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Prediction method of regional economic development level based on SOM algorithm

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ABSTRACT

As a vital but time-consuming task, regional GDP forecasting has high expectations for forecast accuracy in order to provide better guidance and suggestions for the region's economic development in the future. Most traditional GDP pre-methods are linear, but their accuracy has gradually been difficult to meet the demand due to factors such as nonlinearity and GDP uncertainty. This paper proposes a method for forecasting the level of regional economic development based on the SOM algorithm in order to improve forecast reliability and accuracy. These two-dimensional neural networks, with their layers of neurons arranged in a two-dimensional topology, are combined in this paper to create a self-organizing feature map model (SOM). The ANN model converts the SOM's output and outputs the model's final classification result directly. Using this model's algorithm, the model's performance can be greatly improved, while noise samples can be eliminated and the model's accuracy greatly improved. This study predicts future regional GDP using data on prefecture-level city GDP as the regression independent variable from 2001 to 2021. This paper's method successfully predicts the level of economic development in a region, as demonstrated by a large number of experiments.

Keywords: SOM algorithm, GDP predict, regional economic development level, ANN

1. Introduction

Although GDP per capita does not accurately reflect the overall strength of a country, it does accurately reflect the level of social development in a region. It is common practice to evaluate a nation's standard of living based on its gross domestic product (GDP) per capita, which is recognized by many nations as an essential economic indicator[1]. This is an important indicator of China's development because of the country's enormous population, which makes it a useful metric. To put it another way, conducting research on this indicator in order to monitor the state of the economy

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and make informed decisions about how best to exercise economic control is absolutely necessary[2].

At the moment, the relevant personnel have proposed a diverse assortment of approaches for the study of GDP per capita. Methods of exploratory spatial data analysis have been utilized in the conduct of research on China's GDP distribution over the past quarter of a century. The Box-Jenkins model can be used to make predictions regarding China's GDP per capita[3]. A number of academics have turned to grey forecasting in order to make predictions about the future regional economic growth. The motion toward convergence. According to the findings of some researchers, the regression stepwise regression method and the Bootstrap method are the most effective ways to estimate the coefficient functions present in a population growth rate time series.

The forecaster typically creates multiple single forecasting models for the same forecasting problem under different assumptions as a result of these methods. The forecaster then uses a variety of forecasting accuracy measurement methods to select the forecasting model that is the most accurate for the problem. Although the method described above for determining the model can improve the accuracy of predictions, it may also make it challenging to make effective use of some useful information while excluding other prediction models[4]. This is due to the fact that various prediction models each have their own set of benefits and drawbacks. Consequently, the utilization of two or more distinct forecasting models can result in the production of a combined forecasting model. For instance, a combined prediction model is superior to a single prediction model because it not only prevents the loss of useful information but also lessens the effect that mutation has on the results of prediction. The accuracy of a prediction can be increased by making sure it is both comprehensive and supported by evidence. Some researchers in Shenzhen have utilized the combined forecasting method in order to establish the optimal combined forecasting model. They have proposed that the forecasting effect of the combined model is not only superior to that of any single forecasting model, but it also has a higher level of accuracy in its predictions. One of the more pressing problems with this model is determining how much weight to give to each of the different forecasting models[5]. The information that models provide and the degree of precision with which they deliver that information can vary greatly. A comparison of each model is made using a predetermined criterion in order to find out how the weighting should be distributed. The relative error minimum method, the equal-weight average method, and a few others are examples of common approaches that can be utilized when determining weights. Some researchers have proposed a method known as dynamic direct weighting, which generalizes weights to weight sequences and, as a result, improves the accuracy of prediction[6].

In order to achieve distributed storage and parallel processing, one can use something called an artificial neural network (ANN), which is a mathematical model that uses algorithms to simulate the structure and function of biological neural networks. The use of ANN prediction models in real-world applications is becoming increasingly common as a result of the many benefits that these models offer, including nonlinear mapping and high fault tolerance. Because SOM and PNN models are utilized quite frequently in ANN algorithm development[7-8]. The training of a SOM network is a straightforward procedure that requires only a limited amount of data examples and ultimately results in the automatic classification of the input data. PNN is able to use linear algorithms due to its powerful pattern classification function, simple structure, and ability to use linear algorithms. This is made possible by the fact that PNN can complete the work of a nonlinear algorithm using only linear algorithms.

The SOM and the PNN are combined in a series based on the characteristics that are unique to each of them. A topology with only two dimensions is used to acquire data and make predictions. This topology contains two layers of neurons[9]. The output of the SOM is converted by the PNN model, and the PNN model then directly outputs the model's final classification result. By utilizing the algorithm that is contained within this model, the performance of the model can be significantly enhanced, noise samples can be removed, and the model's precision can be significantly improved.

This work's first chapter is titled "Introduction," and it provides an explanation of the purpose of the work, as well as its significance and contribution. The second chapter of this paper provides background information as well as an overview of the previous research that has been conducted on the subject at hand. In the third chapter, "Methods," the SOM and PNN algorithms, along with their respective implementations, take center stage. The superiority of the method is made abundantly clear by the findings of the experiments, which are discussed in the fourth chapter. In order to draw a conclusion and wrap things up, we will examine the benefits, drawbacks, and recommendations for the future of this paper in the discussion and conclusion sections.

2. Related Work

The forecasting of GDP is an important and challenging task that can be broken down into two major components: the selection of variables and the selection of models.

An example of a variable that has a strong correlation to GDP and that can be used to build a multiple regression model of GDP and variables that affect GDP is fixed asset investment. Other examples of variables that have a strong correlation to GDP include total fiscal revenue. A network of three indicators is used to make projections regarding GDP. This is the simpler of the two options. When it comes to forecasting GDP, time series analysis produces more accurate results in the long run compared to quadratic curve regression and ridge regression models[10-12].

There are two primary types of models, namely linear and non-linear prediction methods. Both types of models fall under the category of "models." The study of linear models has historically been of great assistance to those attempting to make economic and social forecasts. Because of the gradual decline in both fit and predictability over the course of time, modern predictions call for a higher degree of precision than can be attained through the use of conventional linear prediction methods[13]. In spite of this, it is difficult to maintain a belief in the continuity of a time series when confronted with sudden shifts in a situation, and the predictions that are produced as a result frequently deviate from what actually transpires. Combining different models can help to make up for the shortcomings of each other. The random walk hypothesis and test on China's GDP data from 1978 to 2004 demonstrated that the GDP data can be regarded as a random walk process with a random trend after the second-order difference, and that it is challenging to be highly fitted by a straightforward linear model due to its nonlinear nature. The data were analyzed for the period from 1978 to 2004. As can be seen, despite the fact that the linear method is helpful in certain circumstances, it is difficult to describe the nonlinear characteristics of GDP forecasts, which makes it easy for large forecast errors to occur. This is the case even though the linear method is useful in certain circumstances. It is important to conduct research on, and make use of, nonlinear models because of their superior fit and superior predictive power[14].

In the 1940s, a theoretical framework for neural networks was initially developed. Researchers were given a significant amount of motivation by the introduction of the perceptron in 1957, which was the first artificial neural network recognition device. The use of neural networks for prediction was first published in the journal in 1987. Subsequent generations of researchers confirmed that the method can be applied to any nonlinear function, which contributed to its widespread acceptance and utilization[15]. In the past, researchers from China have also looked into and utilized this model in their work. The linear prediction model is constrained in its ability to estimate the true value of the data, but the neural network model is able to solve problems involving nonlinearity and time variation. This breaks the constraint. Along with uncertainty and time variation, this is one of the characteristics of GDP that has been the subject of speculation from various academics. Some researchers make use of the self-learning and nonlinear characteristics of the BP neural network method in order to model and obtain reasonably satisfactory results when forecasting GDP. A model for estimating GDP was developed by a team of analysts who made use of an artificial neural network developed by BP and enhanced with a genetic algorithm[16-17]. The findings are compelling evidence of the model's high degree of precision. The BP neural network has the unique ability to learn, which distinguishes it from other linear models and makes it one of the most popular models for GDP forecasting. Consider the widespread application of the BP neural network, which finds use not only in the field of stock forecasting but also in other areas such as the prediction of traffic flow[18-20].

The study of neural networks has advanced, and a number of researchers have dug deeper into the question of why the neural network model is more accurate than the general linear model. One explanation could be that the linear time trend is overly restrictive, giving the impression that the growth rate typically slows down as time passes when in fact this is not the case. Neural network models are superior in terms of their ability to filter out actual time trends. In the year 2020, a group of researchers created a model of an artificial neural network that had multiple layers by compiling GDP data from a variety of countries, including Japan, China, Germany, Spain, and others[21]. It has been established that the accuracy of the model in predicting the future is lower than 2%. Researchers used thirteen machine learning regression models to model and calculate the historical data from 1997 through 2019 using a GDP growth indicator system[22]. This allowed them to make projections about future GDP growth. Indicators for evaluating models were used to make a decision regarding which gradient boosting regression tree model would provide the best generalization ability for predictions[23].

The majority of studies, in order to enhance the model, increase the baseline value, modify the initial value form, broaden the data range and time span covered, and combine with other methods. This is the most common approach that can be taken to improve a model. The GDP in 2006 was predicted, and corresponding suggestions were made, after applying the BP network with momentum term and adaptive learning rate to the data on China's GDP from 1993 to 2005 as a baseline[24]. Some academics have proposed BP-based forecasting models, and they argue that such models can only make use of nonlinear GDP annual increment percentage series[25]. BP-based forecasting models have been developed. According to the findings of the simulations, the error caused by the improved model is 1.64 percentage points lower than that caused by the single model. Some researchers chose to use an accumulating sequence, a mean sequence, and an earlier historical sequence as the input vector[26]. The GDP values for a particular region from 1980 to 2016 were used as the output vector. The predictions produced by the BP network training were superior to those produced by the initial model. The researchers have suggested incorporating additional factors into the model, such as the structure of the company, the dynamics of the market, and the characteristics of the population[27]. The findings of this study could be improved by taking into account a large number of other factors as well. Additional research into the financial data included looking at the difference in yield between the interest rates in the United States and Canada, as well as looking at the rate on 90-day corporate bonds and changes in the total volume of M2 currency[28]. When compared to the forecast errors generated by the linear model from 1989 to 1999, the errors generated by the neural network for year-on-year output growth are approximately 0.25 percentage points lower per quarter. Some academics believe that artificial neural network models are more accurate than ARIMA models when input variables including commodity prices, trade, inflation, and interest rates are used. In addition, some researchers conduct application research in the field of economics by combining a genetic algorithm with a neural network. This helps the neural network learn faster and make more accurate predictions, as well as improves the researchers' ability to conduct application research[29].

3. Method

Kohonen came up with the idea for the SOM, which is an unsupervised competitive learning feedforward network. The goal of the model is to achieve clustering, and it does so by first utilizing neural network learning to extract significant features or internal laws from the data, and then by dividing the data into a number of distinct regions. Not only is it possible to observe, through the use of SOM, how the input vector is classified throughout the training process, but also how it is dispersed across the network. Clustering in SOM is determined by the characteristics of the distribution of the input vectors as well as the functions of the neurons. To kick off the entire learning process, we need only supply the neural network with some unlabeled data. It will then automatically find a law that applies to both sets of data, adjust the weights in an adaptive manner, and finish the data classification process.

The SOM network has a two-layer structure, which is comprised of an input layer and an output layer. Each of the n input vectors is represented by one of the nodes that make up the input layer, and there are n total nodes. Each neuron in both layers is connected to a weight through their shared connection. All of the information that has been gathered is guaranteed to be communicated to the output neurons thanks to the comprehensive interconnection that exists between the input and output layers. The structure of the SOM neural network is illustrated in Figure 1.

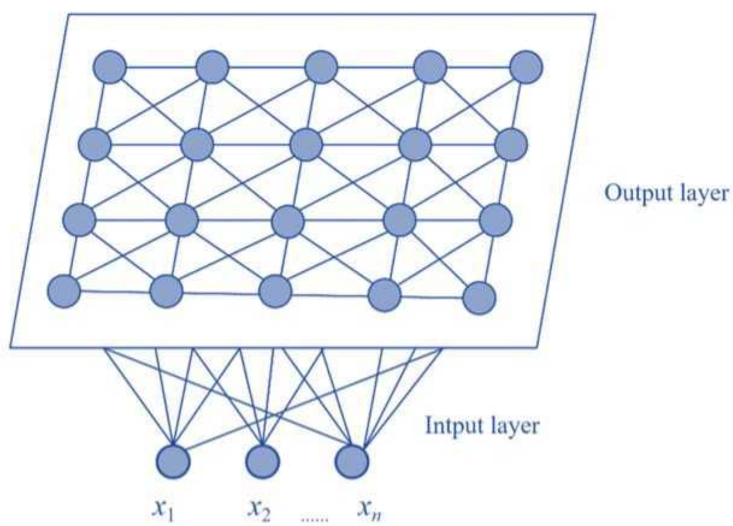

Fig. 1. Flowchart of traditional collaborative filtering-based travel route recommendation

The SOM training process is as follows:

1) Initialize the weights and error threshold.

2) Input vector $X=\left(x_1(t), x_2(t), \ldots, X_m(t)\right)^T$ to the input layer.

3) Calculate the distance between output layer neurons w_j and X.

$$d\left(X, w_j\right)=\sqrt{\sum_{i=1}^m\left(x_i(t)-w_{ij}(t)\right)^2} \tag{1}$$

$$w^*=\min\left(d\left(X, w_j\right)\right) \tag{2}$$

4) Update weights

$$w_{ij}(t+1)=w_{ij}(t)+\alpha \exp\left(-\frac{d\left(w_i,w_j\right)^2}{2q^2(t)}\right)\left(x_i-w_{ij}(t)\right) \tag{3}$$

$$q(t+1)=\left[(q(t)-1)\left(1-\frac{t}{T}\right)\right] \tag{4}$$

where α is the learning rate, T is the total learning times.

5) Back to step 2, repeat.

The PNN model utilizes a deformed version of the radialbasis function as its foundation. The fundamental idea behind it is to combine the classification rules developed by Bayes with the concepts of probability and statistics. Processing a number of different samples or patterns ultimately leads to the development of judgment and decision-making skills. The theories of probability and statistics can provide an explanation for it. The core concepts and how they should be applied. The straightforward construction of the model and its speedy convergence are assets when applied to nonlinear pattern recognition issues. In a similar fashion to the SOM neural network, the PNN is a feedforward neural network. The minimum risk criterion developed by Bayes is used in the PNN judgment process. PNN is a structure for modeling that consists of several layers: an input layer,a pattern layer, a summation layer, and a decision layer.

Both the SOM and PNN models, which are used for data classification, have shortcomings, despite the fact that both models are used. In spite of the fact that SOM has a higher recognition rate, it is unable to produce the final classification category that it seeks. This limitation is circumvented by the PNN algorithm; however, the amount of memory and computation required for classification is proportional to the number of samples. If we have a large number of samples, this can easily lead to a significant increase in the amount of memory being used as well as a significant decrease in the amount of time it takes to complete the processing. Only the flaws that are common to both models can be improved upon by combining them. In order to solve this problem, the authors of this paper suggest a number of neural network models that use both SOM and PNN.

Suppose there are k training sets $X_1,X_2,\cdots,X_k$, and the model trained by $X_1,X_2,\cdots,X_k$ is $S_1,S_2,\cdots,S_k$, he number of prototype vectors in S_k is E_k, then the number of samples in X_k that map to output O_k is

$$N\left(O_k,X_k\right)=\left|x\middle|x\in X_m,x^*=O_k\right| \tag{5}$$

The importance of O_k is calculated as

$$I\left(O_k\right)=N\left(O_k,X_k\right) \tag{6}$$

The probability density of class k is

$$f_k(x)=\frac{1}{\sqrt[d]{4\pi^2}\sigma k}\sum \exp\left(-\frac{\left(x-O_k\right)^T\left(x-O_k\right)}{2\sigma^2}\right) \tag{7}$$

After incorporating Equation 6, the probability density of class k is

$$f_k(x)=\frac{1}{\sqrt[d]{4\pi^2}\sigma k}\sum \frac{I\left(O_k\right)}{\sum I\left(O_k\right)}\exp\left(-\frac{\left(x-O_k\right)^T\left(x-O_k\right)}{2\sigma^2}\right) \tag{8}$$

The flow chart of this method is shown in Figure 2.

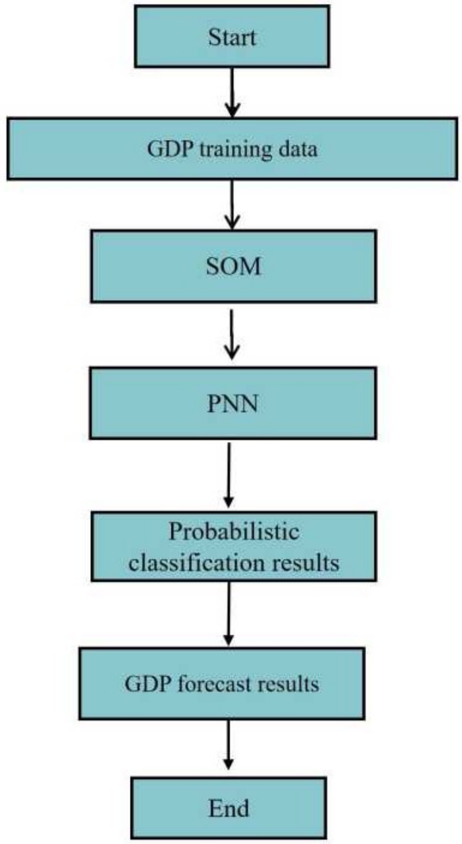

Fig. 2. Flow chart of our GDP predict model

4. Results

The data from one province in China is chosen, with the capital city of the province serving as the primary focus of the analysis, and five other major cities, for a total of six cities, chosen because they are part of the regional economy. The gross domestic product (GDP) of each of the six cities in the region from 2001 to 2021 is considered an independent variable for the purpose of this study, while the GDP of each of those cities from 2001 to 2015 is considered a dependent variable. The GDP of the metropolitan area in 2019-2021 is estimated using data from prefecture-level cities in 2016-2018. This estimation is based on the fitting of data and the construction of models over the first fifteen years.

In addition, we need to normalize the data, the formulas are as follows

$$x_k = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

$$x_k = \frac{x_k - x_{mean}}{std\left(x_k\right)} \tag{10}$$

Because there is no interference from any other heterogeneity independent variables, the data standardization and logarithm of the data show that dividing the dependent variable and the independent variable by 1000 at the same time can satisfy the BP neural network. This method, in contrast to both the standardization of data and the logarithmization of said data, is straightforward, user-friendly, and accurate to a high degree.The per capita GDP of the region from 2001 to 2021 is shown in Figure 3. It can be seen that the per capita GDP of the region is on the rise as a whole, with a larger increase after

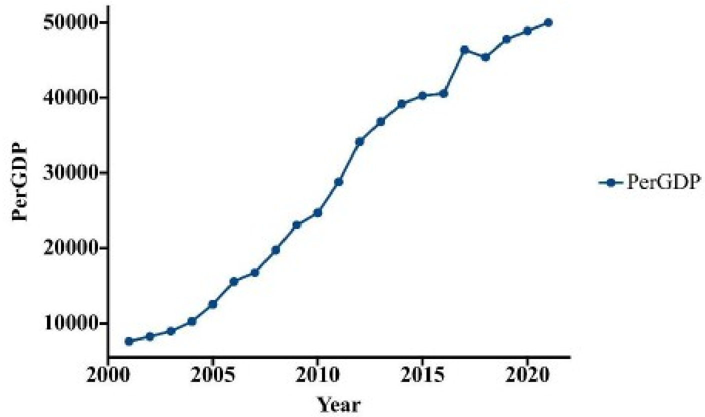

Fig. 3. Per capita GDP change curve of regional economy from 2001 to 2021

Figure 4 presents the fitting curve for our reference. The fact that the fitted value point and the real value are practically identical provides conclusive evidence that the methodology presented in this paper is capable of providing a good fit to the data.

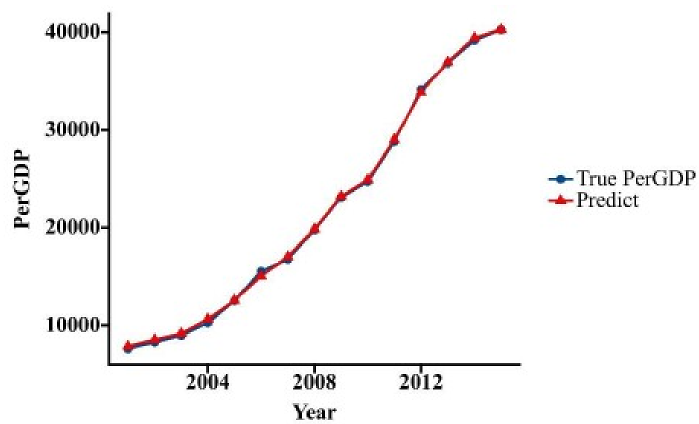

Fig. 4. Per capita GDP fitting curve of regional economy from 2001 to 2015

The region's GDP per capita forecast as well as the forecast error is displayed in Figure 5. The method used in this paper, which is based on historical data, forecasts that the regional per capita GDP will be 48759.99 yuan in 2019, with a prediction error that is 979.99 times greater than that of other years. The regional GDP per capita increased by 13.23 percent in 2018, but the growth rate has decreased to a 12.80 percent increase in 2019 as the region transitions from low-quality, fast growth to quality, medium-speed growth. This is reflected in the fact that the growth rate increased by 12.80 percent. The methodology presented in this paper projects that the regional per capita GDP will be $46371.04 in 2017, with the least amount of error in the forecast coming in at 9.13 percent. It has been a full six years since then. The average amount of error in predictions is 645.11.

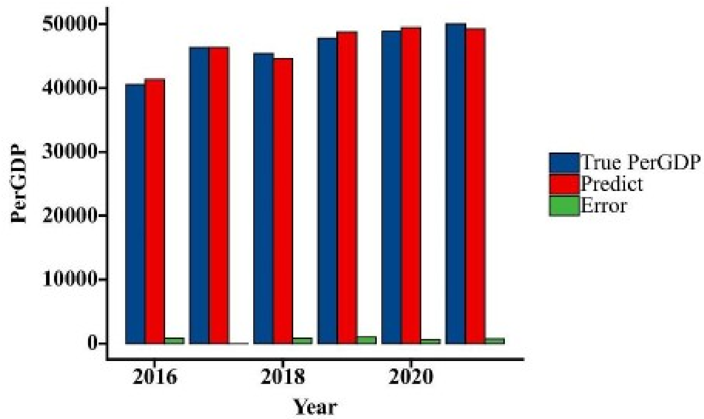

Fig. 5. Histogram of GDPper capita forecast and forecast error

Further, we compare the method in this paper with SOM and BPNN. The selected comparison indicators are MAE and RMSE. The comparison results are shown in Figure 6.

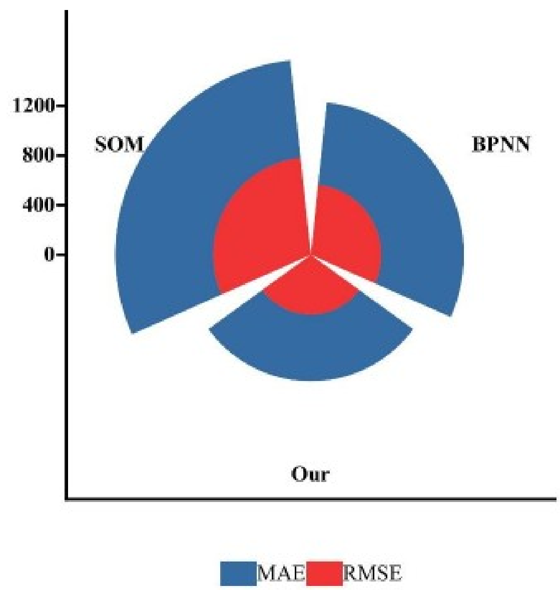

Fig. 6. Comparison ofprediction performance of different methods in MAE and RMSE

Both the fitting error and the prediction error of the method in this paper are very small, and the RMSE and MAE values are much lower than other methods, both in terms ofthe fitting effect ofGDPin previous years and in terms ofthe comparison ofthe prediction accuracy offuture years. This can be seen from the perspective ofthe fitting effect ofGDP in previous years, and it can also be seen from the comparison of the prediction accuracy of future years. There is a significant increase in both the validity and accuracy ofthe prediction.

5. Conclusion and Discussion

Forecasting regional GDP is an important but time-consuming task, and there are high expectations for the accuracy of the forecast. This is done in order to provide better guidance and suggestions for the future economic development of the region. Even though the majority of traditional pre-methods for GDP are linear, it has become increasingly difficult to meet the demand for their accuracy due to factors such as nonlinearity and GDP uncertainty. In order to improve the reliability and accuracy of forecasts, the authors of this paper propose a method for forecasting the level of regional economic development that is based on the SOM algorithm. In this paper, a self-organizing feature map model is created by combining these two-dimensional neural networks, each ofwhich has layers of neurons arranged in a two-dimensional topology. The output of the SOM is converted by the PNN model, and the PNN model then directly outputs the model's final classification result. By utilizing the algorithm that is contained within this model, the performance of the model can be significantly enhanced, noise samples can be removed, and the model's precision can be significantly improved. This study forecasts future regional GDP using data on prefecture-level city GDPas the regression independent variable from 2001 to 2021. The time period covered by this study is from 2001 to 2021. According to the results of a significant number of experiments, the methodology presented in this paper is able to accurately forecast the level of economic development that exists in a particular region. In the future, we will introduce deep learning methods to consider more economic factors that affect the regional economy to achieve more accurate forecasts of regional economic development levels.

Availability of data and material

The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests

We Declares that we has no conflict of interest.

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None

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