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The Prediction of the Epidemic Trend of COVID-19 Using Neural Networks

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Abstract—In this paper, a BP neural network and an LSTM network are applied respectively to the prediction of Coronavirus Disease 2019 (COVID-19) in Wuhan, China and South Korea. The methods do not require specific theories of modelling and the predicted values can be obtained as long as the conventional parameters are set. The mean absolute percentage error (MAPE) of all the experiments are below 5% and the values of the determinable coefficient \(R^2\) are all larger than 0.9. The experiments show that the models can fit the actual values well and make relatively accurate predictions. As of March 29, 2020, the cumulative number of confirmed cases in Wuhan is expected to reach 50,068 using BP neural networks and 49,972 using LSTM network, respectively. As of April 13, 2020, the cumulative number of confirmed cases in South Korea is expected to reach 8,862 using BP neural networks and 8,716 using LSTM network, respectively. The models of neural networks are effective in predicting the trend of the COVID-19 epidemic, which is meaningful to prevent and control the epidemic.

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I. INTRODUCTION

Since December 2019, multiple cases of pneumonia caused by the new coronavirus [1] have been discovered in Wuhan City, Hubei Province, China, known as COVID-19. As a result of the fact that Wuhan is the largest transportation hub in Chinese middle-area, the epidemic has spread rapidly domestically and internationally. The South Korea is one of the countries with a severe epidemic outside China. As of March 13, 2020, the cumulative number of confirmed cases in South Korea has reached 8,565. All provinces in China activated the first-level response to the major public health emergencies in January 2020. On January 23, 2020, Wuhan's city buses, subways, ferries, and long-distance passenger transportation were temporarily suspended, and the passageways out of Wuhan such as the airport and railway station were temporarily closed. Countries in the world, including South Korea, take different epidemic prevention measures according to their national conditions.

Traditional prediction methods of epidemics need to establish underlying mechanism models, such as exponential, susceptible-exposed-infectious-recovered (SEIR) model and so on. Some of the predictions about COVID-19 have been done in other works using these methods. Zhao et al. [2] fit a simple exponential growth model with adjustment for January 23 travel ban based on the internationally confirmed cases to simulate the distribution of infection time. Wu et al. [3] use confirmed cases internationally exported from Wuhan and data of flight bookings to estimate 75,815 individuals infected in Wuhan as of Jan 25, 2020. Yang et al. [4] establish a modified SEIR model to the prediction of the epidemics trend of COVID-19 in China under public health interventions and draw a conclusion that the implementation of control measures is effective. These methods require complex theories of modeling and rely on some assumptions, which can result in large prediction errors.

Artificial neural network (ANN) [5-7] is a machine learning method inspired by the neural on networks of the human brain and has been applied to many fields such as information [8], medicine [9], economics [10], transportation [11] and so on, which is a "soft model" that learns to extract X-Y relationships from training samples. The method does not require particularly theories of modelling and the predicted values can be obtain as long as the conventional parameters are set. The back-propagation (BP) [12] is the most well-known algorithm, which continuously adjusts the connection weights of neurons in each layer through the back propagation of errors in order that the network output error is minimized or reduced to an acceptable range. This algorithm has strong non-linear mapping capabilities, high self-learning and adaptive capabilities, and fault tolerance capabilities. Bai et al. [13] have applied BP neural network to predict epidemic of severe acute respiratory syndrome (SARS), improving existing calculation methods, and obtaining better prediction accuracy.

With the continuous improvement of neural network theories, Recurrent Neural Network (RNN) [14][15] is qualified to store information and process new inputs, which is very suitable for processing time series data, but it is prone to
problems such as gradient disappearance and gradient explosion [16]. Long short-term memory (LSTM) [17] effectively avoids these problems and is a special RNN model. Yang et al. [4] apply the LSTM network to predict the new confirmed cases of COVID-19. They believe that the pathogenic mechanism and infection path of 2003 SARS-CoV are highly similar to that of COVID-19, so the data of 2003 SARS-CoV is used to train the network. The difference in our work is that we still train the network with the data of COVID-19, and we test the predictions with the rest.

In this paper, a BP neural network [7] and an LSTM network [4] are used respectively to predict the epidemic situation of COVID-19 in Wuhan and the South Korea and the prediction results are evaluated. The rest of this paper is organized as follows. We give a brief introduction to related work in Section II. In the next section, prediction models including BP neural network and LSTM network are introduced. In Section IV, we conduct experiments for the prediction of cumulative confirmed cases in Wuhan, China and the South Korea respectively. Then we obtain some results and evaluate them. Finally, the conclusion of this paper is drawn and our future work is briefly described in Section V.

II. RELATED WORK

A. BP Neural Network

After the concept of ANN [18] was proposed, the limitations [19] of the perceptron's logical reasoning could not be resolved, which made ANN research stop. It was not until 1974 that Werbos [20] first applied the back-propagation algorithm to ANN, which effectively solved the problem of insufficient computer processing power and improved the feasibility of training multi-layer networks, thus setting off a wave of deep learning again. Now the BP neural network has been widely used in various fields, such as face recognition, medical diagnosis, speech recognition, machine translation, infectious disease prediction and so on. In December 2002, atypical pneumonia caused by SARS broke out in China. Bai et al. [13] applied BP neural network to predict the epidemic trend in Beijing, China and Shanxi, China, whose model is simple and results are relatively accurate. In addition, Wu et al. [21] used a BP neural network to establish acquired immunodeficiency syndrome (STD/AIDS) prediction model for immigration personnel which established a good early warning mechanism for STD / AIDS surveillance at various ports. Husin et al. [22] established dengue prediction model with BP neural network to help governments develop emergency plans to mobilize human and material resources that may be needed in response to the dengue epidemic. Qiang et al. [23] constructed a novel method with BP neural network to predict the transmissibility of avian influenza A viruses, which is very important for public health.

B. LSTM Network

As a deep learning algorithm, LSTM network was proposed by Hochreiter and Schmidhuber [17] in 1997. The traditional BP network does not consider the influence of time series, and needs to manually determine the input data form. However, LSTM network has long-term memory and is particularly appropriate for the prediction and analysis of big data time series [24] and has been applied in the field of infectious disease prediction. Amendola [25] used the LSTM network to develop a new method for predicting influenza-like illnesses so as to better provide pandemic warnings. Yang et al. [4] apply the LSTM network to predict the new confirmed cases of COVID-19, which is simple and accurate. Jia et al. [26] use multiple methods including LSTM networks to predict the number and time of hand-foot-mouth disease outbreaks. LSTM makes it relatively easy to remember and “understand” historical data. It can follow up and down trends well based on the results and then automatically transfer important information to the next point in time.

III. PREDICTION MODELS

It is very crucial to correctly predict the scale of epidemics, which can play a guiding role in the work of the government on epidemic prevention and control. Compared with traditional prediction models, Neural network method has incomparable advantages, such as strong ability of learning and fault tolerance, simple modelling. The BP neural network is the most widely used neural network. The LSTM network, as a kind of RNN, is especially suitable for the processing and analysis of big data time series. Both have different characteristics and can solve this problem. We apply these two neural networks to establish prediction models in order to verify the effectiveness of them and compare the results. The procedures of modeling are shown in this section.

A. BP Neural Network

This paper uses a 5-3-1 three-layer BP neural network, which includes an input layer, a hidden layer, and an output layer. Suppose that the number of nodes in the input layer is N (N = 5), the number of nodes in the hidden layer is M (M = 3), and the number of nodes in the output layer is 1. Then the input sample vector is represented as \( x^\mu = (x^\mu_1, x^\mu_2, ....., x^\mu_T) \), \( (1 \leq \mu \leq P) \), and P is the number of input samples. The specific network structure is shown in Fig.1.

The bias of \( j^{th} \) node of the hidden layer is \( \theta_j \). The weight coefficient between \( i^{th} \) input node and \( j^{th} \) hidden node is expressed as \( \omega_{ij} \). The activation function from the input layer to the hidden layer is \( f \). Then the output of \( j^{th} \) node of the hidden layer is

\[
y_j^\mu = f(r_j^\mu) = f(\sum_{i=1}^{N} \omega_{ij}x_i^\mu - \theta_j) \quad (1)
\]

The weight coefficient between \( j^{th} \) hidden node and the output node is expressed as \( W_j^\mu \). The activation function from the hidden layer to the output layer is \( g \). The bias is \( \phi \). Then the output of the output layer is

\[
O^\mu = g(H^\mu) = g(\sum_{j=1}^{M} W_j^\mu y_j^\mu - \phi) \quad (2)
\]

The expected output value corresponding to the input sample \( x^\mu \) is \( T^\mu \). Then the mean square error \( \epsilon^\mu \) between the expected output \( T^\mu \) and the actual output \( O^\mu \) is

\[
\epsilon^\mu = \frac{1}{2}(T^\mu - O^\mu)^2 \quad (3)
\]
BP neural network minimizes errors by continuously adjusting the connection weight coefficients of neurons in each layer. In general, gradient descent algorithm is used to adjust the connection weight coefficients, which ignores the second derivative term, causing that the final stage is linear convergence, and the speed is slow. In our work, the Levenberg Marquardt (LM) [28] algorithm is applied for neural network training to achieve the adjustment of the weight coefficients. The LM algorithm is the combination of the fast gradient descent algorithm [29] and the Gauss-Newton [27] method, which can shorten the convergence time and improve the convergence performance of the neural network.

The activation function of the hidden layer is the Sigmoid function \( f(x) = \frac{1}{1 + e^{-x}} \), while the activation function of the output layer is a linear function \( g(x) = x \). After the adjustment of weight coefficient is completed, the input sample vector \( x^e \) of related cases is input into the neural network, and the number of cases \( O^e \) in the next day can be obtained. The input sample vector \( x^e \) is continuously updated to continuously predict the number of subsequent cases.

**B. LSTM Network**

LSTM has been widely used in processing time series data. Each LSTM unit is composed of three gates that control information storage and inflow, and a memory cell. The three gates are an input gate, an output gate, and a forget gate. At time \( t \), the LSTM unit has three inputs and two outputs. The inputs are the input \( x_t \) at the current moment, the output \( h_{t-1} \) of the previous LSTM unit at the previous moment and the cell state \( C_{t-1} \) at the previous moment. The outputs are the output \( h_t \) and the cell state \( C_t \) at the current time. The internal structure of LSTM is shown in Fig.2.

The LSTM prediction model includes three layers: an input layer, a hidden layer, and an output layer. A layer of LSTM network is set as receiving inputs of the hidden layer, and a layer of fully connected dense network is used as the output, whose activation function is a linear function. The time slice step of the data sample is set to 3. The case data \( \xi^a = (\xi(t-2), \xi(t-1), \xi(t)), (1 \leq a \leq Q) \) from the first three days are transferred to the input layer of the LSTM prediction model to get the predicted value \( \xi(t+1) \) in the next day. The network structure of the prediction model is shown in Fig.3. A blue ring denotes an input node, a yellow ring denotes a hidden node, and a green ring denotes an output node. The internal structure of \( H_i (1 \leq i \leq 25) \) in LSTM Unit 1, 2, 3 is shown in Fig.2. The yellow dotted arrow indicates that the output \( h_{t-1} \) and the cell state \( C_{t-1} \) of the previous LSTM unit are transmitted to the next unit.

**IV. EXPERIMENTS**

**A. Data Set**

According to the daily outbreak data reported by the National Health Committee of China [30], the cumulative number of confirmed cases of COVID-19 in Wuhan has been collected from January 15, 2020 to March 9, 2020 (a total of 55 days). And the cumulative number of confirmed cases of COVID-19 in South Korea has been collected from February 1, 2020 to March 18, 2020 (a total of 47 days). In general, case data collected can be expressed as \( \zeta = \{\zeta(t) \mid 1 \leq t \leq T \} \cdot C \) is 55 for Wuhan while 47 for South Korea. The raw data of the cases in Wuhan is shown in Fig.4, and the raw data of the cases in South Korea is shown in Fig.5.
for confirmed cases is liberalized on this day in order to ensure that patients can be treated in time. As a result, following previous strict criteria, some suspected cases have not been detected and diagnosed in time, leading to a low cumulative number of confirmed cases reported in the early stage. Until February 12, 2020, the previously accumulated suspected cases were all detected under relatively loose criteria, leading to a sudden increase in data.

\[ N = \{ N(t) \mid 2 \leq t \leq 55 \text{ and } N(t) = \zeta(t) - \zeta(t-1) \} \].

Then the basic number of the new confirmed cases on February 12 is
\[ N_i(t_i) = (N(t_i-1) + N(t_i+1))/2 \].

The difference is \[ \Delta = (N(t_i) - N_i(t_i))/\text{count}(2 \leq t \leq 29) \] and \( \text{count}(\varphi) \) denotes the calculation of the number of days included in \( \varphi \). According to these formulas \( N(t) = N(t) + \Delta \times (2 \leq t \leq 28) \) and \( N(t) = N_i(t_i) + \Delta \), the collection of new confirmed cases \( \{ N(t) \mid 2 \leq t \leq 55 \} \) is updated. After that, the collection of cumulative confirmed cases in Wuhan, China is updated using the formula \( \zeta(t) = \zeta(t-1) + N(t), (2 \leq t \leq 29) \). Finally, the cumulative number of confirmed cases after preliminary processing are obtained, as shown in Fig.4.

**B. Methods & Results**

**Evaluation:** In order to evaluate the goodness of fit between predicted values and actual values, the determinable coefficient \( R^2 \) and the mean absolute percentage error (MAPE) are calculated for predicted values. The closer \( R^2 \) is to 1, the better the model fits predicted values.

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \]

\[ MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \]  \hspace{1cm} \text{(5)}

**BP neural networks:** The input sample vector is \( \{ x_i^1, x_i^2, x_i^3, x_i^4, x_i^5 \}, (1 \leq \mu \leq C - 5) \) and every term in this vector satisfies Equation (6), which denotes the number of cases today, the number of cases yesterday, the number of cases the
day before yesterday, the average number of cases in the past three days and the average number of cases in the past five days, respectively. Due to the relatively small amount of data, the first 70% of data is used to train the BP neural network, and the last 30% of data is used as the test set to test the performance of the optimal model that is finally selected. The input data needs to be normalized so as to eliminate the magnitude difference between the data of different dimensions and avoid causing large network errors. Finally, we need to restore the output data of the neural network in the reverse direction. The number of confirmed cases in Wuhan is estimated from January 20, 2020 to March 29, 2020 while the cumulative number of confirmed cases in South Korea is estimated from February 6, 2020 to April 13, 2020.

LSTM networks: The input vector of the LSTM network is
\[
\mathbf{z}^\alpha = \left( \mathbf{z}(t-2)^\alpha, \mathbf{z}(t-1)^\alpha, \mathbf{z}(t)^\alpha \right) = \left( \mathbf{z}(t-2), \mathbf{z}(t-1), \mathbf{z}(t) \right),
\]
\((1 \leq \alpha \leq C-3)\) which denotes the number of cases today, the number of cases yesterday, the number of cases the day before yesterday. Similarly, due to the relatively small amount of data, the first 70% of data is used as the train set to train the neural network, and the last 30% of data is used as the test set. The input data needs to be normalized so as to eliminate the magnitude difference between the data of different dimensions and avoid causing large network errors. This model selects the Adam optimizer and the mean square error function (MSE) for the loss function. The number of confirmed cases in Wuhan is predicted from January 18, 2020 to March 29, 2020 while the cumulative number of confirmed cases in South Korea is predicted from February 4, 2020 to April 13, 2020.

Results: The curves of the cumulative confirmed cases in Wuhan and South Korea predicted by BP neural network and LSTM network are shown in Fig.6. and Fig.7., respectively. The evaluation indexes of the predicted results are shown in TABLE I. As can be seen from TABLE I, the values of \( R^2 \) are all larger than 0.9. The MAPEs of all the experiments is below 1%. Therefore, these predicted results can be considered to be credible. The BP neural network prediction model needs to input five indicators, and the LSTM prediction model only needs to input 3 indicators. This can make the prediction effect of BP neural network slightly better than that of LSTM network. Besides, the setting of parameters and its own network structure may also affect the results of experiments. As a consequence, it is difficult to analyze such differences.

As of March 29, 2020, the cumulative number of confirmed cases in Wuhan is expected to reach 50,068 using BP neural networks and 49,972 using LSTM network, respectively. As of April 13, 2020, the cumulative number of confirmed cases in South Korea is expected to reach 8,862 using BP neural networks and 8,716 LSTM network, respectively. The predicted values of LSTM network are slightly less than that of BP neural network. It can be seen from Fig.6. and Fig.7 that the slope of the curve of cumulative confirmed cases increases and then decreases, and then gradually approaches zero. It can be considered that at the initial stage, the scale of the epidemic changed in a similar exponential function. Due to human intervention (wearing masks, washing hands frequently, etc.) and social intervention (traffic blockades, cancellation of large-scale gatherings, isolating the patient, etc.), the slope of cumulative confirmed cases slowly decreases. Therefore, it is indicated that the adoption of isolation measures and some intervention is effective for epidemic prevention and control.

|                | \( R^2 \) | MAPE% |
|----------------|-----------|-------|
| Wuhan, China   | 0.978     | 0.294 |
|                | LSTM      | 0.946 | 0.401 |
| South Korea    | 0.988     | 0.601 |
|                | LSTM      | 0.936 | 0.421 |

Figure 6. The curve of cumulative confirmed cases in Wuhan

Figure 7. The curve of cumulative confirmed cases in South Korea
V. CONCLUSION AND FUTURE WORK

The prediction of epidemics using appropriate methods will play a very important role in preventing and controlling the epidemic. In this paper, neural networks are applied to epidemic prediction, which can obtain relatively high accuracy and does not require specific theories of modelling. Neural networks show strong ability of learning and fault tolerance. The Levenberg Marquardt algorithm is used for the training of neural networks, which can shorten the convergence time and improve the convergence performance. However, there are some limitations. For example, this method is the "black box" model, which is poorly interpretable and has many parameters difficult to determine. Neural network models require more data than traditional predictive models, so it is difficult to predict with neural networks in the early stage of epidemic.

The traditional BP network does not consider the influence of time series, and requires to manually determine the form of input data. Therefore, the form of input data is designed in our prediction model of BP neural network. However, the LSTM network has long-term memory and is particularly apt for the prediction and analysis of big data time series, so the input data form does not need to be additionally designed. The difference in the final results may be caused by factors such as parameter settings, network structure, and input form, which is difficult to analyze in detail.

In the future, the following work will be carried out. On the one hand, we are going to improve neural network prediction models to obtain how human, environmental, climate, institutional, and other characteristics of different countries affect epidemic trends of COVID-19 and how the scale of epidemic change if different prophylactic and control measures are adopted. On the other hand, we are going to try to combine neural network models and traditional mechanism models to overcome each other's shortcomings for epidemic prediction.

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