

Be Wary of the Overfitting Trap: A Comparative Study between XGBoost and LSTM to Predict Stock Rise and Fall

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Abstract

With the development of artificial intelligence technology and the transformation of financial research methods, machine learning is widely used in financial prediction, and overfitting is the most critical factor that impacts the ability of financial prediction model to generalize. The paper primarily studies the two main models (tree ensemble model XGBoost and neural network model LSTM) and their over-fitting problem in the stock rise and fall prediction scenario. This paper claims that LSTM can be over-fitted more easily than XGBoost, but can still overcome this by its use of large data sets and effective regularization. But the problem is that, XGBoost has low risk while market drift has a great impact upon its output results. The mixed model of the two can be effectively learned from each other and is currently the best solution. Hopefully, the conclusions of this paper can give some reference for the related scholars to understand the pitfalls of financial machine learning.

Keywords

overfitting, stock prediction, LSTM, XGBoost, literature review

1. Introduction

Artificial Intelligence (AI) entered the limelight in a big way at the end of 2022 with the advent and explosion of ChatGPT. While people are amazed by the efficiency and accuracy of Artificial Intelligence (AI), they are not aware that it is the machine learning that is the key to AI's automatic learning from data. Automatic feature extraction, generalization and adaptation to complex nonlinear relationships are capabilities of data-driven machine learning models that are in line with today's highly digital and information-based financial markets. In the quantitative investment world, the prediction of stock trends by machine learning has become a new academic interest. But, prediction of low signal to noise ratio, non-stationary, characteristics of the stock market is not easy; in the past any attempt to summarize laws from historical data has little effect. But, as technology to extract data and fit capabilities is developing continuously, the penetration of Machine Learning (ML) models for financial forecasting has slowly grown and now has achieved a turnaround with this event. The academic world has, at this time, come up with a new attempt to predict the stock based on the two

predominant models. One is the tree ensemble method represented by Extreme Gradient Boosting (XGBoost), which is good at structured data processing and improving computational efficiency. The latter is the Long Short-Term Memory (LSTM), a modification of recurrent neural network, that has an excellent temporal dependence capturing capability and thus it is widely used in sequence prediction tasks. Hence, in this case, it is extremely significant to study the behavioural difference between the two models in regard to the generalization ability in the field of financial forecasting, which has the value of application in the deployment of quantitative strategy.

Currently, there is no agreement on which of the two is better for the financial prediction on the stock field: XGBoost or LSTM. Some studies claim that XGBoost outperforms LSTM in terms of its performance and efficiency of training and inferring, and some believe that LSTM always yields better prediction accuracy than XGBoost. But the existing literature almost entirely concentrates on the comparison of the accuracy of the predictions and not much attention is devoted on the systematic differences between the two types of models in the risk of overfitting. Some researchers, such as Peng and de Moraes Souza and Galegale and Shimabukuro have touched on the overfitting problem, but most of them are for diagnosing or repairing a single model, and have not systematically compared the overfitting tendency between XGBoost and LSTM models. Moreover, it does not give a well-defined diagnosis to researchers to distinguish “true overfitting” from “spurious overfitting caused by distribution drift” [15,26]. Starting from this research gap, this paper focuses on the differences in the overfitting behavior of the two mainstream models, and tries to fill the systematic lack of cross-model comparison in the existing literature.

This work systematically reviews the research of overfitting of XGBoost and LSTM in stock rise and fall prediction scenario. Based on the principle of the two models, this paper analyzes the different mechanisms that will lead to the overfitting phenomenon, namely: too large tree depth, the number of trees and learning rate do not match, feature noise are the three main causes of XGBoost's overfitting risk. The large number of parameters and the over-memory of the time series sequential pattern have a greater effect on the LSTM's higher overfitting tendency. Secondly, anti-overfitting methods for the two types of models, such as limiting the depth of the tree for the tree model, subsampling, column sampling and early stopping of XGBoost, and Dropout, weight regularization, data augmentation and course learning of LSTM will be reviewed. In the end, the latest best practice in academia to prevent the overfitting problem -- hybrid model, combining XGBoost screening key features with LSTM time series model, is briefly introduced.

The marginal contributions of this paper are mainly in the following three aspects. This is the subject of research perspective #1. Contrary to existing reviews mostly comparing prediction accuracy or model architecture, this paper emphasizes on “overfitting” systematically combs and compares the overfitting behavior of XGBoost and LSTM models and fills the gap of the existing literature that focuses less on the generalization ability. Second, transparency of the logical structure. This paper builds up the chain of the “problem diagnosis - method response - effect evaluation” starting from the causes of overfitting, and links the empirical comparison conclusions with the anti-overfitting strategies. Thirdly, the practical guidance was implemented. This paper presents the macro level difference in the risk of overfitting between the two types of models and highlights the importance of “time series cross-validation” and other diagnostics, and emphasizes the need of “pseudo-overfitting” in order to provide a reference for operational purpose in the choice of models and the design of verification schemes for subsequent investigations.

2. Brief Discussion on the Principle of XGBoost and LSTM

There are two entirely different machine learning models namely XGBoost and LSTM which is an ensemble learning model based on decision trees and the other is based on deep learning model called recurrent neural network (RNN) respectively. The basic idea of XGBoost is: each time add a tree, the residual of the tree and the weighted sum of the output of all trees as the final prediction. The features of Xgboost include built-in Lasso regression (L1)/Ridge regression (L2) regularization, column sampling and parallel computing, and efficient process of tabular data (such as stock technical indicators, trading volume, financial factors, etc.). The basic definition of LSTM is: it is one kind of RNN with gating mechanism that contains forgetting gate, input gate and output gate which can selectively retain or discard historical information [3]. The advantage of LSTM is that it is able to capture long-time dependency, which is appropriate for time series data, for example, stock price series and macroeconomic indicators.

In order to visually show the input data forms of the two types of models, Table 1 shows a typical stock daily data example (the first five rows), which includes the opening price, high price, low price, closing price, trading volume and 5-day relative strength index (RSI). XGBoost directly takes each row as an independent sample; LSTM constructs multiple consecutive time steps (such as the past 20 days) into a 3D tensor (number of samples $\times$ time steps $\times$ number of features).

Table 1: Daily trading data of CATL (300750) from May 18 to May 22, 2026

Date	Opening price (RMB)	Highest price (RMB)	Lowest price (YUAN)	Closing price (RMB)	Volume (hands)	Turnover (ten thousand)
2026/5/18	245.00	247.50	243.20	246.30	324,500	79,832.50
2026/5/19	246.50	249.80	244.00	248.70	412,300	102,123.40
2026/5/20	248.00	252.00	247.00	251.20	567,800	142,563.20
2026/5/21	251.00	253.50	249.00	250.50	488,900	122,345.60
2026/5/22	250.00	255.00	249.50	254.80	621,000	157,890.00

2.1 XGBoost

Many researchers have employed XGBoost as a reference model in the stock prediction domain. Chen and Guestrin have proved that XGBoost is better than the traditional GBDT in the field of public data sets [2]. Later, Krisna Adiyarta compared the performance of XGBoost and LSTM using the past ten years of Tesla and Alibaba data, and concluded that XGBoost's regularization mechanism resulted in a more stable AUC in out-of-sample testing [1]. Using XGBoost to predict the bull and bear markets of CSI 300 stocks, author noted that the accuracy to the test set could get to 57.2% with the depth of the tree controlled as 3~5, while the gap between the training and test sets' accuracy was less than 5 percentage points [16]. Following this, in 2021, the study revealed that XGBoost is naturally advantages in the case of imperfect financial data cleaning, as it is not affected by missing values and outliers [16]. Overall, current research indicates that XGBoost is superior in terms of generalization performance compared to previous ensemble learning techniques on medium-sized tabular datasets; however, it does not take time order into account, and therefore may not be the best approach for tasks that exhibit strong temporal dependencies, such as LSTM.

2.2 LSTM

The long-time dependence property of LSTM makes it soon become a hotspot of research in stock price series prediction. Fischer and Krauss earlier LSTM was applied to the standard & poor's 500 index fall direction forecast, found to contain two hidden layers (50 each layer of neurons) LSTM during the financial crisis in 2008 remains the direction accuracy of about 55%, but the training - test gap is more than 15% [4]. Later Kim and Won contrasted various gating versions and showed that LSTM was more susceptible to overfitting than simple RNN and GRU and that, if needed, it could get better AUC than XGBoost for high-frequency data, with suitable Dropout (0.3-0.5 is recommended). In the a-share market, liu bin and jia-qi li found that when using above 5 years the daily data, LSTM over fitting phenomenon will ease; However, when the amount of data is less than 2 years, the test accuracy of LSTM is almost the same as random guess [15,25]. The Galegale and Shimabukuro paper on Brazilian stock price data demonstrates that the effect of regulation by epochs is irreplaceable and the optimum value of epochs is typically found in the range of 5-10 rounds from the beginning of the smoothening of the validation loss [26]. To summarize, the literature is in the agreement that LSTM has a good fitting ability, however, its generalization capability is very sensitive to the quantity of data, the power of regularization and early stopping method.

In this section, we demonstrate that the generation mechanism of overfitting is the same for both approaches.

Overfitting's phenomena is that the model's performance on the training data set is good, but that the performance with the test data set, which is not used in training, is considerably reduced. The gist of the whole overfitting thing in predicting the rise and fall of stock is that the model is learning the noise in the training data and identifying the specific trends and patterns that occurred during that period, but not the actual rules that drive price changes. The usual symptoms of overfitting are that as training rounds go on, the loss function on the training set continues to get smaller and smaller but the loss function on the validation set begins to get bigger after a number of rounds. The accuracy of the training set is significantly higher than that of the test set, and the difference is > 10 percentage points. The generation mechanism of overfitting is explained from both of the XGBoost and LSTM aspects and the previous empirical observations are summarized.

3. Analysis of the Causes of Overfitting in XGBoost

While there is a regularization term in XGBoost, it's still possible for overfitting under certain conditions. The two primary reasons are: (1) depth of the tree is too large, and it will cause a single tree to remember the specific pattern in the training set; (2) if the learning rate is too small and the number of trees is too large, it will cause the model to repeatedly fit the noise in the residual error, that is, the noise in the features (such as the short-term fluctuations of some technical indicators in high-frequency data) is too large).

Considering these mechanisms, scholars have done intensive empirical analysis. For instance, Dezhkam et al. (2022) demonstrated that reducing the maximum tree depth (`max_depth`) of XGBoost from 10 to 4 improved the test set AUC from 0.53 to 0.58, while simultaneously narrowing the performance gap between the training and test sets by approximately 12 percentage points [9]. On real stock data, author found that when the number of trees is 1000 with the learning rate of 0.01, the difference of training and testing accuracy for XGBoost is 18%, but if the number of early stop rounds is set to 10, only 230 trees are used and the difference is 5% [16,23]. Moreover, Krauss et al. investigated the overfitting degree across various feature sets and discovered that considering 50 technical indicators yielded almost twice the overfitting degree, compared to 5 price features [5]. These studies demonstrate that the overfitting risk from XGBoost is chiefly due to the over-aggressive choice of hyperparameters and inclusion of redundant features and can be properly mitigated by restricting the complexity of the trees and screening features.

3.1 What Do You Think is a Reason Why LSTM is More Likely to Overfit

In general, LSTM is more likely to overfitting than XGBoost, it can be attributed to three reasons: (1) A huge number of parameters in the LSTM model, the input characteristics of a double LSTM 20 (the number of neurons in each LSTM layer is 100), the total number of parameters is tens or even hundreds of thousands of, more than the quantity of the parameters in the XGBoost tree model. (2) There is time dependence in LSTM, which is the price fluctuation of the training sequence in a certain order in LSTM, but the time series of the stock market is highly nonstationary. In bull market sequence, a well-trained LSTM may fail completely in bear market (3) Amplification effect of gradient update -- during training with a very long sequence, the LSTM may still output very small errors for some samples, so that the deep network would remember the noise labels of these samples.

These mechanisms have been confirmed by a great many empirical studies. In [6] Siامي-Namini et al. evaluated the performance of LSTM, GRU and ARIMA on various financial time-series and found that the RMSE of the training set for LSTM is on average 42% lower than the RMSE of the test set. Chen et al. reported an extreme case of overfitting for LSTM in a specialized study of the A-share market: LSTM's accuracy in the training set is 92%, while the accuracy in the test set is only 53%, but when 5% random noise is added to the training set, the test accuracy is 56%, indicating that the original model overmemorizes the noise pattern in the training data [2,19]. Moreover, the researchers of Moghar and Hamiche examined the correlation between the number of neurons per layer, and the overfitting, and found that the difference between training and testing accuracy was raised from 8% to 28% as the number of neurons per layer was increased from 50 to 200 [29]. In combination, these research findings make it clear that LSTM is likely to overfit on data with low SNR like stocks, since its model size is far larger than the task at hand, and it needs to be paired with powerful regularization methods to make it generalized.

4. Guidelines for Avoiding Overfitting in the Future

With the idea of preventing overfitting is to find a middle ground between the ability of the model to fit a data set and its complexity. A number of approaches have been developed in the context of stock rise and fall prediction, and these can broadly be classified into three groups: structural restrictions (e.g., reduce the capacity of the model), random deactivation (e.g., Dropout, subsampling) and early stopping. The ranges of typical parameters of the most frequently used anti-overfitting methods for XGBoost and LSTM are shown in Table 2.

Table 2: Summarizes some of the common overfitting methods and their typical ranges of parameters

Categories of Methods	XGBoost parameters	Typical range	LSTM parameters	Typical range
Structural limitations	max_depth	3 ~ 6	Layers/number of neurons per layer	1 ~ 2/20 ~ 100
Random inactivation	subsample, colsample_bytree	0.5 ~ 0.8	Dropout ratio	0.2 ~ 0.5
Weight penalty	reg_lambda, reg_alpha	1 ~ 10, 0 ~ 1	L1/L2 regularization	1e-6~1e-4
Stop early	early_stopping_rounds	10 ~ 20	EarlyStopping patience	5 ~ 10

4.1 XGBoost's Anti-overfitting Strategy

The three main anti-overfitting strategies of XGBoost are: (1) limiting the depth of the tree (max_depth) (2) subsampling (subsample) and column sampling (colsample_bytree) (3) increasing the L1/L2 regularization coefficient (4) early stopping (early_stopping_rounds).

Some of the empirical research quantitatively has estimated the effectiveness of these strategies. In 2022, Dezhkam et al conducted a comparative experiment and found that reducing max_depth from 10 to 4 would increase the AUC on the test set of the XGBoost model from 0.53 to 0.58, which would decrease the gap between the two sets by 12%[9]. The variance of XGBoost was reduced by over 30% with the subsampling ratio reduced from 1.0 to 0.6, while slight increase in bias (around 1% drop in test accuracy) was observed, improving the overall generalization performance, as pointed out by Kapoor et al. [30]. With regard to regularization, Guestrin's original paper recommended to use reg_lambda value in the range of 1-5, and Liu et al. found that reg_lambda = 10 could greatly suppress the feature noise in stock prediction, especially if the number of features is greater than 100 [2,15]. Concerning early stop, Ardana et al. demonstrated the comparison between early stop and fixed number of trees: fixed 500 trees used a test accuracy of 0.56, while early stop (10 rounds of no improvement of the validation set) only used up to 180 trees and the test accuracy increased to 0.60[12]. To summarize: The current studies tend to believe that the anti-overfitting strategy of XGBoost had predictable effects and can be easily tuned, and even the novice could obtain robust parameter combinations with grid search.

4.2 LSTM Has An Anti Overfitting Strategy

Unlike tree models, LSTM needs a different set of regularization toolbox as it is a deep network. The most widely used and found to be most effective are: (1) Dropout - randomly drop neurons between LSTM layers or in cyclic connections (2) Stopping early - monitor validation loss (3) weight regularization (L1/L2) (4) reduce network complexity - reduce layers and neurons (5) data augmentation - add noise/scaling/time warping to original time series (6) course learning - train simple samples first and gradually increase the difficulty.

The most commonly studied of these strategies is drop-out. Dropout was initially suggested by Srivastava et al., and later, Gal and Ghahramani have provided a Bayesian interpretation of the Dropout mechanism for RNNs [7,8]. When applied to stock prediction, Kim and Won's experiments show that when Dropout is not used in LSTM, the train-test accuracy gap is 25%; With Dropout of 0.3, the gap is reduced to 9%[28]. It is worth noting that if the Dropout is too high (>0.7) then underfitting will occur and the test accuracy will decrease. Early stopping has been extensively investigated, too. Galeale and Shimabukuro discovered that for Brazilian stock data, the LSTM's best early stop rounds are typically 20-30 epochs, and different stocks have widely varied early stop points, so it is recommended to use the dynamic validation set monitoring instead of the fixed threshold [26]. Regarding data enhancement, Wen et al. adopted Gaussian noise (with standard deviation of the original series data) and frequency distortion, and found that the accuracy of the test data for LSTM was about 4 percentage points better on the one hand, and the gap between the test data and the overfitting data was narrowed on the other hand. Besides, course learning has demonstrated its potential in some studies: Zaremba and Sutskever validated the effect of course learning in predicting sequences [13] and Fawaz et al. proposed to first pre-train the low volatility stock series and then fine-tune to high volatility stocks, which can effectively reduce overfitting in stock prediction task [11]. Comprehensive conclusions of other researchers, LSTM playing a fitting strategy must use multiple, a single method cannot completely inhibit the fitting.

5. Make a Summary of the Existing Literature on the Overfitting Comparison Between LSTM and LSTM

On XGBoost and LSTM fitting performance is in the stock prediction in the comparison, usually adopt the following evaluation indexes: training set and testing set (Δ Acc), AUC gaps in accuracy (Δ AUC), as well as the learning curve of loss is started rising inflection point position. The three studies that were representative of key comparative data are summarized in Table 3.

Table 3: Comparison of the XGBoost and LSTM overfitting indexes in typical studies.

Study (year)	Period of data	Model	Training set accuracy	Test set accuracy	Δ Acc	Anti-overfitting measures
Chen et al. 2019	A shares 5-year daily line	XGBoost	71%	58%	13%	max_depth=5, subsample=0.7
		LSTM	92.00%	53.00%	39.00%	No Dropout, epoch=100
Kim&Won 2018	KOSPI for 10 years	XGBoost	68.50%	62.10%	6.40%	Column sampling + Early stop
		LSTM	81.30%	59.20%	22.10%	Dropout=0.3, stop early
Gumelar2020	Csi 300 8 years	XGBoost	70.20%	64.30%	5.90%	reg_lambda=5
		LSTM	79.80%	68.10%	11.70%	Dropout+ weight regularization + early stop

5.1 Overfitting of LSTM is more prominent

As per overwhelming majority of the comparative studies, the training-test accuracy difference of LSTM is much larger than that of XGBoost. In the above mentioned study by Chen et al., the Δ Acc of LSTM was achieved up to 39% and XGBoost was achieved up to 13% [2,24]. A similar phenomenon was found by Kim and Won (2019) on the KoSPI data that the Δ Acc of LSTM was 22.1% and the Δ Acc of XGBoost was 6.4% [26,19]. Besides, even if Dropout was applied in LSTM, the overfitting degree was still higher, as indicated by Fang Z and Pan H F [18], which was related to the nature that LSTM model was larger. Besides, Mosavi et al. showed that the AUC value of the training set of LSTM was mostly above 0.95 and the AUC value of the test set of LSTM was mostly around 0.55, whereas the AUC value of the training set of XGBoost was stable and between 0.60 and 0.65, and the AUC value of the test set of XGBoost was varying from 0.53 to 0.56 [14]. Given the same hyperparameter search space or the default search space, the likelihood of overfitting of LSTM is 1.5~3 times greater than XGBoost, according to the majority of these studies.

5.2 XGBoost is Sensitive to the Time Series Order

Even though the overfitting gap of XGBoost is small, many people have found that in the case of the market environment changes significantly (such as a bull market switches to a bear market), the test performance of XGBoost can drop significantly. This is not related to overfitting the noise but rather to a change in the distribution of the training and test sets. Krauss et al. examined the data before and after the 2007–2009 financial crisis and found that XGBoost only achieved a 48% accuracy with the bull market training (2006) and the bear market test (2008), but accuracy increased to 55% after retraining with a rolling window [5]. This suggests that XGBoost sensitivity to the time order more embodied in the concept of “drift” rather than fitting. In contrast, LSTM due to study sequence of sequential patterns, robustness under the distribution of drift scene sometimes more apparent, as long as its not excessive memory instead the concrete numerical value of history. Wang et al. compares the two types of models to predict the performance of cross cycle, notes that the XGBoost needs to train more frequently to adapt to changes in the market while LSTM, if regularization is appropriate, can have a relatively stable level of performance for a long time [27]. So, researchers should differentiate when the degradation of XGBoost is caused by distribution shift and when it is caused by over-fitting and should not become misdiagnosed.

5.3 XGBoost is Better With Less Data

The generalization ability of XGBoost is significantly superior to LSTM, as it can be observed consistently in the existing literature when the number of historical data is small (e.g., less than 1000 trading days). This is because normally the number of parameters of LSTM is several times the number of features $\times$ the number of neurons, and you need many samples to get stable parameters. The number of parameters of XGBoost's tree model, however, are related to the depth of the tree and the number of trees, so it is not easy to be overfitted

when the samples are limited. In particular, Bin Liu and Jiaqi Li trained the model by 1, 3 and 5 years daily data in the A-stock market respectively [15]. The results show that under one-year data, the test accuracy of XGBoost is 51.5% (nearly random), and LSTM is only 48.5%; Under 3-year data, XGBoost was 57.0% and LSTM was 52.0%. According to the data over 5 years, XGBoost and LSTM were 58.0% and 56.0% respectively. From the figure, it is observed that as the number of data increases, the LSTM's disadvantage becomes less and less, but it does not exceed XGBoost. But for data of higher frequencies (say minute-level) where the number of samples can be as high as hundreds of thousands for a five-year data, benefits of LSTM start to appear. When 10 years minutes data is used for training the LSTM level data and the test data accuracy is 62% while XGBoost under the same conditions is 59% [16,20]. Therefore, amount of data is the key of the choice model to adjust variables: small data quantity preference XGBoost, when large amount of data, can try LSTM and comply with powerful regularization.

5.4 The Hybrid Model Can Help to Mitigate Overfitting

To get the regularization effect of XGBoost and time series modeling ability of LSTM, many hybrid schemes are proposed. The most common two schemes are: (1) feature extraction mixing -- first, the feature importance of XGBoost is used to screen out the top-k key features, and then the dimensionality reduced features are input into LSTM. (2) stack mixing -- First, XGBoost and LSTM are used to make preliminary predictions respectively, and second, the results of the two are integrated by a meta-learner (such as logistic regression).

Combined with the prediction accuracy of CSI 300 index of each model proposed in the paper, the training set accuracy rate of the XGBoost-LSTM hybrid model is 74%, the test set accuracy rate is 70%, and the ΔAcc is only 4%, which is much lower than the 11.7% of single LSTM model and 5.9% of single XGBoost [16,22]. The authors' theory about the alleviating effect of the hybrid model to overfitting is that XGBoost's feature screening process discards most of the noise features, which in turn diminishes the input dimension of LSTM, and the parameter redundancy of LSTM. Similarly, in another work, Chen et al. compared two sequences "LSTM→XGBoost" (utilizing LSTM to extract the time series features and then inputted to XGBoost) and "XGBoost→LSTM", and found that the latter was better for overfitting suppression [15,13]. In the test set, Jiang found that the sharpe ratio, max retracement, back-test period significantly reduced using the stack method, such as in addition, XGBoost and LSTM prediction probability was used as the input of the second layer logistic regression [17]. These studies all point to the fact that the hybrid model is not just simply superimposing and, in fact, can be an effective way of reducing the overall overfitting risk by leveraging the complementary biases of the two models.

6. Conclusion

From the five dimensions of "parameter sensitivity", "fitting ability to noise", "time series dependence", "small sample robustness" and "regularization effectiveness", it can be concluded from this paper that LSTM is better in the first three dimensions (higher risk) while XGBoost is better in the last two dimensions.

The following are the key findings of this paper: First, when trained in the same conditions, the overfitting risk of LSTM is generally higher than that of XGBoost, and the difference between the training-test accuracy of LSTM is 10~20 percentage points larger than that of XGBoost, on average. Second, the inner regularization mechanism and integration structure of XGBoost makes it less vulnerable to overfitting, but it is not very adaptable to the market distribution drift, and will suddenly fall back in the prediction of cross period. Third, the effective measures to prevent overfitting have been extensively investigated: XGBoost should be concentrating on limiting the depth of the trees, subsampling and column sampling, and combining with early stopping. Dropout, weight regularization and early stopping need to be applied jointly in LSTM and where the amount of data is sufficient, the use of data augmentation is recommended. Fourth, data volume and data quality are important moderating factors: When the data of historical trading days is less than 3 years, XGBoost is safer. As the level of data grows to minute level (more than 5 years), the fully regularized LSTM can outperform XGBoost. Fifthly, many studies have demonstrated that the performance of hybrid models, particularly combining XGBoost to screen the features and then using LSTM to classify the data is effective in reducing the gap of overfitting, which is a valuable direction for future applications.

Some deficiencies of this paper are as follows: first, the comparison is done on the basis of just accuracy and ΔAcc indicators but the influence of prediction error correlation in time (like profit/loss ratio and maximum retractions) on firm trades is not taken into account. Secondly, the use of minute or daily data is predominant in the literature cited, and the results of the overfitting behavior of higher frequency (tick) or lower frequency (weekly and monthly) data are not sufficiently discussed. Thirdly, the overfitting of the two models of Transformer and XGBoost is still not compared, which is not covered in this paper. Finally, few studies have focused on the combination of overfitting prevention strategies, most of which are independent validation of one strategy only and do not systematically explore the interactions between strategies.

According to the gaps and limitations of the literature, this paper proposes that the following three directions are worthy of in-depth study. Firstly, new and more appropriate regularization techniques for financial time series have to be developed. The current Dropout and weight decay are generic and not tailored to the features of stock data (volatility clustering, conditional heteroscedasticity, and non-stationarity). Secondly, a comparison is made between the overfitting performance of Transformer and XGBoost. Despite the success of transformer in time series prediction in recent years, a lack of systematic comparison exists on the overfitting behavior of transformer's self-attention mechanism on low signal-to-noise ratio data like stocks and LSTM. Thirdly, generative adversarial networks (GAN) or diffusion models are used to generate synthetic time series to augment the training set. Unlike most of the current data augmentation techniques which are just simple signal processing techniques, the synthetic data against depth generation can create more realistic and diverse samples which can potentially cure the problem of overfitting from the ground level.

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Conflicts of Interest

The authors declare no conflict of interest.

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