Research on Analysis and Prediction of Elderly Medical Satisfaction Based on Convolutional Neural Network

Jing Gao¹,*, Jiayang Song¹, a and Le Han¹, b

¹Capital University of Economics and Business, Beijing, China

* gaojing@cueb.edu.cn; *songjiayang2020@163.com; b1124267844@qq.com

Abstract. In order to adapt to the development of economic and social aging, solve the practical problem of incomplete medical security system in China, and provide higher quality medical services to more elderly people. In this paper, a comprehensive and effective survey and data collection on the status quo of medical services for the elderly were conducted by means of questionnaire survey, and an evaluation index system affecting the satisfaction with medical services for the elderly was established by using SERVQUAL model. On this basis, this paper will survey the one dimensional data into two dimensional data, taking advantage of computer vision in depth study using convolution neural network model to generate satisfaction evaluation system for the weight of each index, and then using the trained network model as an effective assessment tools, effective training sample sets of the sample satisfaction accurately forecast, forecast results to improve the elderly health work provides some feasible suggestions.

1. Introduction

With the continuous development of China's economy and society, the social demographic structure has undergone tremendous changes. China has entered an aging society, which will bring a series of risks and challenges to China's economic and social development. The increase in the proportion of the population aged 65 and over in China shows that China's aging degree is increasing. It is an urgent problem to solve the problem of aging population in China.

In this context, this paper investigates, analyzes and predicts the quality of medical services for the elderly in Beijing, aiming to build a scientific and effective evaluation model to predict the satisfaction of more elderly people with medical treatment, so as to put forward suggestions for the improvement of medical services for the elderly.

2. Correlation research on elderly medical satisfaction

In recent years, many scholars are also exploring how to strengthen the elderly medical service satisfaction. Ludwig [1] believes that the rapid increase of population has a great impact on the medical security system. In turn, the level of medical security also affects the satisfaction of patients when they seek medical treatment. Therefore, medical services and related medical expenses have a significant impact on medical satisfaction. Ware et al. [2] think that the indicators of medical satisfaction can be studied through the technical level of medical institutions, the timeliness of service and the effect of treatment. Korsch et al. [3] think that when studying the construction of medical services for the elderly, the problems existing in the elderly population due to age restriction should be specially considered. Schutz et al. [4] believe that in the process of medical services, timeliness and convenience have a significant impact on the quality of medical services. [5] conducted a survey in European countries and
found that the timeliness of treatment also has a profound impact on service quality. Jostein et al. [6] believe that the professional level of relevant personnel in medical institutions will have a significant impact on the evaluation of medical institutions by patients. Leighton et al. [7] used SERVQUAL model to evaluate medical satisfaction, and believed that medical staff should increase the responsiveness of patients in order to improve the level of service quality. Justyna et al. [8] found that in addition to basic medical security, humanistic care for patients also affects the level of medical satisfaction of the elderly.

3. Elderly medical satisfaction index system based on SERVQUAL model

3.1. SERVQUAL model construction and questionnaire design

The SERVQUAL model was used to establish a comprehensive evaluation index system to investigate the satisfaction of the existing elderly medical service quality. According to the construction idea of SERVQUAL model, a three-level index evaluation system is established from five aspects of tangibility, reliability, assurance, responsiveness and empathy. The first level index is the satisfaction evaluation of elderly medical services. The second level indicators are five different angles of the model construction, including the elderly's intuitive feelings (i.e., tangible), the degree of fulfilling commitments (reliability), professional skills (i.e., assurance), feedback to the elderly (i.e., responsiveness) and whether I can put myself in the interests of the elderly (i.e. empathy). The third level index is the specific problem under each angle.

The design of this questionnaire survey is mainly divided into two parts. The first part is the basic information of the respondents, including age, gender, residential area and overall satisfaction with the existing elderly medical services. The specific design is shown in Table 1.

| Basic information                  | Option                                                                 |
|------------------------------------|------------------------------------------------------------------------|
| Gender                             | 1. Male 2, female                                                      |
|                                    | 1. 65-69 years old                                                    |
| Age                                | 2. 70-74 years old,                                                   |
|                                    | 3. 75-79 years old                                                    |
| Residential area                   | 1. Xicheng District 2. Dongcheng District                             |
|                                    | 3. Haidian District 4. Chaoyang District                              |
|                                    | 5. Fengtai District 6. Tongzhou District                              |
|                                    | 7. Fangshan District 8. Daxing District                               |
| Overall satisfaction with existing | According to the intuitive feelings, 1-10 points were scored, of which  |
| elderly medical services           | 1 point was very dissatisfied.                                        |
|                                    |                                                                       |

The second part is the elderly medical service satisfaction survey, with Table 1 as the questionnaire specific questions. In terms of the specific score evaluation scale, the survey adopts Likert 5-level scale, which divides the score of each question into five levels. When scoring the expectation of elderly medical service quality, according to the degree of expectation, they were divided into: high expectation (5 points), high expectation value (4 points), average expectation value (3 points), low expectation value (2 points) and low expectation value (1 point). Similarly, in terms of perceived value, according to the actual feelings of the respondents on the quality of existing elderly medical services, they were divided into: very high (5 points), high (4 points), general (3 points), low (2 points) and very low (1 point).
3.2 Reliability test and validity test

The main purpose of reliability analysis is to test whether the data in the questionnaire survey results are consistent and stable, that is, whether the results are credible. There are four methods of reliability test: retest test, duplicate test, half reliability and Cronbach reliability coefficient. In this paper, Cronbach reliability coefficient, which is the most scientific and widely used index, is used.

Cronbach reliability coefficient (Cronbach's alpha) is a method proposed by Cronbach in 1951 to evaluate the internal consistency of questionnaire results. The formula is as follows:

\[ \alpha = \frac{k}{k-1} \times \left(1 - \frac{\sum s_i^2}{s^2}\right) \]  

(1)

Generally speaking, when the value of \( \alpha \) is less than 0.35, it indicates that the reliability of the questionnaire survey results is low; when the value of \( \alpha \) is between 0.35 and 0.7, it indicates that the reliability of the questionnaire survey results is medium; when the value of \( \alpha \) is greater than 0.7, it indicates that the reliability of the questionnaire survey results is high. At the same time, when the value of \( \alpha \) is greater than 0.8, the results of the questionnaire survey have the use value. The results of reliability test are shown in Table 2.

Table 2. Reliability test table.

|                       | Cronbach’s Alpha | Number of items |
|-----------------------|------------------|-----------------|
| Expected value        | 0.886            | 21              |
| Perceived value       | 0.832            | 21              |

It can be seen from Table 2 that the \( \alpha \) coefficients of expectation value and perceived value are both greater than 0.8, and the questionnaire has good reliability and has practical value.

Validity test refers to the accuracy of the questionnaire, mainly reflected in two aspects: first, whether the questionnaire can achieve the purpose of the survey, that is, whether the setting of questions is related to the purpose of the survey, and draw the corresponding conclusions. Second, whether the questionnaire results have accuracy and authenticity. The results are shown in Table 3.

Table 3. Validity test table.

|                                |                        |                  |
|--------------------------------|------------------------|------------------|
| Kaiser-Meyer-Olkin measure of sampling adequacy | 0.834                  |                  |
| Bartlett's sphericity test    |                        |                  |
| Approximate chi square        | 3452.831               |                  |
| df                            | 231                    |                  |
| Sig.                          | 0.000                  |                  |

It can be seen from Table 3 that the Kaiser-Meyer-Olkin value of satisfaction evaluation system for elderly medical services is 0.834, the approximate chi square of Bartlett's spherical test is 3452.831, the df is 231, and the significance is 0.000, which indicates that the index system has good validity.

4. Construction of elderly medical satisfaction prediction model based on convolution neural network

4.1. Model structure and model optimization design

Usually, when using VGGNet network model to solve practical problems, and the number of samples is small, the training ability is poor, which makes the network model unable to extract the image information completely, so that the model appears over fitting problem. In order to better train the existing data, improve the learning ability of the model for small sample data, and avoid over fitting, the network model is optimized and adjusted.
• The number of convolution kernels. Based on the characteristics of the network structure, the number of convolution models in this paper is adjusted to reduce the number of cores.

• Global average pooling. In the whole network structure, the number of parameters in the whole network structure occupies the majority of the parameters of the whole network structure, which affects the training speed. At the same time, it is easy to produce over fitting phenomenon and reduce the generalization ability of the model. Therefore, the global average pooling is used to replace the full connection layer. In other words, after the last convolution, the average pooling operation is performed on all the feature graphs, and the results are flattened and directly input into softmax classifier. Through the global average pooling, the number of parameters and the amount of calculation are greatly reduced, and the over fitting is reduced. The model can be applied to the experiment of small sample data.

The six parts of the optimization model are shown in Table 4.

| Table 4. Model structure |
|--------------------------|
| Model structure | Convolution kernel size | Stride | Padding | Pooling | Pooling mode | Stride | Number of feature maps |
|---------------------|-------------------------|--------|---------|---------|--------------|--------|------------------------|
| 1                   | 1                       | 1      | 1       | 2×2     | mean-pooling | 1      | 32                     |
| 2                   | 3×3                     | 1      | 1       | 2×2     | mean-pooling | 1      | 64                     |
| 3                   | 3×3, 3×3                | 1      | 1       | 2×2     | mean-pooling | 1      | 128                    |
| 4                   | 3×3, 3×3                | 1      | 1       | 2×2     | mean-pooling | 1      | 256                    |
| 5                   | 3×3, 3×3                | 1      | 1       | 2×2     | mean-pooling | 1      | 512                    |
| 6                   | Global average pooling instead of fully connected layer |

4.2. Parameter selection of improved VGGNet model

• Convolution kernel. Compared with the larger 11×11 and 5×5 convolution kernels, the small convolution kernels can reduce the number of parameters and extract more details in the image. Therefore, the 3×3 convolution kernel is used in all the models in this paper.

• Pooling. The pooling core in this article uses a small 2×2 pooling core, which can extract more details and capture image features in all directions. Secondly, the model in this paper adopts mean pooling, which can better reflect the overall characteristics of the picture.

• Activate the function. In this paper, we will use the Relu function. Relu function is a piecewise function, which is zero on the negative semiaxis and linear on the positive semiaxis.

• Loss function. The loss function uses cross entropy loss function. Cross entropy can measure the difference between the real probability distribution and the predicted probability distribution. The smaller the cross entropy value is, the higher the accuracy of the model is. The cross entropy loss function is used with the softmax classifier. The output value is processed by the softmax classifier, and then the cross entropy is used to calculate the loss.

• Learning rate. In this paper, by using the method of gradual attenuation of learning rate index, the model will converge at a faster speed if the learning rate is kept near a large value. When the learning rate is gradually reduced, the model will oscillate in a small interval, so as to be closer to the optimal solution. The specific formula is as follows:

\[ a = a_0 \times \text{decay\_rate}^{\text{epoch\_num}} \]  \hspace{1cm} (2)
Where, $a$ is the current learning rate, $\text{decay\_rate}$ is the attenuation coefficient, $\text{epoch\_num}$ is the current number of training rounds.

- **Sample batch size.** Select the appropriate sample batch size for model training. This paper selects 50 images as a batch.
- **Number of iterations.** The number of iterations is equal to the total training set data divided by the sample batch size. It is worth noting that the updated values of parameters after each iteration will be taken as the initial values of parameters in the next iteration. Through the continuous iteration of neural network, the parameter values are constantly updated, so as to optimize the model and make the predicted values closer to the real values.
- **Training times.** In this paper, 1500 training times are selected.

5. **Experimental results and analysis**

5.1 **Comparison of model effect before and after improvement**

Because of the small amount of data in this paper, it is not suitable to use the deep network model. Therefore, the overall structure of the convolution neural network model adopts the vggnet model with nine layers, that is, the network model after the convolution kernel is reduced, which is taken as the basic model. At the same time, the global average pooling model is used to replace the full convolution model as the optimized comparative model. In this paper, 808 questionnaires were collected as input data, and the ratio of training data to test data was 3:1. The training data and test data are trained on the model before and after optimization. Figure 1 shows the loss curve, abscissa represents the training times of the model, and the ordinate represents the loss value of the model. Figure 2 represents the accuracy rate of the model before and after training, and represents the accuracy rate of the optimized model.

![Figure 1. Model loss curves before and after optimization.](image1)

![Figure 2. Model accuracy curve before and after optimization.](image2)
It can be seen from the loss curve that with the increase of iteration times, the curve gradually tends to be stable, indicating that the model has been fully trained and learned; from the accuracy curve, it can be seen that the curve of training data is basically the same as that of test data, indicating that there is no fitting phenomenon. Therefore, the model training is basically correct. On the whole, the optimized model is more stable and less volatile than the model before optimization, which indicates that the optimized model has stronger generalization ability. Specifically, the accuracy rate of the network model before optimization is stable at about 85%, while that of the network model after optimization is stable at about 88%, which indicates that the accuracy of the optimized model is slightly improved.

When analyzing the efficiency of the two models before and after optimization, we can compare the time used in a single training. Each model is trained 400 times, and a time point is recorded every 20 training. Table 5 shows the time used for a single training.

Table 5. Average time of single training

| Model          | Average training time of model (s) |
|----------------|-----------------------------------|
| Original model | 0.82                              |
| Optimized model| 0.75                              |

It can be seen from table 5 that the training speed of the optimized model is higher than that of the model before optimization, and the average single training time is shortened by 0.07 seconds, which indicates that the network model with global average pooling can improve the training speed to a certain extent.

5.2 The model was used for analysis and prediction

This paper uses convolution neural network to build a satisfaction prediction model. In the model, when testing the test set containing 202 people, the prediction accuracy is finally stable at 88%. Therefore, the establishment of the elderly medical satisfaction analysis and prediction index system and model building, have achieved scientific and effective prediction purposes, and received satisfactory results.

In order to further use the model for prediction and analysis, more questionnaires are collected. After the two-dimensional transformation of the questionnaire data, the constructed convolution neural network model is input to get the prediction value of everyone's satisfaction. After statistics, the satisfaction results are shown in Table 6 and Table 7.

Table 6. The average satisfaction is distributed by gender

| Gender | Mean satisfaction |
|--------|-------------------|
| Female | 6.97              |
| Male   | 7.11              |

Table 7. The average satisfaction is distributed by age

| Age range      | Mean satisfaction |
|----------------|-------------------|
| 65-74 years old| 6.91              |
| 75-84 years old| 7.18              |
| Over 85 years old | 7.48             |

It can be seen from Table 6 that the average satisfaction of women is 6.97, and that of men is 7.11, and that of women is slightly lower than that of men. As can be seen from Table 7, the average satisfaction of the elderly aged 65-74 is 6.91, that of the elderly aged 75-84 is 7.18, and that of the elderly over 85 is 7.48. 65-74 years old people have the lowest satisfaction with the existing elderly medical
care, and the elderly over 85 years old have relatively high satisfaction with the existing elderly medical care.

Based on the above results, we interviewed 7 people with the lowest satisfaction and the highest satisfaction. Among them, 4 people aged 65-74 years had low evaluation on the current elderly medical care; 3 people over 85 years old had relatively high satisfaction with the current elderly medical care. The results of the interview are basically consistent with the predicted results of the model.

Due to the great aging of Beijing, the corresponding degree of aging service has been formed in Beijing. According to the prediction results of the above model, in view of the current situation of medical services for the elderly in Beijing, we should start from the groups with low satisfaction, and focus on the female patients and the elderly aged 65-74 years, so as to improve the satisfaction of the elderly medical services in Beijing.

6. Summary
Based on the SERVQUAL model, this paper investigates the satisfaction of the elderly from five parts (tangible, reliability, responsiveness, assurance, empathy). In order to make better use of the advantages of deep learning in computer vision, this paper proposes to transform the one-dimensional data of questionnaire survey results into two-dimensional matrix as the input of convolutional neural network, which solves the problem that the questionnaire survey results can not be applied to the research of deep learning. The trained network model is used as an effective evaluation tool to make accurate and effective comprehensive evaluation on the samples outside the training sample set, that is, to predict the medical satisfaction of more elderly groups, so as to put forward reasonable and effective suggestions for the improvement of elderly medical care.

Acknowledgment
Project of Education Committee in Beijing (No.SM201810038005, title: Research on the Development of Medical Service System of Elderly in Beijing Based on Deep Belief Network.)

References
[1] Ludwig D, Dana S 2016 The Pertussis Vaccination Program in the Czech Republic in Light of International Experience. *J. Springer US*, 22(2): 237-238.
[2] Ware J E et al 1983 Defining and measuring patient satisfaction with medical care. *J. Pergamon*. 6(3): 247-263.
[3] Korsch B M, Gozzi E K and Francis V 1968 Gaps in doctor-patient communication.1. Doctor-patient interaction and patient satisfaction. *J. Pediatrics*. 42(5): 71-855.
[4] Schutz M S et al 1994 Clues to patient dissatisfaction with conscious sedation for colonoscopy. *J. The American journal of gastroenterology*. 89(9): 9-1476.
[5] Madelon W K, Hans M and Jouke Z 2005 Direct access in primary care and patient satisfaction: A European study. *J. Health policy*. 76(1): 72-79.
[6] Jostein G, Fredrik C and Irene S 2008 Services production and patient satisfaction in primary care. *J. Health policy*. 89(3): 312-321.
[7] Leighton Y, Clegg A and Bee A 2008 Evaluation of community matron services in a large metropolitan city in England. *J. Quality in primary care*. 16(2): 9-83.
[8] Justyna M et al 2015 Needs assessment of elderly people living in Polish nursing homes. *J. Geriatric Mental Health Care*. 2(3): 9-15.