Electronic Journal of Education, Social Economics and Technology
Vol. 6, No. 2, (2025), pp. 1~12, Article ID: 1022
ISSN 2723-6250 (online)
DOI: https://doi.org/10.33122/ejeset.v6i2.1022

SAINTIS publishing

Research Article

Blood Bag Stock Availability Forecasting System at PMI UDD Lhokseumawe City Using the Random Forest Method

Rizka Hilmi Putri, Eva Darnila*, Lidya Rosnita

Department of Informatics Engineering, Universitas Malikussaleh, Lhokseumawe, Indonesia, 24352
*Corresponding Author: eva.darnila@unimal.ac.id | Phone: +6282285866390

ABSTRACT

This study aims to develop a blood bag inventory forecasting system at the Blood Donation Unit (UDD) of the Indonesian Red Cross (PMI) in Lhokseumawe City and the UDD of PMI North Aceh using the Random Forest (RF) algorithm. The background of this study focuses on the imbalance between demand and availability of blood bags, which can have serious implications for patient safety. Using historical data comprising 574 records from the period 2022 to 2025, this study employs a quantitative approach with variables such as month, year, PMI location, blood type, incoming blood, and blood distribution. The research methodology includes preprocessing and feature engineering steps, resulting in 17 features for training the Random Forest (RF) model. This process was completed with hyperparameter optimization using RandomizedSearchCV to improve model accuracy. The results show that the PMI UDD Aceh Utara achieved excellent performance with an RMSE of 9.113 for incoming blood and 8.750 for distribution. On the other hand, the UDD PMI Lhokseumawe had an RMSE of 24.635 and 22.737, respectively. Comprehensive predictions for the 2025-2030 period indicate an optimistic projection with 94% surplus months and a positive net balance of 4,406.7 bags. The implemented web-based system supports real-time forecasting and strategic decision-making in blood bag inventory management within the PMI organization.

Keywords: Forecasting; Blood; Transfution; Stock; RF

1. INTRODUCTION

Forecasting is a process used to predict the future value of variables based on historical data. In various sectors, including healthcare, forecasting plays a crucial role in more informed decision-making. The accuracy of forecasting results significantly impacts the effectiveness of implemented strategies, such as in inventory management, which aims to balance resource availability and demand (Bamba et al., 2021). In the healthcare context, accurate forecasting is essential to anticipate the need for vital resources, such as blood bags.

According to the WHO (2021), approximately 118.5 million bags of blood are collected annually worldwide. However, developing countries like Indonesia still face a significant challenge in the form of a gap between blood demand and availability. This imbalance is exacerbated by various factors, including fluctuations in the number of donors, limited blood shelf life, and unpredictable demand dynamics (Setiawan, 2020). In Indonesia, the average annual blood demand reaches 5.1 million bags, yet the level of blood supply remains suboptimal. With a limited shelf life of blood red blood cells 35–42 days, platelets 5 days, and fresh frozen plasma 1 year stock management is crucial. The blood donation rate of only 6–10 donors per 1,000 residents also indicates that the supply system is not robust enough to meet demand sustainably (Primasari et al., 2021).

A similar situation occurs at the Lhokseumawe City Red Cross (PMI) Blood Donor Unit (UDD). Data from the Lhokseumawe City Red Cross (PMI) (2023) indicates a 23% imbalance between blood bag demand and supply throughout the year. Fluctuating demand, particularly during holidays or pandemics, often results in blood supplies not meeting actual needs. Overstocking can lead to expired blood and waste, while understocking risks the safety of patients requiring transfusions. Therefore, a system capable of predicting blood bag needs more accurately and adaptively is needed.

One approach is to utilize machine learning-based forecasting methods, such as Random Forest. Research by Anshori et al. (2023) demonstrated that the Random Forest method was successfully used to predict cardiovascular disease with a high accuracy rate of 98%. This method is capable of handling data with complex variables and provides superior evaluation results compared to other methods. Furthermore, research by Ananda et al. (2022) demonstrated that Random Forest is also effective in predicting blood demand based on historical hospital data, with an accuracy rate of 85%.

Implementing predictive technology in blood management is a highly potential strategy for improving distribution efficiency, reducing the risk of blood shortages, and ensuring timely blood availability. Considering the urgency of the problem and the effectiveness of the Random Forest method in previous studies, this study aims to design a blood bag availability forecasting system at the Lhokseumawe City Indonesian Red Cross (PMI) Unit (UDD) and the North Aceh PMI Unit (UDD). The primary focus is to produce an accurate and applicable predictive model to support a more responsive and efficient blood distribution system.

2. RESEARCH METHOD

2.1 Random Forest Method

In this research, the Random Forest algorithm is an extension of Decision Tree that uses a combination of k trees to form a forest. Research shows that Random Forest combines prediction results from each tree using a random subset of training data. The research found that this model is able to handle large data variations, produce accurate predictions, and is resistant to outliers through conditional logic calculations (Apriliah et al., 2021).

in this study random forest has advantages in Ensemble Learning Capability and Overfitting Handling (Permana, et al., 2023) while the disadvantage is that Random Forest shows limitations in terms of interpretability (Wungkana et al., 2022).

The stages of Random Forest Development according to (Kesuma, M., 2023) are as follows:

1. Take a random dataset of n (total amount of data) from the training dataset in turn, so that each dataset has the same data.
2. Make a decision tree from the random dataset. Because this research uses regression type random forest, then to determine each tree on the target variable must use the right conditional logic.

   The following conditional logic is used:

   $$f(x) = \begin{cases} A_1 \ if \ X < T_1 \\ A_2 \ if \ T_1 \leq x < T_2 \end{cases} \tag{2.1}$$

   Where:

   f(x) : function for decision tree logic

   T1,T2 : Threshold limits that determine the separation of data

   A1,A2 : The resulting value based on the fulfilled condition
3. After forming the tree, the average prediction of all trees will be calculated, with the following formula:

   $$\hat{Y}_i = \frac{1}{N_{tree}} \sum_{n=1}^{N_{tree}} \hat{Y}_n \tag{2.2}$$

4. Calculating Error Evaluation

   $$Login\_Error = \left| Actual_{Login(i)} - RF_{Blood_{in(i)}} \right| \tag{2.3}$$

   $$Distribution\_Error(i) = \left| Actual_{Distribution(i)} - RF_{Distribution(i)} \right| \tag{2.4}$$

2.2 System Scheme

This research developed a blood bag stock availability forecasting system using the Random Forest algorithm based on historical data obtained from the Lhokseumawe City PMI UDD and the North Aceh PMI UDD for the 2022-2025 period. The system development process was carried out through a series of structured stages described in the prediction system schematic.

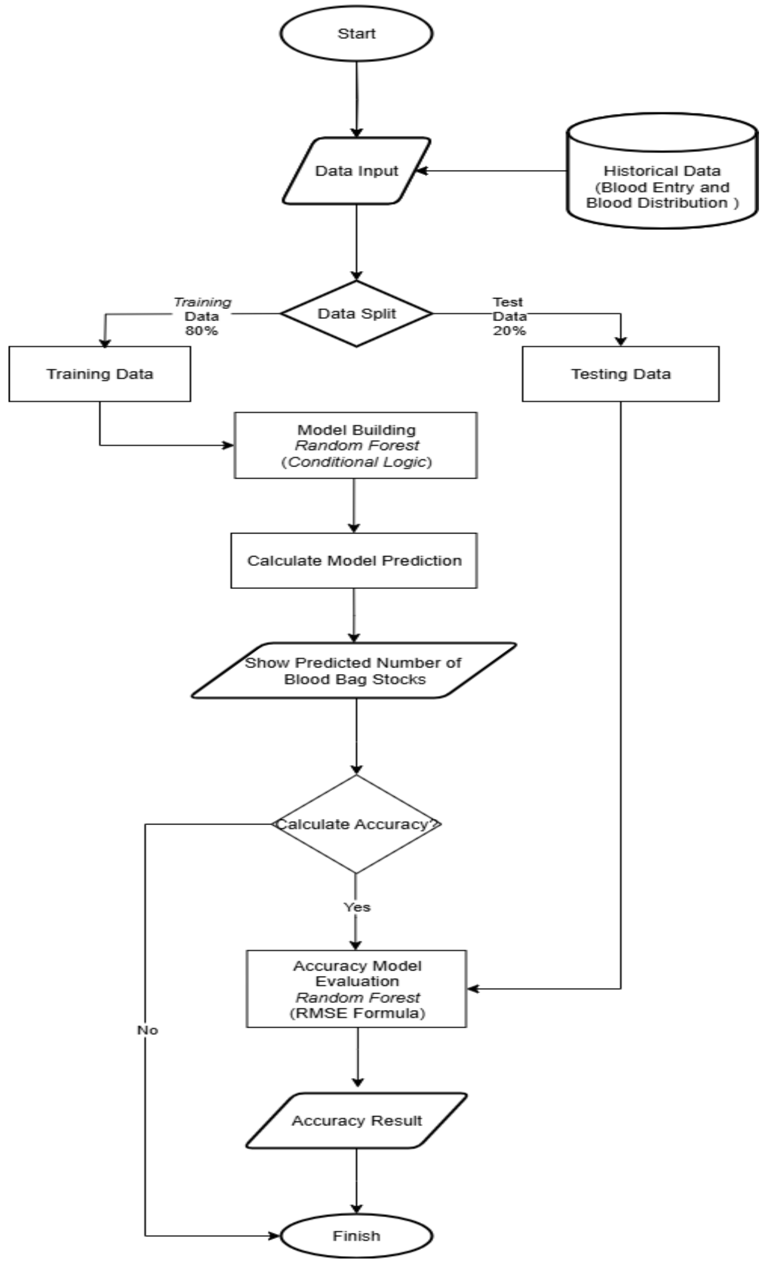

Figure 1. System Schematic

3. RESULTS AND DISCUSSION

3.1 Research Result

This study aims to apply the Random Forest method in forecasting the availability of blood bag stocks at the PMI Blood Donor Unit (UDD) of Lhokseumawe City and North Aceh. The system developed is web-based using the Python programming language, which is designed to provide accurate predictions of blood stock availability based on 574 historical data with 6 variables namely month, year, PMI location, blood type, incoming blood, and blood distribution. In the process of data processing, data cleaning and pre-processing are carried out to improve the consistency and accuracy of forecasting results.

3.1.1 Sample Data Preparation

For the demonstration of the manual calculation of the Random Forest algorithm, a representative data subset consisting of 21 records of observations of the stock of blood bags from UDD PMI North Aceh for the period January to March 2022 was used.

Table 1. Manual Calculation Sample Data

Month	Year	PMI Location	Blood Type	Blood In	Blood Distribution
January	2022	North Aceh	A+	91	81
January	2022	North Aceh	B+	53	56
January	2022	North Aceh	O+	168	159
January	2022	North Aceh	AB+	5	4
January	2022	North Aceh	A-	0	0
January	2022	North Aceh	B-	1	0
January	2022	North Aceh	O-	2	1
February	2022	North Aceh	A+	69	63
February	2022	North Aceh	B+	86	78
February	2022	North Aceh	O+	221	223
February	2022	North Aceh	AB+	2	1
February	2022	North Aceh	A-	2	1
February	2022	North Aceh	B-	0	0
February	2022	North Aceh	O-	1	1
February	2022	North Aceh	O-	1	1
March	2022	North Aceh	A+	62	50
March	2022	North Aceh	B+	45	44
March	2022	North Aceh	O+	157	145
March	2022	North Aceh	AB+	11	10
March	2022	North Aceh	A-	2	2
March	2022	North Aceh	B-	2	2
March	2022	North Aceh	O-	0	0

3.1.2 Categorical Data Transformation

For numerical processing, the month variable was converted normally into a numerical form ranging from 1 to 12, while the blood type was encoded into eight unique numerical classes. A new feature is added, which is the ratio of incoming blood to distribution:

After that, the distribution ratio is calculated:

$$\text{Ratio} = \frac{\textit{Incoming Blood}}{\textit{Blood Distribution}} = \frac{91}{81} = 1{,}12$$

Table 2. Categorical Data Transformation

Month Numeric	Numeric Group	Distribution Entry Ratio
1	1	1.12
1	3	0.95
1	7	1.06
1	5	1.25
1	2	0
1	4	0
1	8	2
2	1	1.10

The resulting transformation tables (**Table 1** and **Table 2**) show the numerical results of each data entry, which are then used as input for each decision tree.

Table 3. Categorical Data Transformation (continued)

Month Numeric	Numeric Group	Distribution_Entry_Ratio
2	3	1.10
2	7	0.99
2	5	2
3	1	1.24
3	3	1.02
3	7	1.08
3	5	1.1
3	2	1
3	4	1
3	8	0

3.1.3 Split Data

In this study, researchers divided the data into 2 parts, namely training data (training data) as much as 80%, namely 458 data and testing data (test data) as much as 20%, namely 116 data. To make it clear, the following randomly selected data samples are presented in the form of a table below:

Table 4. Data Training

No.	Month	Year	PMI Location	Blood Type	Blood in	Blood Distribution
1.	January	2022	Lhokseumawe	O+	162	220
2.	January	2022	Lhokseumawe	AB+	5	4
3.	January	2022	Lhokseumawe	A-	2	2
5.	February	2022	Lhokseumawe	O-	2	2
6.	February	2022	Lhokseumawe	A+	60	57
…	…	…	…	…	…	…
455.	May	2025	North Aceh	B-	0	0
456.	May	2025	North Aceh	A+	73	70
457.	May	2025	North Aceh	B+	61	59
458.	May	2025	North Aceh	B-	2	2

Table 5. Data Test

No.	Month	Year	PMI Location	Blood Type	Blood in	Blood Distribution
1.	January	2022	Lhokseumawe	B+	59	51
2.	February	2022	Lhokseumawe	O+	156	198
3.	February	2022	Lhokseumawe	AB+	6	4
4.	March	2022	Lhokseumawe	A-	1	1
6.	May	2023	Lhokseumawe	O+	210	210
...	...	...	...	...	...	...
106.	July	2024	North Aceh	O+	191	200
107.	July	2024	North Aceh	A-	1	2
108.	August	2024	North Aceh	B+	72	75

3.1.4 Manual Simulation Of Random Forest Algorithm

In this simulation, three independent decision trees (Tree1, Tree2, and Tree3) were constructed based on different data subsets and used to predict two target variables: Blood Intake and Blood Distribution. The simulation was conducted using 21 observation data records from the UDD PMI North Aceh from January to March 2022. This data includes blood type variations, incoming blood volume, and distribution volume, and represents surplus, deficit, and balanced stock conditions.

1. Individual Decision Tree Simulation

Three decision tree models were manually constructed for both targets. The threshold-based tree structure (x_1: month, x_2: blood type) was designed as a piecewise function. An example formula at 2.1 for Tree1 Blood In is:

$f_1(x_1, x_2) = \{$

prediction 50, if $x_1 \leq 2$ and $x_2 \leq 4$

prediction 100, if $x_1 \leq 2$ and $x_2 > 4$

prediction 80, if $x_1 > 2$ and $x_2 \leq 4$

prediction 150, if $x_1 > 2$, and $x_2 > 4$

$\}$

A similar structure is applied for blood distribution prediction with the categories in table 4.2 categorical transformation and customized output values, The threshold-based tree structure (x_1: month, x_2: blood type) was designed as a piecewise function:

$g_1(x_1, x_2) = \{$

prediction 45, if $x_1 \leq 2$ and $x_2 \leq 4$

prediction 95, if $x_1 \leq 2$ and $x_2 > 4$

prediction 75, if $x_1 > 2$ and $x_2 \leq 4$

prediction 140, if $x_1 >2$, and $x_2 > 4$

$\}$

Similar formulas were designed for Tree2 and Tree3, both for Blood Intake and Blood Distribution predictions. Simulations of all three decision trees yielded individual prediction values (Table 5), which were then used in the aggregation process. The following whole tree prediction results are presented in the table:

Table 6. Simulation of Individual Decision Trees Prediction

Tree1_ Blood in	Tree2_Blood Type	Tree3_Blood Type	Tree1_ Distribution	Tree2_ Distribution	Tree3_ Distribution
50	90	80	45	85	75
50	60	40	45	55	35
100	120	80	95	115	75
100	120	80	95	115	75
…	…	…	…	…	…
80	60	90	75	55	85
80	70	90	75	65	85
150	70	90	140	65	85
150	120	130	140	115	125

2. Ensemble Aggregation and Error Evaluation

The final Random Forest prediction is calculated as the average of the three decision trees for each observation. The prediction aggregation formula is written as:

RF Blood_In(x) $=(f_1(x) + f_2(x) + f_3(x))/3$

And

RF Distribution(x) $=(g_1(x) + g_2(x) + g_3(x))/3$

Example ensemble prediction for January A+ record:

RF In = (50 + 90 + 80) / 3 = 220 / 3 = 73.33;

RF Distribution = (45 + 85 + 75) / 3 = 220 / 3 = 68 .33;

Therefore:

In Error = |91 − 73.33| = 17.67

Distribution Error = |81 − 68.33| = 12.67

After the prediction results are obtained, the final step is to calculate the evaluation metric using root mean square error. The first step is to calculate the difference between the actual value and the prediction, namely the input error and distribution error, as follows:

Known:

In Error = 17.67 → for blood type A+ in January.

After that, it can be calculated using the following RMSE formula:

$$\text{RMSE}_{\,Blood\ in} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x-\hat{x}_1)}^{2}$$

$$\text{RMSE}_{\,Blood\ in} = \sqrt{\tfrac{1}{21}\textstyle\sum_{i=1}^{21}(91-73{,}33)^2}$$

$$\text{RMSE}_{\,Blood\ in} = \sqrt{\frac{(17{,}67)^2}{21}}$$

$$\text{RMSE}_{\,Blood\ in} = \sqrt{14{,}86}$$

$$\text{RMSE}_{\,Blood\ in} = 3{,}85$$

Error evaluation is done by calculating the Absolute Error between the actual value and the ensemble prediction, then calculating the average squared error as the Root Mean Square Error (RMSE) for both targets.The final result shows the values:

1. RMSE of Incoming Blood: 76.46
2. Blood Distribution RMSE:73.84

This manual simulation validates the consistency of the Random Forest algorithm that has been implemented in a digital system for PMI blood stock prediction, and demonstrates the importance of ensemble learning in producing a model that is robust to historical data fluctuations.

3.1.5 Prediction Results

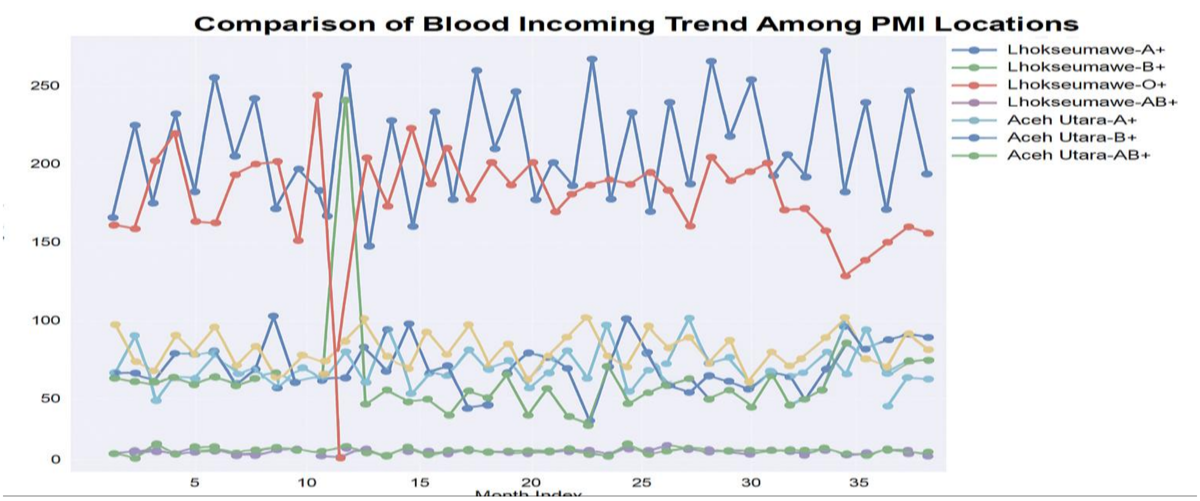

Figure 2. Incoming Blood Trend Comparison Chart

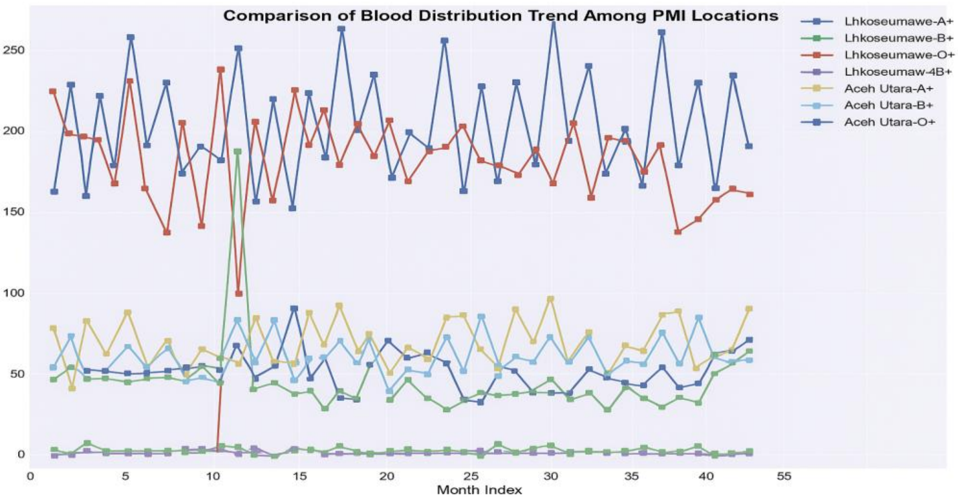

Figure 3. Blood Distribution Trend Comparison Chart

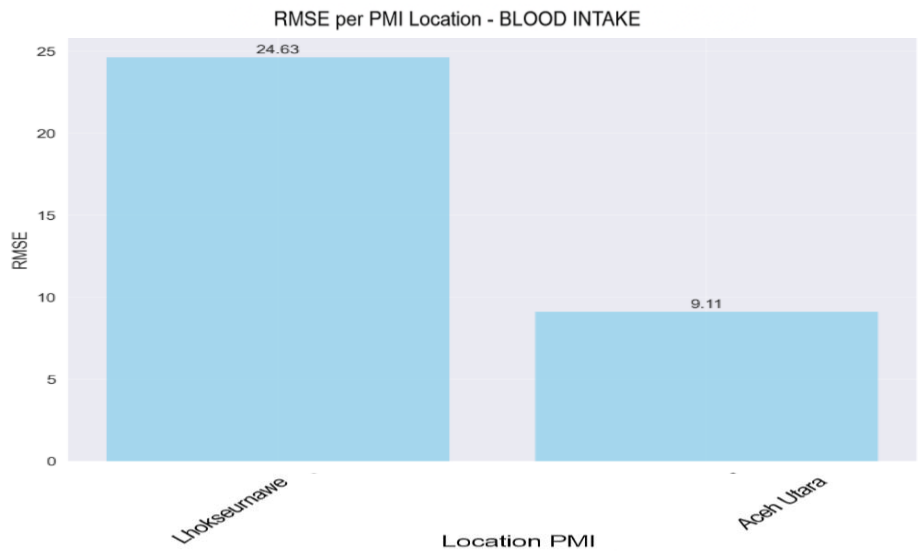

Figure 4. Incoming Blood RMSE Result Chart

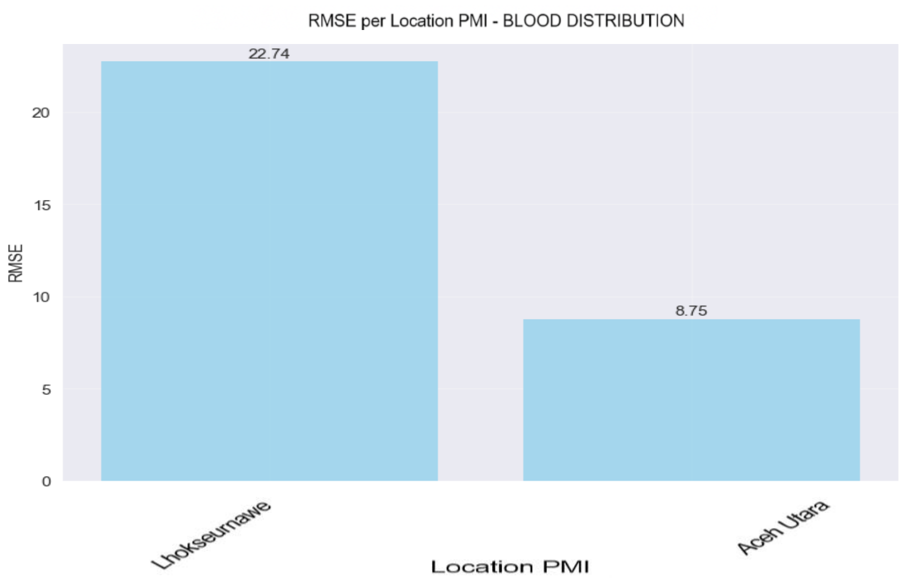

Figure 5. Blood Distribution RMSE Result Graph

3.2 Discussion

3.2.1 System Implementation

1. The login Page

Page is professionally designed and displays the logo, system description, and UDD location options (Lhokseumawe and North Aceh). A simple authentication panel facilitates access for PMI internal users.

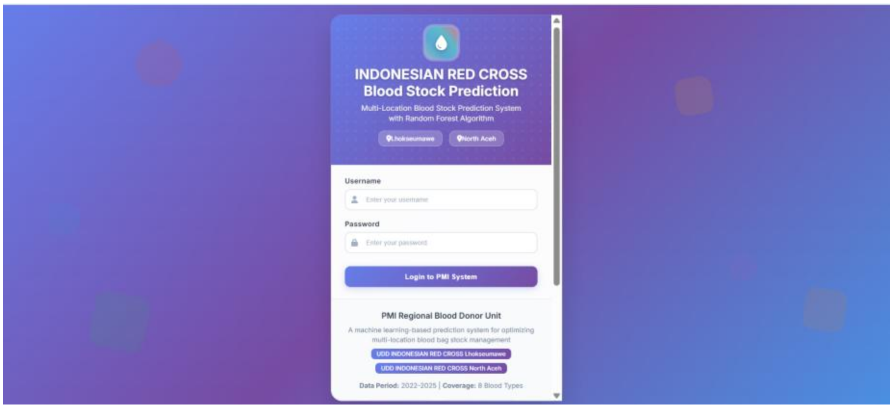

Figure 6. Login Page Display

The Dashboard page presents a navigation menu structured into three categories: Main Menu, Machine Learning, and System. Location statistics are presented separately for the Lhokseumawe and North Aceh UDDs, each displaying 287 records, allowing for visualization of data distribution per location.

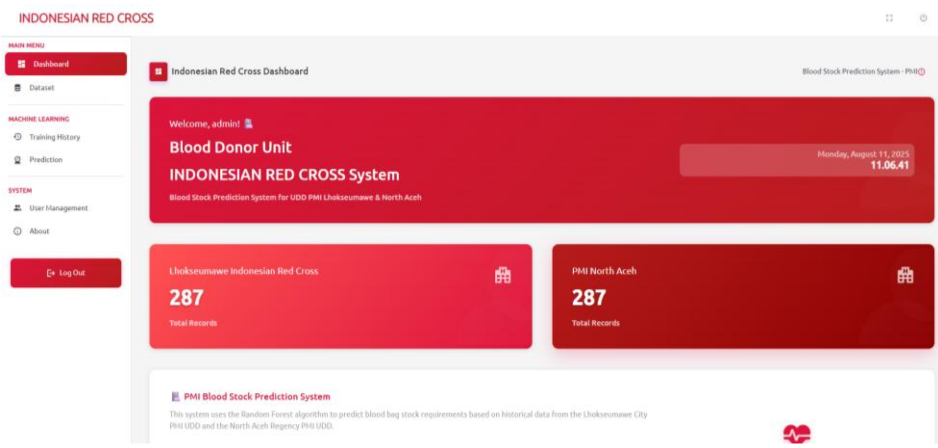

Figure 7. Dashboard Page View

2. Dataset Management

The Research Dataset module allows data filtering by blood type and PMI location. The main table contains key information such as month, year, blood type, number of blood donations, and number of distributions. Each attribute is supported by a visual icon for improved readability. Interactive filters speed up data analysis and efficiently manage data.

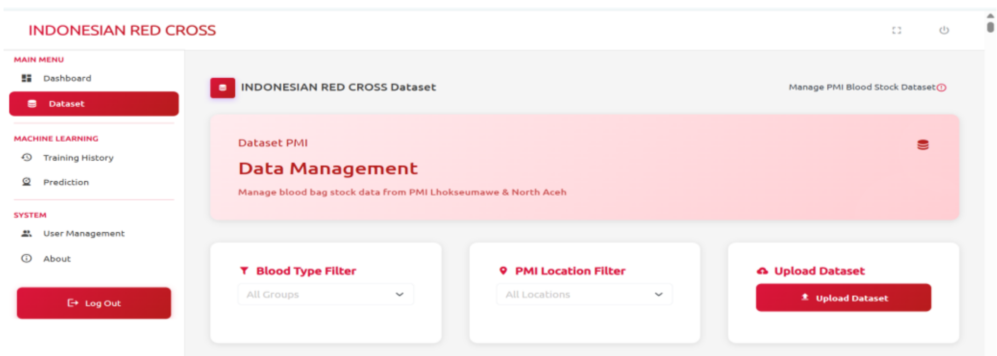

Figure 8. Initial View of the Research Dataset Page

3. Model Training History

On the Training History page, the system records the entire training process of the Random Forest model, including the last training time (June 23, 2025). Four key performance indicators are displayed: RMSE of Blood Intake (18,512), RMSE of Distribution (17,171), number of datasets (574 records), and data coverage (2022–2025). The performance comparison between locations is visualized in the Ranking Table, which confirms the dominance of model accuracy in North Aceh. This finding aligns with strategic recommendations for implementing location-specific prediction strategies.

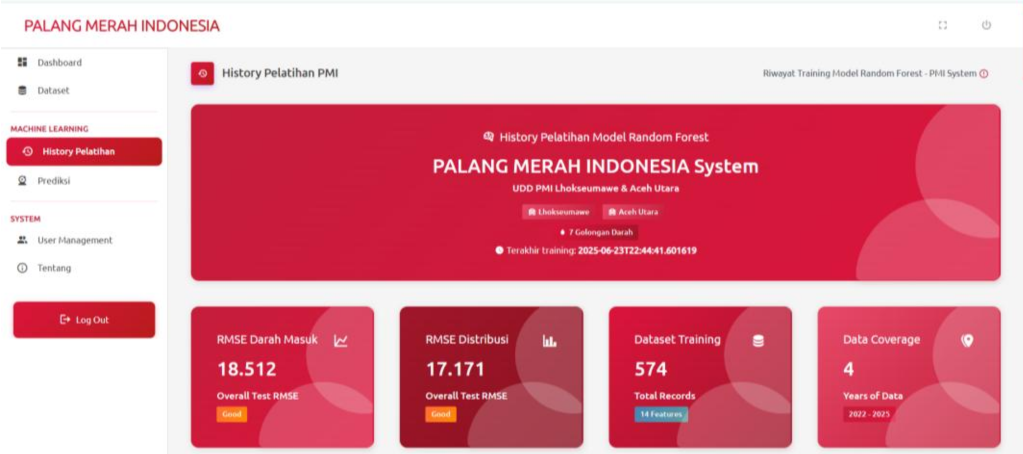

Figure 9. Training History Display

4. Comprehensive Prediction

The Comprehensive Prediction Module allows users to make predictions for all blood types and all months within a specific timeframe. Prediction parameters can be customized, such as PMI location and year range (2025–2030). The system generates a comprehensive report with predictive analysis and visualization.

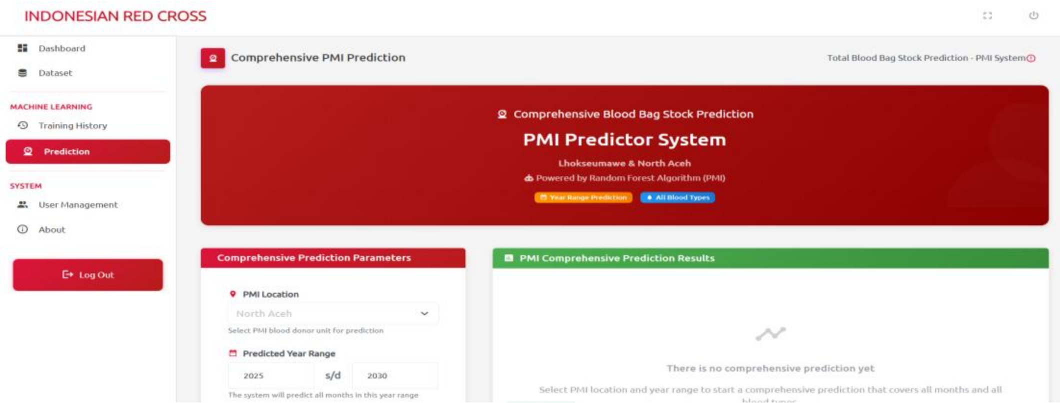

Figure 10. Prediction Page View

The prediction results for the North Aceh PMI show that out of a total of 504 months, 474 (94%) experienced a surplus, 30 (6%) a deficit, and no months were in balance. The total predicted blood received reached 24,245.9 bags, while distribution reached 19,839.2 bags, resulting in a net surplus of 4,406.7 bags. Blood type O- had the highest surplus (1,246.9 bags), while blood type A+ had the lowest surplus (79 bags), indicating the need for a specific strategy for this group. This prediction supports the cross-regional stock distribution strategy to address local deficits.

4. CONCLUSION

Based on the results of the research that has been conducted, it can be concluded that the Random Forest algorithm implemented in the blood bag stock prediction system has succeeded in providing significant performance, especially in the context of the dual PMI system. The model showed excellent predictive performance in the North Aceh PMI UDD with an RMSE value of 9.113 for incoming blood prediction and 8.750 for blood distribution, while the model's performance in the Lhokseumawe PMI UDD still needs to be improved because it showed a higher RMSE value, namely 24.635 and 22.737. The success of this model is inseparable from the effective feature engineering process, where the six original features were developed into 17 features through the addition of temporal, categorical, interaction, and operational variables. These new features have been proven to significantly improve the accuracy and predictive power of the model. Validation of the dual PMI system also showed success in implementing the stratified splitting technique based on the combination of PMI location and blood type. This approach ensures a balanced data allocation of 60% for training, 20% for validation, and 20% for testing, resulting in improved model generalization. The hyperparameter optimization process was performed using Randomized Search CV and 5-fold cross-validation, which were able to identify optimal parameters separately for the target variables of incoming blood and blood distribution, according to the characteristics of each data. Furthermore, the system successfully performed comprehensive predictions for the period 2025 to 2030, specifically for the UDD PMI North Aceh. The prediction results showed that 474 months (94.0%) were projected to experience a blood stock surplus with a total surplus of 4,572.9 bags, while only 30 months (6.0%) experienced a deficit with a total deficit of 166.2 bags. The final balance projection showed a very positive condition with a net balance surplus of 4,406.7 bags. In terms of implementation, the developed web-based system has succeeded in providing an intuitive and user-friendly interface, including dashboard features, dataset management, training history, comprehensive predictions, and user management. This allows PMI UDD staff to access and run prediction processes in real-time to support faster and more accurate operational decision-making.

REFERENCES

Adawiyah, R., & Putra, A. (2021). "Analysis of Blood Availability at the Indonesian Red Cross." Journal of Public Health. Vol. 7. 10(5). Doi: 10.33373/jmb. v4i2.2697

Agusyul, AY, & Firmansyah, F. (2023). Heart Disease Prediction Using the Random Forest Algorithm. Jurnal Minfo Polgan, 12(2), 2239–2246. https://doi.org/10.33395/jmp.v12i2.13214

Annisa, S., Rahkmawati, Y., & Hafid, H. (2025). Peramalan Harga Minyak Mentah Indonesia Menggunakan Algoritma Random Forest. *Jurnal Gaussian*, *13*(2), 472–478. https://doi.org/10.14710/j.gauss.13.2.472-478

Anshori, M., Rikatsih, N., & Haris, MS (2023). Predicting Patients with Cardiovascular Disease Using Random Forest. Tektrika - Journal of Research and Development of Telecommunications, Control, Computers, Electricity, and Electronics, 7(2), 58. https://doi.org/10.25124/tektrika.v7i2.5279

Apriliah, W., Kurniawan, I., Baydhowi, M., & Haryati, T. (2021). Predicting the Probability of Diabetes in the Early Stages Using the Random Forest Classification Algorithm. Sistemasi, 10(1), 163. https://doi.org/10.32520/stmsi.v10i1.1129

Arifin Yusuf Permana, Hari Noer Fazri, M. Fakhrizal Nur Athoilah, Mohammad Robi, & Ricky Firmansyah. (2023). Application of Data Mining in Lung Cancer Prediction Analysis Using the Random Forest Algorithm. Scientific Journal of Informatics and Communication Engineering, 3(2), 27–41. https://doi.org/10.55606/juitik.v3i2.472

Auliasari, K., Kertaningtyas, M., & Kriswantono, M. (2020). Application of Forecasting Methods to Identify Consumer Demand. Informal: Informatics Journal, 4(3), 121. https://doi.org/10.19184/isj.v4i3.14615

Bamba, E.A., Syarli, S., & Harianto, H. (2021). Web-Based Agricultural Yield Forecasting System in Mamasa Regency. Journal of Agricultural Research, 3(1), 357-361. http://dx.doi.org/10.35329/jp.v3i1.2091

Darnila, E., Asrianda, A., & Jannah, R. (2019). Application of Forecasting the Number of Passport Applicants Using the Double Exponential Smoothing Method at the Class II Immigration Office of Lhokseumawe City. TECHSI - Journal of Informatics Engineering, 11(2), 257. https://doi.org/10.29103/techsi.v11i2.1481

Efendi, MS, & Zyen, AK (2024). Application of the Random Forest Algorithm for Sales Prediction and Product Inventory Systems. Resolution: Informatics and Information Engineering, 5(1), 12-20. https://doi.org/10.30865/resolusi.v5i1.2149

Feriyanto, F., & Anjariyah, D. (2024). Deep learning approach through meaningful, mindful, and joyful learning: A library research. Electronic Journal of Education, Social Economics and Technology, 5(2), 208-212. https://doi.org/10.33122/ejeset.v5i2.321

Fuadi, W., Fajriana, F., & M, R. (2021). Rice Harvest Yield Forecasting Using the Double Exponential Smoothing Method in Meurah Mulia District. TECHSI - Journal of Informatics Engineering, 13(1), 26. https://doi.org/10.29103/techsi.v13i1.2772

Hatta, M., & Fauziah Fitri, A. (2020). Blood Stock Inventory Prediction System Using the Least Square Method in the Blood Transfusion Unit: A Case Study of the Indonesian Red Cross (PMI) in Cirebon City. Scientific Journal of Computer Science, 6(1), 41–45. https://doi.org/10.35329/jiik.v6i1.130

Indah, N. (2025). Building Harmony Between Tradition and Progress Through The Actualization Of Iman Gozali's Vision In The Management Of Modern Salaf Pesantren. Electronic Journal of Education, Social Economics and Technology, 6(1). https://doi.org/10.33122/ejeset.v6i1.385

Juliantika, R., & Mulyani, N. (2025). *Single Moving Average (SMA) Analysis for Gold Jewelry Sales a Pegadaian Outlet Labuhan Ruku*. *6*(1), 949–959. https://doi.org/10.33122/ejeset.v6i1.479

Kesuma, M. (2023). Liver Disease Prediction Using the Random Forest Algorithm. Journal of Information and Computer Science, 11(2), 2023. https://doi.org/10.35959/jik.v11i02.499

Lusiana, A., & Yuliarty, P. (2020). Application of Forecasting Methods to Roof Demand at PT X. Innovative Industry: Journal of Industrial Engineering, 10(1), 11–20. https://doi.org/10.36040/industri.v10i1.2530

Lusiana, A., & Yuliarty, P. (2020). Penerapan Metode Peramalan (Forecasting) Pada Permintaan Atap di PT X. *Industri Inovatif : Jurnal Teknik Industri*, *10*(1), 11–20. https://doi.org/10.36040/industri.v10i1.2530

Ngantung, M., Jan, A.H., Peramalan, A., Obat, P., & Jan, A.H. (2020). Analysis of Antibiotic Drug Demand Forecasting at Edelweis Tatelu Pharmacy. EMBA Journal: Journal of Economics, Management, Business, and Accounting Research, 7(4), 4859–4867. https://doi.org/10.35794/emba.v7i4.25439

Nurdin, N., & Rosnita, L. (2024). Implementation of Data Mining for Raw Material Stock Prediction in Clothing Production Using the C4.5 Algorithm Method. *2022*, *2*. https://doi.org/10.29103/icomden.v2.xxxx

PMI. (2021). Indonesian Red Cross Annual Report 2021: Moving Together for Others. South Jakarta: PMI Central Blood Donor Unit.

Pribadi, T., Indrayanti, AL, and Yanti, EV (2020). Increasing Community Participation in Blood Donation Activities in Palangka Raya. Al-Ikhlas Community Service Journal, 3(1), 50–58. https://doi.org/10.33373/jmb.v4i2.2697

Primasari, D., Purnamasari, I., Larasati, M., & Amelia, R. (2021). Increasing Public Awareness of Blood Donation During the Month of Ramadan. Journal of Community Service in Health, 3(2), 41-46. Doi: 10.33373/jmb.v4i2.2697

Purwati, D., Rofinda, ZD and Husni, H. (2020). Characteristics of Blood Transfusion Patients with Crossmatch Incompatibility at the UTD of Dr. M. Djamil Padang General Hospital, Andalas Health Journal, 9(3), 308–312. Doi: 10.25077/jka.v9i3.1328

Putri, M. (2024). Stroke Disease Prediction Using Machine Learning with the Random Forest Algorithm. Jurnal Infomedia: Teknik Informatika, 9(2), 16–21. http://dx.doi.org/10.30811/jim.v9i1.5199

Rahman, A., Setiawan, B., & Pratama, R. (2022). Application of Machine Learning to Predict Blood Needs Using Random Forest. Journal of Information Technology and Computer Science (JTIIK), 9(2), 321-330. http://dx.doi.org/10.35329/jp.v3i1.2091

Safitri, Annisa Anggi; Widuri, Sasi; Reswari, PAD (2021). Blood Donation Socialization Efforts to Fulfill Blood Stocks During the Pandemic at the Surabaya City Indonesian Red Cross Blood Center in 2020. Journal of Community Engagement in Health, Vol. 4 No. 2, 468–474. https://doi.org/10.30994/Jceh.V4I2.271

Salman, H. A., Kalakech, A., & Steiti, A. (2024). Random Forest Algorithm Overview. *Babylonian Journal of Machine Learning*, *2024*, 69–79. https://doi.org/10.58496/bjml/2024/007

Santoso, H., Hakim, L., Afiyati, A., Jokonowo, B., Informatika, T., Buana, U. M., & Artikel, I. (2025). *Implementation of the Random Forest algorithm to predict rice needs in DKI Jakarta*. *22*(1), 20–29. https://doi.org/10.31515/telematika.v22i2.12850

Satmoko, ND, Rosmayati, S., Vikaliana, R., Arum, LPI, Manggabarani, AS, Utomo, KP, Ramadhani, I., Zulfikar, R., Ganika, G., Agustina, T., & Maknunah, LU (2020). Operations management (Theoretical and practical review). Bandung: Widina Bhakti Persada Bandung.

Setiawan, D. (2020). The Role of PMI in Disaster Mitigation in Indonesia. Journal of Humanity and Social Affairs, 5(3), 145-157. https://doi.org/10.59141/comserva.v3i10.1213