Big Data Application in Forecasting Financial Investment of e-Commerce Industry for Sustainability

Yanfeng Zhang
Business School, Sias University, Xinzheng, 451150, China

***Abstract*—With the rapid development of e-commerce, financial investment forecasting in the e-commerce industry has gradually become a concern of relevant personnel. Based on DBN, the study proposes a PVD prediction model. For training and test sample sets, the PLR_VIP algorithm is calculated and min-max normalization is applied to the original financial time series. To determine appropriate network parameters, the DBN network is trained and tested, and then Elliott wave patterns are predicted based on financial time series. The experimental results show that the MSE of the PVD model is 0.4015 and the prediction accuracy is 70.21%, indicating that it can efficiently and accurately identify the Elliott wave pattern of financial time series. Comparing the prediction results of the PVD model with the other five models, the values of the four evaluation indicators of PVD are the lowest among all models, which are 0.6336, 0.4015, 0.9052, and 29.79%, respectively. Compared with the training error changes of other models, it can be seen that the error curve of the DBN network is smoother and the training error is smaller. It shows that it has higher stability, faster convergence speed, higher reliability and accuracy, and shows excellent prediction performance, which is significantly better than other models. Experiments show that under the background of sustainable development, the PVD forecasting model proposed in the study performs well in financial investment forecasting, which provides a reference for the development of financial investment forecasting in the e-commerce industry.**

Keywords—Stainable development; big data; e-commerce industry; financial investment forecast; deep belief network

I. Introduction

The financial investment market plays an important role in today’s social and economic field, and the direction of the financial market will directly affect the core competitiveness of enterprises [1]. The academic community continues to study the changing laws of the financial market, and find reliable means that can describe and predict the changing laws and future trends of the financial market [2]. Neural networks have been developing continuously in recent years, and a large number of related technologies have been applied to various fields, including forecasting the financial investment market [3]. e-Commerce is a new type of networked economic activity. In recent years, it has become an important means for many countries to enhance their economic strength and gain the advantages of global resource allocation. However, the e-commerce industry in China currently has problems such as waste of resources and inconsistent supply and demand, so it is necessary to use effective forecasting methods to forecast the financial investment market in the e-commerce industry [4]. To improve the development ability of financial investment in China's e-commerce industry, the research proposes a PVD (Piecewise Linear Representation VIP DBN) prediction model based on Deep Belief Network (DBN), which uses a deep learning model to model financial time series, and innovatively combines DBN and piecewise linear representation based on very important points (PLR_VIP). It can discriminate the Elliott wave pattern of financial time series and then predict the trend of the financial investment market in the e-commerce industry.

There are two innovation points in the research. First, the financial investment forecast dataset is built against the background of big data; secondly, intelligent algorithm is introduced into financial forecasting to realize automatic forecasting of financial investment. Compared with previous studies, the use of intelligent algorithms and big data technology can more effectively achieve its change prediction, and can more easily update data with the help of Internet technology.

II. Related Work

With the related research and development of big data, deep learning related technologies have been applied to the field of financial forecasting, and many scholars at home and abroad have conducted research on it. Kare et al. used Singular Spectrum Analysis (SSA) and Multi-channel Singular Spectrum Analysis (MSSA) to identify important deterministic cycles in residential property prices, private non-financial sector credit shares. Prediction test results show that the inclusion of financial big data significantly improves the prediction accuracy of financial cycle components [5]. Scholars such as Kelotra proposed a stock market forecasting system that effectively predicts the state of the stock market. First, the calculation of technical indicators is performed on the data from the real-time stock market, indicating that the necessary features are obtained by clustering using Sparse Fuzzy C-means (Sparse-FCM), and then feature selection is performed. The selected features are given to the Deep-ConvLSTM model to perform accurate predictions. Evaluation Based on evaluation metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), the proposed stock market forecasting model obtained the minimum MSE and RMSE of 7.2487 and 2.6923, which showed the effectiveness of the method in stock market forecasting [6]. Chen et al. proposed a new stock price prediction model that combines a Convolutional Neural Network (CNN), a Bidirectional Long Short-Term Memory (BiLSTM) network, and an Efficient Channel Attention (ECA). CNNs are used to extract deep features from stock data to reduce the effects of high noise and nonlinearity. BiLSTM network is used to predict stock prices based on the extracted deep features. At the same time, a novel ECA module is introduced into the network model, which further improves the sensitivity of the network to important features and key information. The results demonstrate the effectiveness and feasibility of the proposed CNN-BILSTM-ECA network model [7]. Lei et al. constructed investor attention factors through Baidu search antecedent index, and then combined other transaction information such as transaction volume, trend indicators, and quotation rate of change as input indicators, and finally used a deep temporal convolutional network (TCN) learning model to predict Volatility under high frequency financial data. Compared with the traditional econometric model, the multi-step forecast results of the TCN model have higher stability, provide a more accurate and reliable method for volatility forecasting of big data, and enrich the index system of volatility forecasting [8]. Scholars such as Yh proposed a new financial data prediction model based on Variational Mode Decomposition (VMD). In this model, the parameters of VMD are optimized by genetic algorithm. VMD then decomposes the data series into long-term and short-term trends. Finally, a long short-term memory (LSTM) network is used to predict future data, and the data input generated by the VMD is used. Experimental results show that the model has high accuracy in the advance forecasting of financial time series and outperforms the baseline model [9].

Researchers such as Bukhari AH proposed a novel hybrid model with fractional derivative strength and its dynamic characteristics of deep learning, long short-term memory (LSTM) networks to predict changes in financial markets; where the ARFIMA model-based filter has a linear trend in the data that outperforms the Autoregressive Integrated Moving Average model (ARIMA) model, and passes the residuals to the LSTM model, which has the help of an external dependent variable The residual value that captures the nonlinearity below. This model not only alleviates the volatility problem, but also overcomes the overfitting problem of neural networks [10]. Luo et al. propose a hybrid model that combines ensemble empirical mode decomposition (EEMD), autoregressive integral moving average (ARIMA), and Taylor expansion using tracking differentiators to forecast financial time series. Specifically, financial time series are decomposed into subsequences by EEMD. Then, the linear part of each subsequence is predicted by the linear ARIMA model, while the nonlinear part is predicted by the nonlinear Taylor expansion model. Combine predictions from linear and nonlinear models into predictions for each subseries. The final prediction result is obtained by combining the predicted values of all subsequences [11]. Scholars such as Darley Olufunke use the ARIMA model to analyze and model the price trend, and propose a model suitable for prediction. The results show that the ARIMA (6, 1, 12) model is the most suitable, based on a combination of the number of significant coefficients and volatility values, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). After two months of experiments, the results show that the prediction accuracy gradually decreases as the number of days in the test period increases [12].

The study proposes a PVD prediction model based on DBN, which performs PLR_VIP algorithm calculation and min-max normalization on the original financial time series to obtain training sample sets and test sample sets, trains and tests the DBN network to obtain appropriate network parameters, and then predicts Elliott wave patterns for financial time series.

III. PVD Financial Investment Prediction Model Based on Deep Belief Network

A. *Fusion of Deep Belief Network and Elliott Wave Model*

DBN is a model of deep learning technology, which is composed of stacking units. The training process of DBN includes two stages: pre-training and fine-tuning. The pre-training adopts an unsupervised greedy layer-by-layer learning strategy to train each Restricted Boltzmann Machine (RBM) from the bottom up, which can feature information in the original data and is extracted layer by layer to abstract the high-level feature representation of the data [13]. Fine-tuning adopts a supervised learning algorithm to adjust the parameters of the network to complete classification and recognition. RBM is a generative model with strong unsupervised learning ability. It consists of two parts: visible layer and hidden layer. Units between different layers are connected by full connection [14]. The structural framework of the DBN network is shown in Fig. 1.

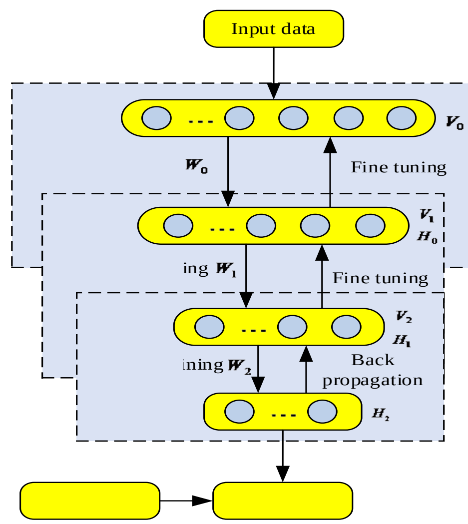


Fig. 1. Structure framework of DBN network

The visible layer consists n of neurons, $v=\left(v_1,v_2,\cdots v_n\right)$, where $v\in\left\{0,1\right\}^n$; the hidden layer consists m of neurons, $h=\left(h_1,h_2,\cdots h_m\right)$, where $h\in\left\{0,1\right\}^m$. A value of 1 indicates that the neuron is activated, otherwise it is not activated. The parameter $\theta=\left\{w,b,a\right\}$ determines the RBM model, in which w is the weight between the visible layer unit and the hidden layer unit, a representing the offset of the visible layer unit and the offset of the b hidden layer unit. The structure of the RBM is shown in Fig. 2.

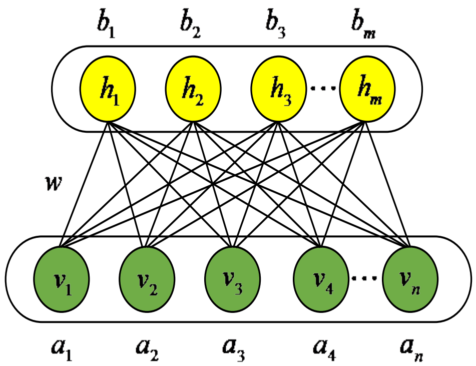


Fig. 2. Structure of RBM

The joint probability distribution of the visible layer and hidden layer units of RBM is shown in formula (1).

$$P(v,h)=\frac{1}{N}e^{-E(v,h)} \quad (1)$$

In formula (1), $N=\sum_{v,h}e^{-E(v,h)}$ is the normalization factor, which $E(v,h)$ is the energy function. It is assumed that the visible layer and the hidden layer of the RBM model obey the Bernoulli distribution, and the energy function is defined as shown in formula (2).

$$E(v,h)=-\sum_{j=1}^{n}a_jv_j-\sum_{i=1}^{m}b_ih_i-\sum_{i=1}^{m}\sum_{j=1}^{n}w_{ij}v_jh_i \quad (2)$$

Exponentiate and regularize the energy function to obtain the joint probability distribution formula, and sum up the states of all neurons in the hidden layer and the visible layer respectively to obtain the edge probability distribution of the visible layer and the hidden layer, as shown in Equation (3).

$$\begin{cases} P(v)=\sum_h P(v,h)=\frac{1}{N}\sum_h e^{-E(v,h)} \\ P(h)=\sum_v P(v,h)=\frac{1}{N}\sum_v e^{-E(v,h)} \end{cases} \quad (3)$$

After the state of the visible layer unit is obtained, i the conditional probability that the first unit of the hidden layer is activated can be calculated as shown in equation (4).

$$P(h_i=1|v)=\sigma\left(b_i+\sum_{j=1}^{n}w_{ij}v_j\right) \quad (4)$$

After the state of the hidden layer unit is obtained, j the conditional probability that the first unit of the visible layer is activated can be calculated as shown in formula (5).

$$P(v_j=1|h)=\sigma\left(a_j+\sum_{i=1}^{m}w_{ji}v_i\right) \quad (5)$$

where σ represents the sigmoid function, $\sigma(x)=\frac{1}{1+e^{-x}}$. The mean square error is used to measure the difference between the reconstructed output of the hidden layer to the visible layer and the input of the RBM.

Set a sample set $v=\{v_0,v_1,\cdots,v_K\}$ and train the RBM model. In order to make the joint probability distribution fit the distribution of the input samples as much as possible and make the system energy stable, it is necessary to find a suitable parameter $\hat{\theta}=\{w,b,a\}$. The maximization likelihood function is used $L(\theta)$, which is equivalent to maximizing the log-likelihood function $\ln L(\theta)$, as shown in equation (6).

$$\hat{\theta}=\arg\max_{\theta}L(\theta)=\arg\max_{\theta}\sum_{t=0}^{K}\ln P(v_t|\theta) \quad (6)$$

The gradient ascent method is used to update the parameters as shown in equation (7).

$$\theta^*=\theta+\eta\frac{\partial\ln P(v)}{\partial\theta} \quad (7)$$

Equation (7) η represents the learning rate, η>0. The log-likelihood function for a single sample is shown in Equation (8).

$$\ln P(v_0)=\ln\frac{1}{N}\sum_h e^{-E(v_0,h)}=\ln\sum_h e^{-E(v_0,h)}-\ln\sum_{v,h}e^{-E(v,h)} \quad (8)$$

The gradient formula of this sample is shown in formula (9).

$$\frac{\partial\ln P(v_0)}{\partial\theta}=-\sum_h P(h|v_0)\frac{\partial E(v_0,h)}{\partial\theta}+\sum_{v,h}P(v,h)\frac{\partial E(v,h)}{\partial\theta} \quad (9)$$

The joint probability distribution cannot be directly calculated, and it needs to be approximated by the sampling method, which $P(v,h)$ can be expressed as $P(h|v)P(v)$, and substitute it into the gradient formula, as shown in formula (10).

$$\frac{\partial\ln P(v_0)}{\partial\theta}=-\sum_h P(h|v_0)\frac{\partial E(v_0,h)}{\partial\theta}+\sum_v P(v)\sum_h P(h|v)\frac{\partial E(v,h)}{\partial\theta} \quad (10)$$

The update formula of the three parameters of the RBM is obtained. The traditional parameter update formula is more complicated and requires a large amount of calculation. Therefore, the Contrastive Divergence (CD) algorithm is used to update the parameters, usually only one step is needed to achieve better results. Using the k-CD algorithm, set a training set v, $\forall v\in v$ take the initial value v^0, and perform k step Gibbs sampling. When the first t step ($t=1,2,\cdots,k$) is reached, it is obtained by sampling, $P(h|v^{(t-1)})$obtained $h^{(t-1)}$ by $P(v|h^{(t-1)})$sampling $v^{(t-1)}$, and obtained after k

sub-Gibbs sampling, $v^{(k)}$ and an approximation of the parameters can be obtained. The gradient formula is as formula (11).

$$\begin{cases} \dfrac{\partial \ln P(v)}{\partial w_{ij}} \approx P\left(h_i = 1 \middle| v^0\right) v_j{}^0 - P\left(h_i = 1 \middle| v^k\right) v_j{}^k \\ \dfrac{\partial \ln P(v)}{\partial b_j} \approx v_j{}^0 - v_j{}^k \\ \dfrac{\partial \ln P(v)}{\partial c_i} \approx P\left(h_i = 1 \middle| v^0\right) - P\left(h_i = 1 \middle| v^k\right) \end{cases} \tag{11}$$

The update formula of the parameters can be estimated by Equation (12).

$$\begin{cases} w_{ij}{}^* \approx w_{ij} + \eta\left(P\left(h_i = 1 \middle| v^0\right) v_j{}^0 - P\left(h_i = 1 \middle| v^k\right) v_j{}^k\right) \\ b_j{}^* \approx b_j + \eta\left(v_j{}^0 - v_j{}^k\right) \\ c_i^* \approx c_i + \eta\left(P\left(h_i = 1 \middle| v^0\right) - P\left(h_i = 1 \middle| v^k\right)\right) \end{cases} \tag{12}$$

Set up a l DBN network with one hidden layer and calculate its joint probability distribution as Equation (13).

$$P(v, h_1, h_2, \cdots, h_l) = P(v|h_1) P(h_1|h_2) \cdots P(h_{l-2}|h_{l-1}) P(h_{l-1}, h_l) \tag{13}$$

Equation (13) $P(h_{l-1}, h_l)$ represents the probability distribution of the top layer of the RBM, which represents $P(h_k|h_{k+1})$ the conditional probability ($k = 0, 1, 2, \cdots, l-1$, where $h_0 = v$) of the hidden layer of h_k each RBM layer when the visible layer is known. h_{k+1} For a n training sample set with one sample $X = \{x_0, x_1, \cdots, x_n\}$, the data label set of the sample is $Y = \{y_0, y_1, \cdots, y_n\}$. The input of the pre-training process X does not require data labels. The k-CD algorithm is used to train the network parameters unsupervised, and the output value obtained by each layer of RBM is input into the next layer of RBM, and the feature vector set of the sample is obtained layer by layer. The pre-training process adjusts the RBM model of each layer to ensure the optimal output of this layer, but cannot guarantee the optimal output of the entire DBN. Therefore, the DBN network parameters need to be adjusted, and the network parameters Y are supervised top-down using the sample data label set [15].

There are two types of Elliott wave cycle modes: driving and adjusting. An impulsive wave is a homeopathic wave that pushes the market to change in the direction of the main trend. It is generally composed of five sub-waves with a simple form, and can be divided into conventional impulsive waves and unconventional impulsive waves. A regular motive wave consists of five waves 1-2-3-4-5 directed upwards or downwards. After the fifth wave ends, there will be a movement in the opposite direction of the trend. This movement is a corrective wave, which is a partial retracement of the driving relative to the previous driving wave of the same level. The structure of corrective waves is more complex than that of driving waves, mainly including three forms: zigzag, flat and triangle [16-17].

B. 2.2 Establishment of PVD Prediction Model based on Deep Belief Network

When analyzing and forecasting financial markets, financial time series are often used to extract financial transaction data. Time series is a collection of measured values obtained over time. The core is to use reasonable technical methods to ignore the small fluctuations of the time series to obtain the concept of data sawtooth, and to identify the corresponding time series on different time scales pattern [18]. Time variables and data variables together make up each data unit of the time series. The research uses deep learning combined with Elliott wave theory to establish a financial market prediction model, extracts transaction price information and abstracts it as a time series, extracts features through deep learning model and obtains the Elliott wave pattern corresponding to the original time series [19]. Since the lengths of the time series corresponding to the same wave pattern are different, but the length of the input sequence needs to remain the same, the length of the input data needs to be fixed, and the original data is preprocessed before input, that is, the data is processed Dimensionality reduction and compression, discarding parts that have less impact on the global. The research uses the PLR_VIP algorithm to process the original data [20].

The basic principle of piecewise linear is to set a n dimensional time series $S = \{s_1, s_2, \cdots, s_n\}$ and extract a new series S of k ($k << n$) pieces that construct an approximate series according to it $S^* = \{s^*{}_1, s^*{}_2, \cdots, s^*{}_{k+1}\}$. Using the PLR method, the adjacent continuous line segments can be approximated as the original time series. The selection of segment points has different degrees of influence on the time series structure, and the degree of influence can be expressed as importance. Select important points on the original time series, keep important points and discard unimportant points. In order to fix the step size of the time series, the segmentation condition is set to a fixed number of segments. When the interval of the time series is fixed, the importance of a point is measured by the distance of the point from the endpoint of the region where the point is located. The raw time series is preprocessed with vertical distance as a measure. An example of the PLR_VIP algorithm is shown in Fig. 3.

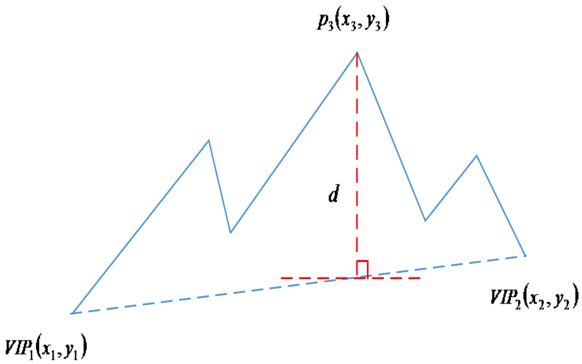


Fig. 3. PLR_VIP algorithm example

The time series shown in Fig. 3 takes the VIP_1 sum as the end VIP_2 point, and the vertical distance between the d calculation point and the two end points is p_3 shown in formula (14).

$$d = \left| \left(y_1 + (y_2 - y_1) \frac{x_3 - x_1}{x_2 - x_1} \right) - y_3 \right| \quad (14)$$

VIP_1 sum VIP_2 is two important points, find the point with the farthest vertical distance from the two endpoints p_3 as the next important point VIP_3, find the point with the farthest vertical distance in the area with the VIP_1 sum VIP_3 as the endpoint and the VIP_2 sum VIP_3 as the endpoint respectively and mark it For important points, the above process is iterated until the number of important points reaches a predetermined number. During the training process of the network, the data of the order of magnitude will mask the contribution of the data of the smaller order of magnitude to the network, thus affecting the accuracy of the network, and the cardinality of the sample and the average value are quite different, which will reduce the convergence speed of the network. Therefore, standardize the sample data, use the min-max normalization method to map the data to the interval [0, 1], and x perform min-max normalization on the first i data of the sample as shown in formula (15). x_i

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (15)$$

The study designed eight types of Elliott wave patterns, each of which consists of eight sub-waves, as shown in Fig. 4.

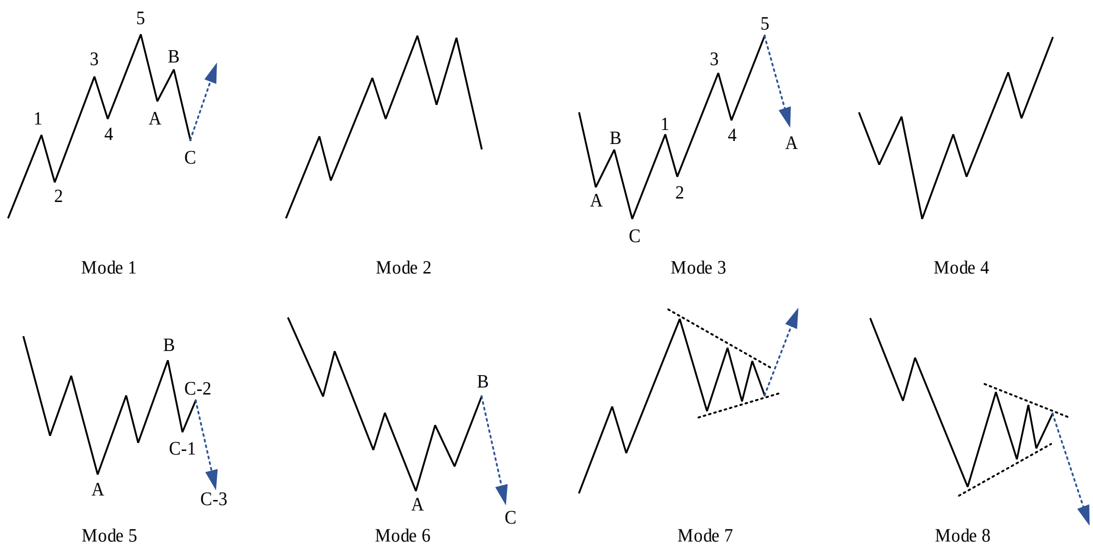


Fig. 4. 8 Elliott Wave Model

Pattern 1 consists of driving waves and zigzag waves. When the financial time series is identified as pattern 1, it means that the market is about to enter a rising stage, and there may be a new round of bull or bear market upward adjustment. Wave 3 is the key sub-wave of the bull market, and wave C is the key sub-wave of the bear market, both of which are the strongest waves under normal conditions. Pattern 2 consists of motive waves and flat correction waves. The types of correction waves are different from those of pattern 1, including spread and trend. When the financial time series is identified as mode 2, it means that the market has entered a rising period and will usher in a trading opportunity. The attribute of the market rising is the same as that of mode 1. Pattern 3 consists of ZigZag and Motivation. When a financial time series is identified as pattern 3, it indicates that the market will enter a downward phase. The falling phase may result from a pullback from the previous driving wave, or it may usher in a new bear market. Pattern 4 is composed of a flat adjustment wave and a driving wave. The type of adjustment wave is different from that of pattern 3. The flat adjustment wave of pattern 4 includes spread and trend. When the financial time series is identified as pattern 4, it means that the market will enter an adjustment phase, and the property of the market falling is the same as that of pattern 3. Pattern 5 represents part of a flat correction, its role is to predict the main decline in the market, and its end indicates the beginning of the main decline. Pattern 6 is an inversion of Pattern 1 and appears as part of a ZigZag. When the financial time series is identified as pattern 6, it means that the financial market is about to enter the main down stage. The purpose of model prediction is to judge the future trend of the financial market, so there is no need to consider whether the triangle is an unconventional driving wave or a corrective wave. When the financial time series completes pattern 7, the financial market will start to rise, and after pattern 8 it will start to fall.

The PVD prediction model proposed by the research mainly includes three parts: PLR_VIP algorithm, min-max normalization processing and DBN network. PVD forecasting models can identify and judge Elliott wave patterns in financial time series. The PLR_VIP algorithm can retain the important points of the original financial time series and standardize the step size of the financial time series. The min-max normalization method can standardize the range of data changes and improve the accuracy and convergence speed of the network. Perform PLR_VIP algorithm calculation and min-max normalization on the original financial time series to obtain a training sample set and a test sample set, train and test the DBN network to obtain appropriate network parameters, and then predict the Elliott wave pattern of the financial time series. The specific process of the PVD prediction model is shown in Fig. 5.

To test the prediction accuracy and performance of the proposed model, four performance indicators are selected as evaluation criteria. The lower the indicator value, the more accurate the prediction results of the prediction model are, as shown in Table I.

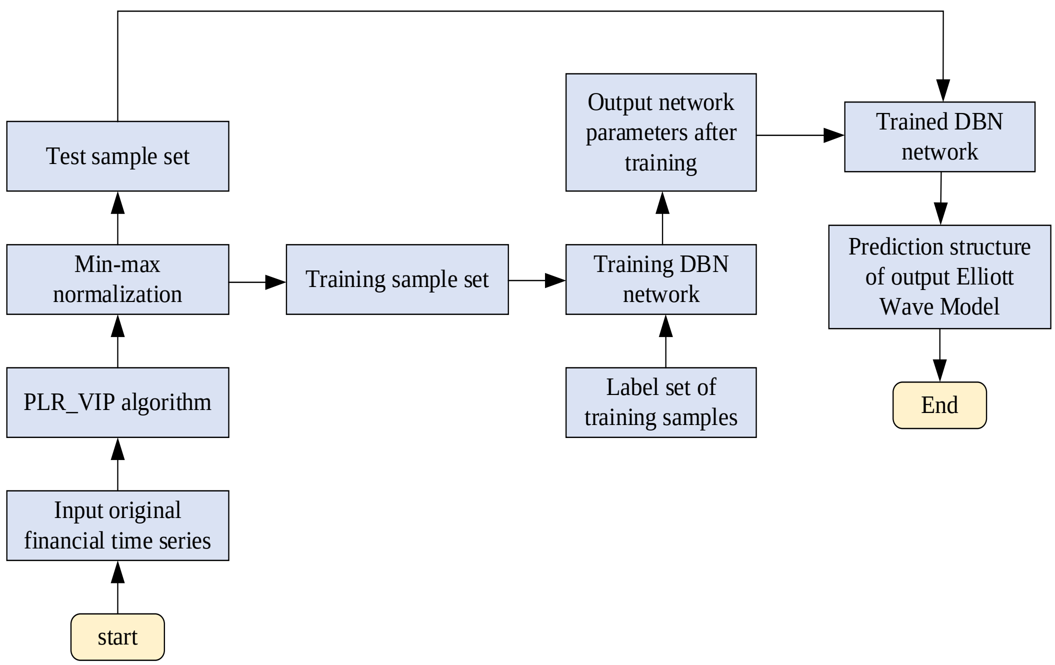


Fig. 5. Specific process of PVD prediction model

TABLE I. PERFORMANCE INDEX

Performance index	Calculation formula
RMSE	$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(T_i-P_i\right)^2}$
MSE	$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(T_i-P_i\right)^2$
MAE	$MAE=\frac{1}{n}\sum_{i=1}^{n}\left\|T_i-P_i\right\|$
ER	$ER=\frac{\sum\left\{1\middle\|Model_P\neq Model_T\right\}}{\sum\left\{1\middle\|Model_P=Model_P\right\}}\times 100\%$

Table I shows that root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE) and relative error (ER) are used to evaluate the prediction performance of the model.

The study selected some data from the historical price data of more than 10 trading varieties in the global stock index, foreign exchange market and bulk commodity markets for the experiment. A total of 6000 relevant financial data were collected in this experiment, 4829 of which were from Internet data and 1171 from books, newspapers and other tools. Take 20% of all data as the test set and the remaining 80% as the training set.

IV. Experimental Analysis of PVD Prediction Model Based on Deep Belief Network

After preprocessing through the PLR_VIP algorithm and the min-max normalization method, the original financial time series sample data of the DBN network for training and testing are obtained. The obtained sample data is input into the DBN network for iterative training. As the number of iterations increases, the training error of the DBN network is shown in Fig. 6.

Using the PVD forecast model to classify and predict the Elliott wave pattern of the financial time series, the classification results show that the MSE is 0.4015, and 70.21% of the financial time series in the sample have obtained the correct classification result, that is, the prediction accuracy of the model is 70.21%. It shows that the PVD forecasting model can effectively identify the Elliott wave pattern of financial time series, and can more accurately predict the trend of the financial market. Taking the S&P 500 index, the US dollar index and WTT crude oil as examples, the prediction effect of the model is shown in Fig. 7.

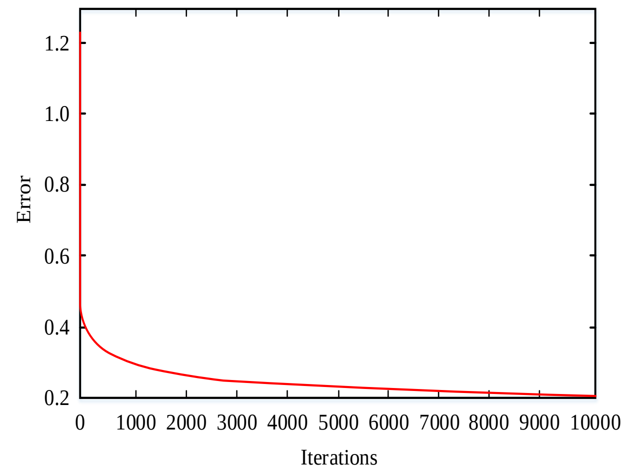


Fig. 6. Training error of DBN network

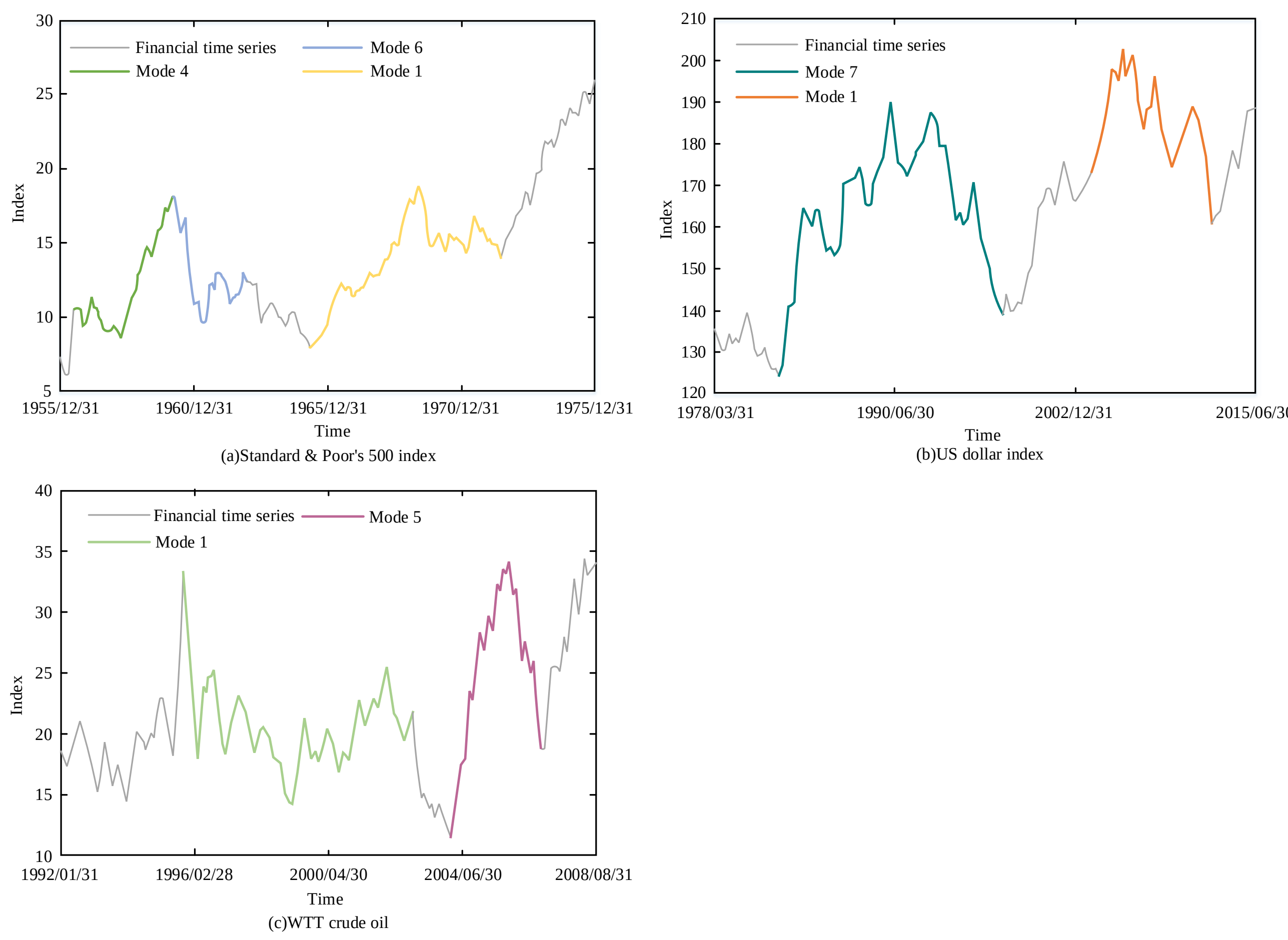


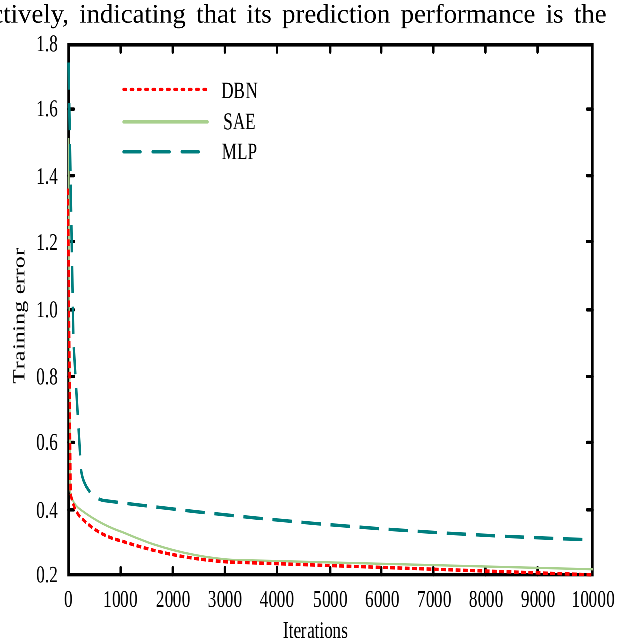
Fig. 7. Prediction effect of the model

The S&P 500 index has a monthly cycle, and its price data is shown in Fig. 7(a). The PVD model accurately discriminates the financial time series between June 1956 and February 1960 as mode 4, and the 1960-2. The financial time series between March 1965 and May 1972 is identified as mode 6, and the financial time series between March 1965 and May 1972 is identified as mode 1. The U.S. dollar index takes a quarterly cycle, and its price data is shown in Fig. 7(b). The PVD model accurately discriminates the financial time series from June 1982 to December 1997 as mode 2, and from December 2003 to 2012. The financial time series June of 2008 is identified as mode 7. WTT crude oil has a monthly cycle, and its price data is shown in Fig. 7(c). The PVD model discriminates the financial time series from September 1995 to September 2002 as mode 5. The financial time series between months is identified as mode 1. A comparative experiment was carried out on the PVD prediction model and the other five models, and the validity of the six prediction models was verified, but the prediction effect of each model was different. The performance comparison of the six models is shown in Table II.

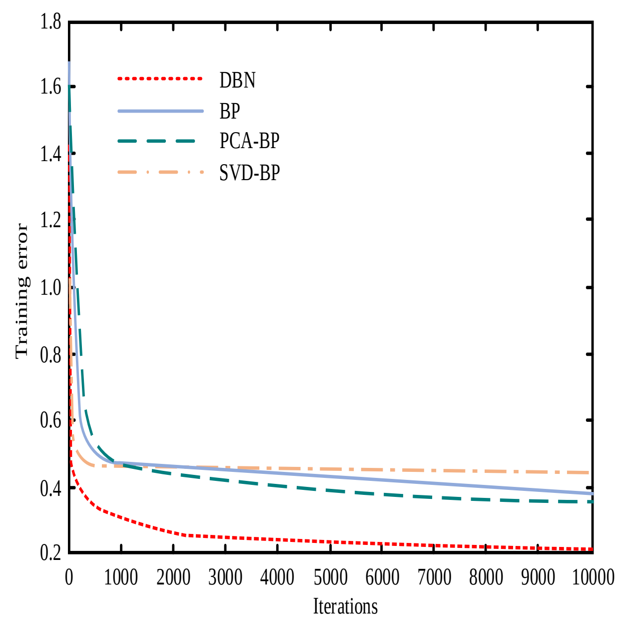
TABLE II. PERFORMANCE COMPARISON OF MODELS

Model	Deep network model			Shallow network model		
	PVD	SAE	MLP	BP	SVD-BP	PCA-BP
RMSE	0.6336	0.6653	0.8367	0.8634	0.9312	0.8314
MSE	0.4015	0.4426	0.7001	0.7455	0.8671	0.6912
MAE	0.9052	0.9648	1.4671	1.4702	1.6310	1.3064
IS	29.79%	35.86%	44.35%	48.49%	78.23%	56.85%

It can be seen from Table II that the deep network model performs better than the shallow network model on the four evaluation indicators, and the mean values of RMSE, MSE, MAE and ER of the deep network model are 0.7119, 0.5147, 1.1124 and 36.67%, respectively. The mean values of RMSE, MSE, MAE and ER of the shallow neural network are 0.8753, 0.7679, 1.469 and 61.19%, respectively. The prediction effect of the deep network model is significantly better than that of the shallow network model. Compared with the four indicators of the shallow network model, the deep network models are reduced by 18.67%, 32.97%, 24.27% and 40.07%, respectively. Among the six prediction models, the values of the four evaluation indicators of PVD are the lowest among all models, which are 0.6336, 0.4015, 0.9052 and 29.79%, respectively, indicating that its prediction performance is the best and significantly better than other models. The values of RMSE, MSE, MAE and ER of the SVD-BP model are the highest, indicating that its prediction effect is the worst and the prediction accuracy is the lowest. Although the training error of the PCA-BP model is smaller than that of the BP network model, its error rate is higher than that of the BP network model, indicating that the algorithm has over-fitting; weaker ability. The main reason why the prediction accuracy of PVD model is significantly higher than that of other models is that the research has introduced in-depth learning into the prediction model, so it can achieve real-time analysis with the help of financial data, and the prediction results will be more accurate. The variation of training error between the deep belief network in the PVD model and other models is shown in Fig. 8.



(a)Comparison of training error with depth network model



(b)Comparison of training error with shallow network model

Fig. 8. Comparison of training error changes

It can be seen from Fig. 8(a) that the error curves of the DBN network and the SAE network are not much different, but the error curve of the DBN is smoother, indicating that the DBN has better stability. The error curve of the MLP network is very flat, indicating that it has higher stability and faster convergence speed, but its training error is higher than that of the DBN network, which is caused by the network falling into a local optimum. It has higher reliability and accuracy, and can effectively improve the local optimal problem caused by the BP algorithm. Compared with the shallow network model, the DBN network has faster convergence speed and higher accuracy. In the classification training process, compared with other models, the DBN network has the fastest convergence speed, the smallest training error and good stability. In general, the PVD forecasting model proposed in this study has high reliability and stability, and can efficiently and accurately identify Elliott waves of various patterns in financial time series. Compared with the other five models, the PVD model has higher stability and accuracy, faster convergence speed due to the use of DBN network, and also has excellent performance in feature extraction. The PVD model improves the prediction performance of the traditional BP network and multi-level classifier, reduces the error of the deep network model, and improves the accuracy of the model with high-frequency trading as the decision criterion. Experiments show that under the background of sustainable development, the PVD forecasting model proposed in the study performs well in financial investment forecasting, which provides a reference for the development of financial investment forecasting in the e-commerce industry.

V. Conclusion

With the rapid development of the e-commerce industry, the financial investment forecast of the e-commerce industry has gradually become a concern of people, and how to do a good job of financial investment forecast in the context of sustainable development is the focus of the industry. Researched and proposed a PVD prediction model based on DBN, and used the deep learning model to model the financial time series to achieve financial investment prediction. The experimental results show that the MSE of the PVD model is 0.4015 and the prediction accuracy is 70.21%, indicating that it can efficiently and accurately identify the Elliott wave pattern of financial time series. The PVD model is compared with the other five models. Among all the prediction models, the values of the four evaluation indicators of PVD are the lowest among all models, which are 0.6336, 0.4015, 0.9052 and 29.79% respectively, indicating that its prediction effect is the best, with the highest prediction accuracy, with good accuracy and stability, and significantly outperforms other models. Compared with the training error changes of other models, it can be seen that the error curve of the DBN network is smoother and the training error is smaller, indicating that it has higher stability, faster convergence speed, and higher reliability and accuracy. Experiment shows that under the background of sustainable development, the PVD prediction model proposed in the study has excellent stability and reliability in financial investment prediction, and can effectively predict the trend of financial investment. However, the research fails to realize the fractal level concept of Elliott wave theory. If the neural network can be combined with the fractal level concept, the prediction performance and prediction accuracy of the model will be effectively improved. Therefore, in the follow-up work, the research will try to combine the concept of neural network and fractal level, propose a more perfect prediction model, and hope to achieve accurate prediction of financial investment in e-commerce industry, and provide strategies for the development of China's economic market.

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