Hospital Management Practice of Combined Prediction Method Based on Neural Network

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ABSTRACT

In this article, the outpatient volume, hospitalization income and drug demand in hospital management are taken as the research objects, and a neural network combined prediction model is established to predict the outpatient volume with the fitting prediction results of cubic polynomial regression model and grey model as the input of the network and the actual statistical outpatient volume as the output. Lasso variable selection method is used to determine the main indexes affecting the income of inpatients in hospital, and a prediction model combining grey prediction and artificial neural network is established to predict the income of inpatients in hospital. By studying the key characteristics of hospital drug demand, BP neural network, RBF neural network and GRNN generalized regression neural network are selected to predict the drug demand. By solving the quadratic programming problem and according to the weight rules, a combination forecasting model based on neural network is established to predict the drug demand, and the accuracy and stability of the model are evaluated.

KEYWORDS

Hospital Management, Neural Network, Combination Forecasting, Hospital Income, Drug Demand

INTRODUCTION

After China's accession to the World Trade Organization, the world's advanced medical technology and hospital management have had a particular impact on China (Ippoliti et al., 2021). At the present stage, the main problems of China's hospital management are the broad scope of hospital management, its numerous contents, and its rapid development, while the current management mode is single, and a targeted management system has not been established. Especially in the management of drugs, subjective factors (such as managers) significantly impact hospitals' failure to pay full attention to management, resulting in economic losses. Regarding personnel management, hospitals adhere to traditional management concepts, resulting in an imperfect internal management mechanism, low efficiency of communication and cooperation among departments, the lack of targeted training for personnel in different positions, and poor income growth, which seriously affects staff enthusiasm

DOI: 10.4018/IJHISI.342091

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(Quasim et al., 2023). At the same time, the unclear division of various duties and positions leads to overlaps and deficiencies, resulting in mutual shirking of responsibilities and delays in the work. Moreover, hospitals fail to pay full attention to the critical cost management factors, focusing only on the accounting results without sufficient market analysis, leading to lower-quality cost management (van Assen et al., 2020). With the gradual modernization of hospital management, statistical forecasting methods are gradually being applied to hospital management. Scientific prediction of the market improves the decision-making ability of hospital management, allows for the development of more scientific management and work plans, and promotes the modernization and scientization of hospital management ability (Elleuch et al., 2021).

Statistical forecasting is widely used to modernize hospital management and has achieved rich research results. Hospital work plans and scientific management models can be rationally formulated by predicting the number of outpatients, hospital income, and drug supply and demand. Shahid et al. (2019) have combined different forecasting methods and determined the weight coefficients of each forecasting method according to its importance, forming a combined forecasting model with fixed weight coefficients (linear) and variable weight coefficients (nonlinear). Due to its simplicity, the combined prediction model with fixed weight coefficients (linear) is widely used. Although the research results of this method are more mature, the unstable prediction results of a single prediction model make it unable to meet prediction needs in practice. Ge et al. (2019) have studied the combined prediction model with variable weighting coefficients. This prediction model has high accuracy and practicality, but its weighting coefficients change over time. Innovative hospital management models are needed to meet the requirements of the current healthcare system (Wang et al., 2023).

With the development of artificial intelligence (AI) technology, one of the most important technologies to emerge is the neural network, which has the characteristics of fast learning ability, powerful nonlinear processing ability, and independence from mathematical models (Nazari-Shirkouhi et al., 2023). Predictive methods of neural networks are widely used in hospital management, especially in hospital staffing, hospital revenue, and drug management. The continuous development of neural network technology and its application in the healthcare industry has dramatically improved healthcare. Hassan et al. (2023) have used AI to allocate healthcare resources during hospital construction in favor of sustainable hospital development. At the same time, this ensures the development of intelligent hospital management by developing an automatic fluid management system that realizes automatic control of infusion flow and real-time monitoring of the patient's blood volume, which solves the problems of duplicated work and waste of human, material, and financial resources (Yang et al., 2023). Ho et al. (2023) have studied the application of AI in hospital personnel management, equipment management, and environmental monitoring and concluded that AI assists doctors in seeing patients, puts higher requirements on them, stimulates doctors' innovation ability, provides advanced technical support for hospital management, and improves the hospital management mode. Establishing a hospital environment information platform creates a good ward and medical environment, ensures medical quality, and improves management efficiency (Panja et al., 2023).

This paper investigates the application of the neural network combination prediction method in outpatient numbers, inpatient income, and drug demand. It establishes a cubic polynomial regression model and a gray model GM neural network combination prediction model to predict the number of outpatients in hospital management. It also constructs a prediction model combining the gray prediction and the artificial neural network to predict the hospital's inpatient income. We selected three neural network combination forecasting models (BP neural network, RBF neural network, and GRNN generalized regression) with complementary properties for forecasting drug demand. The prediction accuracy of the neural network combinatorial prediction models was significantly higher than that of the traditional linear combinatorial models, providing theoretical guidance for applying neural network combinatorial prediction methods in hospital management.

RELATED WORKS

Based on these principles, we chose exponential smoothing, ARIMA, and neural networks to form the combined approach. Zhou (2017) studied the prediction of a service demand using a combined forecasting approach, using the least squares technique to settle the optimal weight coefficients among forecasting methods. Liu et al. (2018) proposed a hybrid forecasting method based on neural networks combined with the K-nearest neighbor (K-NN) method for short-term traffic flow forecasting. In this study, the researchers selected four different neural network models, namely the back-propagation (BP) neural network, radial basis function (RBF) neural network, generalized regression (GR) neural network, and Elman neural network, all of which have been widely applied for short-term traffic forecasting (Liu et al., 2018). Gu et al. (2018) aimed to develop an effective way to predict the inventory demand for agricultural materials. Focusing on the market for agricultural pesticides, the authors introduced the backpropagation neural network (BPNN) and optimized the BPNN inventory prediction model by multiple interpolation methods (Gu et al., 2018). Problems remain, such as a low level of drug inventory management in major hospitals, which directly leads to the stagnation of the drug supply chain and the high cost of hospital management. To improve the efficiency of hospital drug inventory management, based on genetic algorithm and BP neural network, Du et al. (2019) combined the actual situation of hospital drug inventory forecast to build a system model based on hospital drug management mode. Liu et al. (2019) compared four prediction models for unplanned patient readmission for patients hospitalized with acute myocardial infarction (AMI), congestive health failure (HF), and pneumonia (PNA) within the Nationwide Readmissions Database in 2014. Risk-standardized hospital readmission rates calculated from the artificial neural network model that employed embeddings led to the reclassification of approximately 10% of hospitals across categories of hospital performance (Liu et al., 2019). They proposed an improved bagging algorithm, combined with a resampling strategy, a neural network, and a support vector machine (SVM), for in-hospital mortality prediction using imbalanced data with a very uneven ratio of positive and negative samples. Wang et al. (2020) studied in-hospital mortality prediction for heart failure patients using electronic health records and an improved bagging algorithm. To evaluate its effectiveness, they compared this approach with other machine learning algorithms, such as SVM, neural networks, and GBDT. Their results suggest that the proposed method has the potential to be a valuable new tool for in-hospital mortality prediction using electronic health record data (Wang et al., 2020). Yashin et al. (2020) studied an approach to selecting a time series analysis method using a neural network. They described a technique for choosing individual methods in a combined time series forecasting model. The neural network calculates the estimated prediction error for each model from the base set of the combined model (Yashin et al., 2020). Imai et al. (2020) focused on vancomycin-induced nephrotoxicity, adopting a 10-fold cross-validation method for evaluating the resultant artificial neural network. By analyzing the impact of the COVID-19 epidemic on the financial management work of enterprises, Ji (2022) proposed an artificial neural network–based enterprise financial forecasting and early warning method to provide an effective method for enterprise financial management. The experimental results demonstrated that the financial prediction model built by multilayer feed-forward neural networks and recurrent neural networks based on error backpropagation training was inferior to that built using long- and short-term memory networks (Ji, 2022).

Abedinia et al. (2015) studied electricity price forecasts using a combinatorial neural network (CNN) trained by a new stochastic search method. They proposed a CNN-based forecasting engine to predict the future values of price data. The CNN-based forecasting engine is equipped with a new training mechanism for optimizing the weights of the CNN (Abedinia et al., 2015). To solve the low accuracy, slow convergence, and poor robustness problems of the traditional neural network method for water quality forecasting, Jing et al. (2018) proposed a new model of dissolved oxygen content prediction based on a sliding window, particle swarm optimization (PSO), and a BP neural network.

Table 1. Relative error of four single prediction models

Relative error	Cubic exponential smoothing	Box-Jenkins	Cubic polynomial regression	Grey
Maximum	0.0063	0.0021	0.0013	0.0005
Minimum value	0.2532	0.2192	0.1591	0.1423
Average value	0.0824	0.0712	0.0453	0.0328

RESEARCH METHOD

Combined Prediction Model of Outpatient Number Based on Cubic Polynomial Regression Model, Grey Model, and Neural Network

Using the first, second, and third powers of the dependent variable X as independent variables in the regression model, we obtained the following regression equation:

$$Y = \beta 0 + \beta 1X + \beta 2X^2 + \beta 3*X^3 + \varepsilon \quad (1)$$

where Y is the number of visits, X is the characteristic variable, β0, β1, β2, and β3 are the regression coefficients, and ε is the error term. We aim to find the optimal regression coefficients by fitting the dataset to build a reliable prediction model.

To estimate the values of the regression coefficients, the data set can be fitted using the least squares method. Specifically, for the i^{th} sample, it is expressed in the form (xi, yi) and then substituted into the regression equation to obtain the following fitting equation:

$$yi = \beta 0 + \beta 1xi + \beta 2xi^2 + \beta 3xi^3 + \varepsilon i \quad (2)$$

where εi is the error term that represents the difference between the observed value yi and the fitted value:

$$(\beta 0 + \beta 1xi + \beta 2xi^2 + \beta 3xi^3) \quad (3)$$

Our goal is to minimize the sum of squares of the error term εi, that is, $\min \Sigma(\varepsilon i^2) = \min \Sigma(yi - \beta 0 - \beta 1xi - \beta 2xi^2 - \beta 3xi^3)^2$.

To solve for the optimal regression coefficients, we can derive the above objective function and make the derivative equal to 0 to obtain the following system of regular equations:

| n Σ(xi) Σ(xi^2) Σ(xi^3) | | β0 | | Σ(yi) | Σ(xi) | Σ(xi) Σ(xi^2) Σ(xi^3) Σ(xi^4) | | β1 | = | Σ(xiiyi) | Σ(xi^2) Σ(xi^3) Σ(xi^4) Σ(xi^5) | | β2 | | Σ(xi^2yi) | | Σ(xi^3) Σ(xi^4) Σ(xi^5) Σ(xi^6) | | β3 | | Σ(xi^3*yi) | (4)

where n denotes the number of samples. Solving this system of equations yields estimates of the optimal regression coefficients β0, β1, β2, and β3.

Finally, using the estimated regression coefficients, the fit function for the cubic polynomial regression model is obtained:

$$Y = \beta 0 + \beta 1X + \beta 2X^2 + \beta 3*X^3 \quad (5)$$

Currently, the single prediction models of outpatient numbers mainly include the cubic exponential smoothing model, box Jenkins model, cubic polynomial regression model, and grey model. Table 1 gives the relative errors of each prediction model, showing that the prediction result error of the cubic polynomial regression model and grey model is small. In this paper, we selected the cubic polynomial regression model and grey model to establish the combined prediction model of neural networks.

Using a neural network, taking the fitting prediction results of the cubic polynomial regression model and grey model as the input and the actual number of hospital outpatients as the output, we constructed the combined prediction model of neural networks. We used SPSS software to run the cubic polynomial regression model, Excel software to deal with the grey model, and MATLAB to realize the modeling and operation of the neural network model.

According to the improved neural network algorithm, we used MATLAB software to input the fitting results of the cubic polynomial regression model and grey model from 2000 to 2010 into the network, and we took the actual number of outpatients in the hospital as the network output. The optimal connection weight of input and output is obtained through machine learning analysis so that the prediction effect of the combined prediction model is the best. We then put the 2010 data into the model and output the prediction results of the number of outpatients in 2011 to test the accuracy of the combined prediction model of neural networks. In the process of machine learning, we used the maximum and minimum normalization processing methods to improve the network's running speed and accelerate its convergence.

Combined Prediction Model of Grey Prediction and Neural Network for Inpatient Income

The sequence of original data was as follows:

$$x^{(0)} = [x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)] \quad (6)$$

The sequence of grayscale data was as follows:

$$X^{(1)} = [x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)], \text{ where } x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \quad (7)$$

For cumulative generation, the cumulative sequence was as follows:

$$x^{(2)} = [x^{(2)}(1), x^{(2)}(2), ..., x^{(2)}(n)], \text{ where } x^{(2)}(k) = \frac{1}{2}[x^{(1)}(k) + x^{(1)}(k-1)] \quad (8)$$

We established the differential equation:

$$\frac{dx(t)}{dt} + a\,x(t) = b \quad (9)$$

where a and b are the parameters to be estimated.

The estimates of parameters a and b can be obtained using methods such as least squares. For model prediction, based on the estimated parameters a and b, we solved the differential equations to obtain the predicted value of the trend in outpatient visits.

Indicators affecting hospitalization income mainly include hospital indicators and national economic and social development indicators. Hospital indicators mainly include the number of admissions and discharges, the number of operating units, cure rate, bed utilization rate and turnover times, hospitalization days, and hospitalization expenditure per capita. National economic and social development indicators include per capita income, resident consumption expenditure, regional GDP, fiscal revenue, year-end population, total number of beds in regional hospitals, and health professionals and technicians. Because so many indicators need to be selected, LASSO is the most commonly used method for variable selection. In this research, we used LASSO for variable selection, the combined prediction model of grey prediction and neural network to predict hospital income, and Excel for data sorting and statistical analysis.

The grey prediction model sorts the indexes according to the time series through the correlation of known indexes and related indexes, uses differential equation fitting to establish the dynamic process of each index, and realizes the prediction goal through extrapolation. In this research, we established a grey prediction model for each index to obtain the prediction value of each index. A neural network is a mathematical model that simulates the information processing of a biological neural network. The learning process of neural networks is also called training. In this process, the neural network changes due to external stimulation to reflect the external environment. Based on the grey prediction value of each index, this paper forecasts the hospital inpatient income through training using historical data.

Combined Forecasting Model of Drug Demand Based on Neural Network

Although the relevant research on drug demand prediction based on neural networks is increasing, due to the particularity and complexity of drug demand characteristics, a single prediction model cannot predict drug demand. Based on the highly nonlinear characteristics of drug demand, we selected three complementary neural networks (BP neural network, RBF neural network, and GRNN generalized regression) as single prediction methods. We established a combined prediction model of neural networks to improve the accuracy and stability of drug demand prediction. The implementation process includes the following steps:

1. The outlier detection method of distance is used to repair the outliers of drug demand data and obtain the normal drug demand data;
2. According to the characteristics of drug demand, three neural network models with different characteristics are selected to provide the basis for the establishment of a combined prediction model;
3. According to the relative error as the optimal criterion, the most suitable single prediction methods are selected to combine, and the weight of each single prediction method is obtained through quadratic programming;
4. The neural network combination prediction model of drug demand is established according to the weight.

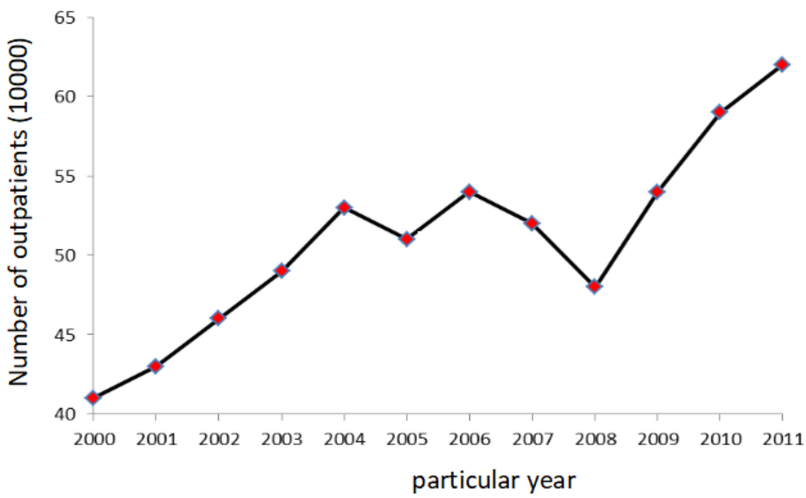
RESULTS AND ANALYSIS

Forecast Results of Hospital Outpatient Number

Regarding research methodology, we plotted data on the number of outpatient visits in the target hospital from 2000 to 2011, as presented in Figure 1. We used the outpatient volume data of a hospital from 2000 to 2011 as the experimental data. The figure shows that the hospital's outpatient volume has been increasing yearly since 2000 with an upward trend. Although environmental factors affected the number of outpatients in 2005 and 2008, overall, the number of outpatients gradually increased. In this study, we modeled data on the number of outpatients from 2000 to 2010 using a BP neural network, and we assessed the accuracy of the model by comparing the predicted data from 2011 with the actual data.

Combining the BP neural network model for outpatient volume prediction with the abovementioned cubic polynomial regression model and the fusion method of the grayscale model creates a more sophisticated and potentially more accurate prediction framework. This integrated framework takes

Figure 1. Sequence diagram of outpatient number



advantage of the cubic polynomial regression model's ability to capture nonlinear relationships, the strength of the grayscale model to handle data trends, and the BP neural network's powerful nonlinear modeling and learning capabilities.

First, we grayed out the raw data series of outpatient visits to generate a gray-scale data series that reveals the inherent patterns and trends in the data.

We performed feature extraction on the processed data using a cubic polynomial regression model. This step helped us capture the complex nonlinear relationships between outpatient volume and time or other relevant variables.

The trained BP neural network model was utilized for outpatient volume prediction.

We completed the training through iterations, observing the change in error until the network model reached a stable convergence, usually when the number of iterations reached about 500. During this process, the BP neural network learned deep relationships between the data.

The BP neural network model was configured in the MATLAB environment, the learning rate was set to 0.05, and the activation function was chosen as the sigmoid function.

We used the BP neural network model to predict outpatient visits, conducting simulation experiments in the MATLAB environment. The learning rate of the model was set to 0.05, and the sigmoid function was used as the activation function. By inputting the network parameters into the model and increasing the number of iterations, we observed a rapid decrease in the error, and the network model essentially reached stable convergence when the number of iterations reached about 500, at which point the weights of the connections between the layers were fixed. This process indicates that after an appropriate number of iterations, the BP neural network can effectively learn and adapt to the data features, thus improving the accuracy of the prediction.

To evaluate and compare the progress of the model prediction, we used two indicators: the average relative error and the root mean square relative error.

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_i - y_i}{f_i}\right| \tag{10}$$

Table 2. Discrimination accuracy table of hospital income prediction

Index	Actual value in 2011	2011 forecast	Prediction accuracy
GDP (100 million yuan)	6214.32	6315.12	98.38%
Regional population (10,000)	8023.14	8342.21	96.02%
Admission number (10,000)	11.08	11.53	95.94%
Inpatient operation volume	11045	10432	94.45%
Bed turnover	47.91	42.13	87.94%
Hospital income (10,000 yuan)	12638	13286	94.87%

$$MSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_i - y_i}{f_i}\right|} \tag{11}$$

where f_i denotes the actual value, and y_i denotes the predicted value.

By comparing the outpatient visits predicted by the neural network combination prediction model with the actual data, we found that the relative error between the two is small, and its average value is only 0.0001. In addition, to test the generalization ability of the neural network combination prediction model, we used the outpatient visits in 2010 as the input, and we successfully predicted the number of outpatient visits in 2011 to be 615,800 visits, with a relative error of 0.0067, for a prediction accuracy of 99.3%.

Based on the prediction results and evaluation feedback, we further adjusted the parameters of the BP neural network (e.g., learning rate, number of nodes in the hidden layer) and the feature selection of the cubic polynomial regression model to improve the prediction accuracy.

We retrained the modified model until satisfactory prediction results were obtained.

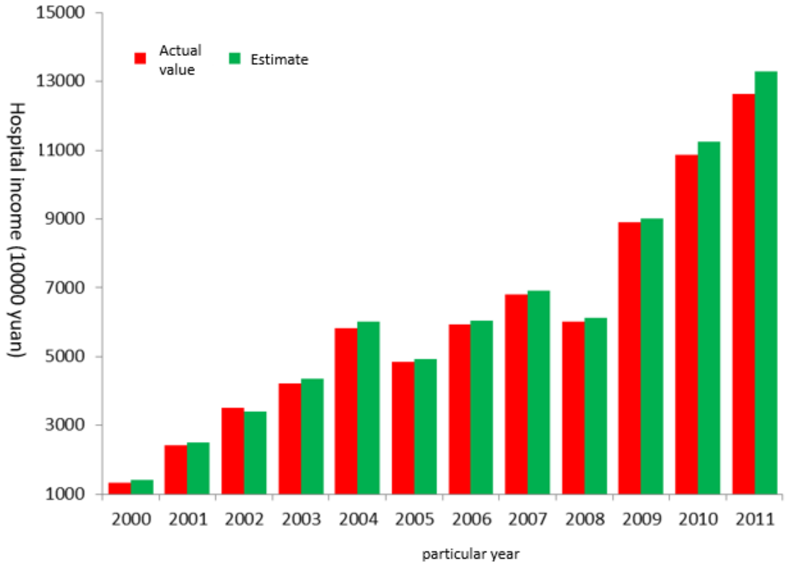
The cubic polynomial regression model provides a basic understanding of the nonlinear relationship of the data, the grayscale model enhances the representation of the data trend, and the BP neural network further refines and utilizes this information for accurate prediction through its powerful learning capability. This integrated strategy provides an effective way to solve complex prediction problems.

Hospital Revenue Forecast Results

Through the statistical analysis of the indicators affecting hospital income, we established the multiple linear regression model between each indicator and hospital income. We used the LASSO variable selection method to obtain the five most important indicators affecting hospital income: GDP, regional population, number of hospitalizations, residential operations, and bed turnover. Based on the statistical data from 2000 to 2010, we established the grey prediction model of hospital income and obtained the predicted values for 2011 (Table 2).

Using MATLAB software combined with the statistical data of various indicators from 2000 to 2010, we established the combined prediction model of neural networks. The accuracy was set to 10–7, and the number of learning cycles was 20,000. We calculated the average value through the results of ten operations. Finally, the predicted value of hospital inpatient income in 2011 was 126.38 million yuan, and the relationship between the annual predicted value and accurate data was drawn (Figure 2). Figure 2 indicates that the combined prediction of neural networks can predict hospital income with high accuracy.

Figure 2. Relationship between predicted value and real data of annual hospital income



Drug Demand Forecast Results

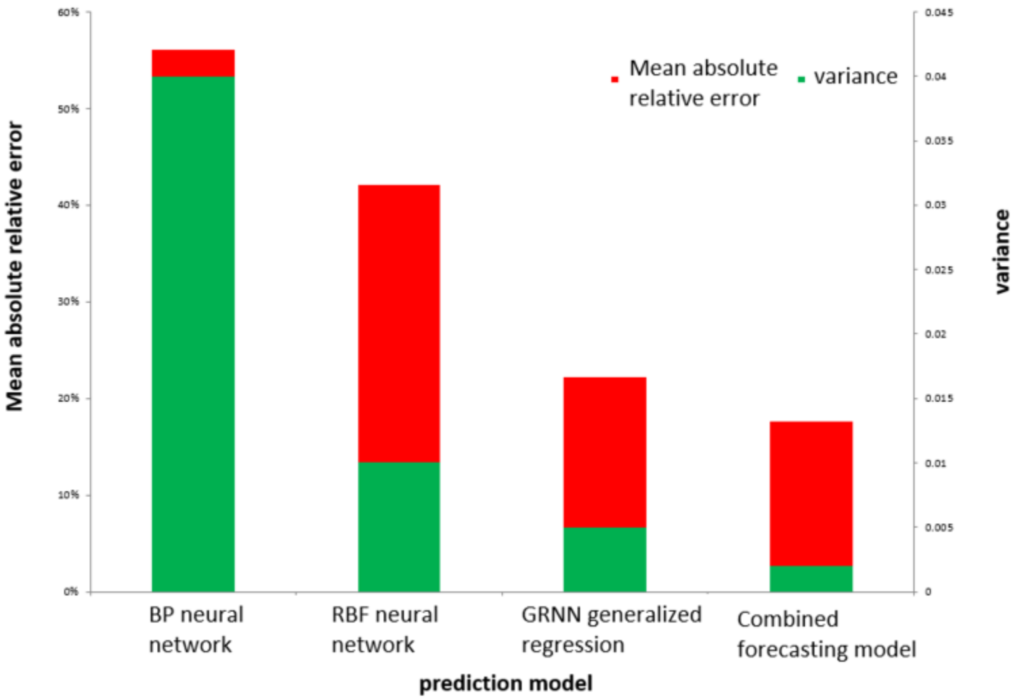
We selected ten kinds of drugs used in the hospital. We predicted the drug demand with the monthly sales of hospital drugs to obtain the relative error and variance results of drug demand prediction by the BP neural network, RBF neural network, and GRNN generalized regression neural network.

Using the quadratic programming function of MATLAB, the combined weight periods of the three neural networks were 4, 5, and 6, respectively, to establish the combined prediction model of neural networks, obtain the average absolute relative error and variance of the drug demand prediction value of the combined prediction model, and make statistics to obtain the average value. Figure 3 shows the average absolute relative error and variance results of the four models. The figure shows that the average absolute relative error of the combined prediction model is the smallest, indicating that its prediction accuracy is the highest. The variance of the combined prediction model is much smaller than that of the other models, suggesting that its prediction stability is the highest. The prediction accuracy and stability of the BP neural network prediction model, RBF neural network prediction model, GRNN generalized regression neural network prediction model, and neural network combination prediction model are reduced in turn.

CONCLUSION

In this paper, we carried out a comprehensive forecasting study of key indicators of hospital management—outpatient numbers, hospital revenue, and drug demand—by combining the cubic polynomial regression model, gray model, and neural network technology. First, we established a combined neural network model for predicting the number of outpatient visits by using the prediction results of cubic polynomial regression and gray model as inputs. It showed a high accuracy of 99.3% when analyzing the 2010 data to predict the number of outpatient visits in 2011, which was better than a single model. Secondly, we used the LASSO variable selection method to determine the five

Figure 3. Average absolute relative error and variance results of four models



main factors affecting hospital revenues (GDP, regional population, number of inpatient admissions, number of inpatient procedures, and bed turnover), and we built a combinatorial neural network prediction model for hospital revenues based on data from 2000 to 2010 using the MATLAB software. It successfully predicted 2011 revenues with an accuracy rate that exceeded that of the traditional gray prediction model. Finally, by analyzing the monthly sales data of hospital drugs, we selected the BP neural network, RBF neural network, and GRNN generalized regression network for drug demand prediction. We calculated the weights of each model using the quadratic programming function and established a combinatorial prediction model with optimal accuracy and stability. The model showed higher prediction accuracy and stability than other models, with the smallest mean absolute relative error and lowest variance, providing an effective theoretical support and prediction tool for hospital management.

Neural network-based combinatorial prediction methods have some limitations in hospital management, such as high data quality and reliability requirements, high model complexity, and poor interpretability. Future research directions include improving data processing, optimizing model structure, enhancing interpretability, automating parameter tuning, real-time modeling, and improving generalization capability. These limitations must be considered comprehensively, and the model must be applied effectively to enhance the science and accuracy of hospital management decisions.

DATA AVAILABILITY

The figures and tables used to support the study's findings are included in the article.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding for this research was covered by the authors of the article.

ACKNOWLEDGMENT

The authors would like to show sincere thanks to those whose techniques contributed to this research.

Received: September 5, 2023, Revision: February 7, 2024, Accepted: February 14, 2024

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