Research Paper
Academic Platform Journal of Engineering and Smart Systems (APJESS) 10(2), 86-93, 2022
ISSN: 2822-2385
Received: 22-Aug-2021 Accepted: 16-Dec-2021
https://doi.org/10.21541/apjess.1078920

Prediction of Demand for Red Blood Cells Using Artificial Intelligence Methods

*[1]Seda Hatice Gökler, [2]Semra Boran

*[1]Department of Industrial Engineering, Kahramanmaraş Sütçü İmam University, Kahramanmaraş, Turkey, 46040, sedahaticegokler@ksu.edu.tr,
[2]Department of Industrial Engineering, Sakarya University, Sakarya, Turkey, 54050, boran@sakarya.edu.tr,

Abstract

Blood is a vital product with limited resources, available only from volunteers. For this reason, the blood components to be sent from the blood bank to the transfusion centers (hospitals) should be accurately predicted. There are many variables that affect the demand prediction. In this study, fifteen different qualitative and quantitative variables were determined. Artificial intelligence (AI) methods are used because the prediction has nonlinear, complex and uncertain relationships and thus it is also difficult to mathematically express on relationship in between input and output variables. AI methods have the feature of predicting the information that is not given or that may occur in the future by learning the past data. In the study, AI methods such as Decision Tree (DT), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Deep Learning (DL) were applied to blood bank providing blood supply to public and private hospitals operating in four provinces. The data obtained from the prediction results of AI methods were compared with performance criteria (MAPE, MSE, MAE RMSE and R^2) and values of overprediction, underprediction, minimum and maximum deviation. The weekly average over predictions are calculated as 9.69, 5.29, 8.45, and 15.65 and weekly average underpredictions as 17.57, 3.03, 3.94, and 14.69 for DT, SVM, ANN, and DL methods, respectively. SVM method was determined as giving the best prediction values. Therefore, it is envisaged that the blood component demand prediction can be calculated using the SVM method.

Keywords: Demand prediction, decision tree, support vector machine, artificial neural network, deep learning.

1. INTRODUCTION

Blood transfusion is an important part of contemporary medicine. 85 million blood transfusions are carried out annually across the globe, which translates to three blood transfusions per second approximately [1,2]. Therefore, sustainable blood donation provided is important. However, measures implemented due to epidemics such as COVID-19 and people's reluctance to go to donation centers reduce blood donation, but the need continues. In addition, although the need for blood increases in disasters such as earthquakes, floods and mass fires, donations decrease in the disaster area. In this case, the most important problem is making the demand prediction correctly. For this reason, blood banks must be sent enough blood components to the hospitals and the disposal of blood components must be prevented due to the expiration date.

Some difficulties on prediction of blood need:

- Blood is an urgent and vital need,
- Demand quantity is uncertain,
- Demand time is uncertain,
- Donation quantity is uncertain,
- Donation time is uncertain,
- Preparation of blood components is time-consuming and the processing time of the blood taken is uncertain because it is affected by external factors,
- Short storage period,
- Storage area requires special conditions,
- High storage cost,
- Different blood groups depending on the blood grouping system,
- It is the necessity of meeting some blood component needs from fresh blood, not from old blood due to special circumstances. For example, the blood component to be given to a premature baby should be selected from the blood of the appropriate donor.

Prediction models can reduce mistakes when deciding about how much blood to donate and produce, making possible better accuracy of product supply from a perspective of time and amount needed. Moreover, predicting reduces a part of uncertainty, so decision-makers establish more realistic production plans. Predicting and stock management methods achieve improving blood inventory management efficiency.

The number of blood component to be demanded from blood banks is usually predicted using quantitative methods in the literature [3,4]. The methods mostly predict based on similar

* Corresponding Author

quantitative variables such as age, blood group and gender. But, the number of blood component demand is heavily influenced by the outside world and is constantly changing. The quantitative prediction methods are not sufficient since the uncertainty is too high, the parameter values affecting the inventory cannot be known precisely and demand can be predicted within the framework of probabilities. It is not possible to manually process and analyze real, large, complex, and contradictory data. In this study, the prediction of red blood cells (RBCs) demand has nonlinear, complex, and ambiguous relationships. Also, expressing the relationship between input and output variables is difficult with a mathematical equation. For this reason, AI prediction methods are used to predict information that is not given to it by learning historical data or that may occur in the future. Several studies have focused on using AI methods to predict blood component demand in the literature. Decision tree [5], support vector machines [6-8], artificial neural network [9-11], and deep learning [12-14] methods are frequently used in prediction models.

In the study, it is aimed is to determine the suitable variables and determine the AI method that predicts the optimum demand and minimizes overstock and shortage. It is aimed to make predictions by taking into account the variables that have not been taken into account in the literature that will affect the prediction. The inputs of the models dealing with the blood demand constitute variables related to human biology such as age, blood group, gender in the literature. However, blood component demand is a dynamic process that is affected by the external environment. Therefore, fifteen different variables such as the number of operations, the population of provinces, and temperature are determined in the study, unlike other studies. In the literature, no study has examined the external variables that affect RBCs demand. Then it is explored which AI method predicts the optimum demand using determined variables. Predictions of the determined AI methods were compared on a weekly, unit, and average basis. As a result of the comparisons, it was determined that the most appropriate prediction method was the support vector machine.

This paper was organized as follows. Material and methods were explained in section 2. The application was described and applied to the data set obtained from a blood bank in Turkey in section 3. In section 4, the overstock and shortage results in the blood bank inventory were compared. In final section 5, the conclusion was summarized.

2. MATERIAL AND METHODS

2.1. Material

Red blood cells (RBCs) which are a life-saving component are used to treat emergency patients [15] and also it has the highest demand among blood components (Table 1).

According to Table 1, 74449 units of RBCs were requested from the blood bank from June 2019 to June 2020. Therefore, the sample size of the data group to be used in prediction methods was predicted to be at least 382 with a 95% confidence level [16]. To better represent the sample size of the population, this study was carried out with 5 transfusion centers, which includes 45000 of the RBCs demand.

Table 1. The number of blood components requested from blood bank (from June 2019 to June 2020)

	RBCs	FF	PS	TOTAL
Amount(units)	74449	33333	15443	123225
Percentage(%)	60.417	27.051	12.532	100

FF: Fresh frozen plasma, PS: Platelet suspension, TOTAL: Total blood component amount

2.2. Methods

AI methods such as decision tree, support vector machine, artificial neural network and deep learning are applied to blood bank providing blood supply to public and private hospitals operating in four provinces.

2.2.1. Decision tree method

Decision tree (DT) is one of the most popular machine learning methods because it is the ability to generate understandable knowledge structures, and handle symbolic and numeric input variables, provisioning a clear indication of which attributes are most important for prediction or classification. It has also a low computational cost when the model is being applied to predict or classify new cases.

DT method brings data with similar criteria to the same class or predicts by applying a set of decision rules to a data set containing many criteria. The most important step is deciding which criteria and how to divide all nodes starting from the root nodes [17]. Therefore, split criteria such as entropy, Gini index, and information gain are calculated.

Entropy is a split criterion of uncertainty that deals with the occurrence of events. It takes values between 0 and 1. If the entropy value approaches 0, the uncertainty decreases, and if the entropy value approaches 1, the uncertainty increases (Eq.1).

$$H = -\sum p\,(x)\ \log\ p\,(x) \tag{1}$$

where H is entropy and p(x) is the frequentist probability of a variable or a class ‘x’ in the dataset.

In addition, the Gini index is used to determine the contribution values of the variables in the branches (Eq. 2). The Gini index varies between 0 and 1, where 0 denotes that all variables belong to a certain class and 1 denotes that the variables are randomly distributed across various classes.

$$Gini\ index\ = \frac{f\,(C_i,\ T)}{|T|} \tag{2}$$

where T is the training set, C_i is ith class.

Information gain (IG) is used to determine which attribute gives the maximum information about a class (Eq. 3). In the DT method, branching is started with the variable with maximum information gain in the data set and the method aims to reduce the level of IG from the root node to the leave nodes.

$$IG\ (S, D) = H\ (S) - \sum_{V \in D} \frac{|V|}{|S|}\ H\ (V) \tag{3}$$

where S is the original data set, D is a split part of the data set and V is a subset of S.

2.2.2. Support vector machine method

Support vector machines (SVM), is developed by Vapnik and Chervonekis in the late 1960s, are the most popular, robust, and widely used AI method that works according to structural risk minimization [18,19]. Structural risk minimization means getting a low error rate on unseen data set (outside training data set) [20]. In contrast to the experimental risk minimization used in traditional machine learning methods, structural risk minimization overcomes multiple training data requirements, local minimums, low convergence rate, and overfitting problems [21].

Today, SVM and other learning-based-kernel algorithms show better results than ANN and other intelligent or statistical models, on the most popular benchmark problems [22]. SVM does not rely so heavily on heuristics and has a more flexible structure [23]. Besides, it is very powerful in realizing complex and nonlinear predictions.

The main purpose of the SVM method is to select the plane or hyperplane that will make the smallest classification or prediction error when encountering unknown or reserved data for testing, but it is impossible to draw the linear hyperplane in nonlinear SVM. In other words, it is not possible to separate complex data with a flat plane. To find the best boundary between nonlinear classes, data is transferred from the original input space to a higher dimensional space using the mapping function (Φ) (Eq. 4) [24].

$$x \in R^d \rightarrow (x)\ \Phi \in R^f \tag{4}$$

However, it is often difficult to obtain the mapping function. Therefore, for non-linear classification problems, kernel function-based SVM is used instead of the mapping function. Kernel function maps training input data of input space R^d onto a higher dimensional feature space H using transformation operator Φ. After this, an optimal separating hyperplane is used to separate the two classes of the two-class pattern classification problem [20].

Kernel functions frequently used in the literature are shown in Eqs. 5-8. C is kernel value, d is polynomial degree and γ is a hyperparameter of the radial basis function (RBF) kernel which is also called gamma parameter and it defines the spread of the kernel.

LF $$C(x_i\ , x_j) = x_i^T\ x_j \tag{5}$$
PF $$C(x_i\ , x_j) = (x_i x_j)^d \tag{6}$$
SF $$C(x_i\ , x_j) = \tanh k\ x_i x_j - \delta \tag{7}$$
RBF $$C(x_i\ , x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right) \qquad \gamma \geq 0 \tag{8}$$

LF: Linear function PF: Polynomial function SF: Sigmoid function RBF: Radial basis function

2.2.3. Artificial neural network method

Artificial neural network (ANN) is an information processing system inspired by biological neural networks, whose main task is to predict the output set corresponding to the data set displayed as input. ANN method is one of the widely used machine learning methods recently [9].

ANN method bases normalized input data, makes generalization, and collects information during the training phase. In the testing phase, it predicts the normalized output that it has never seen before or that may occur in the future.

The normalization increases processing speed and accuracy. The "Min-Max Normalization" method is frequently used in the literature as the normalization method (Eq. 9).

$$X^{\iota} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{9}$$

where X_{min} is the minimum value of dataset, X_{max} is the maximum value of dataset, and X is the actual data.

The training performance varies based on optimization methods. The most popular optimization methods are variants of gradient-based back-propagation algorithms. Levenberg-Marquardt (LM) is the most used algorithm which is used as back-propagation algorithms. In addition, the performance of ANN depends on different criteria such as number of the hidden layer, number of the neurons in hidden layer, transfer function, and number of iteration. Some of the advantages of ANN are being tolerant of errors, adapting to environmental changes, working with incomplete information, and making decisions under uncertainty. Therefore, it can be used in stochastic situations such as nonlinear, complex, and uncertain relationships.

2.2.4. Deep learning method

Deep learning (DL) method is an AI method that uses a multi-layered (deep) architecture to match the relationships between inputs or observed features and the result. It has been used in many fields of science, business, and administration, as it is very good at discovering complex structures in high-dimensional data [25]. There is some advantage of using DL method according to machine learning. It is able to calculate in one layer instead of many layers, to discover even the parameters you need to define in machine learning, and to determine better parameters. The disadvantage of DL is that there is a risk of over-compliance problems [26].

2.2.5. Statistical performance criteria

The statistical performance criteria such as mean absolute percentage error (MAPE), mean square error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) are used to compare the prediction results of methods (Eqs.10-14).

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{|T_i - P_i|}{T_i}\right] x\ 100 \quad (10)$$

$$MSE = 1/N\sum_{i=1}^{N}(T_i - P_i)^2 \quad (11)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|T_i - P_i| \quad (12)$$

$$RMSE = \sqrt{1/N\sum_{i=1}^{N}(T_i - P_i)^2} \quad (13)$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}\left((T_i - \overline{T})(P_i - \overline{P})\right)}{\sqrt{\sum_{i=1}^{N}(T_i - \overline{T})^2 \sum_{i=1}^{N}(P_i - \overline{P})}}\right. \quad (14)$$

where T_i is i[th] actual data, $\overline{T}$ is the mean of actual data, P_i is the i[th] predicted output data and $\overline{P}$ is the mean of i[th] predicted output data in the dataset.

3. AN APPLICATION

The application consists of three phases. The first phase deals with determining the variables, the second phase deals with predicting the blood component demands, and the last phase deals with calculating the overstock and shortage in the blood bank inventory.

3.1. Determining variables

Fifteen independent variables that affect the blood demand were determined by using the brainstorming method with the doctors working in the blood bank (Table 2). As a result of the limited searches, the determined variables in this study were not seen in the literature.

Table 2. Variables affecting the amount of RBCs demanded

Notation	Variables
V_1	The demand for RBCs which couldn't provide by the blood bank in the last period (unit/week)
V_2	The demand for RBCs of BTC in the last period (unit)
V_3	The number of bed available in BTC (number)
V_4	The initiation of new treatment practices (number)
V_5	The total number of medical examination in BTC (number/week)
V_6	The total number of medical examination in the emergency room in BTC (number/week)
V_7	The number of inpatient in BTC (number/week)
V_8	The bed occupancy rate in BTC (number/week)
V_9	The type of BTC (AI, AII, B, C, D)
V_{10}	The number of surgery in BTC (number/week)
V_{11}	The province/district population where the BTC is located (number)
V_{12}	The number of public holidays (number/week)
V_{13}	The number of organ transplantation (number/week)
V_{14}	The number of immigrant (person/year)
V_{15}	The value of temperature (^oC)

BTC: Blood transfusion center

3.1.1. Predicting the number of RBCs demand

A data set was created for AI methods. The data set consisted of a 520 (5 transfusion centers x 104 weeks) x 15 (variables affecting the number of RBCs demand) size matrix. In the AI methods, the variables affecting the RBCs demand were determined as the input variable (Table 2). On the other hand, the weekly RBCs demand requested by the transfusion center from the blood bank was determined as the output variable (Table 3). In all AI methods, 364 units (520 x 0.70 = 364) were separated for training, 94 units (520 x 0.18 = 94) were separated for validation, and 62 units (520 x 0.12 = 62) were separated for testing.

Table 3. Data set used in AI methods

Observation Unit (week)	TC	Variables affecting the number of RBCs demanded					
		V_1	V_2	V_3	. . . .	V_{14}	V_{15}
1st observation unit	H_1 1st week	78	257	3363		2082	-7.1
2nd observation unit	H_1 2nd week	60	288	3363		2082	4.1
3rd observation unit	H_1 3rd week	144	472	3363		2082	4.7
.	.						
.	.						
.	.						
518th observation unit	H_5 518th week	19	209	1817		370	8.4
519th observation unit	H_5 519th week	10	232	1817		370	3
520th observation unit	H_5 520th week	11	223	1817		370	4.4

H_1: 1st transfusion center H_5: 5th transfusion center TC:Transfusion center

3.1.2. Decision tree method

In the DT method, the data set in Table 3 created for AI methods was used. In order to determine the optimum maximum tree depth, different values from 2 to 25 were tried and the value giving the lowest error rate was determined as 10 (Table 4).

Table 4. Determination of optimum parameters in DC method

Maximum tree depth	Lowest error
2	21.7
4	16.8
7	11.8
10	10.5
15	10.5
25	10.5

The first 3 and the last 3 predicted values obtained using DT method are given in Table 7.

3.1.3. Support vector machine method

Different levels were determined for the gamma parameter and kernel value of SVM method. Gamma parameter levels were determined as 0.000, 0.001, 0.010, 0.100, 1,000 and 10.00, C parameter levels were determined as 10, 100 and 1000. The optimum parameter levels were determined as 0.010 for the gamma parameter and 1000 for the C parameter with a 4.6% error rate (Table 5). Besides, the total number of support vectors used in the prediction was found to be 218.

Table 5. Optimum parameters of the SVM method

Gamma	Error rate		
	C		
	10	100	1000
0.000	29	27	16.6
0.001	27	16.9	10.5
0.010	19	10.1	4.6
0.100	16.2	6.7	27.6
1.000	23.6	14.5	13.7
10.00	28.1	27.1	28.3

The first 3 and the last 3 predicted values using SVM method are given in Table 7.

3.1.4. Artificial neural network method

In the ANN model, variables which affect the demand for RBCs was determined as input and the optimum number of RBCs was determined as output. Therefore, in the ANN model, a 15-input and 1-output feed-forward model was used to predict the optimum number of RBCs.

The data set was normalized to make more efficient of training data and shortened training period, using Eq. 9. Then, the dataset was divided three such as in other AI prediction methods

Multi-layer perceptron (MLP), which is effective in determining demand problems, was used in prediction [27]. Besides, the Levenberg-Marquardt algorithm, which is determined as the fastest algorithm in the MLP model, was preferred [28]. The number of hidden layers was also taken as 1 in the model because it has been demonstrated in practice that having more than one hidden layer slows down learning [29].

The other parameters were determined using trial and error method (Table 6).

Table 6. ANN parameters

Parameter	
Training algorithms	BR
Learning functions	Learngdm
Transfer function in the middle layer	Tansig
Number of neurons	20
Transfer function in the output layer	Tansig
Maximum error	10
Number of iterations	1000

BR: Bayesian Regularization

The R^2 value of the training, validation, testing, and all data set obtained by the ANN method is given in Figure 1. According to the figure, the rate of predicting the number of RBCs demand was calculated as 98.60%.

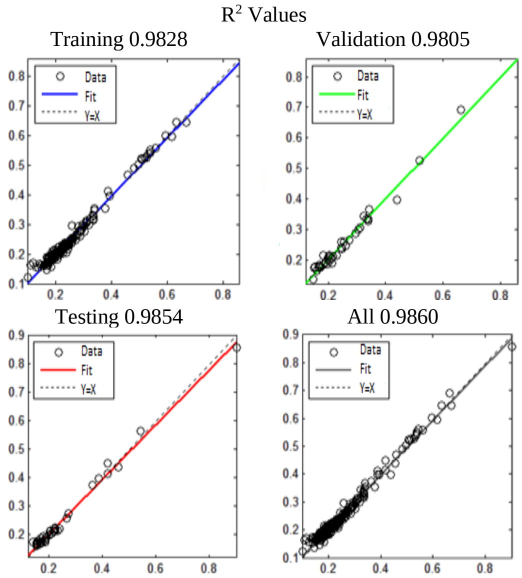

Figure 1. Results of ANN

3.1.5. Deep learning method

In the DL method, firstly, training, and testing data were normalized. The rectified linear unit (ReLU) function was used as the activation function.

The first 3 and the last 3 predicted values obtained by using the deep learning model are given in Table 7.

4. RESULTS AND DISCUSSIONS

To compare the prediction accuracy of the AI methods, five statistical performance criteria, including MSE, RMSE, MAPE, MAE, and R^2 were used. SVM predicted the closest value to the actual number of RBCs demand because it also has minimum prediction errors and largest R^2 value.

Table 7. Real and predicted by AI methods the number of RBCs

Week	Real RBCs demand (unit)	Predicted RBCs demand (unit)			
		DT	SVM	ANN	DL
1	144	148	148	149	163
2	194	187	194	194	173
3	184	187	184	184	157
.	.	.	.	.	.
.	.	.	.	.	.
60	164	159	169	172	161
61	232	232	231	231	218
62	223	220	223	223	210
MSE		687.79	36.983	97.076	419.44
RMSE		26.226	6.0814	9.8527	20.480
MAPE		4.8044	1.3831	2.0254	8.1671
MAE		13.037	3.2411	4.7481	15.403
R^2		0.9960	**0.9990**	0.9860	0.9770

In the blood banks, only the number of RBCs that can be requested should be sent to the transfusion centers, and underprediction/overprediction should be avoided. In Figures 2 - 5, 62-week (y axis) testing data set values were examined. In the figures, negative values (x axis) indicate unmet demand for RBCs, while positive values (x axis) indicate the number of RBCs sent in excess of demand. It had been determined that both the minimum deviation and the maximum deviation had the best value in the SVM method.

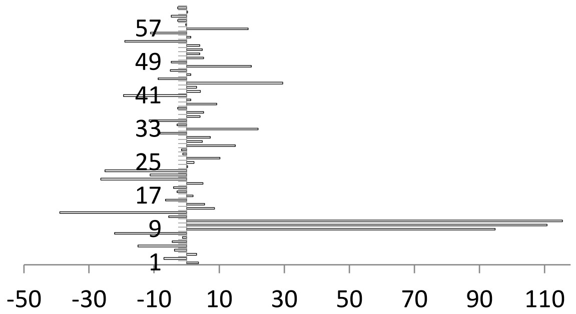

Figure 2. The deviation in unit of RBCs predicted and requested using the DT method

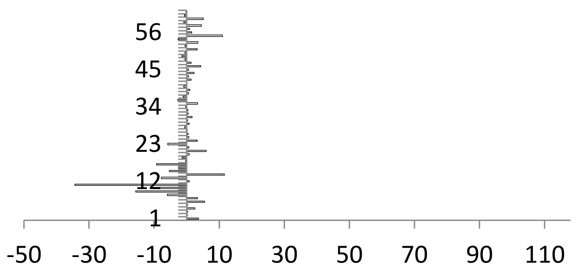

Figure 3. The deviation in unit of RBCs predicted and requested using the SVM method

When AI prediction methods were examined, 20 observation units of RBCs were underpredicted in the ANN method. However, in the SVM method, 24 observation units and 111 total units of RBCs were underpredicted. Similarly, in the SVM method, only 88 units of RBCs were overpredicted, although the 38-week observation unit was overpredicted (Table 8). If these values were averaged on a weekly observation unit basis; in SVM, there was an overprediction of 5.29 units and an underprediction of 3.03 units. Therefore, the SVM method should be preferred for prediction.

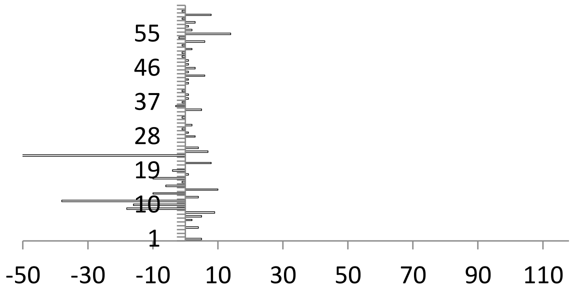

Figure 4. The deviation in unit of RBCs predicted and requested using the ANN method

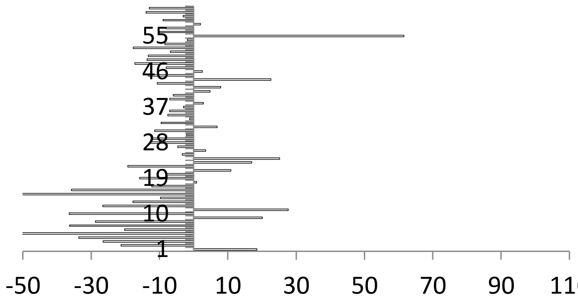

Figure 5. The deviation in unit of RBCs predicted and requested using the DL method

Table 8. Comparing the results of the methods

	Prediction methods			
	DT	SVM	ANN	DL
Underprediction (week)	30	24	20	46
Overprediction (week)	32	38	31	16
Underprediction (unit)	281	111	169	720
Overprediction (unit)	527	88	122	235
Overprediction (Avarage)	9.69	5.29	8.45	15.65
Underprediction (Avarage)	17.57	3.03	3.94	14.69
Maximum deviation	116	12	14	62
Minimum deviation	-39	-34	-44	-50

5. CONCLUSIONS

The transfusion of blood components to sick or injured persons is vital. In addition, the number of blood donations and the time of blood donation are completely variable. But, the blood components in stock should be transferred to the patient or the injured person in the required transfusion center at the required time, in the desired amount, and in the appropriate manner.

This study aimed to predict the blood component demand accurately that will occur in the next period by considering the variables that may affect the blood component demand.

The variables that affect the number of blood components to be demanded were determined differently from other study in literature. Then, AI methods were used to predict the number of demands by using these variables. Although quantitative prediction methods had been widely used on the demand predicting in the blood bank, there had been limited use on ANN and there was no study focusing on the other AI methods such as support vector machine and decision tree.

The proposed model was designed to reduce the demand prediction deviation of fresh frozen plasma and platelet suspension, which are other blood components. Therefore, the model has the ability to use different blood components. In addition, it can be applied to different blood centers. Even if the data changes, the model will be able to determine the demand prediction model that will minimize the deviation.

Author contributions: Literature review, Software, Data collection, Writing- S.H.G; Writing, Draft Preparation - S.B.
Conflict of Interest: No conflict of interest was declared by the authors.
Financial Disclosure: The authors declared that this study has received no financial support.

REFERENCES

[1] J.L. Carson, B.J. Grossman, S. Kleinman, A.T. Tinmouth, M.B. Marques, M.K. Fung, T. Gernsheimer, J.B. Holcomb, L.J. Kaplan, L.M. Katz, N. Peterson, G. Ramsey, S.V. Rao, J.D. Roback, A. Shander, A.A.R. Tobian, “Clinical practice guideline from the AABB: Red blood cell transfusion thresholds and storage,” Ann. Intern. Med., vol. 157, pp. 49-58, 2012.

[2] H. F Soares., E.F. Arruda, L. Bahiense, D.Gartner, L.A. Filho, “Optimisation and Control of The Supply of Blood Bags in Hemotherapic Centres via Markov Decision Process with Discounted Arrival Rate, ” Artif. Intell. Med., vol. 104, no. 101791, 2020.

[3] S.M. Fortsch, E.A. Khapalova, “Reducing uncertainty in demand for blood,” Oper. Res. Health Care., vol. 9, pp. 16-28, 2016.

[4] S. Dharmaraja, S. Narang, V. Jain, “A mathematical model for supply chain management of blood banks in India,” OPSEARCH, vol. 57, pp. 541-552, 2020.

[5] S. Moon, “Predicting the Performance of Forecasting Strategies for Naval Spare Parts Demand: A Machine Learning Approach,” Int. J. Manag. Sci. Eng. Manag., vol. 19, no. 1, pp. 1-10, 2013.

[6] B.M. Brentan, E. Luvizotto, M. Herrera, J. Izquierdo, R. Pérez-García, “Hybrid regression model for near real-time urban water demand forecasting,” J. Comput. Appl. Math., vol. 309, pp. 532-541, 2017.

[7] S. Mouatadid, J. Adamowski, “Using extreme learning machines for short-term urban water demand forecasting,” Urban Water J., vol. 14, no. 6, pp. 630-638, 2017.

[8] M.S. Al-Musaylh, R.C. Deo, J.F. Adamowski, Y. Li, “Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia,” Adv. Eng. Inform., vol. 35, pp. 1-16, 2018.

[9] W-H. Ho, C-S. Chang, “Genetic-algorithm-based artificial neural network modeling for platelet transfusion requirements on acute myeloblastic leukemia patients,” Expert Syst. Appl., vol. 38, no. 5, pp. 6319-6323, 2011.

[10] S. Haghani, M. Sedehi, S. Kheiri, “Artificial Neural Network to Modeling Zero-inflated Count Data: Application to Predicting Number of Return to Blood Donation,” J. Health Sci. Res., vol. 17, no. 3, 2017.

[11] F. Firouzi Jahantigh, B. Fanoodi, S. Khosravi, “A demand forcasting model for the blood platelet supply chain with Artificial Neural Network approach and ARIMA models,” Sci J Iran Blood Transfus Organ., vol. 14, no. 4, pp. 335-345, 2018.

[12] S. Singaravel, J. Suykens, P. Geyer, “Deep-learning neural-network architectures and methods: Using component based models in building-design energy prediction,” Adv. Eng. Inform., vol. 38, no. 2018, pp. 81-90, 2018.

[13] J. Bedi, D. Toshniwal, “Deep learning framework to forecast electricity demand,” Appl. Energy., vol. 238, no. 2019, pp. 1312–1326, 2019.

[14] R. Law, G. Li, D.K.C. Fong, H. Xin, “Tourism demand forecasting: A deep learning approach,” Ann. Tour. Res., vol. 75, no. 2019, pp. 410–423, 2019.

[15] D. Pi, AW. Shih, L. Sham, D. Zamar, K. Roland, M. Hudoba, “Establishing performance management objectives and measurements of red blood cell inventory planning in a large tertiary care hospital in British Columbia, Canada,” ISBT Sci. Ser., vol. 14, pp. 226–238, 2019.

[16] L. Cohen, L. Manion, K. Morrison, Research Methods in Education (6th Edition), London: Routledge. 2000.

[17] L. Breiman, J. Friedman, C.J. Stone, R.A. Olshen, Classification and Regression Trees, Chapman& Hall CRC Presss. 1984.

[18] A.J. Smola, B. Schölkopf, “A tutorial on support vector regression,” Stat. Comput., vol. 14, no. 3, pp. 199–222, 2004.

[19] D. Basak, S. Pal, D.C. Patranabis, “Support vector regression,” Neural Information Processing – Letters and Reviews, vol. 11, no. 10, pp. 203–224, 2007.

[20] B.S. Khehra, A.P.S. Pharwaha, “Classification of Clustered Microcalcifications using MLFFBP-ANN and SVM,” Egypt. Inform. J., vol. 17, no. 1, pp. 11-20, 2016.

[21] V.Vapnik, S. Golowich, A. Smola, “Support vector method for function approximation, regression estimation, and signal processing,” Adv. Neural Inf. Process Syst., vol. 281–287, 1996.

[22] D. Meyer, F. Leisch, K. Hornik, “The support vector machines under test,” Neurocomputing, vol. 55, pp. 169–186, 2003.

[23] E.A. Zanaty. “Support Vector Machines (SVMs) versus Multilayer Perception (MLP) in data classification,” Egypt. Inform. J., vol. 13, no. 3, pp. 177-183, 2012.

[24] C. Cortes, V. Vapnik, “Support-Vector Networks,” Machine Learning, vol. 20, pp. 273-297, 1995.

[25] Y. LeCun, Y. Bengio, G. Hinton, “Deep learning,” Nature, vol. 521, pp. 436–444, 2015.

[26] S.B. Golas, T. Shibahara, S. Agboola, H. Otaki, J. Sato, T. Nakae, T. Hisamitsu, G. Kojima, J. Felsted, S. Kakarmath, J. Kvedar, K. Jethwani, “A machine learning model to predict the risk of 30-day

readmissions in patients with heart failure: a retrospective analysis of electronic medical records data," BMC Med. Inform. Decis. Mak., vol. 18, no. 1, pp. 44, 2018.
[27] E. Öztemel, Yapay Sinir Ağları. 4. Baskı, Papatya Bilim Üniversite Yayıncılığı, İstanbul. 2016.
[28] M.J. Madić, M.R. Radovanović, "Optimal selection of ANN training and architectural parameters using Taguchi method: A case study," FME Trans., vol. 39, pp. 79-86, 2011.
[29] M. Timothy, Practical Neural Network Recipes in C++. Academic Press, pp. 174-175, 1993.