a literature review of related publications published in the last three years. We focused on the implementation of deep learning models to encourage the adoption of published models as baselines. The insights and summaries provided in this review, in addition to the suggested future research directions, will aid researchers working in this area.

This literature review provides a comprehensive summary of practical and theoretical deep learning contributions to the field of financial time series forecasting. In terms of practical aspects, we present a clear and concise workflow that can be easily understood by new researchers in the field, which can serve as a useful guide for implementing the models discussed in this review. From a theoretical perspective, we focus specifically on deep learning techniques, which have been shown to be effective in various applications. Our review covers recent advancements in these techniques for financial time series forecasting. We also offer insights into future research directions for those interested in further exploration of this field.

There are three main limitations to this literature review. First, there is a possibility that relevant studies were not included in the selected databases. While comprehensive keywords were used in the literature search, some studies may have been missed due to the use of less common linguistic terms. Additionally, this review solely focuses on the application of deep learning to price forecasting in financial markets and does not consider its use for classification tasks or other forecasting tasks. Furthermore, while most of the included studies suggest that deep learning is a state-of-the-art technique for predicting financial markets, this review does not aim to provide an exhaustive experimental comparison between deep learning and other prediction methods. Such a comparison would require a significant amount of computational resources and is a topic for future research.

Appendix

Abbreviations

ABC	-	Artificial Bee Colony Algorithm
ADARNN	-	Adaptive Recurrent Neural Network
AE	-	Autoencoder
AM	-	Attention Mechanism
ANN	-	Artificial Neural Network
AR	-	Auto Regressive
ARFIMA	-	Autoregressive Fractionally Integrated Moving Average
ARIMA	-	Autoregressive Integrated Moving Average
ARIMAX	-	Autoregressive Integrated Moving Average with Explanatory Variable
ARMA	-	Autoregressive Moving Average

BARDR	-	Bayesian ARD Regression
BCE	-	Binary Cross Entropy
BERT	-	Bidirectional Encoder Representations from Transformers
BiCuDNNLSTM	-	Bidirectional CuDNNLSTM
BiGRU	-	Bidirectional Gated Recurrent Units
BiLSTM	-	Bidirectional Long Short-Term Memory
BIRCH	-	Balanced Iterative Reducing and Clustering Using Hierarchies
BPNN	-	Back Propagation Neural Network
CapsNet	-	Capsule Network
CART	-	Classification and Regression Tree
CEEMD	-	Complementary Ensemble Empirical Mode Decomposition
CEEMDAN	-	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
CGAN	-	Conditional Generative Adversarial Network
CNN	-	Convolutional Neural Network
CPU	-	Central Processing Unit
ConvLSTM	-	Convolutional LSTM
CSI	-	Cubic Spline Interpolation
CuDNNLSTM	-	GPU-Accelerated LSTM
DA	-	Dual-Stage Attention-Based
DBGRUNN	-	Deep Bidirectional GRU Neural Network
DCGAN	-	Deep Convolutional Generative Adversarial Network
DE	-	Differential Evolution
DGA	-	Domain Generation Algorithm
dLSTM	-	Delayed Long Short-Term Memory
DP	-	Differential Privacy
DNN	-	Deep Neural Network
D-stat	-	Directional Statistical Indicator
DTR	-	Decision Tree Regressor
ECA	-	Efficient Channel Attention
EEMD	-	Ensemble Empirical Mode Decomposition
ELM	-	Extreme Learning Machine
EMD	-	Empirical Mode Decomposition
EMH	-	Efficient Market Hypothesis
ENet	-	Elastic Net
ENN	-	Elman Neural Network
ERNN	-	Elman Recurrent Neural Network
EWT	-	Empirical Wavelet Transform
FC	-	Fully Connected Layer
FFNN	-	Feed-forward Neural Network
FFT	-	Fast Fourier Transform
FTD	-	Fourier Transform Denoising
GA	-	Genetic Algorithm
GAN	-	Generative Adversarial Network
GARCH	-	Generalized Autoregressive Conditional Heteroskedasticity
GBDT	-	Gradient Boosting Decision Tree
GCN	-	Graph Convolution Network
GGM	-	Gaussian Graph Model
GloVe	-	Global Vectors for Word Representation
GNN	-	Graph Neural Network
GPR	-	Gaussian Process Regression
GPU	-	Graphics Processing Unit
GRNN	-	Generalized Regression Radial Basis Neural Network
GRU	-	Gated Recurrent Units
GRUA	-	GRU Neural Network with Attention Mechanism
GRUNN	-	GRU Neural Network
IMF	-	Intrinsic Mode Function
KNN	-	K-Nearest Neighbors
KNR	-	K-Nearest Neighbor Regression
LSTM	-	Long Short-Term Memory
LSTMRT	-	Long Short-Term Memory with Random Time Effective Function

LSSVR	-	Least Squares Support Vector Regression
MAE	-	Mean Absolute Error
MAAPE	-	Mean Arctangent Absolute Percentage Error
MAPE	-	Mean Absolute Percentage Error
MCCS	-	Multiscale Composite Complexity Synchronization
MdAPE	-	Median of the Absolute Percentage Error
MedAE	-	Median Absolute Error
MEEMD	-	Modified Ensemble Empirical Mode Decomposition
MEMD	-	Multivariate Empirical Mode Decomposition
MICDL	-	Multiple-Input Deep Neural Network
MLP	-	Multilayer Perceptron
MRC	-	Multi-scale Residual Convolutional Neural Network
MSE	-	Mean Square Error
MSLE	-	Mean Squared Log Error
NARMAX	-	Nonlinear Autoregressive Moving Average with Exogenous Inputs
NLP	-	Natural Language Processing
NRMSE	-	Normalization Root Mean Squared Error
OATM	-	Orthogonal Array Tuning Method
ORELM	-	Outlier Robust Extreme Learning Machine
OTC	-	Over the Counter
PCA	-	Principal Component Analysis
PR	-	Polynomial Regression
PSD	-	Positive Semi-definite
PSO	-	Particle Swarm Optimization
PSR	-	Phase-Space Reconstruction
R2	-	Coefficient of Determination
RAE	-	Relative Absolute Error
RBF	-	Radial Basis Function
RELM	-	Regular Extreme Learning Machine
ResNet	-	Residual Network
RFE	-	Recursive Feature Elimination
RFR	-	Random Forest Regression
RidgeCv	-	Ridge Regression with Built-In Cross-Validation
RIF	-	Random Inheritance Formula
RKELM	-	Robust Kernel Extreme Learning Machine
RMSE	-	Root Mean Square Error
RMSProp	-	Root Mean Squared Propagation
RMSV	-	Root Mean Square Value
RNN	-	Recurrent Neural Network
RRMSE	-	Relative Root Mean Square Error
RSE	-	Root Relative Squared Error
SAE	-	Stacked Autoencoder
SDAPE	-	Standard Deviation of the Absolute Percentage Error
SDE	-	Standard Deviation of the Error
SFM	-	State-Frequency Memory Network
SGD	-	Stochastic Gradient Descent
SMAPE	-	Symmetric Mean Absolute Percentage Error
SSA	-	Singular Spectrum Analysis
SVM	-	Support Vector Machine
SVNN	-	Support Vector Neural Network
SVR	-	Support Vector Regression
SW	-	Stochastic Time Effective Weights
TI	-	Technical Indicator
TIC	-	Theil Inequality Coefficient
TPU	-	Tensor Processing Unit
VADER	-	Valence Aware Dictionary for Sentiment Reasoner
VAE	-	Variational Autoencoders
VMD	-	Variational Mode Decomposition
WNN	-	Wavelet Neural Network
WNNRT	-	Random Wavelet Neural Network

WPD	-	Wavelet Packet Decomposition
WT	-	Wavelet Transform
XGBoost	-	Extreme Gradient Boosting

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