Economic Development Prediction Model Based on Deep Convolutional Neural Network

Taisong Liu[1, *], Xiaona Cai[1], Songyu Xie[2], Shanting Tan[3], Zihan Ying[4]

[*]Corresponding Author E-mail Address: 2224628031qq.com

College of Economics and Trade, University of Electronic Science and Technology of China, Zhongshan Institute, Zhongshan City, China[1]
College of Management, Guangdong Peizheng College, Guangzho City, China[2]
School of Computing, University of Electronic Science and Technology of China, Zhongshan Institute, Zhongshan City, China[3]
School of Foreign Languages, Guangdong Technology College, Zhaoqing City, China[4]

Abstract: Economic prediction is an essential method for arranging the development strategies and provide reliable data for the managers. However, previous researches about prediction were primary concentrated on the mathematical model by utilizing various statistic or economic theories, which are not considering the real situation parameters including cultural affects, political aspects and real-world factors. In this article, we utilize deep convolutional neural network to train a neural model by utilizing the ten years from 2010 to 2020 economic development parameters and predict the 2021-2022 economic development results in GuangZhou city of China. In our proposed model, the model is consisted by three primary components including pro-processing selector by utilizing the normalization, multiple deep convolutional network and multilayer perceptron to provide the final prediction results. From our extensive experimental steps, we can observe that our proposed mechanism can precisely provide the development tendency in 2021 with acceptable computation cost.

Keywords: Economic prediction, Deep convolutional neural network, Normalization, Multilayer perceptron, Computation cost.

1 INTRODUCTION

Economic prediction is an issue about speculation and estimation of future scenarios of economic phenomena. Researcher [1] based on the history and current situation of the economic development process. Scientific forecasting methods are used to reveal the development law of economic phenomena and the corresponding interconnection parameters between various economic phenomena [2-4] and point out the future development trend and possible level of economic phenomena is proposed by researchers [5]. The content of economic forecasting is very broad. Initially, the forecast of the domestic economic situation, such as the development trend of production, growth rate, economic structure, price change trend, population employment, changes in fiscal revenue and expenditure, and the supply, production and sales of various products is proposed by researchers [6-8].

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At the same time, it is necessary to predict the international economic situation, such as international economic fluctuations and changes in the international market. However, extensive methods were proposed to dispose the economic prediction problems including establishing statistical analysis model, utilizing economic theories construct prediction process, training machine learning to quantify the economic inductors and predictions modelling methods is established by researchers [9-15]. In this paper, we propose a novel deep convolutional construction to predict the economic development tendency and simulate the model with the real economic data to predict the two years of developments.

Economic impacts are mainly divided into direct economic impacts and indirect impacts. The direct economic impact involves industries such as retail sales, tourism, and integrated services. Many aspects are difficult to quantitatively evaluate, and this paper uses deep convolutional neural network models to quantitatively evaluate the impact of retail, tourism, and integrated services.

Following includes the structures of this article. In section 2, we will introduce the basic knowledge of related our proposed method and primary symbols that used in our paper. Section 3 will demonstrate the main framework of our model and section 4 illustrates the experimental results that is simulated with current economic prediction models. Finally, we will conclude our main contributions and provide the future improvements methods in section 5.

2 PRELIMINARY AND SYMBOL DESCRIPTION

In this section, we will introduce the basic theories of deep convolutional neural network and the principles that used in our model. Additionally, we also illustrate the primary symbols and its descriptions in following Table 1.

2.1 Deep Convolutional Neural Network

Deep convolutional neural networks are mainly composed of input layer, convolutional layer, activation function, pooling layer, fully connected layer and output layer. The deep convolutional network can directly take the image as the input of the network, extract features through training, convolution operation, convolution operation and pooling operation, and perform operation output through the fully connected layer.

The convolutional neural network mimics the visual perception mechanism of living organisms, which can carry out supervised learning and unsupervised learning, and its implied convolution kernel parameter sharing within the layer and the sparsity of the interlayer connection make the convolutional neural network can be used to lattice the features with a small amount of computation.

Convolutional neural network is a kind of feedforward neural network with deep structure that contains convolutional computation, and is one of the representative algorithms of deep learning. Convolutional neural networks have the ability of representation learning, and can classify input information by translation invariant according to their hierarchical structure, which is a translational invariant artificial neural network. The convolutional layer simulates human visual perception, that is, local perception function. Convolutional layers are a way of extracting data features.

2.2 Primary Parameter Symbols and Description

Following table contains the primary parameters and corresponding descriptions that were used in this article.

Table 1: Primary parameter symbols and description.

Parameter Symbols	Explanations
x	Input samples
x’	Effective samples
L(x)	Standard division operation
N	Number of samples
Conv	Convolutional operation
MAX	Selection maximum function
ATT	Attention operation function
W	Trained weighted value

3 SYSTEM FRAMEWORKS

In this chapter, we specifically analysis the three components and show the framework in each sub-section.

3.1 Data Pro-processing Stage

Initially, the pro-processing is generating the normalized data and select the effective data for the deep neural network. The general framework of pro-processing procedure is demonstrating in following Figure 1.

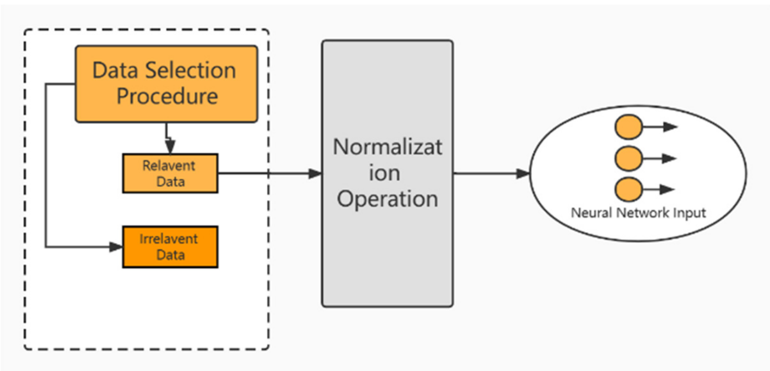

Figure 1: Pro-process stage framework.

In order to eliminate the effect when different attributes of the sample have different magnitude, the difference of orders of magnitude will lead to the dominance of attributes of larger magnitude, and the difference of orders of magnitude will cause the speed of iterative convergence to slow down, and algorithms that depend on sample distance are very sensitive to the order of magnitude of the data. Normalize data based on the mean and standard deviation of the original data. Normalize the original value x to x' using z-score. The z-score normalization method is suitable for situations where the maximum and minimum values of the attribute are unknown, or when there is outlier data that is out of the value range. Generated data is equal to original data minus mean divided standard deviation. Equation (1) demonstrates the detail process of data selection.

$$x' = \sum_{i=0}^{N} (x - \bar{\bar{x}})/L(x) \tag{1}$$

3.2 Framework of Deep Convolutional Neural Network

In this sub-section, we detail demonstrate the multiple layers of our proposed deep convolutional neural network structure and explain the detail function of each layer.

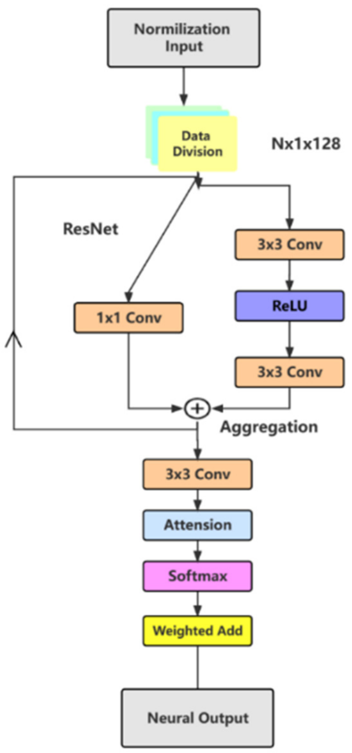

Figure 2: Framework of Proposed Deep Convolutional Neural Network.

In above Figure 2 demonstrates the general structure of proposed deep convolutional neural network including multiple convolutional layers represents as Conv, activation function is utilizing linear activation represents as ReLU layer and softmax layer is working as full-connected with trained weighted edges for each connection.

Additionally, from above figure the utilization of aggregation operation is representing in following Equation (2).

$$agg(a,b) = \frac{1}{2I}\sum_{j=0}^{I} MAX(a_j, b_j) \mid S(a_j, b_j) \tag{2}$$

3.3 Multi-layer Perceptron

The multilayer perceptron is composed of input and output layers and there can be multiple hidden layers in the middle and the prediction information is gradually transmitted from the first layer to the higher level.

A multilayer perceptron is a forward-structured artificial neural network that maps a set of input vectors to a set of output vectors. A multilayer perceptron can be thought of as a directed graph consisting of multiple node layers, each connected to the next. In addition to the input node, each node is a neuronal with a nonlinear activation function called a processing unit. A supervised learning method called the backpropagation algorithm is often used to train multilayer perceptron. Multilayer perceptron is widely used the principles of the human nervous system, learn and make data predictions.

It first learns, then stores the data using weights, and uses algorithms to adjust weights and reduce bias during training, for specifically, errors between actual and predicted values. The main advantage is its ability to solve complex problems quickly.

The parameters of the multilayer perceptron are the connection weights and biases between the layers and all parameters are randomly initialized. After iteratively trained, the gradient and update the parameters are continuously calculated until a certain prediction accuracy is greater than the expected value. Figure 3 demonstrates the detail structure of multi-layer perceptron (MLP) structure and the weighted value is representing as W.

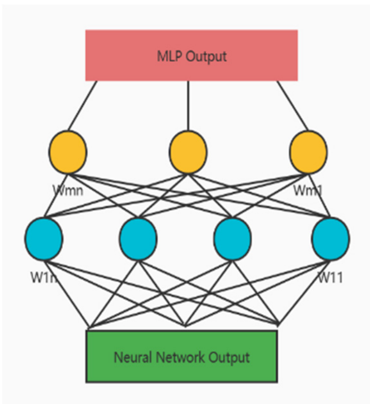

Figure 3: Multi-layer Perception Framework.

4 EXPERIMENTAL RESULT AND ANALYSIS

In this section, we simulate our proposed model to predict the economic development of city Guang Zhou in China and compare our result with other existing prediction models named RBF neural network is proposed by (Bin Li and others, 2022) [16] and normal GM Grey Method is established by (Ying Yu and others, 2022) [17] respectively. From our extensively experimental result and analysis result, we can conclude that our method can basically predict the development of economic and provide specifically economic values for managers.

4.1 Prediction Experimental Result and Comparison

Following Figure 4 demonstrates the trained result and the real situation economic development that measured with Gross National Product (GDP). From following diagram, we can observe that our proposed model can precisely simulate the economic development and provide the reliable predictions.

Additionally, we concentrate the total prediction accuracy that is measured by trained results divided by the real situation. If the accuracy is more than 1 that presenting the current trained value is larger than the real situation and otherwise. Following

From following Figure 5 demonstration, we can observe that our method prediction result representing as orange line is precisely according with the real economic development representing as the blue line that measured with GDP from 2010 to 2019.

The comparison results illustrates that our proposed model performers better accuracy than other existing methods due to other method is much closer to 1 in each prediction iterations.

Subsequently, Figure 5 demonstrates the prediction accuracy that compared with existing two economic prediction method.

4.2 Computation Cost Comparison Results

Another essential indictor is computation cost for the model. Following Table 2 demonstrates the detail computation time cost result compared with mentioned two existing methods.

Table 2: Primary parameter symbols and description.

Data Size Level (GB)	Ours	RBF	GM
20	50s	32s	67s
40	93s	61s	126s
100	214s	142s	312s

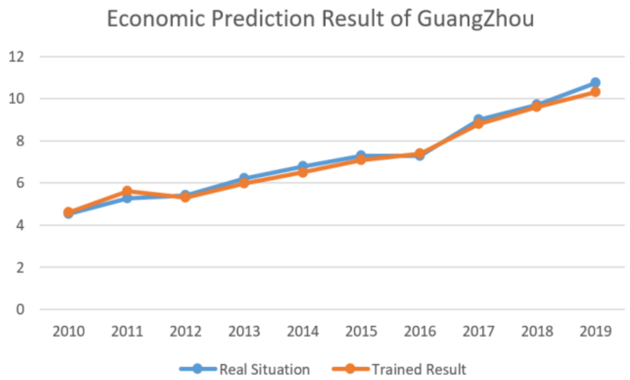

Figure 4: Economic Prediction Result from 2010 to 2019 (Million RMB).

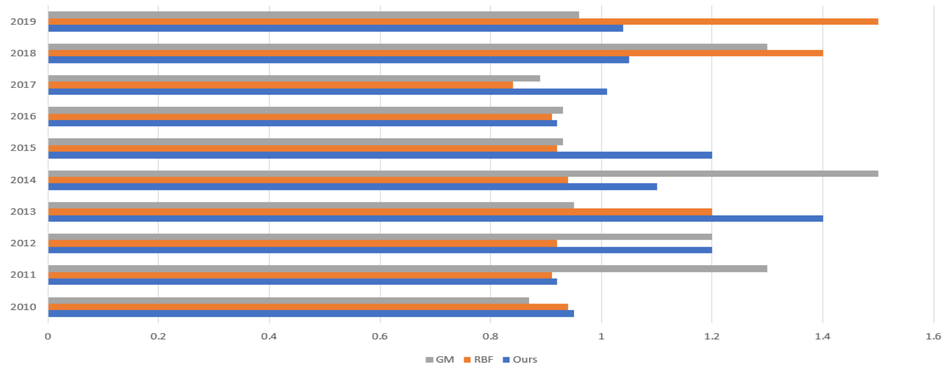

Figure 5: Prediction Accuracy Results.

5 CONCLUSIONS AND FUTURE IMPROVEMENTS

In this paper, we propose a novel structure by utilizing the method of deep convolutional neural network and predict the economic development in the real situation. From our extensive experimental results, we can conclude that our proposed method can be utilized for manager to predict the future economic if the input data is precisely and the number of required data is sufficient. Additionally, from our comparison results, we can observe that our model work with acceptable computation cost and obtain low delay. As for the future improvement, we can dispose the issue about data pro-processing stage and guarantee the model is fairness for each input data and utilize optimization functions to maximize the rewards of neural network.

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