Journal of Natural Sciences and Mathematics Research
J. Nat. Scien. & Math. Res. Vol. 11 No. 2 (2025) 183-197
ISSN: 2460-4453 (Online); 2614-6487 (Printed)
Available online at http://journal.walisongo.ac.id/index.php/jnsmr

Comparative study of artificial Neural Network and Kalman Filter models for blood demand forecasting at PMI Surabaya

Ainin Sofia[1], Teguh Herlambang[1*], Rizqi Putri Nourma Budiarti[1], Endang Sulistiyani[1]
[1] Department of Information Systems, Faculty of Business Economics and Digital Technology, Universitas Nahdlatul Ulama Surabaya, Indonesia

*Corresponding author's e-mail: teguh@unusa.ac.id

ABSTRACT
Blood plays a vital role in human health, making the need for donors and transfusions crucial. Currently, the Indonesian Red Cross (PMI) in Surabaya faces a balance issue between blood supply and demand. To address this, a blood demand forecasting model has been created at the PMI using ANN with a 4% error rate. The Kalman Filter algorithm is known to significantly reduce prediction errors from the prediction and correction process, while an ANN is considered capable of handling data complexity and nonlinearity. Therefore, this study aims to analyze the performance of the ANN and Kalman Filter models and compare the model performance results to determine the model with the best performance level. The modelling uses the CRISP-DM method, which starts from data understanding, data preparation, data modelling, model evaluation, and forecasting. The results of this study indicate that the Kalman Filter model successfully minimizes errors compared to the ANN prediction results, achieving a model accuracy level reaching 93.1%. These results demonstrate that the Kalman Filter model can significantly reduce prediction errors in the prediction and correction process, making it more optimal than the ANN model in forecasting blood demand at the PMI in Surabaya.

Keywords:
Comparison; Forecasting; Blood Demand; ANN; Kalman Filter

Introduction

Blood is a bodily fluid that plays a vital role in human survival, circulating in the heart and blood vessels (Firani, 2018). Individuals voluntarily donate blood, which is then stored for medical use (Harsiwi & Arini, 2018). Based on Law No. 1 of 2018, blood donation activities, blood transfusions, or Red Cross services in Indonesia are mandated by the Indonesian Red Cross (PMI). If the PMI experiences a blood shortage, it will be unable to meet the public's or hospitals' demand for blood in emergencies requiring blood transfusions. Blood shortages can lead to the possibility of human loss, especially for individuals in emergencies, such as patients undergoing surgery in hospitals or accident victims who have lost a significant amount of blood (Djuardi, 2020). Conversely, if the blood stock is excessive, there will be a loss of blood stock. According to the Indonesian Red Cross (PMI), the blood storage period is 30 days. Once the blood has passed its shelf life, staff dispose of the blood (Nafisah et al., 2017). Therefore, the PMI must maintain a balanced blood stock.

The PMI of Surabaya City is one of five pioneering PMIs, along with those in Surakarta, Yogyakarta, Semarang, and Bandung, and was established seven months after the Central PMI (PMI Kota Surabaya, 2025). The PMI of Surabaya City serves as the central blood distribution center for hospitals and Blood Transfusion Units (UTD) in Surabaya. According to PMI Surabaya City officials, blood supply sources fluctuate depending on the availability of donors in Surabaya. Not only is the blood supply dynamic, but the blood demand at the Surabaya City PMI is also dynamic, as it constantly changes according to the needs of each hospital and blood transfusion unit. According to the official Instagram account of the Surabaya City PMI, as of February 4, 2025, the available blood stock consisted of 6,043 blood bags. According to staff at the Surabaya City

Indonesian Red Cross (PMI), blood overstocks frequently occur, leading to the disposal of expired blood. The current situation at the Surabaya City Red Cross is experiencing an imbalance between blood supply and demand.

These conditions emphasize the need for an accurate forecasting system to maintain a balance between blood supply and demand. The characteristics of blood demand data at the Indonesian Red Cross (PMI) in Surabaya present several specific challenges, including high fluctuations due to external factors such as mass donation activities, disasters, or surges in operational activity. The data distribution is irregular and contains noise. The data is nonlinear due to the influence of numerous social and medical variables, and there is a need for real-time predictions to adapt to the latest data quickly.

Given these characteristics, the study requires a predictive model capable of handling nonlinear patterns while simultaneously performing optimal real-time estimation. Two relevant algorithms are the Artificial Neural Network (ANN) and the Kalman Filter. Theoretically, ANN excels at learning the complexity of data patterns without assuming linearity (Indriani, 2013), making it suitable for non-normally distributed blood demand. On the other hand, the Kalman Filter has proven effective in improving real-time prediction accuracy because the Kalman algorithm estimates the optimal state of the system with each new data point, ulitizing prediction and correction steps (Singhal & Wu, 1989). ANN and Kalman Filter employ different approaches. The ANN relies on learning from historical data to recognize nonlinear patterns, whereas The Kalman Filter performs state estimation iteratively by updating predictions as new data becomes available. Thus, these two methods are considered suitable for forecasting blood needs at the Surabaya Red Cross (PMI).

Previous studies have used ANN and Kalman Filter to create prediction models for blood demand and blood stock supply at the Indonesian Red Cross (PMI) (Herlambang et al., 2019; Muhith et al., 2020, 2022). However, these studies were limited to the use of univariate time series data, random parameter selection, and optimal hyperparameter tuning. As a result, the prediction results still exhibit significant discrepancies from the actual data, such as a 260 blood bag difference between the predicted data and the actual data over the last six months (Herlambang et al., 2019). Therefore, this study aims to compare the performance results of the ANN and Kalman Filter models with parameter tuning using data consisting of several influencing variables (multivariate time series), so that a more optimal forecasting model can be obtained, in accordance with the characteristics of blood demand data at the Indonesian Red Cross Surabaya.

Methods

The data used for this study are primary data collected directly from the Surabaya City Indonesian Red Cross (PMI) located at No. 7-15, Embong Ploso Street, Embong Kaliasin, Genteng District, Surabaya, East Java 60271 and the official Facebook page of the Surabaya City PMI. The analyzed data are monthly records covering the variables of incoming blood bags, expired blood, blood stock, and blood demand for the period 2019-2024. To ensure the reliability of the model, the study divides the dataset into two categories: training data and testing data, with proportions of 90:10, 80:20, and 70:30, respectively. Based on data splitting considerations, predictive models may behave differently based on the range of datasets provided for the learning process and testing phase (Tao et al., 2020). Building a model uses Training data, while evaluating the model's performance uses testing data.

This study employs the CRISP-DM (Cross Industry Standard Process for Data Mining) methodology as a research stage (Martinez-Plumed et al., 2021). There are five main processes, namely Data Understanding, Data Preparation, Modelling, and Model Evaluation. Figure 1 represents that each primary process has several sub-processes, along with inputs and outputs. Artificial Neural Networks (ANN) and Kalman Filters (KF) used to build predictive models. The evaluation model uses the RMSE evaluation matrix to calculate the error percentage of each model's RMSE value. The final step was to compare the error percentages of the ANN and KF models to determine which model performed best in predicting blood demand. The research flowchart utilizes different colored arrows to clarify the research flow and to separate the processes, inputs, and outputs of each process. Data analysis performed using Python version 3.11.3.

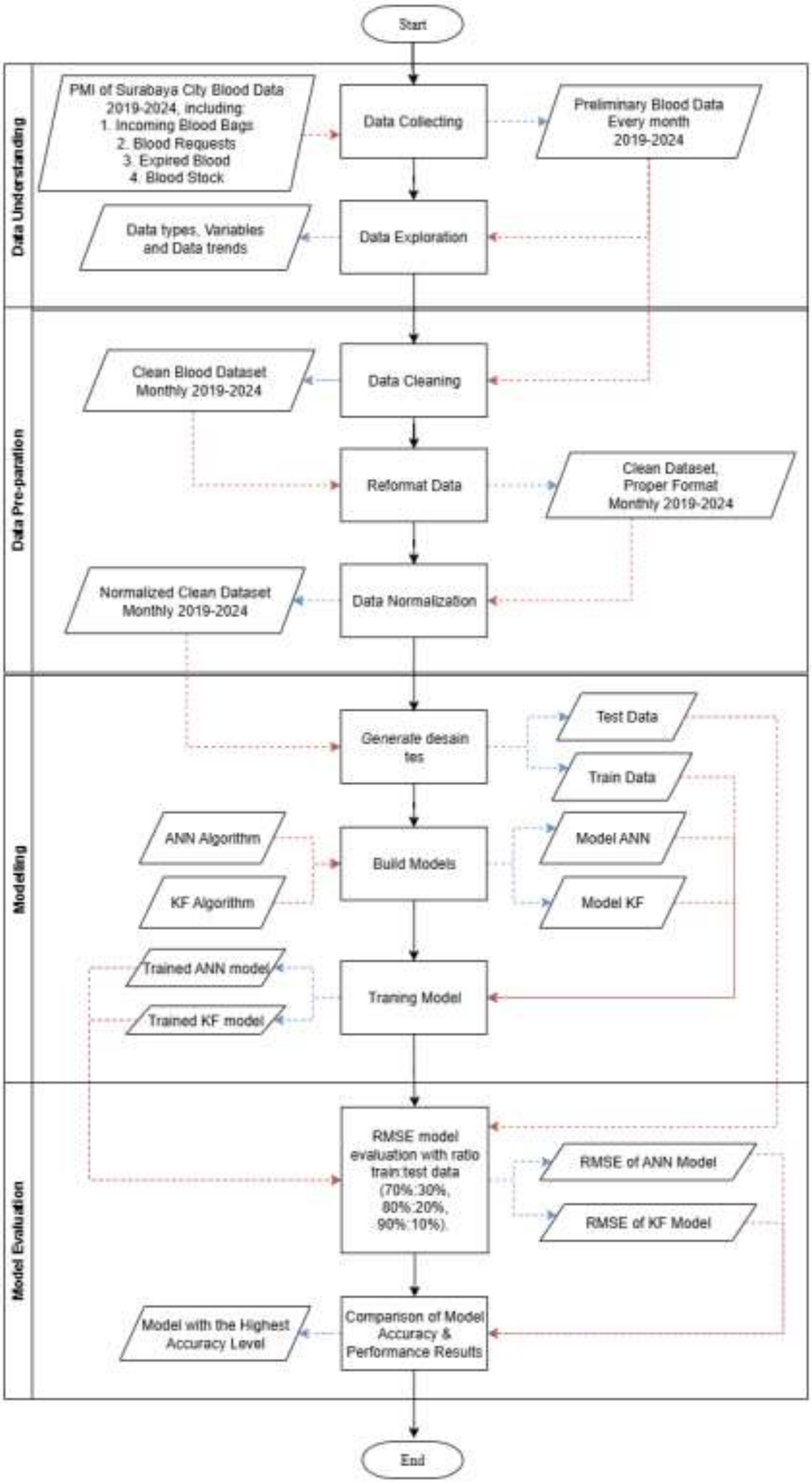

Figure 1. Research Stages Flowchart

Description :

: Process

: Input

: Output

Artificial Neural Network (ANN)

An Artificial Neural Network is a computational model that functions similarly to the human nervous system (Islam et al., 2019). The human nervous system works by receiving electrical and chemical signals from other nerves. Dendrites receive these signals and then transmit them to the nucleus. The nucleus interprets the meaning of these signals. These signals are transmitted by axons through synapses and then forwarded to dendrites in other neurons, repeating the process (Islam et al., 2019). The ANN learning process involves updating the connection strengths (weights) of a node (neuron). By using the difference (error) between the predicted value and the actual value, the network adjusts its weights so that the error value is minimize and the predicted value is as close as possible to the actual value (Han et al., 2018).

The ANN structure consists of layers of interconnected neurons. It consists of three main layers: the input layer, the hidden layer, and the output layer. The input layer receives stimuli or input to be processed. The hidden layer processes the input received by the input layer through an activation function. The output layer generates demand predictions as continuous values. The feedforward error-backpropagation learning algorithm is the most famous procedure for training an ANN. Each iteration in the ANN model training process involves two main activities: Forward activation to produce a solution, and backward propagation of the computed error to modify the weights (Basheer & Hajmeer, 2000).

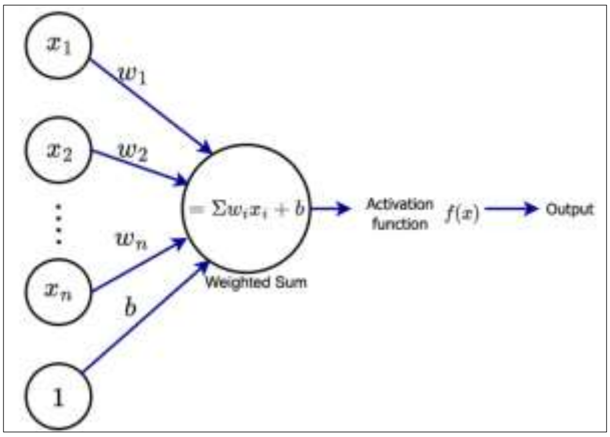

Figure 2. FeedForward ANN Algorithm

Figure 2 presents the FeedForward process that occurs in the ANN algorithm. Symbol $(x_1, x_2, \dots, x_n)$ represents the incoming input, while $(w_1, w_2, \dots, w_n)$ depicts the weight value. The process randomly initializes the initial weight parameters and then processes the input in the nucleus. This process involves calculating the input value, multiplying it by the weight and adding a bias.

$$Z_{-in_j} = \sum_{i=1}^{n} x_i\, w_i + b \qquad (1)$$

Defined:

x_i : Input values at period n
w_i : weight values at period n
b : bias
Z_{-in_j} : output for the unit in period Z_j

The results of the calculation in Equation (1) depend on the activation function used to produce an output between 0,+1,-1 and +1. The magnitude of the activation obtained represents the new signal that moves to the next layer. In this study, the activation functions used are ReLu and Tanh. ReLU is the most widely used activation function among deep learning practitioners and researchers. The success of ReLU depends on its superior training performance compared to other activation functions, such as logistic sigmoid (Rasamoelina et al., 2020). While Tanh is preferred over the sigmoid function because it has an infinite gradient to vary in a given direction, and is centered at zero (Sharma et al., 2020)

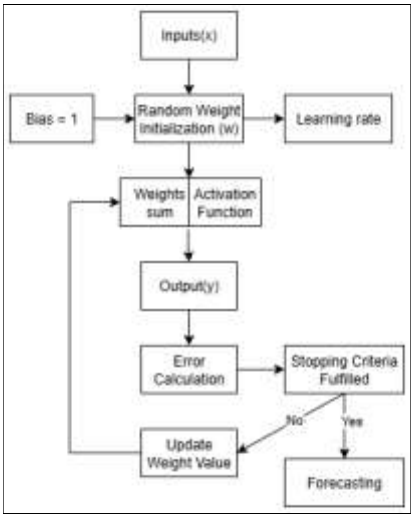

Figure 3. Artificial Neural Network Algorithm

The same procedure of calculating the net effect is repeated for each hidden node and for all hidden layers. The net effect(s) calculated at the output node(s) are consequently transformed into activation(s) using a transfer function. The output of this feedforward calculation may deviate significantly from the target solution due to the randomly chosen interconnection weights. In the backpropagation process, the difference (i.e., error) between the ANN output and the target output adjusts the interconnection weights, starting from the output layer and proceeding through all hidden layers to the input layer, as illustrated in Figure 3. The forward and backward processes take place carefully until the ANN solution matches the target value within a predetermined tolerance.

In this study, the ANN input consists of four primary variables from the Surabaya PMI dataset: the number of blood bags received (x_1), the number of expired blood bags (x_2), and the blood stock (x_3). The ANN output is the number of monthly blood demand (y). Updating weights and biases using the backpropagation algorithm take place until the error reaches a minimum value. The ANN calculation process for each layer in this study is as follows:
Input layer:

$$x = [x_1, x_2, x_3] \tag{2}$$

Hidden Layer:

$$h^j = f\left(\sum_{i=1}^{n} x_i\, w_i{}^j + b^j\right) \tag{3}$$

Where $f(.)$ is the activation function (ReLu/Tanh).
Output Layer:

$$\hat{y} = \sum_{i=1}^{m} h_i\, w_i{}^{out} + b^{out} \tag{4}$$

To calculate the error (the difference between the predicted and target outputs), use the actual blood demand value y. This error is then derived (gradient) to update the network weights w.

$$e = \hat{y} - y \tag{5}$$

Kalman Filter (KF)

The Kalman Filter is an algorithm that provides an estimate of an unknown variable based on observed measurements over time. The Kalman Filter is relatively simple and requires little computational power. However, the theory of estimation using the Kalman Filter remains relatively unknown (Kim & Bang, 2018). The name Kalman Filter is from Rudolph E. Kalman, who in 1960 published his famous paper describing a recursive solution to the problem of filtering linear discrete data (Laaraiedh, 2012). To estimate the state of a linear dynamic system in a state-space format, the Kalman Filter can be used, where the state equation and output equation describe the dynamic system (Govaers, 2019).

The state equation describes how the state of the system changes over time (evolution from k to k), while the output equation describes how the system output is related to the system state. Using this format, the Kalman filter can estimate the system's state based on observed output measurements. The process model that defines the state equation is as follows (Simon, 2001).

$$x_k = Fx_{k-1} + Bu_{k-1} + w_{k-1} \tag{6}$$

$$w \sim N(0, Q) \tag{7}$$

Defined:
F, B : State matrix
k : Time index
x : System State
u : System Input
w : Disturbance or noise state

Vector w is a random and independent variable which is assumed to be a normal probability distribution or a Gaussian distribution, with a mean of zero with a covariance Q (Kim & Bang, 2018; Laaraiedh, 2012). The process model affects the state of the system at time step k, referred to as the measurement model or output equation.

$$z_k = Hx_k + v_k \tag{8}$$

$$v \sim N\ (0, R) \tag{9}$$

Defined:
z : Measurement output
k : Time index
H : Measurement Matrix
v : Disturbance or noise measurement

In this study, the observed phenomenon was the demand for blood (y_k). Therefore, the Equation of state describes how the state of the system (x_k) changes over time, so $x_k = y_k$. The system input variables, (u_k), affect the state of system. The system input variables that influence changes in the system state over time are the number of blood bags received ($u_{1,k}$), the number of expired blood bags ($u_{2,k}$) and the blood stock ($u_{3,k}$). So the equation of state of the blood demand model is as follows:

$$x_k = \begin{bmatrix} 1 & 0.05 & 0.02 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} (x_{k-1}) + \begin{bmatrix} 0.01 & 0.01 & 0.005 \\ 0.1 & 0 & 0 \\ 0 & 0.1 & 0 \end{bmatrix} \begin{bmatrix} u_{1,k} \\ u_{2,k} \\ u_{3,k} \end{bmatrix} + w_{k-1} \tag{10}$$

The Kalman Filter algorithm consists of two stages, namely the prediction and update stages, also often referred to as propagation and correction (Laaraiedh, 2012). The first stage is to initialize the initial estimate of the state estimate ($\hat{x}_0^+$) and initial estimate of the error covariance matrix (P_0^+). Figure 4 shows the detailed process of the Kalman Filter algorithm. In the prediction stage, the Kalman Filter uses the system model to predict the next state and its uncertainty. Then, in the update stage, the Kalman Filter combines the prediction with actual measurement data to produce a more accurate estimate, while also updating the uncertainty level or error covariance. Repeating the process at each time step and each new data point available, resulting in an optimal state estimate based on the system model and measurement information.

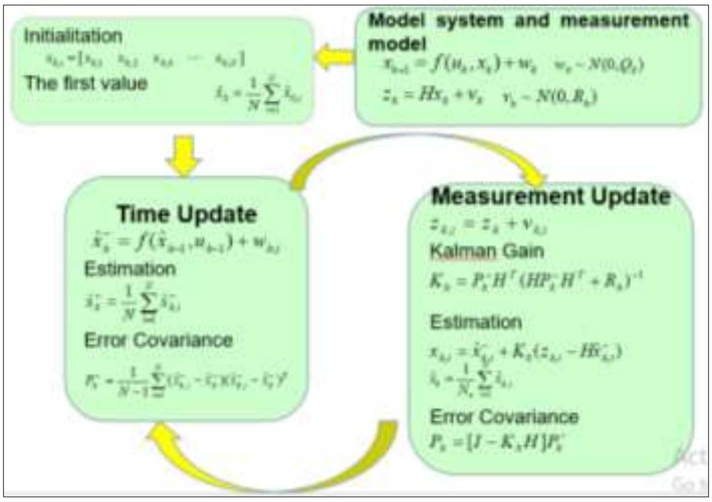

Figure 4. Kalman Filter Algorithm

Model Evaluation

Prediction accuracy is the most crucial factor in choosing a forecast model. (Rajagukguk et al., 2020). Root Mean Squared Error (RMSE) is a standard metric often used for model evaluation. No single metric is inherently better. RMSE is optimal for Gaussian errors. (Hodson, 2022). RMSE is the square root of the Mean Squared Error (MSE). Taking the square root does not affect the relative ranking of the models, but produces a metric with the same units, which practically represents a normally distributed error. The mathematical equation for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (11)$$

Defined:

n : Number of observations
y_i : Actual value for observation in period i
$\hat{y}_i$: Predicted value for observation in period i

The error percentage can show the accuracy of a model. This error percentage is calculated by dividing the known RMSE value of each model by the data range, and multiplying by 100. To calculate the error percentage of a model, use the following mathematical function

$$\text{Error Percentage} : \frac{\text{RMSE}}{\text{rentang data(test)}} \times 100\% \qquad (12)$$

The model performance evaluation is classified based on the range of error percentage values as shown in **Table 1** (Chang et al., 2007). There are four categories of the percentage error level: error 1-10% falls into the "Excellent" category, error 10-20% into the "Good" category, error 20-50% into the "Reasonable" category, and error greater than 50% into the "Bad" category.

Table 1. Model Performance Criteria

Error Percentage	Model Performance Criteria
<10%	Excellent
10 – 20%	Good
20 – 50%	Reasonable
>50%	Bad

Results and Discussions

In this section, the research results will be presented and discussed. The RMSE evaluation matrix evaluates the prediction results of the Artificial Neural Network (ANN) and Kalman Filter (KF) models to determine the performance of each model. Comparison of evaluation results determines the model with the best level of accuracy in forecasting blood demand.

Dataset

The data used in this study are primary blood distribution data for the 2019-2024 period from the Indonesian Red Cross (PMI) of Surabaya City, located at Jl. Embong Ploso No. 7-15, Embong Kaliasin, Genteng District, Surabaya, East Java 60271. The dataset consists of 72 entries with five columns: Date, Incoming Bags, Blood Requests, Expired Blood, and Blood Stock. The last four columns are numeric (int64), while the Date column is of object type, and there are no empty values in any column of the dataset.

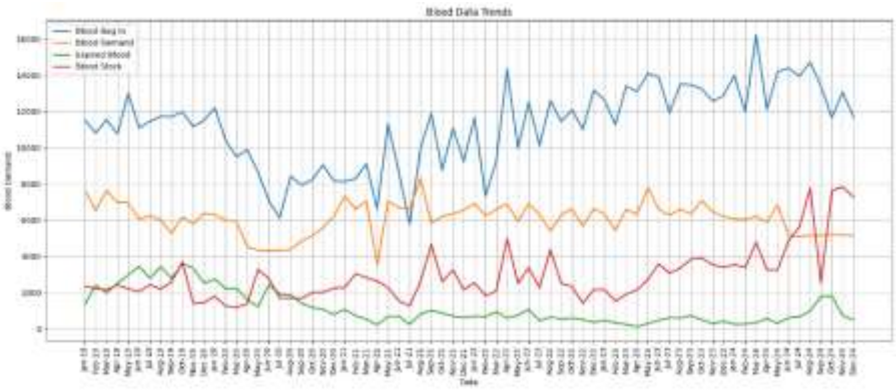

Figure 5. Dataset Trend Pattern

Figure 5. Dataset Trend PatternThe Dataset trends are very volatile, the patterns or trends of the four variables do not significantly influence each other. When the number of blood bags received increases significantly, blood stocks tend to increase as well, but blood demand and the number of expired blood bags remain stable. This means that an increase in blood supply does not necessarily trigger an increase in demand or lead to more expired blood. This could be due to external factors influencing blood demand, such as disease outbreaks, accident rates, and the number of surgical procedures in hospitals in East Java.

ANN Model Evaluation

The performance of the ANN model was evaluated using three training and testing data divisions: 90%:10%, 80%:20%, and 70%:30% based on the best parameter architecture of the ANN model determined from the results of parameter tuning using RandomSearch from Keras Tuner. Experiments were conducted on three data split ratios. For each, Keras Tuner evaluated various combinations of parameters, namely:

1. Neurons in each layer : 16 to 128 neurons
2. Hidden layer : 1 to 3 layers
3. Activation Function : ReLU and Tanh

The results of the parameter tuning process yielded the configuration of the input layer, hidden layer, the number of neurons in each layer, and the activation function that is best for the ANN model at each data split ratio between training and test data, as shown in **Table 2**.

Table 2. ANN Parameter Tuning

Data train/test (%)	Best Parameter Configuration
90:10	Input layer : 128 neuron, tanh 2 hidden layers : 48 and 112 neurons, relu
80:20	Input layer : 48 neuron, tanh 2 hidden layers : 128 and 32 neurons, tanh
70:30	Input layer : 96 neurons, relu 2 hidden layers : 80 dan 16 neuron, tanh

Visualization of the comparison between predicted results and actual data at a 90:10 training-to-test data ratio is presented in Figure 6. The ANN model prediction results are based on the bottom 10% of the entire datasetspecifically for the period from May to December 2024. The ANN prediction results at test size 0.1 show a pattern that does not fully reflect the actual demand dynamics. This indicates that while the ANN model is capable of following general trends, it still has limitations in following extreme variations that appear in actual data.

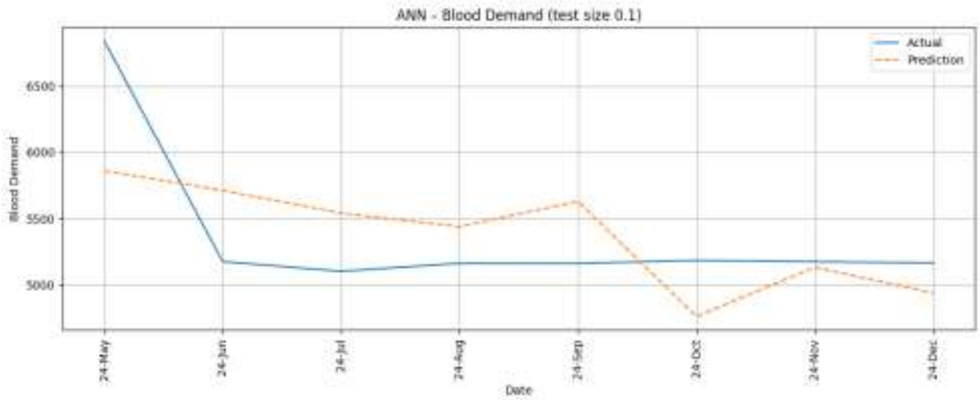

Figure 6. Comparison of Actual and Forecasted ANN Model 0.1

A Comparison of predicted results and actual data for test and training data 80:20 is visualized in Figure 7. This graph displays 20% of the dataset, namely October 2023 to December 2024. The graph shows that the ANN model can follow the general pattern of demand trends, but is not very responsive to extreme changes that appear in the actual data.

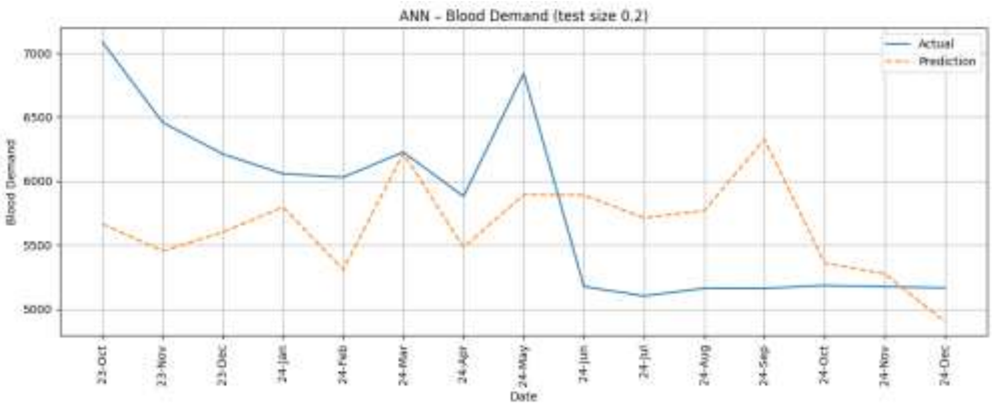

Figure 7. Comparison of Actual and Forecasted ANN Model 0.2

The 70:30 distribution of training data and test data is visualized in **Figure 8**, showing the comparison of predicted results and actual data. The graph displays the time range in this scenario, showing March 2023 to December 2024. The ANN model's prediction results at a test size of 0.3 accurately followed the primary trend of the actual blood demand data. This indicates that the model is quite successful in learning the seasonal patterns of the actual data, but still shows limitations in capturing the dynamics of sudden changes and sharp fluctuations in the actual blood demand data.

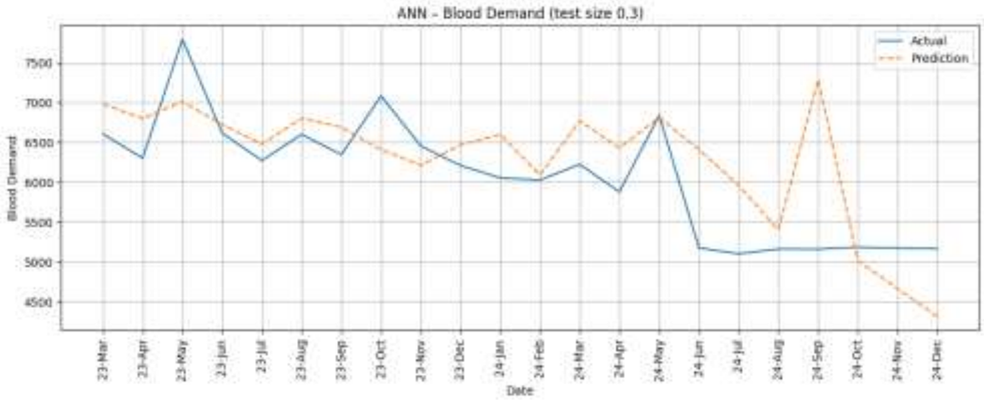

Figure 8. Comparison of Actual and Forecasted ANN Model 0.3

Table 3. ANN Model Evaluation Results

Data train/test (%)	RMSE	Error Percentage
90:10	640.37	42.6%
80:20	719.08	28.7%
70:30	505.60	20.2%

The results of the ANN model performance evaluation, based on the optimal parameter architecture configuration obtained from parameter tuning at three ratios of training and test data division, produced varying RMSE values. At a 90:10 training and test data ratio, the highest error value was observed among the others, with an error percentage of 42.6%. At an 80:20 data ratio, the model's performance improved, but the RMSE was still relatively high with an error percentage of 28.7%. This suggests that even having more training data does not constantly improve the accuracy of the predictive model. This may be because the test data is too small to provide any pattern variation. The model performed best with a 70:30 training-to-test data ratio, yielding the lowest RMSE value and a 20.2% error rate. This indicates that the ANN model architecture is most accurate at predicting blood demand on a larger test dataset.

Kalman Filter Model Evaluation

In the Kalman filter model, several configurations of the error covariance matrices Q and R are used. These two error covariances are usually used as tuning parameters that the user can adjust to obtain the desired performance (Kim & Bang, 2018). The experiment was conducted on several variations of the R and Q variables, namely:

1. R = 0.01, Q = 0.01
2. R = 0.001, Q = 0.001
3. R = 0.0001, Q = 0.0001

A Comparison of actual data and predictions from the Kalman filter model, using a 90:10 training and test data split ratio, is shown in

Figure 9. This graph displays the predicted and actual data, as well as the predicted blood demand for the period May to December 2024. Overall, all predictions successfully followed the sharp downward trend that occurred between May and July 2024. Models with parameters of

0.001 and 0.0001 appeared to be the most responsive to changes in the actual data. Conversely, models with a larger parameter value, 0.01, provided estimates that were slightly slower to adapt to changes in the actual data.

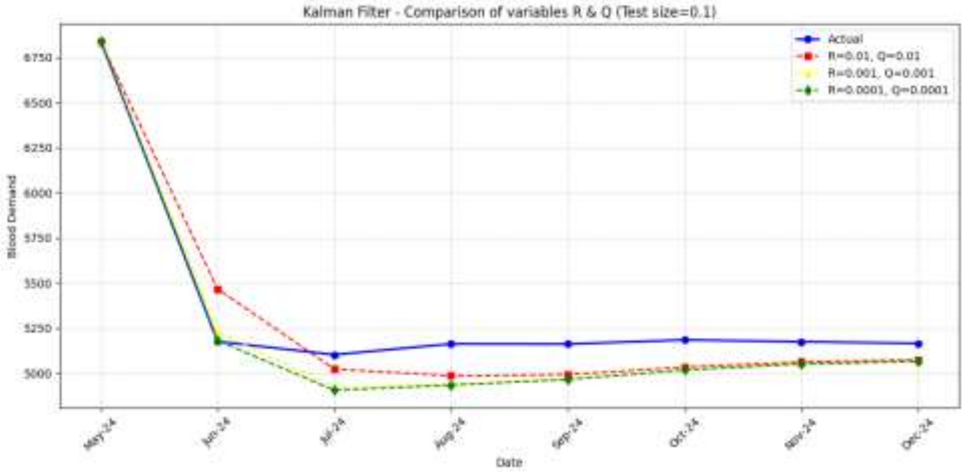

Figure 9. Comparison of Actual and Forecasted KF Model 0.1

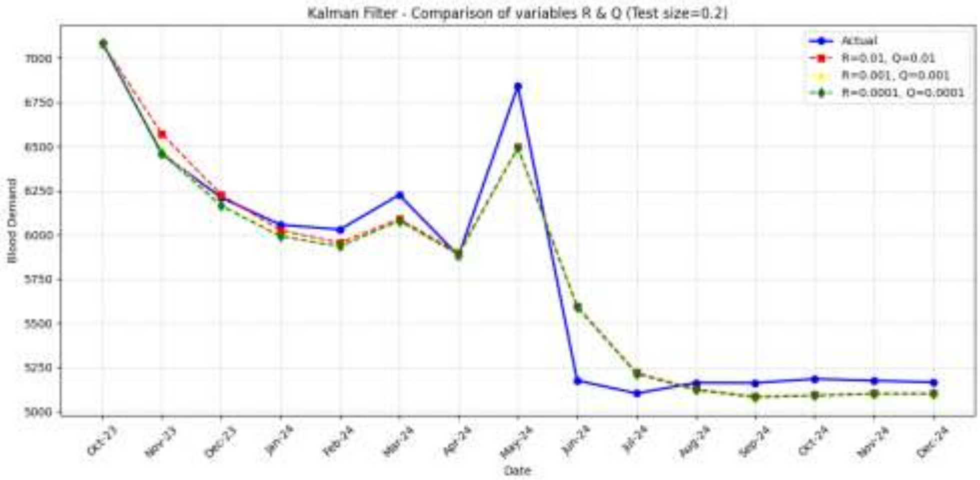

Figure 10. Comparison of Actual and Forecasted KF Model 0.2

With a training and testing data ratio of 80:20, the visualization of the comparison between predicted and actual data spans the time period from October 2023 to December 2024, as shown in **Figure 10.** Comparison of Actual and Forecasted KF Model 0.2. In general, all prediction results can follow the fluctuation pattern of the actual data. Models with smaller noise parameters, especially 0.0001, yield smoother predictions and follow the actual data trend, particularly at points of sudden change. Conversely, configurations with larger R and Q values appear to be slightly less able to adjust points with sudden increases and decreases in the data.

Visualization of the comparison of prediction results with actual data, at a training data to test data ratio of 70:30, provides data for the time span from April 2023 to December 2024, as shown in **Figure 11**. At this ratio, all predicted are similar in each parameter experiment, especially for the R and Q parameters of 0.001 and 0.0001. However, the model with parameter 0.01 appears slightly different from the actual data and other predicted results.

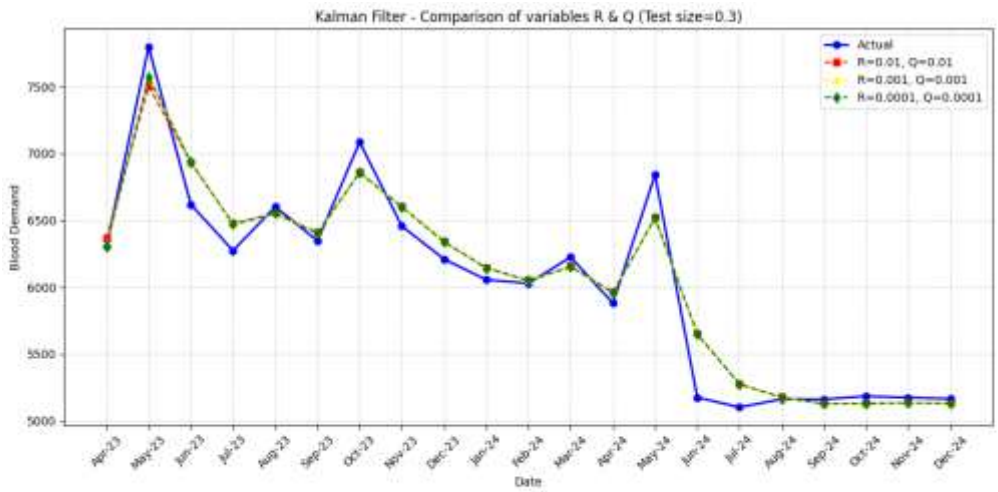

Figure 11. Comparison of Actual and Forecasted KF Model 0.3

The results of testing the R and Q parameters in the blood demand prediction model using the Kalman filter produced RMSE evaluation values that varied considerably, but not significantly, as shown in **Table 4**. The error percentage ranged from 6.9% to 8.9%. The model performed best at a 70:30 data ratio. Despite the considerable RMSE evaluation value, this parameter configuration produced the smallest error percentage, at 6.9%. This was influenced by the data range tested during the model evaluation process. The error percentage was obtained by dividing the error value by the data scale and multiplying it by one hundred. This means that the error percentage is unaffected by the data scale and can be compared across different data ranges.

Table 4. Kalman filter model evaluation results

Data train/test(%)	Parameter R dan Q	RMSE	Error Percentage
90:10	R = 0.01, Q = 0.01	156.08	8.9%
	R = 0.001, Q = 0.001	148.29	8.4%
	R = 0.0001, Q = 0.0001	151.19	8.6%
80:20	R = 0.01, Q = 0.01	158.09	7.9%
	R = 0.001, Q = 0.001	157.23	7.8%
	R = 0.0001, Q = 0.0001	157.49	7.8%
70:30	R = 0.01, Q = 0.01	179.64	7.1%
	R = 0.001, Q = 0.001	174.91	6.9%
	R = 0.0001, Q = 0.0001	**174.39**	**6.9%**

Based on the results of the evaluation and visualization of the Kalman Filter model, it can be seen that the Kalman Filter configuration with smaller noise covariance can be more accurate to the data dynamics. The smaller the error covariance values R and Q, the more accurate the model adjusts to the actual data, thus producing predictions that are closer to the actual data and minimizing bias or prediction errors.

Comparison

After implementing and evaluating the performance of the ANN and Kalman filter models in predicting blood demand at the Surabaya City Indonesian Red Cross (PMI), each model produced highly variable RMSE evaluation values across three training and test data ratios. The ANN and Kalman filter models performed best with a training and test data ratio of 70:30.

Based on the evaluation results presented in **Table 5**, it can be seen that the Kalman Filter model demonstrates superior performance compared to the Artificial Neural Network (ANN) model in forecasting blood needs at various training and testing data split ratios. In the 90:10 scenario, the Kalman Filter model yields a Root Mean Square Error (RMSE) value of 148.29 corresponding to an error percentage of 8.4%. This results in an accuracy of 91.6% which is categorized as "Excellent" performance. In contrast, the ANN model in the same scenario yields an RMSE of 640.37 and an error percentage of 42.6%, resulting in an accuracy of only 57.4%, which is categorized as "Reasonable" performance. A similar trend is also seen in the 80:20 and 70:30 ratios, where the Kalman Filter consistently produces lower RMSE values and higher accuracy than the ANN. This indicates that the Kalman Filter has a more stable and precise ability to capture temporal patterns in blood needs data, especially under limited data conditions. Thus, the Kalman Filter is a more effective approach for the implementing a responsive and accurate blood requirement prediction system.

Table 5. Performance Model Comparison of ANN and Kalman Filter

Train/Test Data (%)	Model	RMSE	Error Percentage	Model Accuracy	Model Performance Criteria
	ANN	640.37	42.6%	57.4%	Reasonable
90:10	Kalman Filter	148.29	8.4%	91.6%	Excellent
	ANN	719.08	28.7%	71.3%	Reasonable
80:20	Kalman Filter	157.23	7.8%	92.2%	Excellent
	ANN	505.60	20.2%	79.8%	Reasonable
70:30	**Kalman Filter**	**174.39**	**6.9%**	**93.1%**	**Excellent**

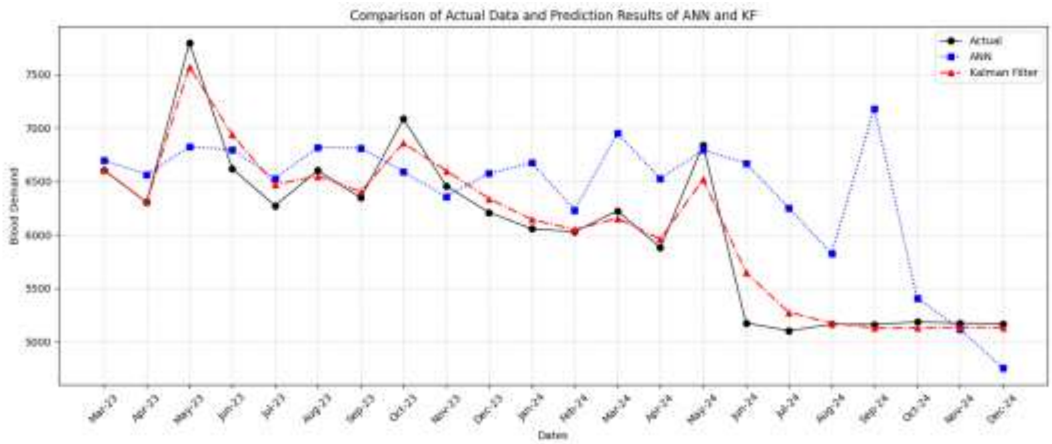

Figure 12. Comparison of Actual and Forecasted KF and ANN Model 0.3

A comparative visualization of actual data and predictions from two modeling approaches, Artificial Neural Network (ANN) and Kalman Filter (KF), for monthly blood demand is shown in **Figure 12**. This graph displays 30% of the testing data, from March 2023 to December 2024. In general, this graph shows that the Kalman Filter predictions are closer to the actual data fluctuation patterns compared to ANN, especially during periods with significant changes in demand. ANN tends to produce smoother predictions but is less responsive to actual dynamics, as reflected by larger deviations at some time points. In contrast, the Kalman Filter demonstrates better adaptive capabilities in following local trends and anomalies, resulting in more accurate and consistent estimates. This visualization reinforces previous quantitative findings, where the Kalman Filter shows lower RMSE values and error percentages than ANN.

Conclusion

This study successfully evaluated and compared the performance of two modelling approaches, namely Artificial Neural Networks (ANN) and Kalman Filter, in predicting monthly blood demand. Based on quantitative analysis and graphical visualization, the Kalman Filter showed superior performance compared to ANN, both in terms of accuracy, prediction stability, and closeness to actual data. The lower RMSE value of 174.39 with an of 6.9% compared to ANN, which produced an RMSE value of 505.6% with an error of 20.2%, indicates that KF is more capable of capturing temporal patterns and blood demand dynamics adaptively. Graphical visualization also strengthens this finding, where KF predictions more consistently follow actual trends compared to ANN which tends to overestimate. Thus, The Kalman Filter can be recommended as a more effective and reliable approach to implementing a blood demand prediction system, especially in the context of data-driven operational decision-making. Suggestions for further research include deploying the model into a prediction system that display an interactive dashboard to predict blood demand in real time.

Acknowledgments

We would like to express our deepest gratitude to Mr. Teguh Herlambang as our supervisor for his valuable time, guidance, and material assistance during this research process. We also extend our gratitude to Ms Rizqi Putri Nourma Budiarti and Ms Endang Sulistiyani as our examiners for their constructive input and evaluation. Furthermore, we would like to express our appreciation to the Institute for Research and Community Service of Nahdlatul Ulama University of Surabaya (LPPM UNUSA) for their financial support and facilities that have made this research possible.

References

Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks: fundamentals, computing, design, and application. *Journal of Microbiological Methods*, *43*(1), 3–31. https://doi.org/https://doi.org/10.1016/S0167-7012(00)00201-3

Chang, P. C., Wang, Y. W., & Liu, C. H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. *Expert Systems with Applications*, *32*(1), 86–96. https://doi.org/10.1016/j.eswa.2005.11.021

Djuardi, A. M. P. (2020). Donor Darah Saat Pandemi Covid-19. *Journal Medika Hutama*, *2*(1), 298–303. http://jurnalmedikahutama.com

Firani, N. K. (2018). *Mengenali Sel Sel Darah dan Kelainan Darah* (Universitas Brawijaya Press, Ed.; 1st ed.). Universitas Brawijaya Press. https://books.google.com/books?hl=id&lr=&id=jMaIDwAAQBAJ&oi=fnd&pg=PR5&dq=darah+adalah+komponen&ots=r2M9JFc1y4&sig=Y7G5MnCgxDTukCnhXWBasFSw3p4

Govaers, F. (2019). *Introduction and Implementations of the Kalman Filter* (F. Govaers, Ed.). BoD – Books on Demand.

Han, S.-H., Kim, K. W., Kim, S., & Youn, Y. C. (2018). Artificial Neural Network: Understanding the Basic Concepts without Mathematics. *Dementia and Neurocognitive Disorders*, *17*(3), 83. https://doi.org/10.12779/dnd.2018.17.3.83

Harsiwi, U. B., & Arini, L. D. D. (2018). Tinjauan Kegiatan Donor Darah Terhadap Kesehatan di PMI Karanganyar, Jawa Tengah Tahun 2018. *Infokes: Jurnal Ilmiah Rekam Medis dan Informatika Kesehatan*, *8*(1). https://doi.org/https://doi.org/10.47701/infokes.v8i1.196

Herlambang, T., Syafiq Kamil, A., & Devi, A. K. (2019). *Peramalan Persediaan Darah Jenis Whole Blood (WB) di PMI Kota Surabaya dengan Neural Network* (Vol. 01, Issue 01).

Hodson, T. O. (2022). Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. *Geoscientific Model Development*, *15*(14), 5481–5487. https://doi.org/10.5194/gmd-15-5481-2022

Indriani, D. (2013). Neural Network Control Chart sebagai Salah Satu Alternatif untuk Diterapkan pada Data Non-Normal. *Jurnal Biometrika Dan Kependudukan*, *2*, 123–130. http://journal.unair.ac.id/download-fullpapers-biometrik3b6813b111full.pdf

Islam, M., Chen, G., & Jin, S. (2019). An Overview of Neural Network. *American Journal of Neural Networks and Applications*, *5*(1), 7. https://doi.org/10.11648/j.ajnna.20190501.12

Kim, Y., & Bang, H. (2018). Introduction to Kalman Filter and Its Applications. *IntechOpen*. https://doi.org/10.5772/intechopen.80600

Laaraiedh, M. (2012). Implementation of Kalman Filter with Python Language. *ArXiv Preprint ArXiv*. http://arxiv.org/abs/1204.0375

Martinez-Plumed, F., Contreras-Ochando, L., Ferri, C., Hernandez-Orallo, J., Kull, M., Lachiche, N., Ramirez-Quintana, M. J., & Flach, P. (2021). CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories. *IEEE Transactions on Knowledge and Data Engineering*, *33*(8), 3048–3061. https://doi.org/10.1109/TKDE.2019.2962680

Muhith, A., Herlambang, T., & Rahmalia, D. (2020). Estimation of Thrombocyte Concentrate (TC) and Whole Blood (WB) using Unscented Kalman Filter. *International Journal of Advanced Science and Technology*, *29*(8s), 25–32.

Muhith, A., Herlambang, T., Rahmalia, D., & Karya, D. F. (2022). Estimation of Packed Red Cells (PRC) in Bojonegoro blood bank using Modified Kalman Filter. *Journal of Physics: Conference Series*, *2157*(1). https://doi.org/10.1088/1742-6596/2157/1/012023

Nafisah, L., Astanti, Y. D., & Nastiti, D. (2017). Simulasi Sistem Dinamis Pengendalian Persediaan Darah Palang Merah Indonesia Kota Yogyakarta. *Prosiding ISLI*.

PMI Kota Surabaya. (2025, February 4). *PMI Surabaya*. Https://Www.Pmikotasurabaya.or.Id/. https://www.pmikotasurabaya.or.id/

Rajagukguk, R. A., Ramadhan, R. A. A., & Lee, H. J. (2020). A review on deep learning models for forecasting time series data of solar irradiance and photovoltaic power. *Energies*, *13*(24). https://doi.org/10.3390/en13246623

Rasamoelina, A. D., Adjailia, F., & Sincak, P. (2020). A Review of Activation Function for Artificial Neural Network. *2020 IEEE 18th World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, 281–286. https://doi.org/10.1109/SAMI48414.2020.9108717

Sharma, S., Sharma, S., & Athaiya, A. (2020). ACTIVATION FUNCTIONS IN NEURAL NETWORKS. *International Journal of Engineering Applied Sciences and Technology*, *4*(12), 310–316. http://www.ijeast.com

Simon, D. (2001). Kalman Filtering. *Embedded Systems Programming*, *14*(6), 72–79.

Singhal, S., & Wu, L. (1989). Training feed-forward networks with the extended Kalman algorithm. *International Conference on Acoustics, Speech, and Signal Processing*, 1187–1190. https://doi.org/10.1109/ICASSP.1989.266646

Tao, H., Al-Sulttani, A. O., Salih Ameen, A. M., Ali, Z. H., Al-Ansari, N., Salih, S. Q., & Mostafa, R. R. (2020). Training and Testing Data Division Influence on Hybrid Machine Learning Model Process: Application of River Flow Forecasting. *Complexity*, *2020*(1). https://doi.org/10.1155/2020/8844367