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Value at Risk Measurement Method under Deep Learning in Analysing the Excessive Financialization of Enterprises

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This study proposes a novel model that integrates the generative adversarial network (GAN) with the value at risk (VaR) measuring method. The objective is to investigate the efficacy of the VaR method in addressing the issue of excessive financialization in enterprises. Firstly, the related concepts and calculation principles of VaR in the financial field are explained, and the autoregressive conditional heteroscedastic (ARCH) family-based VaR calculation method and the basic structure of GAN under the deep learning are introduced. Then, the GAN algorithm is employed to optimize and train the initialization network, transformation network, and structure network of the GAN algorithm. Finally, the optimized GAN is applied to the VaR measurement of 300 stocks in Shanghai and Shenzhen stock market. GAN demonstrates the ability to handle unbalanced data samples, sample minority data, and fit the overall distribution of minority samples. GAN introduces a groundbreaking method for data processing, and its integration with manual efforts yields significant improvements in practical applications. Moreover, GAN demonstrates a positive impact on data set training, offering reliable potential for advancement and serving as a valuable point of reference. In conclusion, the combination of GAN under deep learning with VaR showcases a dependable practicability in assessing the risks associated with excessive financialization.

Keywords: deep learning, excessive financialization of enterprise, value at risk, generative adversarial network (GAN), autoregressive conditional heteroscedastic (ARCH)

1. INTRODUCTION

With the advancement of economic globalization and integration, the high degree of financialization and capitalization of enterprises in various countries has brought wealth to social development, but also revealed the fragility of finance and the greed of capital development [1, 2]. Financial risk control has also become the key point to current enterprise development. The traditional financial risk measurement method intelligently expresses the deviation degree of financial assets, but can't explain the level of loss [3]. Since the continuous development of financial innovation in the 1950s, various financial tools have consistently emerged. Analyzing the "financialization of the economy" has become a more scientific method for observing modern economic operations and financial integration. Proper financialization has the potential to revitalize corporate assets, improve capital structure, and increase cash returns. However, the excessive financialization of enterprises introduces risks to their investments, diverts investment from operational assets, and leads to excessive corporate financing, causing the economy to become "detached from reality

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and overly reliant on virtual financial activities.” Strengthening corporate supervision and improving the capital market are beneficial to the better development of enterprises. Financial risk has become the core of modern financial management. With the complexity of financial markets and financial transactions, the measurement of financial market risks has developed into the current complex measurement technology. Value at risk (VaR) can directly express can calculate the financial risk, so it has been widely used in the financial risk measurement [4, 5]. The VaR calculation method is primarily based on its concepts and principles, lacking a specific calculation structure. As a result, there are certain deficiencies and limitations in using VaR as a measurement tool for financial risk.

For the method of VaR calculation, scholars from various countries have developed a lot of researches. Melina *et al.* [6] used extreme value theory to measure the VaR and expected shortage of investment portfolios [6]. Asdrubali *et al.* [7] adopted a price reduction model to measure the VaR [7]. In addition, Storti *et al.* [8] proposed a dynamic semi-parametric model to predict the VaR [8]. In recent years, VaR measuring methods based on the autoregressive conditional heteroscedastic (ARCH) family have been widely utilized. Scholars have made reliable advancements in the ARCH model, considering the characteristics of VaR. However, its prediction accuracy still fails to meet the requirements of the current financial market development [9-11]. As a new topic in machine learning methods, deep learning can build an artificial neural network (ANN) to learn relevant data characteristics, and finally get more accurate prediction results. Cao *et al.* [12] used the Bayesian network (BN) model to evaluate the liquidity risk of banks [12]. Li *et al.* [13] measured the credit risk of enterprises based on the ANN algorithm [13]. Lu *et al.* [14] adopted a method based on deep belief network (DBN) integration to measure the VaR of currency exchange rates [14]. Based on these studies, it is found that the applying the deep learning in financial market risk prediction can get good results.

2. METHODS

2.1 Related Concepts and Calculating Principles of VaR

VaR reflects the maximum potential loss of financial assets in a certain period under a certain CI [15, 16]. Its expression is shown in Eq. (1).

$$\mathrm{Prob}(Y_t < -VaR) = \theta \tag{1}$$

In Eq. (1), Y_t refers to the rate of return (RR) of financial assets in period t, CI is represented by $1 - \theta$. From a statistical perspective, it has been observed that VaR corresponds to the left-tail quantile of the distribution of financial asset returns under specific confidence interval (CI) conditions [17]. The calculation of VaR involves determining the distribution of financial asset returns.

In traditional approaches, the normal distribution is often employed to approximate the distribution of financial asset returns, simplifying the calculation process for VaR [18-20]. However, contemporary studies have revealed that the returns on assets generally exhibit non-normal distributions. Consequently, using traditional methods to calculate VaR can lead to deviations and inaccuracies [21].

2.2 VaR Measuring Model based on ARCH Family

To calculate VaR, an assumption about the distribution of the RR needs to be made. Initially, a common assumption is that it follows a normal distribution. However, in reality, risk fluctuations are constantly changing, and there is often an aggregation of these fluctuations, known as heteroscedasticity. Therefore, the normal distribution fails to accurately capture such distribution characteristics. To provide a more precise description of the distribution characteristics of asset RR, scholars have proposed the ARCH model. The main concept behind this model is that the conditional heteroscedasticity of the disturbance term is influenced by its lagged values.

The ARCH(q) model is represented with Eq. (2) in general,

$$y_t = \mu_t + \xi_t. \tag{2}$$

Eq. (2) shows its mean value equation.

2.3 Structure of GAN

Models under deep learning include discriminative models and generative models. Since the gnerative adversarial network (GAN), it has become a very successful model in recent years and attracted more and more attention. The primary objective of machine learning is to train a model capable of predicting output values based on given input values.

Machine learning encompasses two main methods: generative methods and discriminant methods. The models learned using these methods are referred to as generative models and discriminative models, respectively. The discriminative model employs the discriminant method to predict the learned model through the learning decision function $f(X)$ or the conditional probability distribution $P(Y|X)$. The generative model learns the joint distribution $P(X|Y)$ using the generated data, and subsequently predicts the conditional probability distribution $P(Y|X)$ of the predictive model. The equation representing this relationship is as follows,

$$P(Y|X) = P(X, Y)P(X). \tag{3}$$

In comparison to the discriminant method, the generative model places greater emphasis on capturing the internal relationships among the data and requires learning the joint distribution. Conversely, the discriminant model focuses more on the input variable X and aims to predict the corresponding output variable Y. In a GAN, the discriminator and generator networks engage in an adversarial relationship, whereby the generator aims to generate synthetic data that closely resembles real data, while the discriminator distinguishes between the generated data and real data. The noise input provided to the generator typically follows a uniform or normal distribution. The generator utilizes this noise to generate synthetic data, while the discriminator assesses and distinguishes the authenticity of the data. Through an iterative process of confrontation and improvement, the two networks strive for convergence. This convergence drives the generated data closer to reality (Fig. 1).

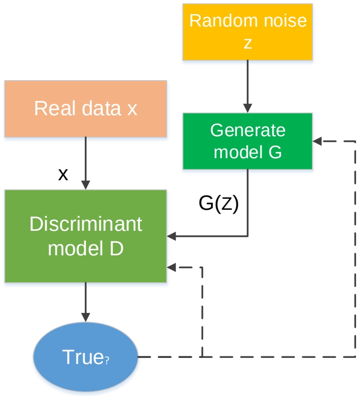

Fig. 1. Schematic diagram of GAN.

2.4 VaR Model Based on Deep Learning

GAN is composed of two types of networks: generation and discrimination (Fig. 2). The input source represents the original input data, while the target denotes the real target data. The black dashed box and the yellow dashed box represent two components of the U-net architecture. The black box encompasses a convolution operation that extracts a multitude of data features, while the yellow dashed box is responsible for determining the consistency between the input original data and the generated data. The confrontation and game are generated here, and the Pair-loss loss updates G. The original data and the target data may have different appearances, but they share the same underlying characteristics. The original data generates a feature map in the black box, and then uses the F-loss loss among the multiple features to update the target domain in G.

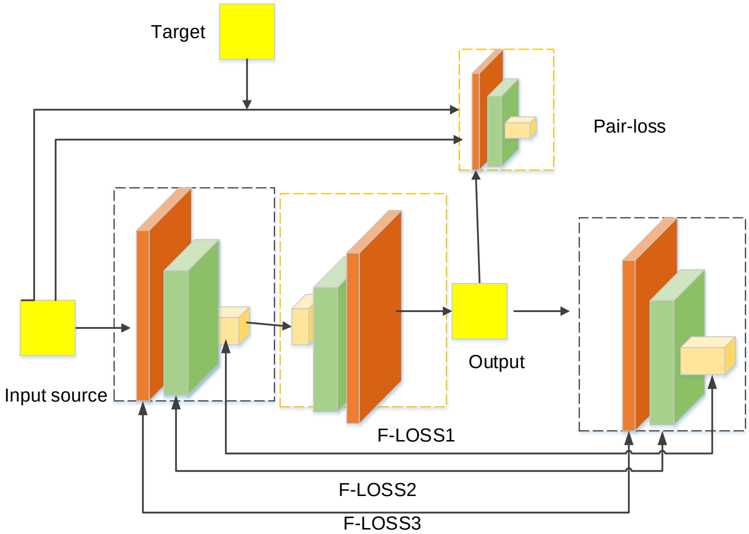

Fig. 2. Schematic diagram of grid structure.

The pseudocode input steps of the algorithm are shown in Fig. 3. Firstly, the training set $W = ((x1, y1)(x2, y2)\ldots(xn, yn))$.

Number of training cycles N Learning algorithm (such as GAN network and decision tree) or classifier
Output: combination classifier – compound model E^* Step 1: for $i = 1$ to t do Step 2: there is a replay sampling training set W Step 3: training of the algorithm or a weak classifier, and there are K different classifiers $E1$, $E2$, …, En. Step 4: endfor Step 5: using a combined classifier and K models for Y classification, and then returning to majority voting.

Deep learning networks are comprised of a multitude of neurons designed to mimic the neural structure of the human brain and carry out data processing tasks. ANN encompass various types of neurons that differ based on their connection methods. Among them, the Multilayer Perceptron is a mathematical model formed by connecting multiple neurons together. Fig. 3 provides an illustration of the components of a perceptron. The input vector a is combined with the weight *w* to obtain the perceptron's input. This input is processed using the transfer function *b* and the bias function *f*. The activation function *h* introduces nonlinear factors to map the output of the perceptron.

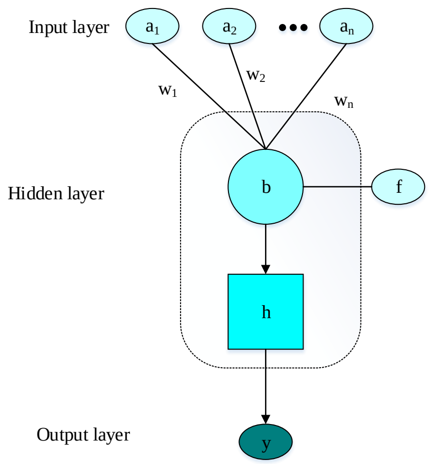

Fig. 3. The schematic diagram of the perceptron.

2.5 Statistical Methods

The SPSS21.0 is adopted for statistical processing of experimental data. Measurement data conforming to the normal distribution are expressed as mean ± standard deviation ($\bar{x} \pm s$), and independent sample t test is used for difference comparison. When $P < 0.05$, the difference is considered to be statistically significant.

3. RESULTS

3.1 Analysis on Prediction Results of Simulating the Stock Data

The RR data of 2,000 stocks are simulated in this study and 1,993 RR data are selected as the learning sample. The VaR prediction model is established with the help of the learning sample data to predict and analyze the remaining 7 data. The stock data with the ARCH(1) effect are simulated firstly by taking the ARCH(1) model as a reference to compare the prediction accuracy of VaR under different confidential intervals (CIs). Then, the RR data with the ARCH(2) effect are simulated, and corresponding ARCH(2) model and the VaR model based on deep learning are established targeting to the simulated stock RR data.

Deep learning is employed in this study to conduct time series prediction and regression prediction in order to investigate the VaR of stocks. The actual RR is averaged and squared to obtain the loss value for each period, which represents VaR. By lagging the loss series, different time series prediction models are constructed with varying lag periods. The lagged loss series serves as the dependent variable, while the series with one-period and two-period lags are used as independent variables. This framework enables the generation of FRPM for different lag periods, facilitating the analysis and estimation of VaR in the context of stock market risk. The prediction accuracy of VaR under different CIs is compared and analyzed based on the ARCH family model. The comparison results of the last 7 data are shown in Fig. 4 below.

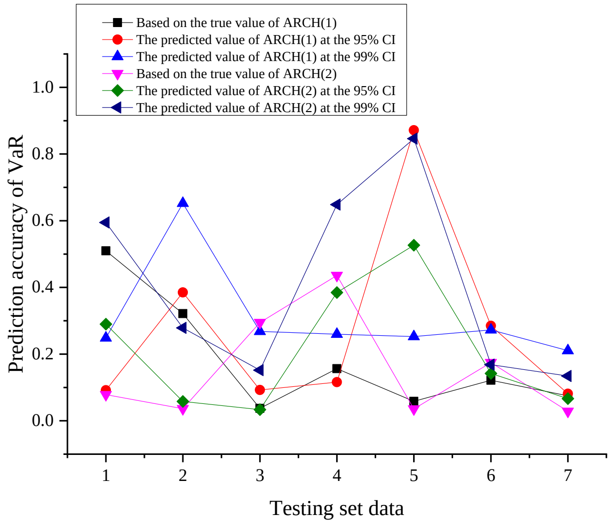

Fig. 4. The prediction accuracy on VaR of the ARCH family under different CIs.

Fig. 5 illustrates that the mean square error (MSE) for prediction accuracy of ARCH(1) on VaR is 0.122 and 0.275 when the CI is 95% and 99%, respectively. The prediction accuracy of ARCH(2) for VaR varies depending on the chosen CI. This observation indicates that the CI value significantly affects the model's prediction accuracy, with larger CI values resulting in higher MSE of prediction accuracy. The prediction accuracy of VaR based on the time series prediction model under deep learning is compared and analyzed when the CI is 95% after different ARCH family models are used. The comparison results of the last 7 data are shown in Fig. 5.

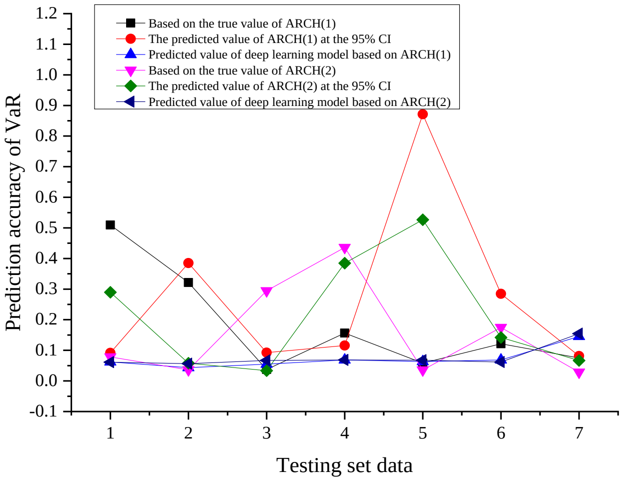

Fig. 5. The prediction accuracy of VaR based on the time series prediction model under deep learning at 95% CI.

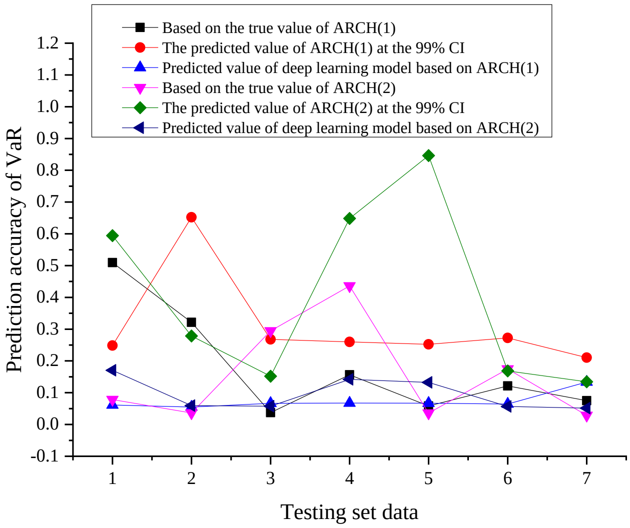

Fig. 6. The prediction accuracy of FRPM on VaR based on deep learning under 99% CI.

Fig. 6 demonstrates that when the CI is set to 95%, the time series model based on deep learning achieves a MSE for prediction accuracy of approximately 0.087 and 0.157 when compared to the ARCH(1) and ARCH(2) reference models, respectively. This suggests that the prediction accuracy of the deep learning-based time series model is influenced by the model parameters of the ARCH family. The time series prediction model based on deep learning outperforms the ARCH family model, delivering superior prediction results. Furthermore, the prediction accuracy of the FRPM for VaR based on deep learning under a 99% CI is analyzed and compared across different ARCH family models. The comparison results for the last 7 data points are depicted in Fig. 6.

Fig. 7 discloses that when CI is 99%, the FRPM based on deep learning has a MSE of prediction accuracy of 0.088 with ARCH(1) taken as the reference model, and it is 0.159 when ARCH(2) is taken as the reference model. Thus, the prediction accuracy of FRPM based on deep learning is also affected by the parameters of the ARCH family model, and the FRPM based on deep learning has a better prediction effect in contrast to the ARCH family model. Based on the ARCH(1) model, the prediction accuracy of the deep learning-based time series prediction model and the deep learning-based FRPM is analyzed and compared under different CIs. The comparison results of the last 7 data are given in Fig. 7.

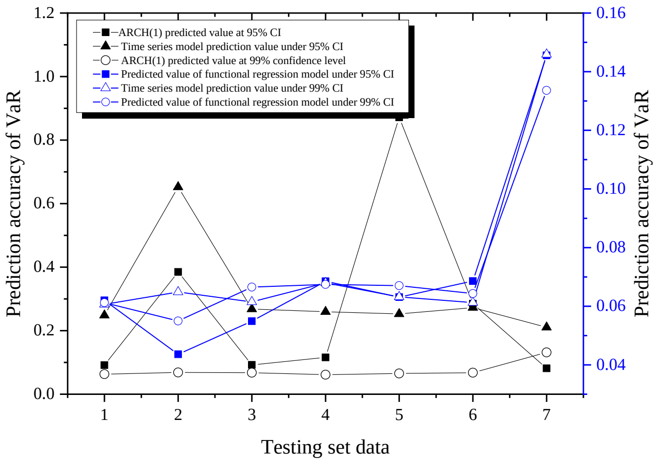

Fig. 7. The prediction accuracy of the deep learning-based prediction models taking ARCH(1) as reference.

Fig. 8 reveals that when ARCH(1) is undertaken as the reference model, the time prediction model and the FRPM based on deep learning have better prediction effects than the ARCH model. In addition, the prediction accuracy of the deep learning-based time series prediction model and the deep learning-based FRPM is analyzed and compared under different CIs based on the ARCH(2) model. The results of the last 7 data are illustrated in Fig. 8.

Fig. 9 demonstrates that when ARCH(2) is employed as the reference model, the prediction models based on deep learning consistently exhibit superior prediction results. The results of the comparative analysis of prediction models on simulated stock RR data indicate that the FRPM based on deep learning achieves the highest prediction accuracy, as evidenced by the MSE of prediction accuracy. When applying deep learning to directly predict the loss sequence itself, the accuracy surpasses that of traditional methods. This suggests that the VaR model based on deep learning exhibits superior predictive ability in financial VaR prediction. The findings support the conclusion that deep learning is an effective approach for improving the accuracy of VaR prediction in the financial domain.

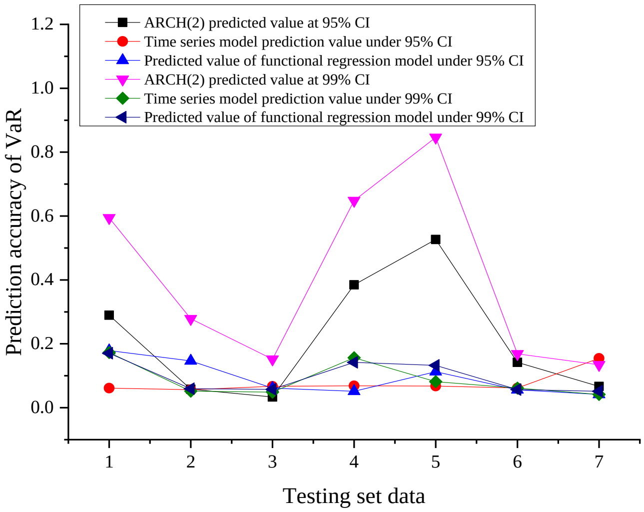

Fig. 8. The prediction accuracy of the deep learning-based prediction models taking ARCH(2) as reference.

3.2 Empirical Analysis of Different ARCH Family Calculation Models

To analyze and validate the proposed calculation model, the closing prices of the Shanghai and Shenzhen 300 index in the stock market are selected as the research objects. The stock price index is a widely used indicator to assess the overall price fluctuation and trend in the stock market. By selecting high-frequency data, the model avoids potential parameter changes that may occur when using low-frequency data, and it ensures an adequate sample size for model construction. This selection of high-frequency data enables a more accurate and reliable analysis of the forecasting model. The model constructed in this study is applied smoothly. The data selected contains the closing price data of the 300 index of Shanghai and Shenzhen stock markt from November 1, 2018 to February 15, 2019. There are 2,407 closing price data, the first 2,400 prices are included in the sample set, and the corresponding VaR model is established based on the sample set. The last 7 pieces data are considered as the testing set to verify the proposed VaR model.

Based on certain distribution assumptions, the ARCH(1) and ARCH(2) models are constructed based on the 300 index log RR sequence in the Shanghai and Shenzhen stock market. The parameter estimation table of the ARCH(1) model is shown in Table 1.

Table 1. The parameter estimation table of the ARCH(1) model.

Parameter estimation	*t* distribution	Normal distribution	Generalized error distribution
β	0.196541	0.148517	0.181524
ω	7.72E-07	8.2E-07	7.31E-07
v	3.686945	–	1.068451
μ	4.52E-07	–7.15E-06	6.44E-08
SC	–11.2913	–11.013	–11.2574
AIC	–11.2946	–11.0542	–11.2694

Table 1 presents the estimated values of the parameter β for the three different models, all of which fall within the range of 0 to 1. This indicates that the models exhibit stability. Based on the SC and AIC criteria, it can be concluded that the ARCH(1) model provides the best fit under the assumption of a *t*-distribution, followed by the generalized error distribution and the normal distribution.

Under the assumption of a *t*-distribution, the thickness of the tail of the distribution varies with changes in the degree of freedom v. A smaller value of v corresponds to a thicker tail, while a larger value of v results in a thinner tail. As v approaches infinity, the *t*-distribution approaches a normal distribution. In this study, the degree of freedom in the *t*-distribution is estimated to be 3.686945, indicating that the fluctuation of the sequence exhibits sharp peaks and thick tails.

Under the assumption of generalized error distribution, the value of the parameter v also controls the thickness of its tail. When $v > 2$, the generalized error distribution has lower kurtosis than the normal distribution, and its tail is thinner. When $v < 2$, the generalized error distribution has higher kurtosis and thicker tails than the normal distribution. When $v = 2$, the error distribution shows a normal distribution trend. In the model assumption, the degree of freedom v is 1.068451, which proves that the fluctuation of the sequence presents a characteristic of a relatively obvious peak and thick tail. The parameter estimation table of the ARCH(2) model is shown in Table 2.

Table 2. The parameter estimation table of the ARCH(2) model.

Parameter estimation	*t* distribution	Normal distribution	Generalized error distribution
β	0.166821	0.130819	0.147568
ω	6.73E-07	7.24E-07	6.42E-07
λ	0.138684	0.131954	0.129653
v	3.686945	–	1.068451
μ	2.21E-07	–1.03E-06	–1.98E-06
SC	–11.2954	–11.0636	–11.2672
AIC	–11.3013	–11.0742	–11.2754

Table 2 reveals that the estimated values of the parameters β and λ in the three models are all greater than 0, and the sum of β and λ is less than 1. It proves that the model is relatively stable. Under such a premise, it is concluded based on the SC and AIC criteria that the ARCH(2) model under the t distribution assumption presents the best fitting effect on the sample data.

Under the assumption of *t* distribution, v in the model is 3.814856; and it is 1.064851 under the generalized error distribution. It proves that the sequence is featured with obvious sharp peak and thick tail. Based on the above analysis, the ARCH(1) and ARCH(2) models are constructed under the assumptions of t distribution. In addition, the 300 index from the Shanghai and Shenzhen stock market is selected to model its logarithmic RR sequence, and the VaR is calculated using this model.

Due to the small values of stock RR, the variance calculation can result in values around a.bcE-08. When performing data processing on a computer, rounding calculations can introduce significant errors. To facilitate intuitive and comparative analysis of the calculation results without altering the statistical characteristics of the original data, it is common practice to scale all the data simultaneously. To avoid processing errors, the RR data in this study are multiplied by a factor of 1,000, thereby allowing for more meaningful and accurate comparisons of the corresponding calculation results.

The ARCH(1) model is undertaken as a reference model to compare and analyze the accuracy of VaR predicted by the VaR model based on deep learning under different CIs. The prediction accuracy comparison of the last 7 data is shown in Fig. 9.

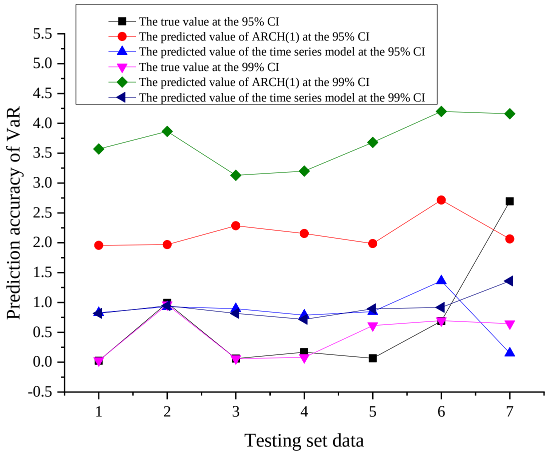

Fig. 9. The prediction accuracy comparison at different Cis taking ARCH(1) as reference.

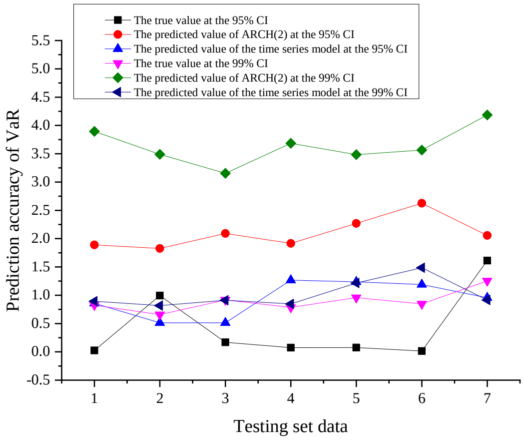

Fig. 10. The prediction accuracy comparison at different Cis taking ARCH(2) as reference.

Fig. 10 discloses that when the CI is 95% or 99%, the prediction accuracy of VaR calculated by the time series prediction model based on deep learning is higher than that of ARCH(1), and the MSE of its prediction accuracy is 0.871. When the VaR of the logarithmic return of the 300 Index in Shanghai and Shenzhen stock market is predicted, the value of CI does not have a great impact on the model prediction results, but the prediction model based on the deep learning shows a significantly higher prediction accuracy in contrast to the ARCH(1) model.

The ARCH(2) model is undertaken as a reference model to compare and analyze the accuracy of VaR predicted by the VaR model based on deep learning under different CIs. The prediction accuracy comparison of the last 7 data is shown in Fig. 10 below.

Fig. 11 indicates when ARCH(2) is considered as the reference model, the MSE of the prediction accuracy of the time series prediction model based on deep learning is 0.87, while that of the ARCH(2) model is 1.629. Thus, it means that the MSE of the time series prediction model based on deep learning to predict the VaR is significantly less than that of ARCH(2), suggesting that the prediction model based on deep learning has better prediction effect. The prediction model proposed can be applied in the risk measurement of 300 index logarithmic RR in the in the Shanghai and Shenzhen stock market well.

3.3 Error Fitting Comparison on the Data Set

Deep learning is a learning algorithm that extracts meaningful features from raw data. Through training and learning processes, the discriminator network enhances its ability to distinguish and discriminate by improving feature representation. As a result, the model's classification performance improves, leading to a better fit of the error on the dataset. A smaller error signifies a closer approximation to the true value. Fig. 11 provides a visual comparison of the fitting results on different datasets. Following the testing and training of the GAN network, the prediction error in the data is substantially reduced, resulting in more accurate evaluation values.

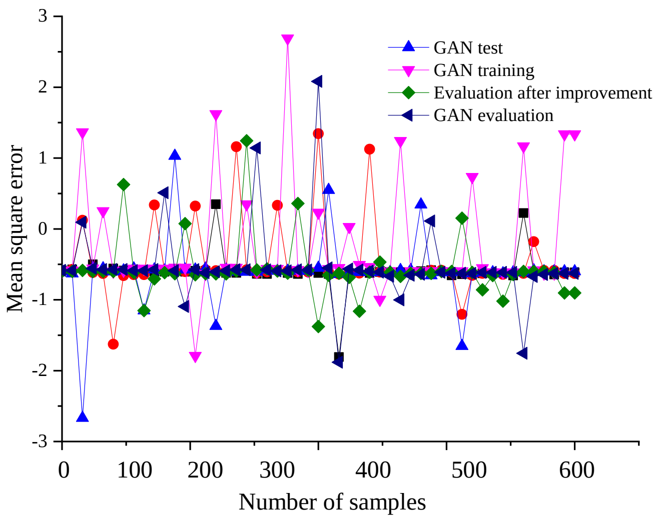

Fig. 11. Comparison on fitting of various data sets.

The GAN is utilized to compare the up-sampling and down-sampling methods with the few data samples generated by the sample set. The results are presented in Table 3. The superiority of GAN in terms of stability and evaluation accuracy is clearly apparent compared to up-sampling and down-sampling techniques. The generation process of GAN involves sampling from the root of the original sample, leading to generated samples that possess greater representativeness of the common characteristics and saliency present in the original sample. In contrast to random sampling, the utilization of GAN yields more favorable outcomes and enhanced stability.

Table 3. Different evaluation results of different sample processing methods.

	Accuracy	Stability
Up-sampling	56.0%	66.2%
Down-sampling	58.0%	57.0%
GAN	63%*	78.3%*

Note: * indicates statistically obvious difference ($P < 0.05$).

4. DISCUSSION

In addition to the data set, GAN primarily leverages simulated data to augment its applicability to real-world scenarios. Occasionally, the collection of real data poses significant challenges, and training models solely on simulated data may not effectively generalize to real tasks. Within this study, the utilization of GAN in conjunction with the VaR measurement method in deep learning aims to optimize data training. Notably, the evaluation accuracy rate of the GAN network reaches 63%, surpassing the performance of up-sampling and down-sampling techniques. GAN training learning shows relative better error fitting in contrast to the GAN-training and GAN evaluation. When the CI is 99%, the MSE of the ARCH(1) model when predicting VaR is 3.242. The time series prediction model based on deep learning has a MES of 0.87 in predicting the VaR. The FRPM based on deep learning has a MSE of 0.828 in predicting VaR. When the ARCH(2) model predicts VaR, the MSE is 3.069.

5. CONCLUSION

This study endeavors to tackle the prevalent problem of excessive financialization in enterprises and puts forth a VaR measurement model utilizing GAN within the realm of deep learning. The reported evaluation metrics for GAN encompass an accuracy of 63% and a stability level of 78.3%. GAN exhibits remarkable aptitude in handling imbalanced data samples, effectively sampling minority data, and precisely capturing the overall distribution of such minority samples. The MSE stands at 3.069 when VaR is predicted using the ARCH model. Conversely, the MSE for the GAN network, which leverages deep learning in conjunction with VaR for time series prediction, is computed to be 0.871. The integration of GAN network with VaR demonstrates a dependable practicability in assessing excessive financialization risks. GAN represents a novel approach to data processing, effectively enhancing real-world applications when combined with manual efforts, and exhibiting reliable potential for data set training and advancement. Nevertheless, certain limitations exist within this study. The practical application of the proposed model remains restricted and lacks the support of hands-on experience. Therefore, it necessitates further application to a wider range of authentic financial data sets in the future, along with comparison and verification against traditional financial risk assessment methods. Additionally, in order to enhance the reliability of the model, collaborative efforts with industry practitioners are essential to refine and validate it through their professional expertise and experience.

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