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Capability of Hybrid Long Short-Term Memory in Stock Price Prediction: A Comprehensive Literature Review

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ABSTRACT

Stocks are financial instruments representing ownership in a company. They provide holders with rights to a portion of the company's assets and earnings. The stock market serves as a means for companies to raise capital. By selling shares to the public, companies can obtain funds needed for expansion, research and development, as well as various other investments. Though significant, predicting stock prices poses a challenge for investors due to their unpredictable nature. Stock price prediction is also an intriguing topic in finance and economics due to its potential for significant financial gains. However, manually predicting stock prices is complex and requires in-depth analysis of various factors influencing stock price movements. Moreover, human limitations in processing and interpreting information quickly can lead to prediction errors, while psychological factors such as bias and emotion can also affect investment decisions, reducing prediction objectivity and accuracy. Therefore, machine processing methods become an alternative to expedite and reduce errors in processing large amounts of data. This study attempts to review one of the commonly used prediction algorithms in time series forecasting, namely hybrid LSTM. This approach combines the LSTM model with other methods such as optimization algorithms, statistical techniques, or feature processing to enhance the accuracy of stock price prediction. The results of this literature review indicate that the hybrid LSTM method in stock price prediction shows promise in improving prediction accuracy. The use of optimization algorithms such as GA, AGA, and APSO has successfully produced models with low RMSE values, indicating minimal prediction errors. However, some methods such as LSTM-EMD and LSTM-RNN-LSTM still require further development to improve their performance.

1. Introduction

The stock market is one of the most critical financial instruments in the modern economy [1]-[3]. Stocks represent ownership in a company traded on the stock market. They entitle holders to a portion of the company's assets and income [4]-[6]. Stockholders have rights to a share of the company's profits, known as dividends, and possess voting rights in shareholder meetings [7], [8]. The stock market serves as a means for companies to raise capital. By selling shares to the public, companies can acquire funds necessary for expansion, research and development, and various other investments. Stock prices on the stock exchange are difficult to predict, posing a challenge for investors [9]-[12].

Stock price prediction remains a perennially intriguing topic in finance and economics due to its potential for significant financial gains [13]-[16]. Manual stock price prediction is a complex process requiring in-depth analysis of various factors influencing stock price movements [17]. Investors and analysts must consider a vast amount of data, including company financial reports, industry news, macroeconomic conditions, and market sentiment. This process involves fundamental and technical analysis, evaluating company financial performance such as revenue, net income, financial ratios, and stock price chart patterns. The sheer volume and dynamic nature of data can lead to prediction errors due to human limitations in processing and interpreting information accurately and swiftly. Additionally, psychological factors such as bias and emotions can influence investment decisions, reducing prediction objectivity and accuracy [18]-[21]. Hence, the presence of a machine processing method becomes an alternative to accelerate and reduce misinterpretation errors of large amounts of data.

Long Short-Term Memory (LSTM) methods offer a solution for stock price prediction [22], [23]. LSTM, as a type of artificial neural network designed specifically to address time series problems, has the ability to recognize and learn from complex historical data patterns. By leveraging memory cell structures and gate mechanisms, LSTM can handle long sequences of data and capture long-term dependencies [24]-[26]. However, given the critical nature of stock predictions for investors and analysts, optimizing LSTM as a prediction method is essential, one such method being Hybrid-LSTM. Hybrid LSTM allows the integration of LSTM with other techniques such as statistical techniques, machine learning algorithms, other deep learning techniques, and various other methods to enhance prediction accuracy and address limitations that standard LSTM may have [27]-[29].

In 2021, several studies on stock price prediction using hybrid LSTM approaches showed promising results. H. Widiputra *et al.* [30] analyzed financial time-series data from various stock markets using a multivariate CNN-LSTM model. The results showed that the model outperformed individual CNN and LSTM models, achieving an Root Mean Squared Error (RMSE) of 0.0084 on Japanese stocks. In another study, L. Sun et al. [31] applied CNN-LSTM to predict stock prices and obtained Mean Squared Error (MSE) of 0.0024, RMSE of 0.0490, and Mean Absolute Error (MAE) of 0.0288. Meanwhile, H. Song and H. Choi [32] developed a new hybrid model, including CNN-LSTM, to predict stock market indices such as DAX, DOW, and S&P500. The results indicated that CNN-LSTM performed better than LSTM with MSE of 0.0027 and MAE of 0.0456 on DOW stocks. These findings were further supported by W. Xu [33], who used CNN-LSTM to predict stock prices in the Shanghai market with MSE below 0.002. Additionally, research by P. Singh *et al.* [34] affirmed the superiority of the hybrid CNN-LSTM model in stock selection and portfolio optimization, achieving an RMSE of 0.0138. Furthermore, there are many other studies supporting the use of hybrid LSTM approaches in stock price prediction [35]-[45].

Therefore, the contribution of this research is to provide a comprehensive overview of the capabilities of hybrid LSTM models in stock price prediction, by analyzing various hybrid approaches proposed and their applications in stock market data. Additionally, this research will compare several hybrid LSTM approaches and suggest potential future research directions. By synthesizing existing research, this review aims to provide a consolidated understanding of the capabilities of hybrid LSTM in predicting stock prices and identify areas for further improvement.

2. Methods

2.1. LSTM

LSTM is a specialized architecture within Recurrent Neural Networks (RNN) designed to address the limitations of conventional RNNs, particularly the vanishing gradient problem that hinders the model's ability to learn from long sequences of data [46]-[49]. Conventional RNNs tend to lose important information as the sequence length increases because the gradients flowing through the network tend to diminish and vanish. LSTM overcomes this issue by introducing more complex memory units that enable the model to retain relevant information over longer periods.

The basic structure of LSTM consists of LSTM cells, which have three main gates: the input gate, the output gate, and the forget gate [50]-[53]. The input gate controls the amount of information from the current input to be stored in the memory [54]. This is done through a sigmoid mechanism that regulates how much information will be added (Equations (1)-(2)) [55]. The output gate determines what information will be extracted from the memory cell to be used as output at the current time step. This gate also uses a sigmoid function to ensure that only relevant information is passed through (Equations (3)-(4)). The forget gate plays a role in deciding how much information from the memory should be discarded or retained, ensuring that the memory cell remains relevant to the data being processed (Equation (5)) [56].

In addition to the three main gates, LSTM also has a memory cell responsible for storing information throughout the data sequence [57]. The information stored in the memory cell can be updated or erased based on the decisions made by the three gates (Equation (6)). This allows LSTM to maintain and manipulate information over longer periods compared to conventional RNNs, which is extremely useful for tasks requiring long-term context understanding such as machine translation, sentiment analysis, and time series prediction. The architecture of LSTM is illustrated in Fig. 1.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{1}$$

$$\check{C}_t = tahn(W_C[h_{t-1}, x_t] + b_C) \tag{2}$$

$$o_t = \sigma\ (W_o\ [h_{t-1}, x_t] + b_o) \tag{3}$$

$$h_t = o_t * \tanh(C_t) \tag{4}$$

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \check{C}_t \tag{6}$$

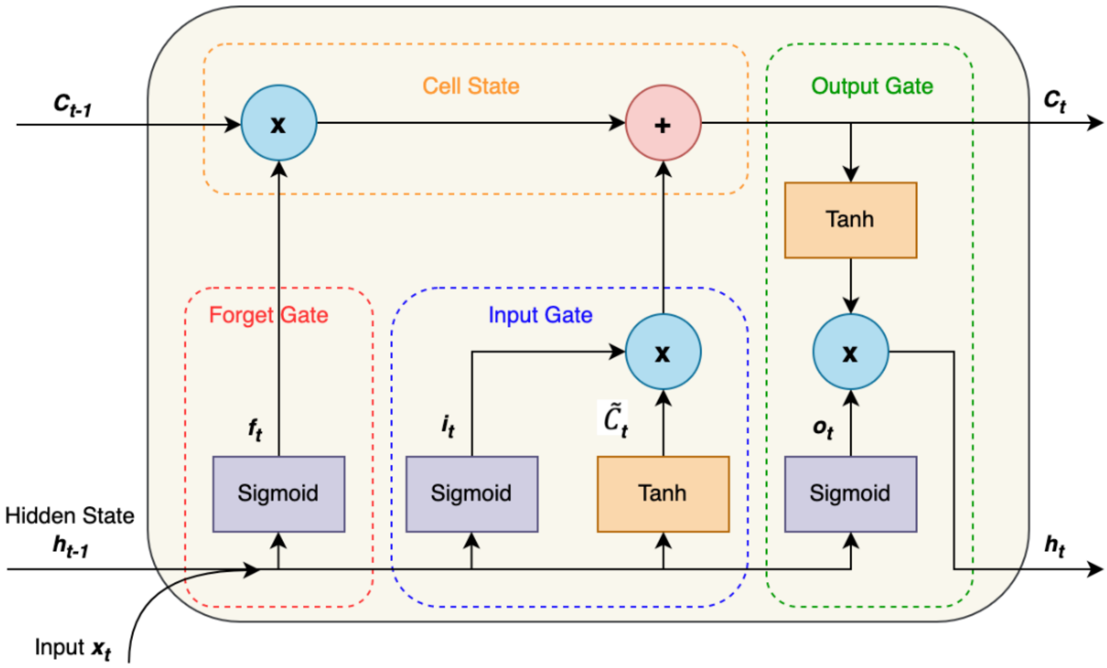

Fig. 1. Architecture of LSTM

2.2. Hybrid LSTM

Hybrid LSTM is an approach that combines the strengths of LSTM with various other methods to enhance performance across multiple applications such as natural language processing, image analysis, and time series prediction [46], [58]-[61]. This approach leverages LSTM's capability to handle long and complex sequences of data, while the accompanying methods or models contribute additional specific benefits tailored to the task at hand. Methods paired with LSTM in this hybrid approach can include special feature extraction and data noise filtering, which are crucial processes for improving data quality. Noise filtering ensures that processed data maintains high quality by eliminating irrelevant or disruptive elements, thereby enhancing prediction accuracy.

Furthermore, hybrid LSTM methods can also function as optimization algorithms, information processing and model adjustment techniques, statistical and econometric methods, as well as data pre-processing and feature enhancement techniques [62]-[64]. Data pre-processing involves normalization, standardization, and handling missing values, all of which aid in preparing data before it is fed into the LSTM model. The overall visualization of hybrid LSTM is depicted in Fig. 2, while in more complex cases, the structure of hybrid LSTM can be far more intricate than depicted.

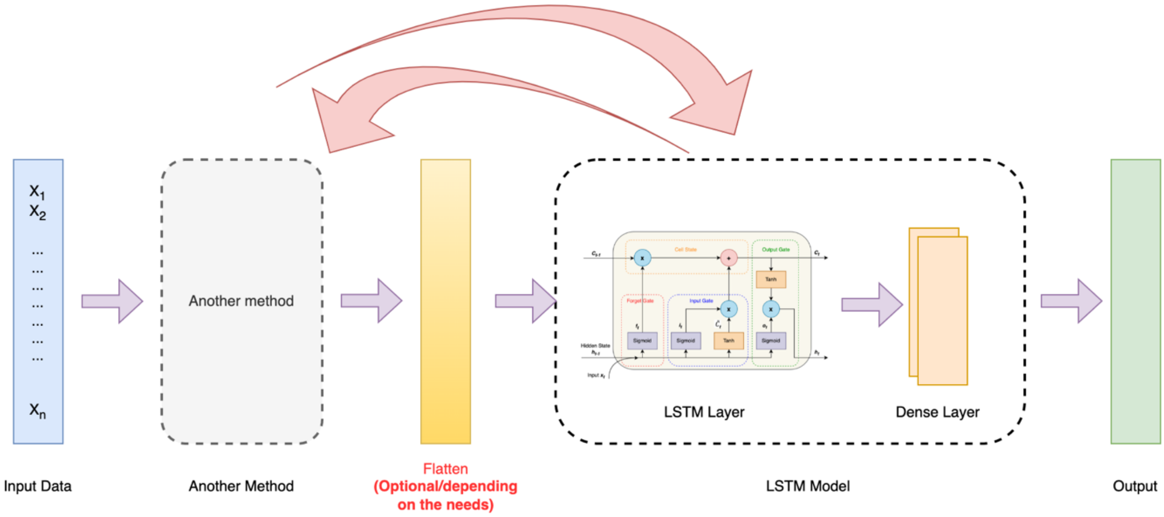

Fig. 2. General Visualization of Hybrid LSTM [34]

2.3. Evaluation Metrics

In this review process, the evaluation metrics used to assess the performance of predictive models are MAE [65]-[67], MSE [68]-[70], and RMSE [68], [71], [72]. MAE is a metric that measures the average of the absolute differences between the values predicted by the model and the values observed in the actual data [73]. In other words, MAE provides an indication of the average error of predictions against the actual data. The formula for MAE is shown as in Equation (7) [74], [75]. Meanwhile, MSE is a metric that measures the average of the squared differences between the predicted and observed values [76], [77]. By using MSE, larger errors are given higher weight because these values are squared. However, the units of MSE are no longer on the same scale as the original data, making its interpretation more difficult (Equation (8)) [78].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (9)$$

To address this, RMSE is used, which is the square root of the MSE [79]. RMSE provides a more intuitive interpretation because it presents the metric in the same units as the original data. Thus, RMSE measures the average difference between the predictions and the actual data in appropriate units (Equation (9)). In the context of this review, RMSE is chosen as the main evaluation metric due to its ability to provide a clear understanding of how well the model predicts the data, as well as its ease of use in comparing performance across different studies and case studies.

3. Results and Discussion

3.1. Hybrid LSTM in Stock Prediction in Previous Research

In the realm of stock price prediction, hybrid LSTM models have been extensively studied and applied to various datasets over the years, showcasing significant improvements in predictive performance by integrating different feature extraction methods. Here is a comprehensive explanation of the literature based on the year of study.

3.1.1. Year 2018

- M. A. Hossain et al. [44] applied a hybrid GRU-LSTM model to the S&P500 dataset, achieving MAE of 0.0630, MSE of 0.008000, and RMSE of 0.0894. Their approach demonstrated the effectiveness of combining GRU with LSTM for stock price prediction by capturing both long-term dependencies and recent trends.

3.1.2. Year 2020

- A. H. Bukhari et al. [35] employed an ARFIMA-LSTM (Autoregressive Fractional Integrated Moving Average) model on the PSX Company dataset, with results showing MAE of 0.0269, MSE of 0.002904, and RMSE of 0.0539. This study highlighted the advantage of using ARFIMA for modeling long memory effects in stock prices before applying LSTM.
- U. F. I. Abdulrahman et al. [80] utilized an ARIMA-LSTM model on the GSE dataset, with MSE of 0.000003 and RMSE of 0.0017. The integration of ARIMA for trend and seasonality extraction with LSTM for capturing temporal dependencies proved beneficial.
- Y. Yujun et al. [45] explored LSTM-EEMD and LSTM-EMD models on the DAX and ASX datasets. For the LSTM-EEMD model, the DAX dataset resulted in MAE of 0.0816, MSE of 0.010304, and RMSE of 0.1015, while the ASX dataset showed MAE of 0.2477, MSE of 0.105174, and RMSE of 0.3243. For the LSTM-EMD model, the DAX dataset showed MAE of 0.2177, MSE of 0.163192, and RMSE of 0.4040, while the ASX dataset resulted in MAE of 0.0456, MSE of 0.004386, and RMSE of 0.0662. These results underscored the effectiveness of EMD and EEMD in decomposing stock prices into intrinsic mode functions before prediction.

3.1.3. Year 2021

- H. Widiputra et al. [30] applied a CNN-LSTM model to various datasets, including N225, STI, HIS, and JSX. Their model achieved MSE values of 0.000071, 0.000222, 0.000282, and 0.000317, and RMSE values of 0.0084, 0.0149, 0.0168, and 0.0178, respectively. The study demonstrated how CNN layers can effectively extract spatial features from time-series data before LSTM layers handle the temporal aspects.
- L. Sun et al. [31] used a CNN-LSTM model on an unspecified dataset, achieving MAE of 0.0288, MSE of 0.002400, and RMSE of 0.0490. This work highlighted the general applicability of CNN-LSTM models for different stock datasets.

- S. Chen and C. Zhou [39] implemented a GA-LSTM model on the China Construction Bank and CSI300 datasets, with MSE values of 0.004200 and 0.004300 and RMSE values of 0.0648 and 0.0656, respectively. The incorporation of GA helped optimize the LSTM parameters, improving predictive accuracy.

3.1.4. Year 2022

- X. Zeng et al. [40] developed an AGA-LSTM model applied to multiple datasets, including DJIA, S&P500, HangSeng, Nifty50, Nikkei225, and CSI300, with MAE values ranging from 0.0039 to 0.0147, MSE from 0.000035 to 0.000508, and RMSE from 0.0059 to 0.0225. Their approach combined adaptive GA with LSTM for enhanced parameter tuning and prediction accuracy.
- G. Kumar et al. [38] used APSO-LSTM on the S&P500, Sensex, and Nifty50 datasets, achieving MSE values of 0.000172, 0.000449, and 0.000463 and RMSE values of 0.0131, 0.0212, and 0.0215, respectively. They also applied GA-LSTM and PSO-LSTM models, highlighting the robustness of hybrid approaches combining optimization algorithms with LSTM.
- C. Bulut and B. Hüdaverdi [36] employed ARIMA-EGARCH-LSTM and ARIMA-LSTM models on datasets such as NSE, DAX, NASDAQ, and BIST100. For ARIMA-EGARCH-LSTM, the NSE dataset resulted in MAE of 0.0077, MSE of 0.000100, and RMSE of 0.0103. For ARIMA-LSTM, the NSE dataset showed MAE of 0.0099, MSE of 0.000180, and RMSE of 0.0137. These models demonstrated the effectiveness of combining ARIMA for trend extraction and EGARCH for volatility modeling with LSTM for sequential prediction.
- W. Xu [33] applied a CNN-LSTM model to the Shanghai (SSEC) dataset, achieving MSE of 0.002000 and RMSE of 0.0447, further proving the effectiveness of CNN-LSTM models in stock price prediction.

3.1.5. Year 2023

- P. Singh et al. [34] used a CNN-LSTM model on the NSE dataset, achieving MAE of 0.0097, MSE of 0.000190, and RMSE of 0.0138, showing consistent performance in the hybrid approach.
- Y. Ding [43] applied a CNN-LSTM model to the AAPL dataset, achieving MSE of 0.000332 and RMSE of 0.0182, demonstrating the model's effectiveness in handling large-cap stock data.
- H. Song and H. Choi [32] used CNN-LSTM models on DOW, S&P500, and DAX datasets, with results showing MAE values of 0.0421, 0.0466, and 0.1635, MSE values of 0.002500, 0.003000, and 0.017500, and RMSE values of 0.0500, 0.0548, and 0.1323. Their study highlighted the model's capability to capture market dynamics across different indices.
- E. J. Prasetyo and K. D. Hartomo [81] implemented a GRU-LSTM model on the IDX-IC dataset, achieving MAE of 0.0160, MSE of 0.000441, and RMSE of 0.0210, showing the hybrid model's strength in handling Indonesian market data.

3.1.6. Year 2024

- H. Yeng and M. Siahaan [37] applied an ARIMA-LSTM model to the LQ45 dataset, with MAE of 0.5660, MSE of 0.007800, and RMSE of 0.0883, indicating the model's effectiveness in predicting the Indonesian stock index.
- A. Khalil [42] used Wavelet-LSTM-ARO and Wavelet-LSTM models on various datasets, including GE, AT&T, MSFT, AAPL, PG, and XOM. For Wavelet-LSTM-ARO, MAE values ranged from 0.0143 to 0.0261, MSE from 0.000274 to 0.005338, and RMSE from 0.0166 to 0.0731. For Wavelet-LSTM, MAE values ranged from 0.0203 to 0.0303, MSE from 0.000281 to 0.004533, and RMSE from 0.0168 to 0.0673. These results underscored the effectiveness of wavelet transforms in decomposing time series data before prediction with LSTM.

- S. Dutta et al. [41] explored LSTM-RNN-LSTM models on MSFT, Sensex, and Nifty50 datasets, with MAE values of 0.0880, 0.1090, and 0.1280, MSE values of 0.022000, 0.029000, and 0.121000, and RMSE values of 0.1483, 0.1700, and 0.3500, demonstrating the hybrid model's ability to capture complex temporal patterns in stock prices.

Research on hybrid LSTM methods for stock prediction has shown varying levels of activity over the past few years. In 2022, there was a significant surge with 31 case studies contributing to the field, indicating increased interest and advancements in utilizing hybrid LSTM models for stock market prediction. In 2024, research activity remained robust with 22 studies, reflecting sustained interest and ongoing innovation in the application of these models. However, it should be noted that some publications may use different datasets and methods for the same research, so this count is based on the number of case studies and not the number of previous research publications. The distribution of hybrid LSTM case studies in previous research by year is shown in Fig. 3.

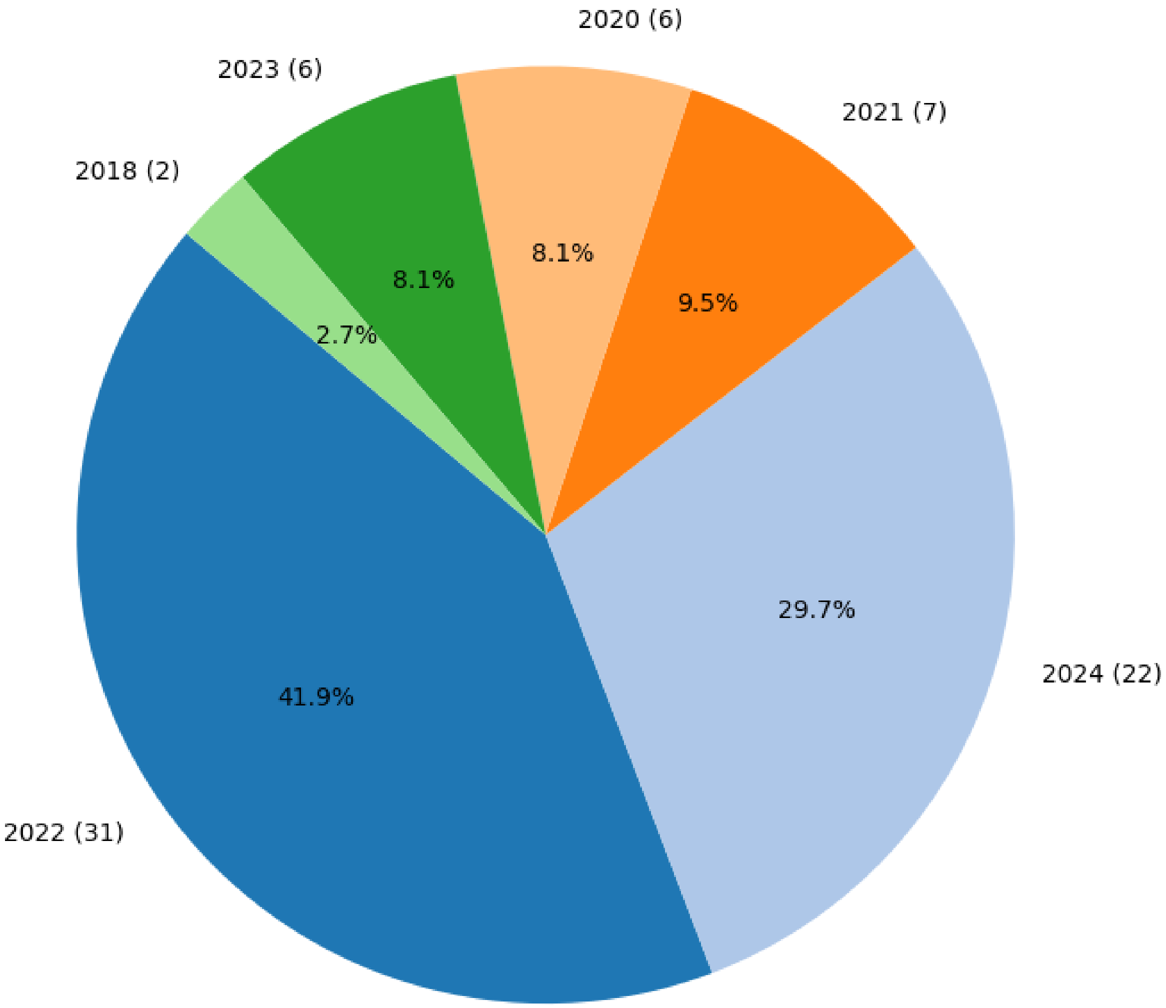

Fig. 3. Distribution of hybrid LSTM case studies in previous research by year

The previous studies have demonstrated that hybrid LSTM models are capable of delivering superior performance in predicting stock prices by integrating various methods with LSTM. By incorporating techniques such as ARIMA, ARFIMA, GA, AGA, APSO, PSO, EMD, EEMD, CNN, GRU, EGARCH, and wavelet with LSTM, previous research has significantly improved prediction accuracy. These studies encompass various global stock datasets, showcasing the flexibility and effectiveness of the hybrid LSTM approach in various stock market contexts. The distribution of case studies in previous research based on the hybrid method used is shown in Fig. 4, while the distribution based on the stock dataset used is illustrated in Fig. 5.

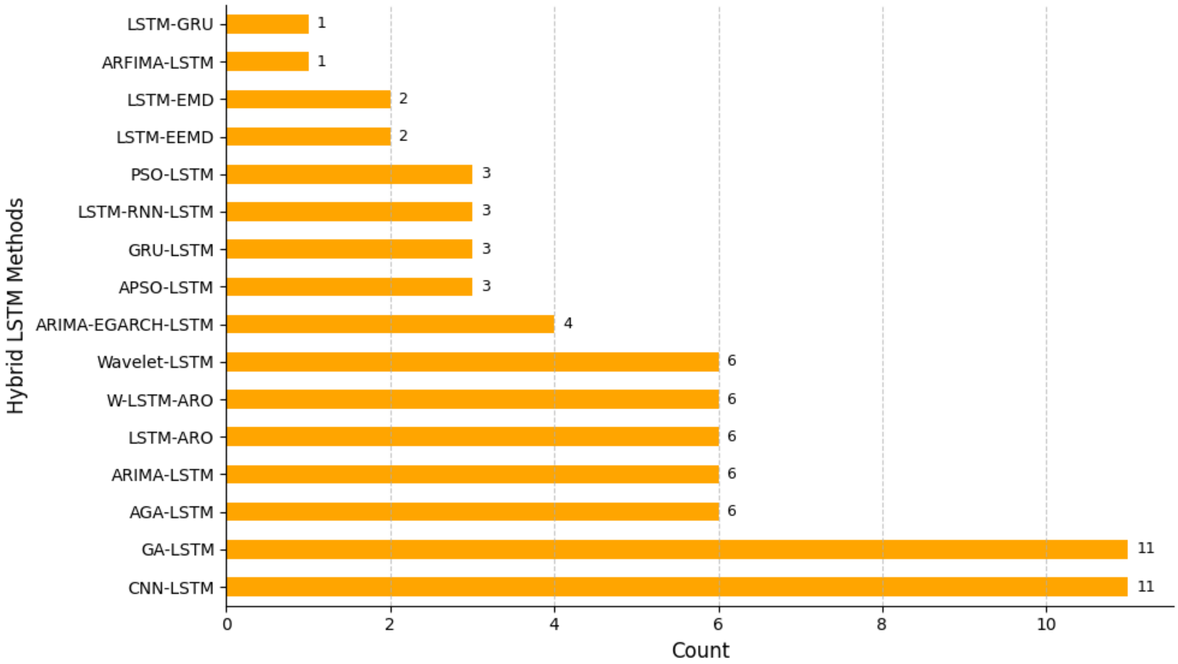

Fig. 4. Distribution of case studies in previous research based on the hybrid method used

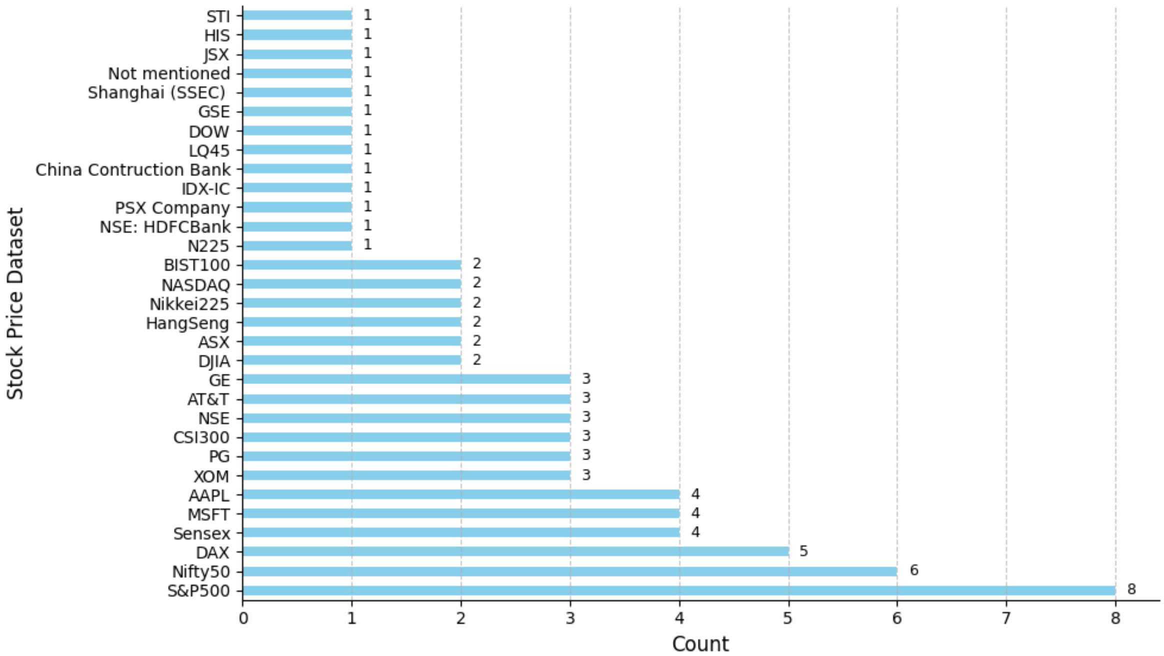

Fig. 5. Distribution of case studies in previous research based on the stock dataset used

The distribution of case studies in previous research based on the hybrid methods used indicates the diverse approaches explored in predicting stock prices (Fig. 4). The CNN-LSTM and GA-LSTM models emerge as the most frequently used methods, with 11 case studies each. CNN-LSTM leverages CNN architecture to extract features from corporate news texts, while GA-LSTM utilizes GA to optimize LSTM model settings. Additionally, AGA-LSTM, ARIMA-LSTM, LSTM-ARO, W-LSTM-ARO, and Wavelet-LSTM each have 6 case studies, highlighting the popularity and effectiveness of various hybrid techniques in the literature. Regarding the stock datasets used (Fig. 5), the distribution of case studies also shows significant variation. The S&P500 dataset is the most commonly used in previous research, with 8 case studies. This could be attributed to its popularity as a representation of the US stock market. Additionally, the Nifty50, DAX, Sensex, MSFT, AAPL, and XOM datasets also receive significant research focus, each with 4 to 6 case studies. This distribution reflects researchers' interest in testing and comparing the performance of hybrid LSTM models across various global stock markets, from the US to Asia. Previous research on hybrid LSTM in stock data has been summarized in Table 1.

Table 1. Summary of previous research on hybrid LSTM in stock data

Ref.	Year	Stock Price Dataset	Hybrid LSTM Method	Evaluation Metrics		
				MAE	MSE	RMSE
X. Zeng, et al. [40]	2022	DJIA	AGA-LSTM	0.0039	0.000035	0.0059
X. Zeng, et al. [40]	2022	S&P500	AGA-LSTM	0.0042	0.000038	0.0062
X. Zeng, et al. [40]	2022	HangSeng	AGA-LSTM	0.0045	0.000052	0.0072
X. Zeng, et al. [40]	2022	Nifty50	AGA-LSTM	0.0062	0.000065	0.0081
X. Zeng, et al. [40]	2022	Nikkei225	AGA-LSTM	0.0079	0.000145	0.0120
X. Zeng, et al. [40]	2022	CSI300	AGA-LSTM	0.0147	0.000508	0.0225
G. Kumar, et al. [38]	2022	S&P500	APSO-LSTM	-	0.000172	0.0131
G. Kumar, et al. [38]	2022	Sensex	APSO-LSTM	-	0.000449	0.0212
G. Kumar, et al. [38]	2022	Nifty50	APSO-LSTM	-	0.000463	0.0215
A. H. Bukhari, et al. [35]	2020	PSX Company	ARFIMA-LSTM	0.0269	0.002904	0.0539
C. Bulut and B. Hüdaverdi [36]	2022	NSE	ARIMA-EGARCH-LSTM	0.0077	0.000100	0.0103
C. Bulut and B. Hüdaverdi [36]	2022	DAX	ARIMA-EGARCH-LSTM	0.0083	0.000140	0.0121
C. Bulut and B. Hüdaverdi [36]	2022	NASDAQ	ARIMA-EGARCH-LSTM	0.0099	0.000180	0.0134
C. Bulut and B. Hüdaverdi [36]	2022	BIST100	ARIMA-EGARCH-LSTM	0.0095	0.000180	0.0135
U. F. I. Abdulrahman, et al. [80]	2020	GSE	ARIMA-LSTM	-	0.000003	0.0017
C. Bulut and B. Hüdaverdi [36]	2022	NSE	ARIMA-LSTM	0.0099	0.000180	0.0137
C. Bulut and B. Hüdaverdi [36]	2022	NASDAQ	ARIMA-LSTM	0.0131	0.000310	0.0177
C. Bulut and B. Hüdaverdi [36]	2022	DAX	ARIMA-LSTM	0.0129	0.000310	0.0177
C. Bulut and B. Hüdaverdi [36]	2022	BIST100	ARIMA-LSTM	0.0135	0.000350	0.0189
H. Yeng and M. Siahaan [37]	2024	LQ45	ARIMA-LSTM	0.5660	0.007800	0.0883
H. Widiputra, et al. [30]	2021	N225	CNN-LSTM	-	0.000071	0.0084
H. Widiputra, et al. [30]	2021	STI	CNN-LSTM	-	0.000222	0.0149
H. Widiputra, et al. [30]	2021	HIS	CNN-LSTM	-	0.000282	0.0168
H. Widiputra, et al. [30]	2021	JSX	CNN-LSTM	-	0.000317	0.0178
L. Sun, et al. [31]	2021	Not mentioned	CNN-LSTM	0.0288	0.002400	0.0490
W. Xu [33]	2022	Shanghai (SSEC)	CNN-LSTM	-	0.002000	0.0447
P. Singh, et al. [34]	2023	NSE	CNN-LSTM	0.0097	0.000190	0.0138
Y. Ding [43]	2023	AAPL	CNN-LSTM	-	0.000332	0.0182
H. Song and H. Choi [32]	2023	DOW	CNN-LSTM	0.0421	0.002500	0.0500
H. Song and H. Choi [32]	2023	S&P500	CNN-LSTM	0.0466	0.003000	0.0548
H. Song and H. Choi [32]	2023	DAX	CNN-LSTM	0.1635	0.017500	0.1323
S. Chen and C. Zhou [39]	2021	China Contruction Bank	GA-LSTM	-	0.004200	0.0648
S. Chen and C. Zhou [39]	2021	CSI300	GA-LSTM	-	0.004300	0.0656
X. Zeng, et al. [40]	2022	DJIA	GA-LSTM	0.0036	0.000031	0.0055
X. Zeng, et al. [40]	2022	S&P500	GA-LSTM	0.0048	0.000043	0.0065
X. Zeng, et al. [40]	2022	HangSeng	GA-LSTM	0.0050	0.000060	0.0078
X. Zeng, et al. [40]	2022	Nifty50	GA-LSTM	0.0065	0.000073	0.0086
X. Zeng, et al. [40]	2022	Nikkei225	GA-LSTM	0.0079	0.000148	0.0122
X. Zeng, et al. [40]	2022	CSI300	GA-LSTM	0.0132	0.000469	0.0217
G. Kumar, et al. [38]	2022	S&P500	GA-LSTM	-	0.008900	0.0943
G. Kumar, et al. [38]	2022	Sensex	GA-LSTM	-	0.013100	0.1140
G. Kumar, et al. [38]	2022	Nifty50	GA-LSTM	-	0.015800	0.1260
M. A. Hossain, et al. [44]	2018	S&P500	GRU-LSTM	0.0630	0.008000	0.0894
D. V. Trivedi and S. Patel [82]	2022	NSE: HDFCBank	GRU-LSTM	0.0374	0.002700	0.0524

Ref.	Year	Stock Price Dataset	Hybrid LSTM Method	Evaluation Metrics		
				MAE	MSE	RMSE
E. J. Prasetyo and K. D. Hartomo [81]	2023	IDX-IC	GRU-LSTM	0.0160	0.000441	0.0210
A. Khalil [42]	2024	GE	LSTM-ARO	0.0143	0.000274	0.0166
A. Khalil [42]	2024	AT&T	LSTM-ARO	0.0231	0.000967	0.0311
A. Khalil [42]	2024	MSFT	LSTM-ARO	0.0134	0.001174	0.0343
A. Khalil [42]	2024	AAPL	LSTM-ARO	0.0166	0.001685	0.0411
A. Khalil [42]	2024	PG	LSTM-ARO	0.0260	0.001735	0.0417
A. Khalil [42]	2024	XOM	LSTM-ARO	0.0241	0.001874	0.0433
Y. Yujun, et al. [45]	2020	DAX	LSTM-EEMD	0.0816	0.010304	0.1015
Y. Yujun, et al. [45]	2020	ASX	LSTM-EEMD	0.2477	0.105174	0.3243
Y. Yujun, et al. [45]	2020	ASX	LSTM-EMD	0.0456	0.004386	0.0662
Y. Yujun, et al. [45]	2020	DAX	LSTM-EMD	0.2177	0.163192	0.4040
M. A. Hossain, et al. [44]	2018	S&P500	LSTM-GRU	0.0230	0.000980	0.0313
S. Dutta et al. [41]	2024	MSFT	LSTM-RNN-LSTM	0.0880	0.022000	0.1483
S. Dutta et al. [41]	2024	Sensex	LSTM-RNN-LSTM	0.1090	0.029000	0.1700
S. Dutta et al. [41]	2024	Nifty50	LSTM-RNN-LSTM	0.1280	0.121000	0.3500
G. Kumar, et al. [38]	2022	S&P500	PSO-LSTM	-	0.004400	0.0661
G. Kumar, et al. [38]	2022	Nifty50	PSO-LSTM	-	0.005200	0.0724
G. Kumar, et al. [38]	2022	Sensex	PSO-LSTM	-	0.007200	0.0847
A. Khalil [42]	2024	GE	Wavelet-LSTM-ARO	0.0144	0.000280	0.0167
A. Khalil [42]	2024	AAPL	Wavelet-LSTM-ARO	0.0148	0.001375	0.0371
A. Khalil [42]	2024	MSFT	Wavelet-LSTM-ARO	0.0174	0.001503	0.0388
A. Khalil [42]	2024	AT&T	Wavelet-LSTM-ARO	0.0261	0.002387	0.0489
A. Khalil [42]	2024	PG	Wavelet-LSTM-ARO	0.0242	0.003291	0.0574
A. Khalil [42]	2024	XOM	Wavelet-LSTM-ARO	0.0261	0.005338	0.0731
A. Khalil [42]	2024	GE	Wavelet-LSTM	0.0203	0.000281	0.0168
A. Khalil [42]	2024	MSFT	Wavelet-LSTM	0.0208	0.001594	0.0399
A. Khalil [42]	2024	AAPL	Wavelet-LSTM	0.0223	0.001915	0.0438
A. Khalil [42]	2024	AT&T	Wavelet-LSTM	0.0303	0.002026	0.0450
A. Khalil [42]	2024	PG	Wavelet-LSTM	0.0238	0.002492	0.0499
A. Khalil [42]	2024	XOM	Wavelet-LSTM	0.0261	0.004533	0.0673

3.2. Role of Hybrid LSTM Algorithms

3.2.1. Algorithm Optimization

The hybrid LSTM companion methods in this category include Genetic Algorithm (GA), Adaptive Genetic Algorithm (AGA), Particle Swarm Optimization (PSO), Adaptive Particle Swarm Optimization (APSO), and Artificial Rabbits Optimization (ARO). The role of these methods is to optimize LSTM model parameters to achieve better performance in terms of prediction accuracy. Optimization algorithms help find optimal parameters by exploring parameter space more efficiently compared to traditional optimization methods. Here are some hybrid LSTM research studies for algorithm optimization:

- AGA-LSTM is utilized by X. Zeng, et al. [40] on the DJIA, S&P500, HangSeng, Nifty50, Nikkei225, and CSI300 datasets.
- GA-LSTM is employed by S. Chen and C. Zhou [39] on the China Construction Bank and CSI300 datasets, as well as by X. Zeng, et al. [40] on the DJIA, S&P500, HangSeng, Nifty50, Nikkei225, and CSI300 datasets.
- PSO-LSTM is used by G. Kumar, et al. [38] on the S&P500, Sensex, and Nifty50 datasets.

- APSO-LSTM is employed by G. Kumar, et al. [38] on the S&P500, Sensex, and Nifty50 datasets.
- LSTM-ARO is applied by A. Khalil [42] on the GE, AT&T, MSFT, AAPL, PG, and XOM datasets.

Based on the research by X. Zeng et al. [40], in hybrid LSTM, GA can perform stochastic optimization mimicking the evolutionary mechanism of natural selection to seek optimal solutions. GA operates through a natural evolution process involving chromosomes, populations, offspring, and parents to find the best solution. The basic steps in GA include gene encoding, initial population formation, chromosome selection, chromosome crossover, and chromosome mutation. In addition to GA, AGA also plays a role in optimizing LSTM parameters based on individual fitness values, enhancing optimization capability, and accelerating convergence by dynamically adjusting crossover and mutation rates according to individual fitness values.

Another algorithm like PSO is employed in an effort to optimize the initial weights and biases of LSTM and Fully Connected Layer (FCL) in the Deep Neural Network (DNN) model in study by Kumar, *et al*. [38]. PSO assists in determining optimal initial parameters, which are then allocated to the DNN and trained using the Adam optimizer. By setting good initial parameters, PSO ensures that the model training process is on the right track, enhancing the efficiency and accuracy of stock price prediction. Besides PSO, APSO is introduced to address early convergence issues often encountered in standard PSO. APSO enhances the inertia coefficient to strengthen the global particle search capability, prevents particles from being trapped in local optimum solutions, and balances exploration and exploitation in the solution search process. Here, APSO also helps mitigate issues such as overfitting/underfitting and vanishing/exploding gradient in LSTM networks, obtaining optimal values for initial input weights, recurrent weights, and biases of both LSTM and FCL in the DNN model. Meanwhile, in the study by A. Khalil [42], hybrid LSTM-ARO is proposed as a stock prediction solution, with ARO's role in optimizing LSTM hyperparameters. ARO selects the best hyperparameters that enable LSTM to achieve high-accuracy predictions on the dataset used by measuring prediction errors. This optimization is conducted to enhance the performance of LSTM models in predicting data.

3.2.2. Statistical and Econometric Methods

Hybrid LSTM can also be effectively combined with statistical and econometric methods such as Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH), Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Fractionally Integrated Moving Average (ARFIMA). These methods are utilized to address linear components and volatility within time series data before being processed by LSTM to capture more complex nonlinear patterns. Here are some hybrid LSTM research studies combined with statistical and econometric methods:

- ARFIMA-LSTM is employed by A. H. Bukhari, et al. [35] on the PSX Company dataset.
- ARIMA-LSTM is utilized by C. Bulut and B. Hüdaverdi [36] on the NSE, NASDAQ, DAX, BIST100 datasets, by U. F. I. Abdulrahman, et al. [80] on the GSE dataset, and by H. Yeng and M. Siahaan [37] on the LQ45 dataset.
- ARIMA-EGARCH-LSTM is applied by C. Bulut and B. Hüdaverdi [36] on the NSE, DAX, NASDAQ, and BIST100 datasets.

A. H. Bukhari et al. [35] elucidate that ARFIMA plays a role in hybrid LSTM by processing the white noise residuals from the ARFIMA model to detect patterns with exogenous variables as input. This process begins by decomposing the time series data into linear and nonlinear components, where the linear part is represented by the ARFIMA model. The residuals from the ARFIMA model are then processed by the LSTM neural network to model the remaining signals with the assistance of external variables. The combination of the ARFIMA model for linear components and LSTM for nonlinear components allows the model to capture both linear and nonlinear data trends, thereby enhancing prediction accuracy.

In the hybrid model proposed by U. F. I. Abdulrahman et al. [80], ARIMA is employed to handle the linear components of stock time series data, while LSTM handles the nonlinear components [37]. The first step in this model involves decomposing the time series data using a low-pass filter from the Discrete Fourier Transform (DFT), separating the data into linear and nonlinear components. Subsequently, ARIMA predicts the linear part of the data, and LSTM predicts the nonlinear part. The final prediction is obtained by summing the results from the ARIMA and LSTM models.

In another study proposed by C. Bulut and B. Hüdaverdi [36], the ARIMA method in hybrid LSTM is utilized to model the linear components of time series data. ARIMA addresses linear data structures by modeling the relationship between past observations and random errors, thus identifying trends and linear patterns in the data. Meanwhile, EGARCH is used to model time series volatility. EGARCH takes into account asymmetry effects in volatility and can handle changing volatility over time. By using EGARCH, the model can estimate the variability or volatility of the residuals generated by the ARIMA model, providing further insights into fluctuations in the data.

3.2.3. Data Preprocessing Techniques and Feature Enhancement

Complementary methods such as Wavelet Transform, Empirical Mode Decomposition (EMD), and Ensemble Empirical Mode Decomposition (EEMD) are employed for data preprocessing, breaking down data into simpler components before being processed by LSTM. This technique aids in capturing different frequency patterns and enhances prediction accuracy. Here are some hybrid LSTM research studies combined with data preprocessing techniques and feature enhancement methods:

- Wavelet-LSTM is utilized by A. Khalil [42] on the GE, MSFT, AAPL, AT&T, PG, and XOM datasets.
- Wavelet-LSTM-ARO is employed by A. Khalil [42] on the GE, MSFT, AAPL, AT&T, PG, and XOM datasets.
- LSTM-EMD is used by Y. Yujun, et al. [45] on the ASX and DAX datasets.
- LSTM-EEMD is employed by Y. Yujun, et al. [45] on the DAX and ASX datasets.

In addition to pairing LSTM-ARO, A. Khalil [42] also attempted to combine Wavelet-LSTM. In this proposed hybrid W-LSTM model, Wavelet Transform plays a role in removing noise from time series data and provides new coefficients for the LSTM model. Wavelet Transform transforms the input data from time series form into sets of low and high frequencies. The resulting coefficients assist the LSTM model in capturing long-term and short-term data patterns. The utilization of Wavelet and ARO results in the combination of Wavelet-LSTM-ARO, where ARO functions as the hyperparameter optimization for LSTM.

In the hybrid LSTM-EMD/EEMD model, EMD and EEMD act as data preprocessing techniques to decompose data signals into several Intrinsic Mode Functions (IMFs) that are simpler and more stable. EMD is used to decompose time series data into components that are easier to predict by the LSTM model. EEMD, an enhancement of EMD, helps address mode mixing issues by adding white noise and generating multiple IMFs. Both techniques enhance LSTM's ability to predict data by reducing the complexity of the original signal, allowing LSTM to capture more complex and varied data patterns. This has been elucidated by Y. Yujun, et al. in their research on hybrid stock prediction [45].

3.2.4. Information Processing and Model Adjustment

In this category, hybrid LSTM companion methods are used for information processing and model adjustment. Methods that can play a role in this category include GRU and RNN. Both of these methods fall into the category of neural networks, just like LSTM. Here are some of their applications in hybrid LSTM:

- LSTM-GRU is utilized by M. A. Hossain, et al. [44] on the S&P500 dataset.

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- GRU-LSTM is employed by M. A. Hossain, et al. [44] on the S&P500 dataset, D. V. Trivedi and S. Patel [82] on NSE: HDFCBank, and E. J. Prasetyo and K. D. Hartomo [81] on the IDX-IC dataset.
- LSTM-RNN-LSTM is applied by S. Dutta et al. [41] on the MSFT, Sensex, and Nifty50 datasets.

In the hybrid LSTM-GRU model for stock price prediction, M. A. Hossain et al. utilized GRU to enhance the performance of the hybrid LSTM model. GRU is positioned after the LSTM layer to refine initial prediction results more efficiently and rapidly address long sequential data. In this regard, GRU plays a crucial role in information processing and model adjustment, enabling the hybrid model to overcome their respective weaknesses and enhance computational efficiency [44]. On the other hand, in the GRU-LSTM model, GRU acts as the first hidden layer, primarily capturing dataset attributes. The advantage of GRU lies in its efficiency in addressing vanishing gradients with fewer parameters, accelerating model training and reducing computational complexity [81], [82]. Additionally, there exists a hybrid LSTM-RNN-LSTM architecture proposed by S. Dutta et al [41]. In this case, the role of RNN is to take the output from LSTM layer 1 and process it using a Simple RNN layer. The RNN layer is designed to process sequence data, suitable for tasks like time series prediction, thus allowing information from LSTM Layer 1 to be presented in a simpler and more continuous form, which can be further interpreted by the subsequent LSTM layer.

3.2.5. Special Feature Extraction and Data Noise Filtering

The role of auxiliary algorithms in feature extraction within the context of Hybrid LSTM is to prepare the data by extracting relevant information before it is processed by the LSTM. This feature extraction process is crucial as it helps identify significant patterns in the data, thereby enhancing the accuracy and efficiency of the LSTM model. The following methods are used in feature extraction and their roles in Hybrid LSTM:

- CNN-LSTM utilized by H. Widiputra et al. [30] on the N225, STI, HIS, and JSX datasets; by L. Sun et al. [31] on unspecified datasets; by W. Xu [33] on the Shanghai (SSEC) dataset; by Y. Ding [43] on the AAPL dataset; by H. Song and H. Choi [32] on the DOW, S&P500, and DAX datasets; and by P. Singh et al. [34] on the NSE dataset.

In a hybrid LSTM-CNN model for time series analysis, CNN plays a crucial role in extracting key features from time series data through convolutional and pooling layers. CNN helps reduce the initial data complexity and enhances the model's ability to recognize hidden patterns, which is vital for predicting movements in time series data like stock market indices. After CNN extracts the primary features, the results are used as input for LSTM, which then performs predictions based on the processed data [30], [33], [43].

Additionally, CNN in a hybrid CNN-LSTM model can also play a role in extracting spatial features from company news text. CNN employs a hierarchical structure to process text from the sentence level to the company level, capturing semantic features at various levels. CNN converts each sentence in the news corpus into sentence vectors, then converts these into company vectors, which are then used to link company news with stock prices [31]. In the model proposed by H. Song and H. Choi [32], CNN aids in filtering noise, extracting spatial features, and reducing the number of model parameters through one-dimensional convolutional layers. Causal convolution ensures that the influence of input comes only from previous time points, maintaining the temporal order of the data. One-dimensional convolutional layers are used to extract relevant features before the data is passed to LSTM for sequential prediction.

3.3. Best Hybrid LSTM Method

The best hybrid LSTM method is determined and concluded based on the evaluation metrics obtained from previous research in each case. Table 1 contains three evaluation metrics for each research case study: MAE, MSE, and RMSE. These three evaluation metrics play a crucial role in evaluating model performance, particularly for the hybrid LSTM model under review. These values represent the error obtained by the model during training and testing. The smaller the value obtained, the better the model performance. Although there are three evaluation metrics summarized in Table 1, to determine the best hybrid LSTM method, we only compare one of these values, which is the RMSE. The RMSE value is used for comparison between studies because it provides a clear understanding of how well the model predicts the data and is in the same unit as the original data. To see how the performance compares across the reviewed studies, a plot of the RMSE values for all the studies in Table 1 can be seen in Fig. 6.

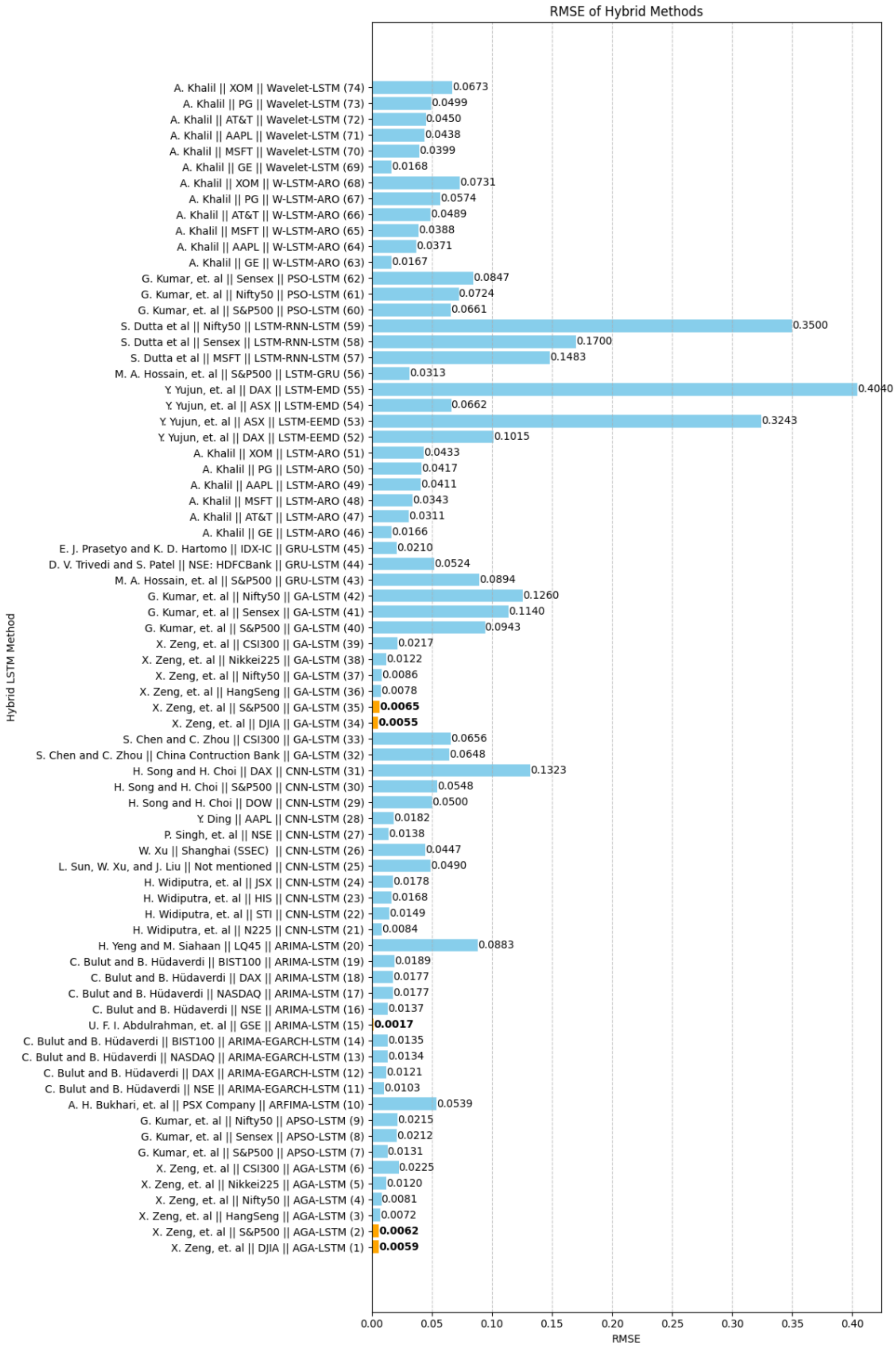

Fig. 6. RMSE levels in each hybrid LSTM case study on stock data from previous research

Based on Fig. 6, the studies with the five best RMSE values are highlighted in orange. The top-performing study is by U. F. I. Abdulrahman, et al. (2020), which used the ARIMA-LSTM method on the GSE dataset. This study shows an RMSE value of 0.0017, indicating that the hybrid LSTM model combined with the ARIMA method is very accurate in predicting stock prices. This result reflects a very small prediction error, making it the best-performing study among all the reviewed studies.

Next, the study by X. Zeng, et al. (2022), which used the GA-LSTM method on the DJIA dataset, recorded an RMSE of 0.0055. This study demonstrates the model's excellent performance in predicting DJIA stock prices, with a very low prediction error. Similar results were also obtained with the AGA-LSTM method on the DJIA dataset with an RMSE of 0.0059, indicating that both methods are very effective. Not only on the DJIA dataset, but the models produced using the GA-LSTM and AGA-LSTM methods were also implemented on the S&P500 dataset, resulting in RMSEs of 0.0065 and 0.0062, respectively. This indicates that these models are also very accurate in predicting stock prices for different data.

On the other hand, the study with the worst results among the reviewed studies is the LSTM-EMD method on the DAX dataset. This study recorded an RMSE of 0.4040, indicating that this model has a very large prediction error compared to the other studies. This result shows that the LSTM-EMD method is not effective in predicting DAX stock prices, and its performance is far below the other studies. Nevertheless, model optimization is still very possible in future research. For a different perspective, the minimum, average, and maximum values for each type of hybrid LSTM method are shown in Fig. 7.

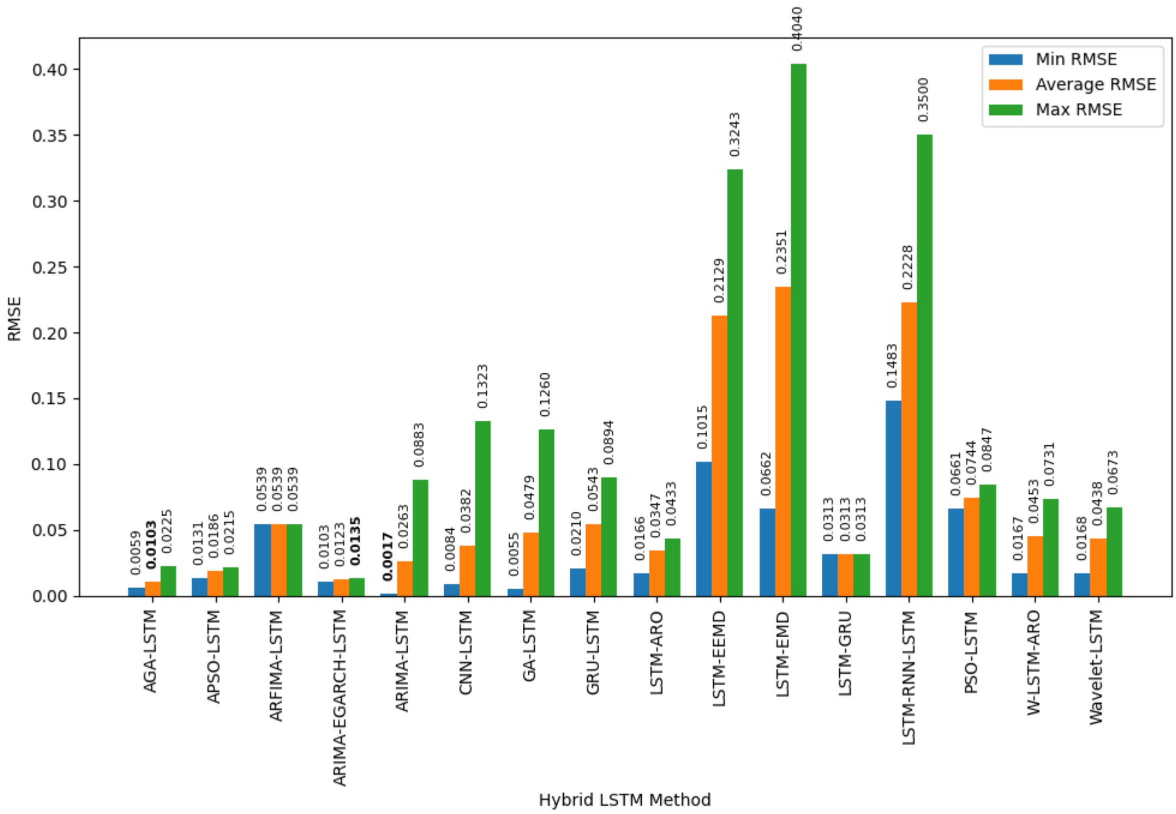

Fig. 7. Minimum, average, and maximum values for each type of hybrid LSTM method

Fig. 7 shows that the method with the best average RMSE value is AGA-LSTM, with a value of 0.0103 from six referenced case studies. It is followed by ARIMA-EGARCH-LSTM and APSO-LSTM, which have average values of 0.0123 and 0.0186, respectively. Meanwhile, LSTM-EMD, LSTM-RNN-LSTM, and LSTM-EEMD are still the methods with the least optimal results, as indicated by their minimum, average, and maximum values, which are still very high and significantly different compared to studies using other methods. This RMSE comparison helps in understanding the prediction accuracy across various studies within the scope of hybrid LSTM on stock data, which can be evaluated and adopted by future researchers.

Based on this evaluation, future research can focus on several areas of improvement. Although AGA-LSTM shows good performance, there is potential for enhancement by exploring more adaptive and dynamic optimization algorithms, such as hybrids between AGA and other current optimization methods like Bayesian Optimization or Hyperband, which can improve LSTM parameters more efficiently. Additionally, data preprocessing methods such as EMD and EEMD, which showed suboptimal results in previous studies, can be improved by combining more advanced preprocessing techniques, such as a combination of variational mode decomposition (VMD) with machine learning-based filtering, providing cleaner and more structured input data for LSTM. Furthermore, research can investigate ensemble methods that combine the strengths of several different models, thereby increasing the robustness and accuracy of LSTM predictions.

4. Conclusion

The hybrid LSTM method in stock price prediction has significant potential in improving prediction accuracy. Hybrid LSTM incorporating optimization algorithms such as GA, AGA, and APSO has shown performance improvement by efficiently searching for optimal parameters compared to traditional methods. GA-LSTM and AGA-LSTM have demonstrated excellent results with low RMSE values across various datasets, reflecting minimal prediction errors in the constructed models. Additionally, combining methods with statistical and econometric approaches like ARIMA-LSTM and ARIMA-EGARCH-LSTM has also yielded very good prediction results. However, some methods like LSTM-EMD, LSTM-EEMD, and LSTM-RNN-LSTM still exhibit suboptimal performance with high RMSE values, indicating the need for further optimization. Nevertheless, the capability of hybrid LSTM in predicting stock prices hinges on the selection of companion methods and appropriate parameter values. Hence, there remains potential for further development, especially in enhancing the capabilities of methods derived from previous research.

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