Automatic Surgery Duration Prediction Using Artificial Neural Networks

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ABSTRACT

Cost control has become an important issue in hospital management. As a very important part of a hospital, the operating room consumes a great amount of resources. If operating rooms are put to their optimal use, a large amount could be saved. However, high uncertainty in the duration of operation procedures results in the difficulty in scheduling the use of operating rooms. The operating room use duration is related to the duration of surgery, and this is difficult to predict. In this study, we used artificial neural network (ANN) to construct a surgery duration prediction model. Experimental results show that the prediction accuracy of the prediction model is acceptable.

CCS CONCEPTS

• **Computing methodologies**; • **Machine learning**; • **Learning paradigms**; • **Supervised learning**;

KEYWORDS

Artificial neural network, Multilayer perceptron, Prediction, Surgery duration

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1 INTRODUCTION

In recent years, cost saving has become an increasingly important issue for hospitals. The operation room is the core department of a hospital [1]. In some hospitals, the laminar flow operation center consists of several operation rooms. In this center, in the same time interval, the energy consumption cost of using three operating rooms is almost the same as that of using only one operating room. However, the energy consumption cost of using one operating room for three hours is three times that of using three operating rooms for one hour. Therefore, there is no doubt that a balanced operation rooms scheduling can save the cost. However, performing a balanced operation room schedule is difficult, mostly due to high uncertainty of operating room use duration [2]. If the operating room scheduling sets aside less time for an operation than the realized duration, the next operation will not start on time. However, if the planned operation duration is longer than the realized duration, the operating room will have to remain vacant, which may cause a waste of operating room resources. In contrast, if the operating room scheduling is reasonably arranged, it will reduce the resource consumption caused by the difference between the estimated time and the actual time required to occupy the operating room.

Operating room managers generally schedule the operation rooms by manually predicting the duration of the surgery and the anesthesia emergence. The surgery duration implies the time from the beginning of the surgery to the end of the surgery. The anesthesia emergence duration indicates the time from the end of the surgery to the time when a patient wakes up. Operating room managers schedule operation rooms based on the average duration of previous similar procedures (prior experience) or a rough estimate of operating room time based on the type of surgery, characteristics, and so on [3]. However, this prediction approach is a relatively rough and unscientific estimation of a large range, which often leads to large errors in the duration of operation and anesthesia emergence and causes resource wastage in the operating room. In few existing studies, scholars selected a few factors and used a simple multiple regression method to predict the duration of certain types of operations [4], which also has certain limitations.

In recent years, many artificial intelligence methods have been developed and applied to many prediction problems with good prediction performance. For example, the artificial neural network (ANN) has been used to solve the ship detection problem [5] and predict the recidivism rate of commuted prisoners [6]. The support

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vector machine (SVM) has been used to solve the reclaim wafer defect classification problem [7]. The association rule (AR) has been used to solve the driver lane-keeping ability in fog problem [8]. Among these methods, the ANN has been used to solve several types of prediction problems and could derive a better accuracy than SVM in supervised learning [7, 9]. Therefore, in this study, to predict the operating room duration more accurately for more efficient operating room scheduling, we used ANN to construct the prediction system for the duration of surgery. According to the experimental results, the prediction accuracy of the surgery duration prediction system was 94.85%, which is acceptable.

The remainder of this paper is organized as follows. Section 2 introduces the ANN, perceptron, and multilayer perceptron (MLP). Section 3 describes the conducted experiments. Section 4 discusses the experimental results of the surgery duration prediction system. Finally, conclusions and suggestions for future research are provided in Section 5.

2 LITERATURE REVIEW

2.1 Artificial Neural Network

An ANN is a complex artificial system, its mathematical model is similar to the function, structure and information processing of human brain and nervous system [10]. Similar to human brain, the ANN is a self-learning system, which can learn the predicted output by performing multiple iterations. All types of nodes of neural network are similar to neurons in human brain, and each neuron is used as the input of the next node after the weighting function [11]. In the learning process, a systematic algorithm is used to update the weights. In order to obtain better output accuracy, the backpropagation (BP) learning algorithm is usually used in the ANN; this algorithm refers to using a certain set of weights and biases to perform an iteration and calculating the error with the output and actual value, then propagating backwards, and updating the weights and bias by the error to ensure that, after several such forward and backward propagations, the output accuracy is quite high and reliable [12]. After the training of ANN is complete, we can predict or classify new data according to the received stimulus (new input data), weights and biases.

The ANN is a powerful tool for learning and modeling complex linear or nonlinear relationships. More precisely, the model it builds is similar to a "black box": we cannot understand the nature of the relationship between input and output data [13]. The ANN has been widely used by many researchers to solve a series of problems in many fields, including engineering [14], biology [15], mathematics [16], and analysis and prediction of various diseases in medicine [17].

2.2 Perceptron

The perceptron model is derived from MP model established by McCulloch and Pitts [18]. MP model describes the mathematical principle and network structure of artificial neuron by simulating the principle and process of neural cells in biology, and proves that a single neuron can realize a logic function. In detail, the MP model includes input, output, and calculation functions. Between them, the input and output are similar to dendrites and axons of neurons respectively, while the calculation function is similar to nucleus, and each synapse has its own weight.

Inspired by the MP model, the perceptron model consists of two layers. The first layer is called input layer, which receives the stimuli and transmits them to the last layer. The last layer is called output layer. In the output layer, all input stimuli are multiplied by their respective weights, and then the perceptron adds all weighted stimuli and bias through the summation function. Finally, the perceptron uses the activation function to simulate the process of data processing by the brain [19].

2.3 Multilayer Perceptron

To deal with nonlinear problems better, Hecht-Nielsen proposed a multilayer perceptron, in which one or more additional neuron layers are placed between the input layer and the output layer [19]. There are two basic components in the structure of MLP: neurons and the links between them. The neurons are the processing elements and the links are the interconnections. Each link has its own weight parameter or bias parameter. When a neuron receives stimuli from other neurons through the links, it processes the information and produces an output signal. In addition, consider that these intermediate layers are not disturbed by the external environment, they are called hidden layers, and their nodes are called hidden nodes. Similar to the perceptron, the input neurons receive external stimuli, and the output neurons transmit the output signals. Using similar neuronal dynamics, the hidden neurons receive the stimuli from the neurons at the front of the network and transmit the output signals to the neurons at the back of the network [6].

3 EXPERIMENTS

3.1 Data Setting

The investigation samples were provided by Affiliated Hospital of Panzhihua University. These samples are the operation records for a period of nearly one and a half years, from January 2019 and July 2020. The data are merely used for academic study that predict the duration of surgery. To protect personal privacy, the samples were preprocessed. The total number of samples collected for this study was 15,754. The samples for patients who suffered from hepatic and renal disease were excluded. All samples for emergency surgery patients or patients who are admitted to ICU after surgery were excluded to eliminate the potential factors that could affect the operation time. Thus, only records for patients with complete case data were included in the study. There are 24 input variables of the surgery duration prediction system, which are gender, body mass index (BMI), systolic blood pressure (SBP), diastolic blood pressure (DBP), pulse rate (PR), respiration rate (RR), body temperature, heart function classification, red blood cell (RBC), hemoglobin (HB), hematocrit (HCT), platelet (PLT), potassium (K), sodium (NA), chlorine (CL), activated partial thromboplastic time (APTT), prothrombin time (PT), thrombin time (TT), American society of anesthesiologists (ASA) classification, anesthesia type, surgeon title, seniority of surgeon, age of surgeon, and surgical grade. The output variable of the surgery duration prediction system is the duration of surgery. As shown in Table 1, the duration of surgery is divided into four scales: no more than 1 hour, 1–2 hours, 2–3 hours, and 3–4 hours.

Table 1: Output Variable of the Surgery Duration Prediction System

Variables	Name	Description
Output (original)	Duration of surgery (T)	(1) ≤ 1 hour (2) 1-2 hours (3) 2-3 hours (4) 3-4 hours
Output (statistical)	Duration of surgery (T)	(1) 1000 (2) 0100 (3) 0010 (4) 0001

Appropriate data preprocessing is extremely important for a successful ANN. Hence, data transformation [20] and inspection, and deletion of outliers [21] were applied to preprocess all the data in this study. After data preprocessing, a total of 6,507 surgery samples were retrospectively used to predict the duration of surgery. In addition, normalizing the data is recommended to avoid premature saturation that prevents the learning process [22], and all the data were normalized between 0.1 and 0.9. Meanwhile, balancing and enrichment of data plays an important role in classification problems [23]. Therefore, data balancing was used in this study. After data balancing, the data were mostly enhanced to three times in beginning experiments and ten times in the final experiment. Moreover, data representation is a necessary part of a successful ANN [21]. In this study, the output variable was categorized according to four binary numbers, namely, 1000, 0100, 0010, and 0001, where the location of 1 represents the category.

3.2 Computing Environment Settings

We used Python 3.7 (64 bit) as the compiler to write the program to find a solution. The devices included an Intel Core (TM) i7-10510U (2.3 GHz) CPU, 8GB of memory, and a Windows 10 Home Edition (64 bit) operating system.

3.3 Experimental Structure

In this study, we used MLP to construct the surgery duration prediction model. To determine the optimal architecture of the model, we conducted one group of experiments, and the total dataset was divided into three datasets, namely, training, testing, and validation, according to the respective proportion of 60%, 20%, and 20% [23].

In MLP, the Adam optimizer was used to adjust the weights, and the cross-entropy loss function was used to calculate the loss of the prediction model. The batch size was set to 100, and the number of training cycles was set to 200, but 1,000 in the final experiment of the optimal architecture. The number of hidden layers and the number of hidden nodes in each layer are crucial to the results of the experiment [19, 23]. We used the trial-and-error method to identify the suitable number of hidden layers and hidden nodes. Among them, the number of hidden layers was set to 3, 4, 5, and 6, respectively, and the number of hidden layer nodes of each layer was set to 64, 128, 256, and 512, respectively. Thus, the experimental results of 16 parameter combinations were obtained for comparison and analysis. To reduce the stochastic effects of the experiments, we conducted 10 experiments for each parameter combination.

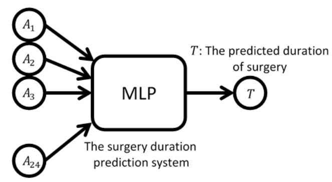

Figure 1: MLP Structure to Predict Duration of Surgery.

Finally, we obtained the optimal architecture of the surgery duration prediction model. Figures 1 shows the MLP structure of the surgery duration prediction model.

4 EXPERIMENTS AND ANALYSIS

We used the trial-and-error method to identify the final architecture of the surgery duration prediction model. The experimental results are shown in Tables 2-6. Tables 2-4 present the prediction accuracy of the surgery duration prediction model in the testing, training, and validation datasets, respectively. In addition, to further explore the performance of several different architectures of MLP, the experiment results were analyzed through the t-test, as shown in Table 5. Table 6 presents the running time cost of each architecture. We determined the final architecture of MLP according to the maximum prediction accuracy and the reasonable running time cost.

In Tables 2-4, Mean and Std imply the average prediction accuracy and the standard deviation of 10 experiments, respectively. Max indicates the maximum prediction accuracy during 10 experiments, and Min is the minimum prediction accuracy during 10 experiments. Here, 3-64 denotes the MLP model with 3 hidden layers and 64 hidden neurons in each hidden layer. In the three hidden layer architecture, in Table 2, the 3-512 architecture has the maximum average prediction accuracy (0.7254) in the testing dataset. The maximum and minimum prediction accuracies of the 3-512 architecture (0.7491 and 0.7108, respectively) are higher than other architecture. These results mean that in the testing dataset, the 3-512 architecture has the better prediction performance. However, in Table 3, we notice that the 3-256 and 3-512 architectures have the same maximum average prediction accuracy (0.7996) in the training dataset. In Table 4, we notice that the 3-256 architecture has a better average prediction accuracy (0.7266) than the 3-512 architecture (0.7261) in the validation dataset. Moreover, in Table

Table 2: The Prediction Accuracy of the Surgery Duration Prediction System in the Testing Dataset

Layers-Neurons	Mean	Std	Max	Min
3-64	0.6013	**0.0127**	0.6173	0.5737
3-128	0.6830	0.0174	0.6991	0.6374
3-256	0.7252	0.0131	0.7418	0.7056
3-512	**0.7254**	0.0131	**0.7491**	**0.7108**
4-64	0.6506	0.0124	0.6655	0.6260
4-128	0.7340	0.0118	0.7498	0.7078
4-256	**0.7711**	**0.0115**	**0.7919**	**0.7560**
4-512	0.7639	0.0156	0.7878	0.7312
5-64	0.6614	**0.0111**	0.6790	0.6421
5-128	0.7359	0.0138	0.7582	0.7182
5-256	**0.7601**	0.0195	**0.7854**	**0.7272**
5-512	0.7584	0.0168	0.7817	0.7366
6-64	0.6701	**0.0126**	0.6916	0.6464
6-128	0.7201	0.0168	0.7491	0.6948
6-256	**0.7493**	0.0161	**0.7749**	**0.7200**
6-512	0.7281	0.0233	0.7548	0.6792

Table 3: The Prediction Accuracy of the Surgery Duration Prediction System in the Training Dataset

Layers-Neurons	Mean	Std	Max	Min
3-64	0.6614	0.0140	0.6758	0.6308
3-128	0.7507	0.0160	0.7656	0.7117
3-256	**0.7996**	0.0135	**0.8233**	0.7797
3-512	**0.7996**	**0.0117**	0.8179	**0.7836**
4-64	0.7180	0.0090	0.7305	0.7053
4-128	0.8084	**0.0087**	0.8269	0.7955
4-256	**0.8468**	0.0118	0.8675	**0.8303**
4-512	0.8402	0.0186	**0.8681**	0.8049
5-64	0.7335	**0.0108**	0.7481	0.7139
5-128	0.8116	0.0129	0.8331	0.7950
5-256	**0.8386**	0.0189	**0.8608**	0.8059
5-512	0.8365	0.0154	0.8569	**0.8140**
6-64	0.7424	**0.0158**	0.7656	0.7110
6-128	0.7960	0.0173	0.8269	0.7717
6-256	**0.8297**	0.0161	**0.8605**	**0.7994**
6-512	0.8046	0.0234	0.8345	0.7588

6, we notice that the 3-512 architecture has a longer running time (1806.50 s) than the 3-256 architecture (584.24 s). In other words, among three hidden layer architecture, the 3-256 architecture saves 67.66% of the runtime cost compared with the 3-512 architecture. Therefore, in three hidden layer architectures, we settle for the 3-256 architecture prediction model.

In 4, 5, and 6 hidden layer architectures, in Table 2, we note that the 4-256, 5-256, and 6-256 architectures have the maximum average prediction accuracies (0.7711, 0.7601, and 0.7493, respectively) in the testing dataset. Besides, in Table 3 and 4, we note that the

Table 4: The Prediction Accuracy of the Surgery Duration Prediction System in the Validation Dataset

Layers-Neurons	Mean	Std	Max	Min
3-64	0.6033	**0.0105**	0.6171	0.5789
3-128	0.6863	0.0122	0.7010	0.6567
3-256	**0.7266**	0.0160	**0.7556**	**0.7098**
3-512	0.7261	0.0117	0.7401	0.7093
4-64	0.6536	0.0115	0.6729	0.6323
4-128	0.7349	**0.0087**	0.7564	0.7254
4-256	**0.7714**	0.0124	**0.7918**	**0.7564**
4-512	0.7656	0.0161	0.7877	0.7352
5-64	0.6624	**0.0100**	0.6771	0.6468
5-128	0.7329	0.0123	0.7471	0.7165
5-256	**0.7636**	0.0182	**0.7885**	0.7347
5-512	0.7559	0.0149	0.7848	**0.7376**
6-64	0.6680	**0.0144**	0.6863	0.6368
6-128	0.7201	0.0158	0.7533	0.7033
6-256	**0.7499**	0.0165	**0.7740**	**0.7163**
6-512	0.7271	0.0204	0.7574	0.6858

4-256, 5-256, and 6-256 architectures also have the maximum average prediction accuracies in the training and validation datasets. In other words, too many or too few artificial neurons would reduce the prediction accuracy. Therefore, in 4, 5, and 6 hidden layer architectures, we settle for the 4-256, 5-256 and 6-256 architecture prediction models.

In all architectures, in Table 2-4, the experimental results provide two findings that are worth noting. First, in general, the prediction system with fewer artificial neurons (such as 3-64) could has the lower standard deviation (Std). In other words, the prediction system with fewer artificial neurons has a better robustness. However, the prediction system with fewer artificial neurons has a poor prediction accuracy. In this study, we would like to construct a more accurate surgery duration prediction system. Therefore, the prediction accuracy of the prediction system is more important than its robustness, and then we determine the optimal architecture of the prediction system based on the prediction accuracy rather than the robustness.

Second, the 4-256 architecture has the maximum average prediction accuracies (0.7711, 0.8468, and 0.7714) in the testing, training, and validation datasets, respectively. In Table 5, the 4-256 architecture is significantly better than the 3-256 and 6-256 architectures, but not significantly better than the 5-256 architecture. However, the p-value (0.0710) is quite close to 0.05. In other words, the 4-256

Table 5: The T-Test of Each Architecture

Architecture	4-256	5-256	6-256
3-256	0.0000*	0.0001*	0.0009*
4-256	—	0.0710	0.0013*
5-256	—	—	0.0979

Table 6: The Running Time Cost of Each Architecture

Architecture	Time(s)	Architecture	Time(s)
3-64	339.72	4-64	375.72
3-128	404.73	4-128	474.83
3-256	584.24	4-256	756.63
3-512	1806.50	4-512	2480.10
5-64	404.15	6-64	448.18
5-128	560.63	6-128	622.16
5-256	923.48	6-256	1072.77
5-512	3325.30	6-512	4155.28

Table 7: The Effect of Dropout Mechanism on the 4-256 Architecture

dropout	Testing Dataset		Training Dataset		Validation Dataset	
	Mean	Std	Mean	Std	Mean	Std
Without	0.7711	0.0115	0.8468	0.0118	0.7714	0.0124
0.1	0.7287	0.0115	0.8112	0.0120	0.7298	0.0122
0.2	0.6562	0.0058	0.7263	0.0056	0.6558	0.0048
0.3	0.5930	0.0085	0.6471	0.0096	0.5930	0.0087

architecture is almost significantly better than the 5-256 architecture. The 4-256 architecture saves 18.07% of the runtime cost compared with the 5-256 architecture. Therefore, we determined that the final architecture of the surgery duration prediction system is the 4-256 architecture.

After we determined the best architecture of the surgery duration prediction model, we further improved the prediction accuracy through dropout mechanism, data enrichment, and longer training time. The experimental results are shown in Tables 7 and 8. Table 7 presents the effect of dropout mechanism, and Table 8 presents the impact of the data enrichment and the longer training time on the 4-256 architecture, respectively. In Table 7, we note that the 4-256 architecture without the dropout mechanism has the maximum average prediction accuracy (0.7711) in the testing dataset. With the increase in the dropout probability, the average prediction accuracy decreases. In other words, the dropout mechanism could not improve the prediction accuracy of the surgery duration prediction model. We enriched the data 10 times, and in Table 8, the 4-256 architecture with 10 times data had a better average prediction accuracy (0.8788) in the testing dataset. We also increased the training time to 1,000 epochs, and we identified that the average prediction accuracy increased to 0.9485 in the testing dataset. Data enrichment and longer training time improved the surgery duration prediction model. Finally, the architecture of the surgery duration prediction models was the 4-256 architecture without dropout mechanism, trained with 10 times the data over 1,000 epochs.

5 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we used the MLP model to construct the surgery duration prediction model. We identified the main attributes affecting the prediction of surgery duration based on the available patient data and performed the corresponding data preprocessing. Extensive experiments and comparisons were carried out to determine the final architecture of the prediction model. The experimental results provide several findings that are worth noting. First, based on the prediction accuracy and the running time, the final architecture of the surgery duration prediction model was the 4-256 architecture. The smaller the architecture, the lower the accuracy. Conversely, the larger the architecture, the longer the running time. Second, overtraining did not occur; therefore, the dropout mechanism could not improve the prediction accuracy of these two prediction models. However, data augmentation and longer learning period improved the prediction models.

It is worth noting that the duration of surgery and anesthesia emergence constitute the operating room duration. As we mentioned in Section 1, operating room managers generally predict the duration of the surgery and the anesthesia emergence manually based on the average duration of previous similar procedures (prior experience) or a rough estimate of operating room time based on the type of surgery, characteristics, and so on. However, this prediction approach is a relatively rough and unscientific estimation. Therefore, we suggest that, in the future, we could use the MLP model to construct the anesthesia emergence duration prediction model. Besides, we still have many variables that have not been considered in this study, such as the data of before surgery physical examination. Therefore, we suggest that, in the future, depending on the organs that are subject of surgery, we could use specific physical examination items to predict the surgery duration and the anesthesia emergence duration and obtain a more accurate prediction system.

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Table 8: The Impact of the Data Enrichment and the Longer Training Time on the 4-256 Architecture

Multiple	Epochs	Testing Dataset		Training Dataset		Validation Dataset	
		Mean	Std	Mean	Std	Mean	Std
3	200	0.7711	0.0115	0.8468	0.0118	0.7714	0.0124
10	200	0.8788	0.0134	0.8920	0.0128	0.8738	0.0138
10	1000	0.9485	0.0055	0.9530	0.0046	0.9473	0.0059

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