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Artificial Neural Network Based Prediction Model Back Propagation on Blood Demand and Blood Supply

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Abstract

The balance between blood demand and supply at the Indonesian Red Cross Blood Transfusion Unit (UTD-PMI) is crucial. This condition needs to be maintained to reduce unused or expired blood supplies. Despite the situation at UTD-PMI, where the blood supply exceeds the demand, there is still a shortage of blood when needed by patients. This research aims to model the prediction of blood demand and supply for each blood type using the Back Propagation artificial neural network approach. Data from the last 3 years, from 2020 to 2022, were utilized in this research process. There are three stages in this research process. The first stage involves the training process, using data from January 2020 to December 2021. The testing process utilizes data from January 2021 to December 2022. The prediction process involves displaying forecasted data for the next 12 months from January to December 2023. The accuracy of the calculations is assessed using the Mean Square Error (MSE). Ultimately, the research results present the prediction model for the four blood types regarding blood demand and supply. These findings can serve as a reference for regulating future blood donation activities carried out by the UTD-PMI.

Keywords: neural network; backpropagation; blood demand; blood supply

1. Introduction

The blood transfusion process in hospitals occurs every day. Meanwhile, the blood supply at blood bag storage facilities such as public hospitals and the Indonesian Red Cross Blood Transfusion Unit (UTD-PMI) experiences fluctuations. This is also the case at UTD-PMI Kupang City, which serves the blood demand in 12 hospitals and clinics located in Kupang (city or region). Based on data from UTD-PMI, in 2022, the blood supply (27,657 bags) was greater than the blood demand (24,351 bags).

The surplus in the number of blood bags in comparison to the demand leads to a considerable amount of unused or expired blood. Furthermore, another issue arises in critical situations and becomes a common problem when patients urgently require blood, but the blood supply is depleted. Family members of patients make efforts, such as searching for the nearest relatives or voluntary donors to donate blood.

The surplus of blood bag supplies compared to the demand leads to a significant amount of unused or expired blood. Furthermore, another issue arises in critical situations and becomes a common problem when patients urgently require blood, but the blood supply is depleted. Efforts made by the patients' families include searching for the nearest relatives or voluntary donors to donate blood.

This issue requires a solution for UTD-PMI Kupang City, which is tools to predict blood demand and supply for each blood type in the upcoming month. The prediction results serve as a basis for organizing blood donation activities to reduce expired blood due to surplus supply. Scheduling blood donation activities can be adjusted based on the current blood demand and supply predictions.

Efforts to maintain the balance between blood demand and supply have been made. MOUNCIF Chaimae integrated research on blood collection management to address blood transfusion issues, creating awareness and knowledge of blood collection, and promoting blood donation [1]. Daily blood bag supply management with daily demand forecasting helps address patients' difficulties in obtaining blood quickly, especially when patients are in need of platelets [2]. A GAMS model was developed to address the uncertainty of blood demand and determine the location of blood supply centers that remain operational during disasters [3]. Information systems were also modeled to manage the imbalance between blood demand and supply [4].

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A model utilizing the Epsilon-Constraint method is used to address complex stochastic issues related to blood supply and demand [5]. Operational scheduling platforms need to be provided, including blood demand forecasting, blood donation site locations, and supply chain security for the specified timeframe [6]. This is done to optimize daily inventory levels and minimize blood bag expiration and shortages [7].

The use of prediction methods is applied in various fields. In agriculture, stock price prediction for agriculture and mining using Artificial Neural Networks (ANN) demonstrates that the deviation of the Back propagation ANN values from the actual values is relatively low. This is supported by the values of MAE, MSE, RMSE, and MAPE corresponding to the use of varying hidden layers and epochs [8]. Predicting agricultural product sales can be effectively achieved using Neural Networks (both Backpropagation and Recurrent NN), especially for weekly and monthly data, and it is suitable for large-scale data. When compared to ARIMA models, this prediction method is more suitable for monthly data [9].

In the field of trading, machine learning-based predictions are widely used nowadays. Some of these include the analysis and prediction of five multivariate data models using Backpropagation ANN. The accuracy and execution time vary in the prediction process for these five multivariate data models, considering different variables and data sizes [10]. Backpropagation Neural Networks are highly effective for predicting bitcoin prices compared to ARIMA models [11]. When predicting stock price patterns, using Backpropagation ANN is more effective than deep learning fuzzy models, and the prediction results are influenced by the range of transaction data used [12]. The accuracy of prediction results is affected by the selection of weight values in the single exponential smoothing method. Apart from comparing three forecasting methods, optimization techniques are used in weight selection, and accuracy is measured using MAPE and RMSE [13].

In the field of healthcare, prediction methods are also widely used. Machine learning techniques, such as Neural Networks (NN), are employed to predict glucose levels up to 1 hour ahead. The results obtained match the accuracy of state-of-the-art technology. The accuracy of this method is assessed using RMSE and a specialized glucose matrix called the surveillance error grid (SEG) [14]. The use of trained artificial neural network models can reduce daily costs by approximately 29% compared to current policies, which is crucial in addressing large-scale optimization problems, as seen in the case of blood supply chain management [15].

Apart from machine learning, Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA, Seasonal Exponential Smoothing Method (ESM), and Holt-Winters models are used in the prediction process. In specific cases, the use of ESM and ARIMA yields better results than machine learning, as indicated by the error values produced [16].

Other research related to blood supply at UTD-PMI has also been conducted. Forecasting the supply of whole blood (wb) in PMI Surabaya using neural networks [17]. Forecasting the demand for Packet Red Cells (PRC) blood at PMI Surabaya using the Backpropagation Artificial Neural Network method [18]. Blood supply control for patients with low hemoglobin levels using the backpropagation method [19]. Predicting the number of blood donations and requests at the Indonesian Red Cross (PMI) Medan using the ID3 method [20]. In addition, in specific cases, such as emergencies and disasters, research related to blood supply and demand has been conducted. This includes studies related to efficient blood supply chains during crises. Neural learning methods are used, considering six blood supply and demand areas during disasters [21]. There is a need for a flexible, strong, and stable blood supply chain network design. Integer programming models are used to support location and capacity selection decisions simultaneously [22], [23]. Supply chains considering risks such as disaster scenarios. With the Lagrangian relaxation algorithm, this problem can be addressed [24], [25]. Hospital blood banks need integration and coordination of needs with the Central Blood Bank to avoid negative impacts on patients due to damaged products. One method to address demand uncertainty is through stochastic programming using Monte Carlo simulation [26]. In addition to Monte Carlo simulations, stochastic optimization models can be performed with machine learning. Artificial neural network models, one of the machine learning techniques, can reduce costs in dealing with large-scale optimization prediction solutions, including blood unit deliveries in hospitals [15], [27].

This research aims to predict blood demand and supply for each blood type using 36 data points, representing the past 3 years. The method employed is Backpropagation Neural Networks (BP-NN). A total of 8 input data variables are used to predict 8 output models, which encompass 4 demand models for 4 blood types and 4 supply models for blood types. The accuracy of prediction results is assessed using the Mean Square Error (MSE) parameter.
This research places a greater emphasis on efforts to maintain a balance between blood demand and supply. The predicted data for the upcoming months can serve as a reference for making decisions regarding blood donation activities in collaboration with UTD-PMI.

2. Research Methods

This research is an experimental study with the following stages:

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The research begins with problem identification through direct observation, surveys, and interviews with UTD-PMI Kupang City.

Data Collection: The results of the interviews are followed by data collection. Blood demand and supply data are gathered from UTD-PMI.

Data Preprocessing: This process involves filtering the required data, such as the number of blood demand data per blood type per month over the last 3 years.

Data Selection: Data selection is performed to extract the demand data for each blood type for every month over the last 3 years.

Implementation of the Artificial Neural Network-Backpropagation (ANN-BP) Method: The ANN-BP method is applied to predict blood demand for each blood type using the collected data.

Analysis: Analysis is used to evaluate the performance of the ANN-BP method, including the training, testing, and prediction stages.

Conclusion: The conclusion consists of the performance evaluation of the ANN-BP method in predicting blood demand and supply.

The data in Table 1 and Table 2 represent the blood demand and supply for each blood type over the last three years.

Table 1. Blood Demand for the Last 3 Years

Year	Blood Types			
	A	B	AB	O
Jan-20	445	729	187	988
Feb-20	322	352	130	544
Mar-20	208	332	80	686
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
Oct-22	355	625	93	888
Nov-22	366	708	86	875
Dec-22	272	761	83	774

Table 2. Blood Supply for the Last 3 Years

Year	Blood Types			
	A	B	AB	O
Jan-20	1068	1509	255	2385
Feb-20	1005	1452	372	2109
Mar-20	945	1266	246	2037
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
Oct-22	846	1515	267	2025
Nov-22	870	1293	186	1626
Dec-22	966	1308	276	1308

From Table 1 and Table 2, the blood demand and supply for the last 3 years are depicted in Figure 1 and Figure 2, respectively.

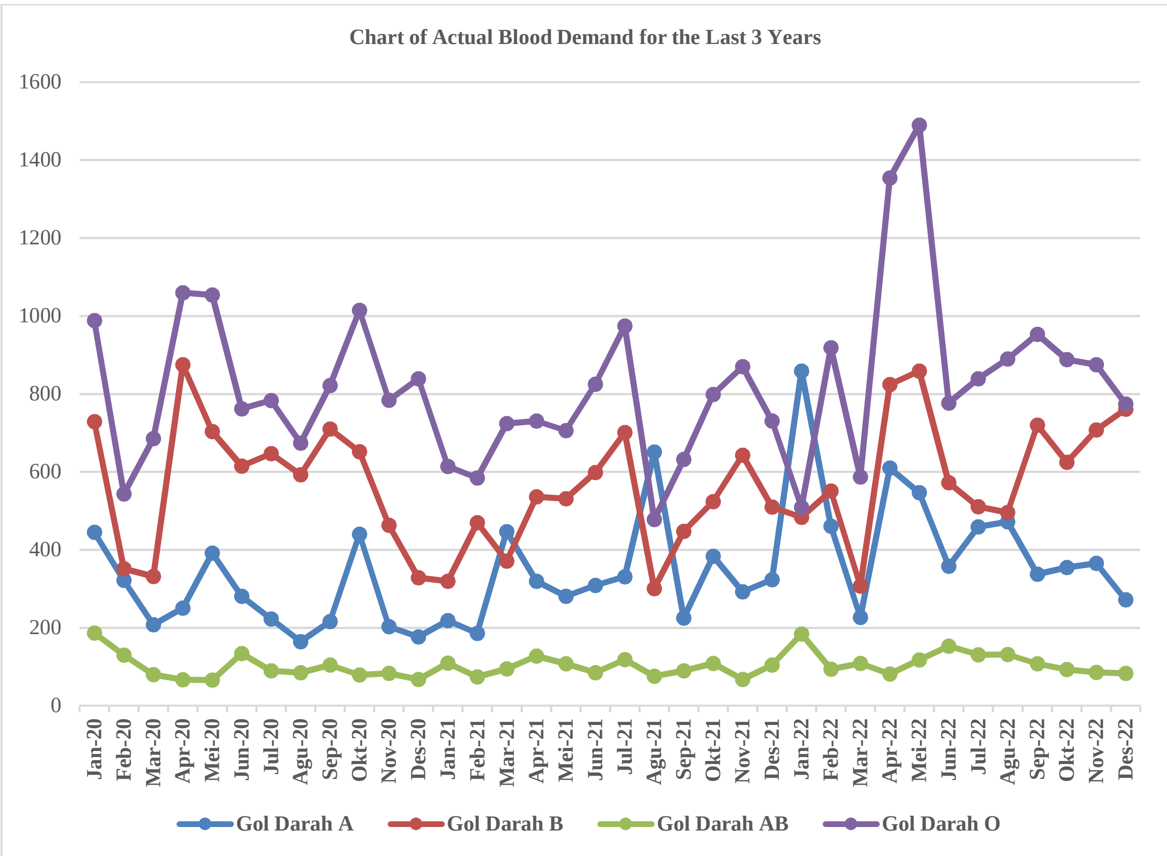

Figure 1. Chart of Blood Demand for the Last 3 Years

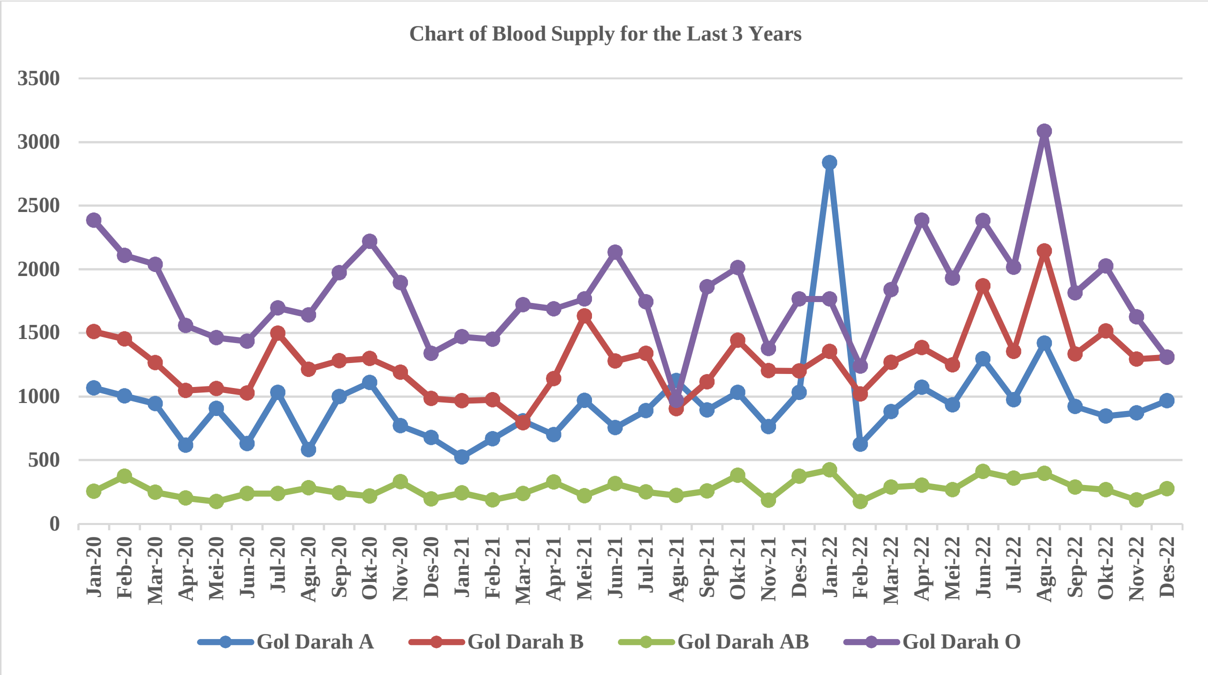

Figure 2. Chart of Blood Supply for the Last 3 Years

The Artificial Neural Network (ANN) learning used in this study employs the backpropagation algorithm, which is a part of supervised learning algorithms. The interconnected weights between neurons in the hidden layers are adjusted. In the input layer, data patterns are provided as training patterns, which are then forwarded to the units in the hidden layer before reaching the units in the output layer. Subsequently, the units in the output layer respond as the network's output. If the network's output does not match the expected output, the error is propagated backward to the hidden layers and further passed on to the units in the input layer. Accuracy is measured using the Mean Square Error (MSE) as a performance parameter. Figure 3 depicts the architecture of the network used.

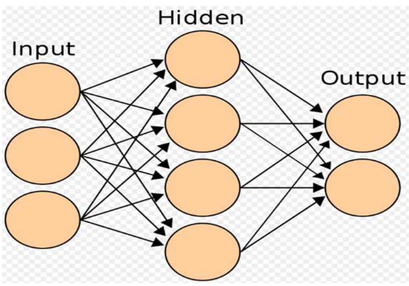

Figure 3. ANN Architecture

There are three stages involved in the Backpropagation algorithm:

Training Stage: The training data used consists of 24 months, from January 2020 to December 2021. The training data comprises 12 months (in the year 2020), and the target data consists of 12 months (in the year 2021). The neural network parameters used in this stage are:

The number of neurons is set to 100; The activation function uses the binary sigmoid. The activation function for binary sigmoid is expressed as Formula 1.

$$f(x) = \frac{1}{1+e^{-x}} \quad (1)$$

With derivatives:

$$f'(x) = f(x)\big(1 - f(x)\big) \quad (2)$$

The training function uses the Levenberg-Marquardt function as in Formula 2.

Testing Stage: There are several differences between the training stage and the testing stage, including the data used. In the testing stage, data from a total of 24 months is employed. The testing data spans from January 2021 to December 2021, and the target data covers the period from January 2022 to December 2022.

Prediction Stage: The prediction stage involves forecasting the demand and supply of blood bags for each blood type in the upcoming period, which is from January 2023 to December 2023. To determine the accuracy of the ANN method, Mean Square Error (MSE) is calculated using the formulations shown in Formula 3 and 4.

$$e_t = X_t - X_{t-1} \quad (3)$$

$$MSE = \frac{1}{n}\sum e_t^2 \quad (4)$$

e_t is the difference between the target value and the prediction, X_t is the target data, X_{t-1} is the predicted data, and n is the number of data.

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3. Results and Discussions

3.1 Result

The input data model used consists of a total of 8 types, which are blood demand for each blood type and blood supply for each blood type.

The simulation results using ANN, including the number of hidden layers, the number of epochs, the activation function used, and performance, are displayed in Figure 4.

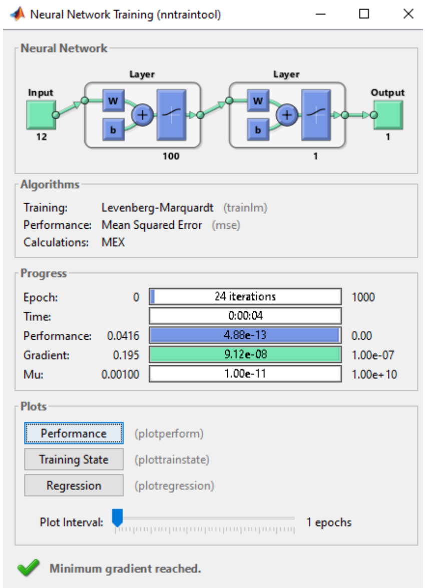

Figure 4. ANN Training Phase Simulation

Training Phase: The target data and results during the training phase for blood type A are displayed in Table 3.

Table 3. Data for target and results of demand and supply for blood type A

Periode	Demand		Supply	
	Target	Result	Target	Result
Jan-21	219	219	525	525
Feb-21	186	186	666	666
Mar-21	447	447	807	807
Apr-21	320	320	699	699
May-21	281	281	969	969
Jun-21	309	309	756	756
Jul-21	331	331	888	888
Aug-21	651	651	1125	1125
Sep-21	225	225	894	894
Oct-21	384	384	1032	1032
Nov-21	293	293	762	762
Dec-21	324	324	525	525

Testing Phase: The results of the simulation using NN, along with the target data and results during the testing phase, are shown in Figure 5. Table 4 presents the demand and supply data as well as the MSE values for each month and the average MSE during the testing phase.

Prediction Stage: This stage presents the predicted data for blood demand and supply for blood type A. Figure 6 displays the graph depicting the prediction of blood demand and supply for blood type A in the year 2023.

Table 5 provides the predicted data for blood demand and supply in 2023, along with the differences.

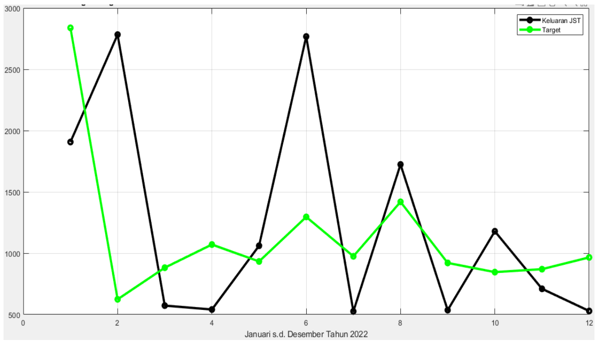

Figure 5. ANN Testing Phase Simulation

Table 4. Target and actual data for blood demand and supply for blood type A

Period	Demand			Supply		
	Exam Results	Data Target	MSE	Exam Results	Data Target	MSE
Jan-22	641	859	0,2290	2838	1907	0,2157
Feb-22	288	461	0,0884	624	2783	0,6273
Mar-22	379	227	0,0640	882	573	0,0991
Apr-22	293	610	0,0863	1071	541	0,1055
May-22	697	547	0,2413	933	1061	0,0566
Jun-22	662	358	0,1792	1296	2767	0,5951
Jul-22	497	459	0,0777	975	526	0,1204
Aug-22	387	472	0,0768	1419	1724	0,1229
Sep-22	540	338	0,0840	921	536	0,1261
Oct-22	567	355	0,0865	846	1179	0,0563
Nov-22	845	366	0,3933	870	710	0,0909
Dec-22	561	272	0,0794	966	529	0,1265
	Average MSE		0,1405	Average MSE		0,1952

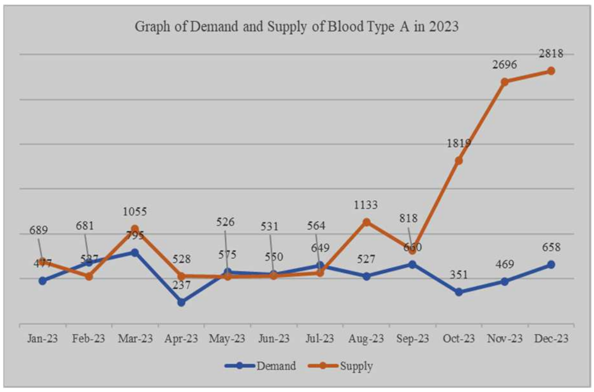

Figure 6. ANN Testing Stage Prediction

Table 5. Predicted Data for Blood Demand and Supply for Blood Type A in 2023

Period	Demand	Supply	Difference
Jan-23	477	689	212
Feb-23	681	527	154
Mar-23	795	1055	260
Apr-23	237	528	291
May-23	575	526	49
Jun-23	550	531	19
Jul-23	649	564	85
Aug-23	527	1133	606
Sep-23	660	818	158
Oct-23	351	1819	1468

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Period	Demand	Supply	Difference
Nov-23	469	2696	2227
Dec-23	658	2818	2160

To determine the blood demand and supply for blood type B, the same steps are followed as for blood type A.

Training Phase: The target data and results during the training phase for blood type A are displayed in Table 6.

Table 6 shows that the target values and the results for blood demand are identical. Similarly, for blood supply, the target values and the results are also the same. This training stage indicates that the Levenberg-Marquardt function used has high accuracy. During the training phase, the ANN-Back Propagation has learned well to predict the training data, indicating a good model at this stage.

Tabel 6. Data for target and results of demand and supply for blood type B

Period	Demand		Supply	
	Target	Result	Target	Result
Jan-21	320	320	966	966
Feb-21	470	470	975	975
Mar-21	371	371	792	792
Apr-21	536	536	1140	1140
May-21	531	531	1632	1632
Jun-21	599	599	1278	1278
Jul-21	701	701	1338	1338
Aug-21	301	301	903	903
Sep-21	448	448	1116	1116
Oct-21	524	524	1443	1443
Nov-21	643	643	1203	1203
Dec-21	510	510	1293	1293

Table 7. Target and actual data for blood demand and supply for blood type B

Period	Demand			Supply		
	Exam Results	Data Target	MSE	Exam Results	Data Target	MSE
Jan-22	301	484	0,1570	1353	792	0,1086
Feb-22	850	551	0,3852	1020	876	0,0876
Mar-22	357	307	0,1109	1269	1620	0,1196
Apr-22	593	824	0,0591	1383	2138	0,4503
May-22	301	859	0,2284	1248	854	0,1128
Jun-22	339	572	0,2372	1869	804	0,1147
Jul-22	343	511	0,2298	1353	862	0,1273
Aug-22	301	496	0,2605	2145	1581	0,0759
Sep-22	745	720	0,1686	1335	1629	0,0808
Oct-22	303	625	0,3063	1515	1677	0,0855
Nov-22	309	708	0,3085	1200	1607	0,0669
Dec-22	386	761	0,2044	1308	793	0,2585
	Average MSE		0,2213	Average MSE		0,1407

In Table 7, the testing phase shows that the MSE values are smaller for blood supply data compared to blood demand data. The testing phase for blood supply for blood type B is better than for blood demand.

Table 8. Predicted Data for Blood Demand and Supply for Blood Type B in 2023

Period	Demand	Supply	Difference
Jan-23	579	2145	1566
Feb-23	845	2136	1291
Mar-23	301	2104	1803
Apr-23	679	2078	1399
May-23	447	795	348
Jun-23	489	2004	1515
Jul-23	609	2121	1512
Aug-23	301	2144	1843
Sep-23	873	1870	997
Oct-23	301	2082	1781
Nov-23	596	2099	1503
Dec-23	333	2139	1806

Table 8 shows that in the prediction phase, the predicted blood demand and supply for the next 12 months are displayed. The historical data indicates that for blood type B, the supply has been greater than the demand. The prediction results also follow this pattern, with significant differences observed for each period.

Training Phase for Blood Type AB as inTable 9 reveals the same pattern observed during the training phase for the two previous blood types. For blood type AB, the target values and results are identical, both for demand and supply. The Levenberg-Marquardt function used during the training phase demonstrates high accuracy. This model performs very well during the training stage with the available data.

Table 9. Data for target and results of demand and supply for blood type AB

Period	Demand		Supply	
	Target	Result	Target	Result
Jan-21	110	110	243	243
Feb-21	74	74	186	186
Mar-21	95	95	237	237
Apr-21	128	128	327	327
May-21	108	108	219	219
Jun-21	85	85	315	315
Jul-21	119	119	249	249
Aug-21	76	76	222	222
Sep-21	90	90	258	258
Oct-21	109	109	381	381
Nov-21	68	68	183	183
Dec-21	105	105	372	372

Table 10 displays the MSE values as an indicator of the testing phase, comparing the target and actual results. The average MSE values for blood demand in blood type AB are better than those for blood supply.

Prediction Stage in Table 11 presents the predicted blood demand and supply results for the next 12 months for blood type AB. The comparison of the predicted blood demand and supply data shows a significant difference. However, the difference is not as large as the one observed for blood type B.

Table 10. Target and actual data for blood demand and supply for blood type AB

Period	Demand			Supply		
	Exam Results	Data Target	MSE	Exam Results	Data Target	MSE
Jan-22	78	184	0,0474	423	375	0,5091
Feb-22	87	94	0,0811	174	362	0,4488
Mar-22	158	109	0,2499	288	404	0,5904
Apr-22	171	82	0,3407	303	312	0,3291
May-22	93	118	0,0626	267	291	0,3089
Jun-22	123	153	0,0839	411	273	0,3029
Jul-22	112	131	0,0679	357	397	0,5278
Aug-22	178	132	0,3849	396	417	0,5638
Sep-22	172	108	0,2931	288	418	0,5210
Oct-22	164	93	0,2167	267	402	0,4616
Nov-22	168	86	0,2561	186	360	0,3758
Dec-22	162	83	0,2004	276	397	0,4692
	Average MSE		0,1904	Average MSE		0,4507

Table 11. Predicted Data for Blood Demand and Supply for Blood Type AB in 2023

Period	Demand	Supply	Difference
Jan-23	183	413	230
Feb-23	183	377	194
Mar-23	164	393	229
Apr-23	167	414	247
May-23	184	415	231
Jun-23	184	411	227
Jul-23	177	385	208
Aug-23	171	395	224
Sep-23	181	391	210
Oct-23	176	404	228
Nov-23	178	385	207
Dec-23	169	370	201

Training Phase for Blood Type O in Table 12 demonstrates that the Levenberg-Marquardt function during the training phase for blood type O is highly effective, resulting in identical values for blood demand and supply targets and results.

Table 12. Data for target and results of demand and supply for blood type O

Periode	Demand		Supply	
	Target	Result	Target	Result
Jan-21	614	614	1470	1470
Feb-21	585	585	1449	1449
Mar-21	724	724	1722	1722
Apr-21	731	731	1689	1689
May-21	706	706	1767	1767
Jun-21	825	825	2133	2133
Jul-21	974	974	1743	1743
Aug-21	478	478	969	969
Sep-21	632	632	1863	1863
Oct-21	799	799	2013	2013
Nov-21	870	870	1377	1377
Dec-21	731	731	1767	1767

Testing Phase in Table 13 displays the target and actual data for blood demand and supply for blood type O. The average MSE values for blood supply in blood type O are better than those for blood demand.

Prediction Stage in Table 14 provides the predicted blood demand and supply results for the next 12 months for blood type O. The comparison of the predicted blood demand and supply data shows significant differences at the beginning of the year (from January 2023 to March 2023). This pattern is also repeated in May, June, August, and September. The large differences indicate a surplus of blood bags during those months.

Table 13. Target and actual data for blood demand and supply for blood type O

Peiod	Demand			Supply		
	Exam Results	Data Target	MSE	Exam Results	Data Target	MSE
Jan-22	1258	509	0,2965	1767	2333	0,1200
Feb-22	860	919	0,0400	1239	1431	0,0340
Mar-22	1426	587	0,4781	1839	1057	0,1060
Apr-22	478	1354	0,0840	2385	975	0,1336
May-22	615	1490	0,0783	1929	1724	0,0308
Jun-22	1464	777	0,4581	2382	3071	0,4201
Jul-22	1274	839	0,2690	2016	2125	0,0638
Aug-22	1476	890	0,4914	3084	1007	0,1759
Sep-22	482	953	0,2197	1815	2942	0,2586
Oct-22	965	888	0,0755	2025	2494	0,1104
Nov-22	1473	875	0,3901	1626	2451	0,1004
Dec-22	1428	774	0,3405	1308	3020	0,2813
	Average MSE		0,2684	Average MSE		0,1529

Table 14. Predicted Data for Blood Demand and Supply for Blood Type O in 2023

Period	Demand	Supply	Difference
Jan-23	616	3080	2464
Feb-23	1489	2999	1510
Mar-23	677	2393	1716
Apr-23	538	988	450
May-23	591	2519	1928
Jun-23	588	2948	2360
Jul-23	1226	1060	166
Aug-23	1428	2588	1160
Sep-23	478	2624	2146
Oct-23	959	970	11
Nov-23	1039	1208	169
Dec-23	479	1024	545

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As a contribution from this research, Table 15 and Table 16 display the predicted results of blood demand and supply per blood type for the months from January 2023 to December 2023. The predicted data in these tables can serve as a reference for blood donation activities during those months to avoid excess blood expiration.

Table 15. Data on the prediction of monthly blood demand in 2023 for each blood type

Period	Blood Types			
	A	B	AB	O
Jan-23	477	579	183	616
Feb-23	681	845	183	1489
Mar-23	795	301	164	677
Apr-23	237	679	167	538
May-23	575	447	184	591
Jun-23	550	489	184	588
Jul-23	649	609	177	1226
Aug-23	527	301	171	1428
Sep-23	660	873	181	478
Oct-23	351	301	176	959
Nov-23	469	596	178	1039
Dec-23	658	333	169	479

Table 16. Data on the prediction of monthly blood supply in 2023 for each blood type

Period	Blood Types			
	A	B	AB	O
Jan-23	689	2145	413	3080
Feb-23	527	2136	377	2999
Mar-23	1055	2104	393	2393
Apr-23	528	2078	414	988
May-23	526	795	415	2519
Jun-23	531	2004	411	2948
Jul-23	564	2121	385	1060
Aug-23	1133	2144	395	2588
Sep-23	818	1870	391	2624
Oct-23	1819	2082	404	970
Nov-23	2696	2099	385	1208
Dec-23	2818	2139	370	1024

3.2 Discussion

The training phase, for the 8 types of processed training data models, demonstrates high accuracy. The available data has identical target values and actual data for blood demand and supply for each blood type. The Levenberg-Marquardt function used in this phase exhibits a high level of accuracy. The errors generated approach a value close to 0. The MSE values for the 8 training data models are shown in Table 17.

Table 17: The comparison of MSE values and the number of iterations during the training phase

	Blood Type	MSE	Number of epochs
Demand	A	1,1117E-14	6 iteration
	B	3,0251E-12	32 iterations
	AB	1,5173E-20	10 iterations
	O	2,4648E-12	40 iterations
Supply	A	4,8781E-13	24 iterations
	B	2,4792E-15	59 iterations
	AB	2,0584E-17	9 iterations
	O	1,7734E-11	73 iterations

Table 17 shows that the highest number of iterations occurs in the blood type O data model for both demand and supply. Meanwhile, the lowest number of iterations is observed in the blood type A data model for demand and blood type AB for supply.

In the testing phase, the MSE values vary for the 8 data model types. For blood demand, the lowest MSE is observed in the blood type A data model, and the highest is in blood type O. For blood supply, the lowest MSE is found in the blood type B data model, and the highest is in blood type AB.

Table 18. The MSE values for the 8 data model types in the testing phase

Blood Type	Average MSE	
	Demand	Supply
A	0,1405	0,1952
B	0,2213	0,1407
AB	0,1904	0,4507
O	0,2684	0,1529

In the prediction phase, the predicted results are shown for the period from January 2023 to December 2023 for blood demand and supply for each blood type. It is evident that there is a significant stock of blood supply for every blood type. These predicted results serve as a reference to ensure that blood donation activities are organized in such a way that blood does not expire, thereby preventing wastage.

4. Conclusion

The Levenberg-Marquardt training function used in ANN-BP for the 8 data model types exhibits very high accuracy. Blood demand and supply predictions for the 4 blood types have been successfully obtained. The low MSE values in the testing process indicate that the ANN-BP method should be used to predict the amount of blood demand and supply for each blood type in the next 1-year period. Machine learning with the Back Propagation-Neural Network method is highly reliable in predicting blood demand and supply for each blood type. As a reference for the Indonesian Red Cross-Blood Transfusion Unit (UTD-PMI) in Kupang City, the predicted results for blood demand and supply can be used to guide blood donation activities. Although this research successfully predicts blood demand and supply for the next year with a small error during the testing phase, there are still shortcomings. As shown in Table 14, there is a significant difference between the blood demand and supply units. There is a need for an additional system that can manage the supply chain between blood demand and supply, integrated with the demands of multiple hospitals.

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