

Research Article

Research on Community Public Service Information Collaborative Governance Based on Deep Learning Model

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The communities have significantly increased in number and the environment has become complex. There are problems such as poor information collection in community public service information governance, lack of relevant analysis standards and models, and unreliable prediction results. In order to forecast and manage the risk information of the community, this research analyzes the public information of the community through the collaborative deep learning model. First of all, the information characteristic factors are selected that affect social risks based on the correlation analysis theory. Secondly, the convolutional neural network is used in deep learning for simulation of the community risk prediction model. Finally, through the comparative analysis of the model prediction results, it can be concluded that the accuracy rate of the proposed prediction model reaches 92.5%. An effective collaborative deep learning model is used to govern community public service information.

1. Introduction

The analysis and research of community public service information directly affects the governance of community public security. Only a good community safety management environment can effectively protect the interests of the broad masses of the people. Our party attaches great importance to this. In the report of the 19th national congress, it proposed to sink social governance to the grass-roots level [1] and published the opinions on strengthening the construction of community public security prevention and control system on relevant government websites, emphasizing the importance of community public security prevention and control [2]. An intuitive indicator of community risk quantification is the number of community public security cases. Through the research on community public service information, accurate prediction of the number of community cases can not only effectively prevent and reduce the number of community public security cases, but also provide auxiliary support for relevant public security organs [3], so as to improve the ability to crack down on relevant illegal and criminal acts, reduce the risk of community governance, and make more effective use and analysis of community public

service information. At present, most of the research related to community public service information governance takes the risk event of theft as the measurement standard [4]. Theft occurs most frequently in the community, and it is generally considered that theft is the most typical case type in the community. However, based on the actual situation, other case types are also very important for the result prediction of risk governance [5]; at the same time, most of the existing prediction models are based on convolutional neural networks, but the existing analytical neural networks are basically single channel prediction models [6]. In this paper, the existing single channel prediction model is improved and the multichannel convolution neural network prediction model is used to improve the accuracy of the prediction model. It better adapts to the characteristics of too many characteristic factors and various types of community public security cases. At the same time, the impact of natural disasters is added to the overall risk prediction, which greatly improves the accuracy of the model prediction. Therefore, this paper comprehensively considers all kinds of case types, takes all kinds of case types as a whole, and makes model prediction through multichannel convolutional neural network.

To conclude, it is stated that a large correlation exists between the predicted and the actual values of CART regression tree prediction model. As a result, the prediction performance was better. Moreover, the correlation between the actual and predicted values of the comprehensive prediction model is good. The comprehensive prediction is higher than the single prediction model, and its prediction's accuracy is also higher.

Initially, this study organizes and examines the collected data. The characteristic factors affecting social security are preliminarily selected by using relevant analysis theory. Irrelevant factors are removed through data cleaning to establish a reliable data source. Secondly, the convolutional neural network prediction model based on deep learning is finally established by the improvement of the single channel convolutional neural network and use of the multichannel convolutional neural network to expand the data acceptance and prediction ability of the neural network. The experimental results show that the accuracy of the prediction model reaches 92.5% which is higher than the single prediction model. Compared with the first mock exam model, the integrated prediction model has higher accuracy and robustness. Finally, the collaborative depth model is realized to calculate the community public service information and manage the community risk.

The rest of the paper is organized as follows:

- (i) Section 2 provides some fine points of the related works
- (ii) Section 3 presents the proposed method in detail
- (iii) Section 4 analyzes and discusses the results
- (iv) Section 5 concludes the paper

2. Related Work

Community public service information analysis and governance is a very complex project, and the information is often massive. However, in the process of information processing, there are often problems such as insufficient manpower, high operation cost, and being unable to respond quickly to the processing results [7]. However, the emergence and development of deep learning algorithms in recent years show their strong prediction ability. Therefore, in recent years, deep learning technology is widely used at home and abroad to analyze and predict community public service information, so as to realize the collaborative governance of public service information [8]. For example, the Memphis police department analyzed and predicted the community public service information by using the in-depth learning model, which has greatly reduced the violent crime in the past five years. At the same time, it was found that the accuracy of big data analysis and prediction based on in-depth learning is much higher than that of traditional methods [9]. Based on the deep learning model, the prediction of community public service information in China started a little later than that in foreign countries, but it has also made great progress in recent years. For example, Tianjin University undertakes the research on building a

smart and safe community, which is to predict the community public service information based on the in-depth learning model and improve the governance efficiency of the community [10].

Chinese scholars An Simin and others combined community information data and related crime data to build a community crime rate analysis and prediction system based on data mining method [11]. On this basis, Li and Li [12] proposed a crime prediction model and algorithm based on deep learning model big data analysis. At present, the common algorithm is the random forest algorithm. Xiao and Yong [13] proposed the degradation decision tree algorithm based on the random algorithm to obtain accurate prediction conclusions. Taking Shanghai as an example, Yun and Shi others established the quantitative relationship between crime susceptibility and community public service information characteristic factors based on deep learning algorithm and analyzed the action equation of influencing factors [14]. In the analysis and research of some community spatial location data and crime space-time, He and others identified and analyzed the theft spatial aggregation area through community personal location data clustering and clustering with the help of GIS data analysis software and spatial analysis tools based on the nearest neighbor index analysis method [15]. According to the different types of community public service information obtained and the predicted objects and technologies, the in-depth learning network models used are also different. For example, the fuzzy backpropagation (BP) neural network model is usually used to predict the number of community risk events. The time prediction technology of community events is usually based on Support Vector Machine (SVM) prediction model. The prediction technology of crime time of relevant risk cases is based on Autoregressive Integrated Moving Average-Least Square Support Vector Machine (ARIMA-LSSVM) hybrid model. At the same time, relevant scholars applied this theoretical knowledge to reality, carried out research on big data + smart policing, and built smart cities with AI and big data. Among them, the war epidemic Golden Shield Project has demonstrated excellent scientific and technological achievements of the reporting system in the fight against epidemic diseases. At the same time, it has covered the health information of nearly 40,000 residents and real-time data of enterprises in 56 communities under the jurisdiction of Beijing Economic Development Zone, providing a strong guarantee for the collaborative management of community public service information.

Through the above research on the current situation at home and abroad, in terms of community public service information analysis technology, we usually use big data analysis to quickly and efficiently analyze massive data based on deep learning network model and conduct risk assessment on the community based on the existing big data model. However, at present, there are relatively single evaluation characteristic factors. When collecting the risk factor characteristics of community public information services, most researchers only consider the characteristic factors of a single risk event, such as theft cases, and ignore the characteristic factors of various types of public security

cases in the community, resulting in the imperfect level of community public service information collection, which affects the subsequent risk assessment, prediction, and governance. In addition, the first mock exam model is the single model formed by many weak learning devices. Although homogeneous or heterogeneous learning in single channel is higher than that in traditional prediction models, the integration of multichannel learning and weak learning has never been carried out.

3. Method

Compared with the deep learning model, the traditional machine learning algorithm has worse learning effect when the number of multichannel training bases is large, but at the same time, the traditional machine learning algorithm performs better when the number of trainings is low. Most of the data sets used in this paper come from community public information and involve certain confidentiality. Therefore, the data and base are not large, and the performance will be better than that of traditional machine learning algorithms. Therefore, our prediction model here selects the decision tree model. The decision tree model is one of the classical model algorithms used for prediction in traditional machine learning. It has low requirements for the amount of data, easy construction, and high operation efficiency. In the decision tree model, this paper selects Classification And Regression Tree (CART) decision tree algorithm, whose algorithm structure is dichotomy. CART is basically a classification algorithm which builds a decision tree on the basis of Gini's impurity index as splitting criterion. This algorithm operates repetitively in three steps: (i) finding the best split of each feature; (ii) finding the best split of node; (iii) using the best node split from the first two steps to split the node until stopping criterion is satisfied. The whole algorithm is in the shape of a binary tree, involving classification and regression. Therefore, the algorithm can be used for both classification and regression, which depends on the target task of decision-making. When the prediction result expected by the decision task is discrete data, the Classification And Regression Trees (CART) algorithm automatically generates the classification decision tree. On the contrary, when the large prediction result required by the decision task is continuous data, the CART algorithm automatically generates the classification decision tree. At the same time, when CART generates a classification decision tree, the inflection point of its prediction result is the Gini value according to node splitting. When CART generates a regression decision tree, the inflection point of its prediction result, i.e., node splitting, is based on Mean Squared Error (MSE) (standard variance of prediction result). Since the final prediction result of this paper is the risk degree of the community, and its quantitative index is expressed as a continuous value by the number of community cases, CART regression algorithm is selected here. The specific algorithm is as follows:

$$\text{MSE}(D) = \frac{1}{M} \sum_1^M (y_m - \bar{Y})^2. \quad (1)$$

Firstly, the optimal feature selection method of the algorithm is determined. According to the number and type of prediction data sets, CART regression tree and mean square error are used for model measurement. In formula (1), y_m is the actual observation value in the prediction process, and \bar{Y} is the model prediction value. Then, a CART regression tree is established based on the decision tree. By inputting the training set D , it is necessary to determine the threshold of the number of samples to avoid affecting the prediction results due to the size of the data set and output the decision tree T :

$$\min_{j,s} \left[\min_{C_1} \sum_{x_1 \in R_1(j,s)} (y_1 - c_1)^2 + \min_{C_2} \sum_{x_1 \in R_2(j,s)} (y_1 - c_2)^2 \right]. \quad (2)$$

In formula (2), the training set is recursively divided into two subregions by constructing a binary decision tree, and the output value is obtained. In this process, the variable j can be traversed to obtain the minimum value pair (j, s) . By continuously calling in the two subdomains divided by the dichotomy, the output values $R_1(j, s)$ and $R_2(j, s)$ satisfying the conditions are found. Then the input control is divided into M regions according to $R_1(j, s)$ and $R_2(j, s)$ to generate decision tree T . Note that, during the application of the formula, if the input features are used up, that is, there are no features available for use, the output values $R_1(j, s)$ and $R_2(j, s)$ will be stopped during splitting operation. If the input characteristic elements are of the same class, the output results have been divided completely, and the dichotomy operation is no longer carried out to distinguish, the splitting decision will be stopped. If all samples have been used up in the final child node, the node no longer has samples to divide and stop splitting.

However, the decision tree has overfitting phenomenon when executing the decision algorithm for result prediction. In order to solve the problem of overfitting phenomenon caused by training, we regularize the prediction results of CART regression number (pruning of regression tree). Through regularization, the learning ability of CART decision model for sample data set can be effectively increased. The CART regularization used in this paper adopts the postpruning method. After generating the CART regression tree through formula (2), the cross validation method is used to verify the pruning effect of the CART regression tree, so as to select the pruning strategy with the strongest effect. The whole process can be roughly divided into two steps. Firstly, the generated CART regression tree is regularized through different pruning strategies; secondly, the efficiency and performance of CART pruning strategy are verified by cross validation method. Finally, the CART regression tree with the best effect and performance is selected as the final prediction algorithm model. The specific algorithm formula is as follows:

$$C_a(T_t) = C(T_t) + \alpha|T_t|, \quad (3)$$

$$C_a(T) = C(T) + \alpha, \quad (4)$$

$$\alpha = \frac{C(T) - C(T_t)}{|T_t| - 1}. \quad (5)$$

Formula (3) indicates that if there is no pruning process, any subtree T_1 located in a child node T is the loss value of the input data value in the prediction process. Formula (4) indicates that, in the process of regularization, if only the number of children T_1 is cut, the loss value of the root node is retained. At the same time, when α is zero or infinitely approaches zero, the index T_1 is cut off, and the loss value of the reserved root node is greater than the loss value of T_t under any index of t for any child node. When α continues to increase, the inequality is reversed, and the loss value satisfies formula (5) according to the size of α . α is the regularization degree parameter, and $C(T_t)$ represents the ground error between the predicted value of the deep learning model algorithm and the input actual value. In this paper, MSE (square error) is selected to measure the fitting degree of the algorithm training data. C is the number of T leaf nodes in the subtree of the regression tree. $|T_t|$ is the number of T leaf nodes in the subtree of the dichotomy regression tree. When α is zero, the regularization degree parameter is zero; that is, the prediction process is not regularized; then the generated cart regression number is the optimal subtree. When α tends to infinity, it means that the degree of regularization is infinitely close to the maximum. At this time, the regularization intensity is the maximum, and the number composed of the root node of the CART regression number is the optimal index. To sum up, between zero and infinity, the greater the α value, the greater the degree of regularization and the stronger the pruning, and the smaller the error of the generated optimal index compared with the initial CART number. When the α value is constant, the loss function is the smallest when there are unique subnumbers. Formula (5) can calculate the threshold value of whether each subtree needs pruning and then judge. Finally, through cross validation, the optimal regularization α value is selected as the final result. The overall structural frame is shown in Figure 1.

After determining the algorithm based on deep learning model, we also need to formulate risk identification and evaluation criteria, so as to judge whether the risk event is or not. The risk assessment here refers to the analysis and research on the risk based on the collected and analyzed community public service information through the in-depth learning model algorithm to evaluate the probability of risk events and provide the basis for the follow-up evaluation and processing methods according to the prediction results. Common risk assessment methods include fuzzy analytic hierarchy process, Delphi method, D-S evidence theory method, and fuzzy comprehensive evaluation method. The risk assessment method adopted in this paper is the disaster risk assessment model proposed in the report "coexistence with risk" of the United Nations Bureau for international

strategy for disaster reduction (ISDR). Its specific assessment algorithm is shown in formula (6).

$$R = H \times \frac{V}{C}, \quad (6)$$

where R represents risk degree, H represents vulnerability, V represents disaster risk degree, and C represents emergency capacity. Formula (6) evaluates the risk from three aspects: vulnerability, disaster risk degree, and emergency response capacity, making the risk model more suitable for the management of community public service information and evaluating the possible risks. The three dimensions of the assessment model also correspond to the three aspects of community disaster causing factors, community vulnerability, and community emergency response capacity of community risk assessment. Among them, the risk degree of disaster causing factors is positively correlated with the overall risk of the community. The higher the risk degree of disaster causing factors, the greater the overall risk of the community. Vulnerability is also positively correlated with the degree of risk. The higher the vulnerability, the greater the risk. The capacity of disaster reduction is negatively correlated with the total risk of the community. The stronger the capacity of disaster reduction, the smaller the risk.

After determining the algorithm prediction model and relevant risk assessment standards, we began to extract the community security risk factors from the community public service information based on the deep learning model. The data source of this time is mainly the public service information of N community in M city (hereinafter referred to as N community) as the main source, and the acquisition method is reference online materials. The data referred to in this paper are mainly the public security prevention and control data of M city from 2017 to 2019, the weather and climate data of M city from 2017 to 2019, the second-hand house price data of N community from 2017 to 2019, etc. After desensitization and simple analysis of the existing data, we can see that, in the occurrence of community risk events, the main time is theft, but there are still other case types, and the other 73 case types also account for a certain proportion every day. It can be inferred that they also have a certain impact on the final prediction results. Therefore, in the process of collaborative governance of community public service information based on deep learning model, we must consider the impact of the overall case types and consider the case types other than theft, rather than only considering the case types with a large proportion and ignoring the prediction and analysis of other cases. At the same time, according to psychologists' experimental research, weather has a great impact on people's mood. In the criminal environmental determinism, it is also mentioned that the quality of the environment not only affects people's health, but also has an impact on social harmony and stability beyond our imagination. Therefore, in the process of public service information collection and analysis based on depth model, this paper will also consider the great impact of climate on people's mood and add climate characteristic factors to the final result prediction. Finally, we captured the

historical weather data of M city from the historical weather website. Capture dimensions include date, weather, wind direction, wind force, maximum and minimum temperature, city, etc. In addition, housing is a major event related to the national economy and the people's livelihood, and house prices are also crucial to social stability. At the same time, house prices are usually used to measure the environment around the community and to some extent reflect the quality of life of community residents, community supporting facilities, and security conditions. After climbing the second-hand house price in M city on the second-hand trading house data website and comparing the number of cases at relevant time, we find that there is a certain correlation between the second-hand house price and the number of community risk events, which fluctuated within a certain range from March 2018 to December 2019, and the fluctuation trend is similar. In addition to the above data, we also investigated the area of the community and the number of registered residents in the community through community property, the geographical location information of the community, and other publicly available information on the Internet. 2017 to 2019 years of housing price changes is shown in Figure 2.

In the process of collecting data, there may be problems such as data missing or wrong value in the process of data statistical transmission, which greatly affects the final prediction effect. Therefore, after data collection, data preprocessing is very important. This paper mainly does missing value filling and deletion processing, data normalization processing, and generating derived data items for the collected community public service information.

The preprocessing of missing values depends on the magnitude and nature of missing values. For missing values that will not affect the objectivity and effectiveness of the prediction results, the deletion method is usually used directly. Due to the large amount of data, deleting individual missing value data has little impact on the overall prediction results of the case, which ensures the objectivity and accuracy of the prediction results to the greatest extent. For the missing values with less missing magnitude but more important and certain impact on the prediction results, the method of manual supplement is usually adopted, which is confirmed and filled manually through secondary collection of information. For the data that has absolute influence on the case and cannot be collected again, regardless of its magnitude, this paper uses the moving window mean filling method to fill the missing value. If the number of community risk events is missing on a certain day, the missing data of risk events is defined as the average value of risk events in the first three days and the next three days of the event, which is used as the number of risk events on that day and filled in. The algorithm is as follows:

$$\chi_m = \frac{1}{6} (\chi_{m-3} + \chi_{m-2} + \chi_{m-1} + \chi_{m+3} + \chi_{m+2} + \chi_{m+1}). \quad (7)$$

In the process of analyzing characteristic factors, the unit and magnitude of each characteristic factor are different. For example, the house price of second-hand houses is usually

calculated in 10000 units, while the occurrence of community risk events is usually calculated in single digits. At this time, in the analysis of relevant factors, the second-hand house price with larger magnitude usually masks the impact of less magnitude, such as the occurrence of risk events. Therefore, the difference between the unit magnitudes of different characteristic factors needs to be normalized. The processing algorithm is as follows:

$$y = \frac{\chi - \text{Min}}{\text{Max} - \text{Min}}, \quad (8)$$

$$Y = \alpha + \frac{\chi - \text{Min}}{\text{Max} - \text{Min}} \times (\beta - \alpha).$$

In addition, in the subsequent model construction process, there are some characteristics that cannot be directly reflected by data, and a series of preprocessing should also be carried out, such as weather characteristic factors, which are usually displayed as sunny or rainy days, rather than intuitive data quantification. Here, we use scoring processing. The worse the weather, the higher the score. Similarly, the quantization and feature selection of holidays are processed, and the algorithm is as follows:

$$\rho = \frac{P_1 + P_2 + \dots + P_n}{S},$$

$$R = \frac{\sum_1^n (\chi_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_1^n (Y_i - \bar{Y})^2} \sqrt{\sum_1^n (X_i - \bar{X})^2}},$$

$$R_m = \frac{\sum_1^n (\chi_i - M_i)(Y_i - \bar{Y})}{\sqrt{\sum_1^n (Y_i - \bar{Y})^2} \sqrt{\sum_1^n (X_i - M_i)^2}}, \quad (9)$$

$$\alpha = \frac{R(a) - R(A_a)}{|N_{A_a}| - 1},$$

$$R(a) = r(a) \times p(a).$$

4. Result Analysis and Discussion

Through the correlation analysis method to analyze the factor characteristics of the original input data, we finally get that the correlation between the actual data and the predicted data in the first seven days is 0.978. In the data of the first six days, the correlation between the actual data and the predicted data is 0.982. From this, we can see that the predicted data in the first seven days and the data in the first six days are more accurate and have a high correlation. In order to enrich the amount of input data, we changed the structure tree in the dichotomy and set the maximum tree depth as 4 and the minimum leaf node as 5. The experimental results are shown in Figure 3.

Figure 3 through the comparison between the predicted results on the data set and the actual input results, it can be seen that the CART regression tree prediction model performs well. The abscissa is the date and the ordinate is the amount of community risk events. The blue solid line is the

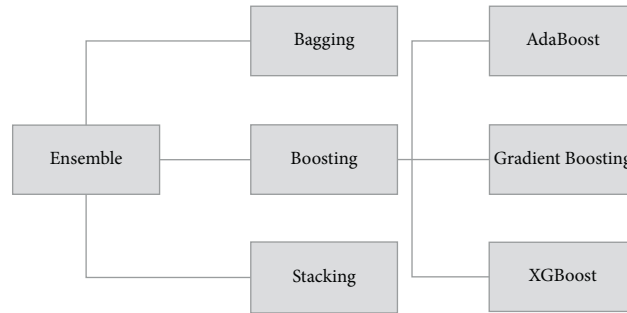


FIGURE 1: Ensemble model structural framework.

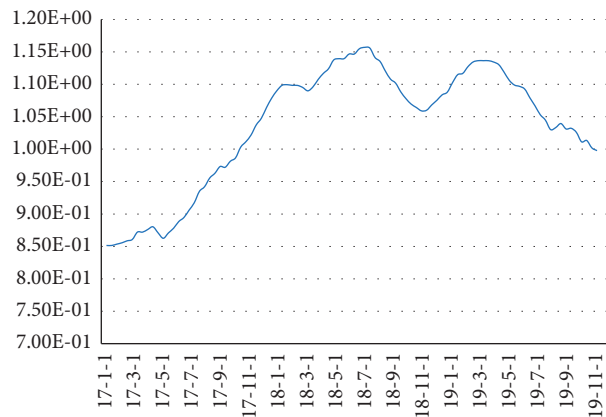


FIGURE 2: 2017 to 2019 years of housing price changes.

input data set, M is the real number of cases per day in a year, and the orange is the prediction result of CART regression tree model, that is, the number of community risk events per day in that year. It can be seen that the trend of the orange line is basically consistent with that of the blue line. The final results show that the correlation coefficient is 86.2%, the error coefficient is 74.3%, and the variance is 0.971. To sum up, we can think that there is a large correlation between the predicted value and the actual value of CART regression tree prediction model, and the prediction performance is good.

Neural network model is a very powerful model to calculate and simulate the nonlinear relationship. It has strong applicability no matter what the relationship between variables is. In the first mock exam, traditional convolution neural network is used to predict the results. The deep learning framework is constructed by building multiple single models and integrating into multichannel convolution neural networks. Multiple single network models do not need complex relationships between them, and the multichannel deep learning model can integrate different information sources. Each connected information source has a parameter called weight, and the information is converted and learned between different neurons according to different weights. In the multilayer sensing mechanism, layers are fully connected, and each neuron in the upper layer is connected with all neurons in the lower layer. In the multilayer sensing mechanism, the bottom layer is the input layer and the data to be trained. In the middle is the hidden

layer data, which is continuously transmitted and learned between the hidden layers. Finally, the output layer outputs the final result. The specific structure is shown in Figure 4.

Finally, the prediction results are analyzed based on the comprehensive prediction model, and the results are shown in Figure 5. The data is based on the granularity of one day, the abscissa is the date, and the ordinate is the occurrence of community risk events. The blue solid line is m , which is the real amount of risk events in the community every day in 2019, and the orange is the prediction result of the comprehensive prediction model. It can be seen that the change trend of blue solid line is basically the same as that of orange solid line. At the same time, compared with the single prediction model, it can be seen that the result of the comprehensive prediction model is significantly better than that of the single prediction model. The final results show that the correlation coefficient between the actual data and the predicted data of the comprehensive prediction model is 92.5%, the error value is 85.5%, and the variance is 0.703. To sum up, the correlation between the actual value and the predicted value of the comprehensive prediction model is good, which is higher than that of the single prediction model, and the accuracy of the prediction results is also higher, which is higher than that of the single prediction model. Comparison of results of comprehensive prediction model is shown in Figure 5.

To conclude, it is stated that a large correlation exists between the predicted and the actual values of CART



FIGURE 3: Comparison diagram of prediction results of CART regression tree model.

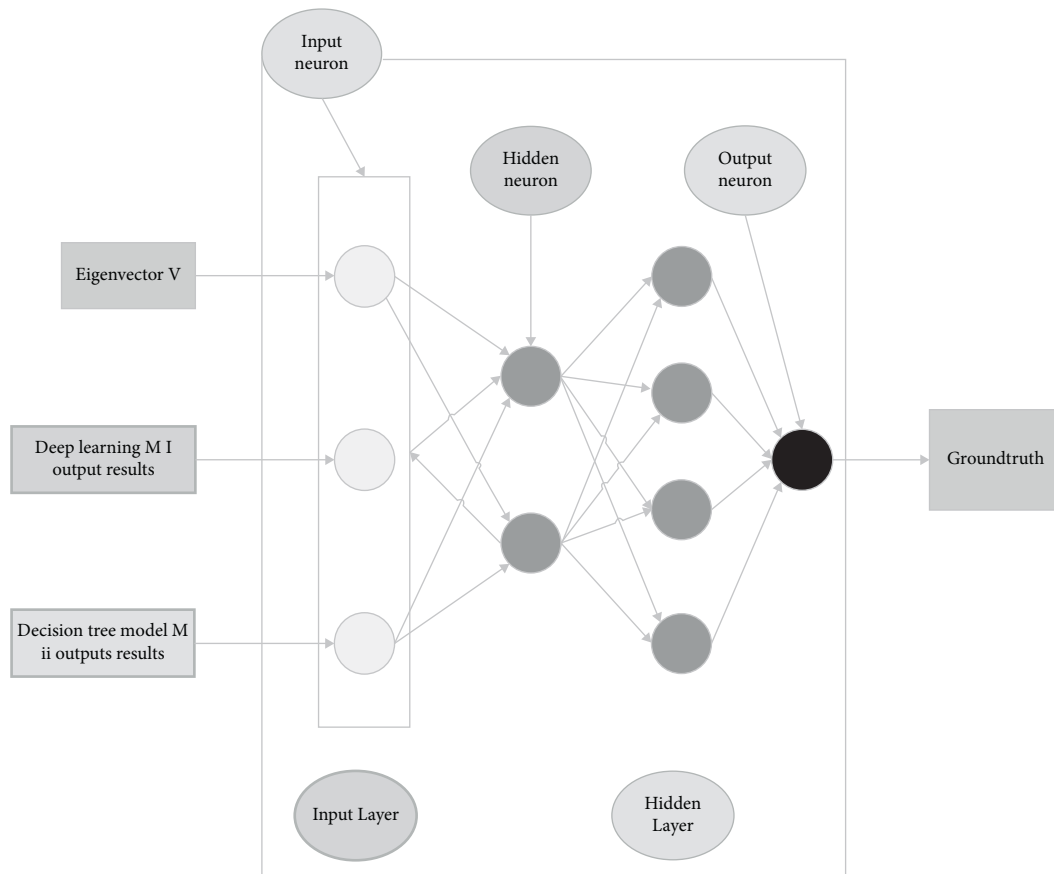


FIGURE 4: Neural network structure of synthetic prediction model.

regression tree prediction model. As a result, the prediction performance was better. Moreover, the correlation between the actual and predicted values of the comprehensive

prediction model is good. The comprehensive prediction is higher than the single prediction model, and its prediction's accuracy is also higher.

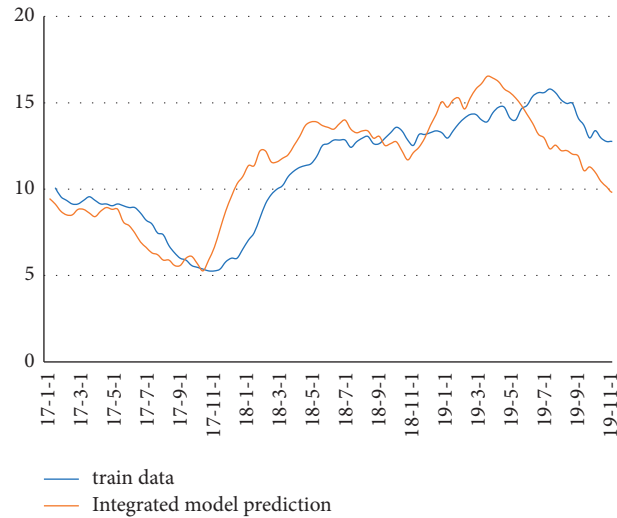


FIGURE 5: Comparison of results of comprehensive prediction model.

5. Conclusion

This paper carried out the research on the basis of deep learning model. The proposed study could be explained into a few major stepwise points as follows: (i) initially, the screening of characteristics of community related risk factors was carried out, (ii) then, the construction models took place, i.e., CART regression tree prediction model and multichannel convolution neural network model, respectively; breaking the traditional prediction method, multiple single channel models were integrated into multichannel prediction model; (iii) finally, the experimental verification showed that the multichannel prediction model can not only improve the processing ability of community public service information, but also well predict the occurrence of community public service security governance problems. Although the model greatly improved the prediction accuracy and processing speed of risk events, in the processing algorithm, more consideration was given to the time-dependent sequence model. Further, no more in-depth analysis was made on the impact of spatial factors on the prediction accuracy of the model. Therefore, the impact of community spatial location will be considered in the next stage. At the same time, it is hoped that this research will provide some ideas and methods for the current community public service information collaborative governance on the basis of deep learning model.

Data Availability

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

Conflicts of Interest

The author declares that he has no conflicts of interest.

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