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Optimizing Windowing Techniques to Improve the Accuracy of Artificial Neural Networks in Predicting Outpatient Visits

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Abstract

Hospitals are healthcare institutions that play an important role in providing health services to the community. To optimize the service, hospitals need to predict the number of outpatient visits. The objectives of this research are (1) determine the effect of window size on the accuracy of predicting the number of outpatient visits, and (2) identify the best window size and accuracy of neural networks in predicting the daily number of outpatient visits. To achieve the research objectives, the following steps were undertaken: data collection of outpatient visits at RSUD dr. Soedirman Kebumen from 2018 to 2023, preprocessing, applying different window sizes, modeling neural networks, and testing by calculating the RMSE value for each window size. The test results show that the lowest RMSE for 2018 was 1.267 with a window size of 34, for 2019 was 1.262 with a window size of 34, for 2020 was 1.515 with a window size of 17, for 2021 was 1.81 with a window size of 18, for 2022 was 1.282 with a window size of 20, and for 2023 was 1.263 with a window size of 29. These window sizes indicate the cycle of outpatient visits each year. By understanding these visit cycles, the number of outpatient visits can be predicted at any time.

Keywords: Artificial Neural Network; Outpatient; Prediction; Windowing.

Introduction

Estimating the number of patient visits is very important for hospitals because it can help hospital management in planning and implementing policies [1]. During the Covid-19 pandemic, it has reduced visits to hospitals, which has an impact on hospital fund balances during the pandemic [2]. Artificial Neural Network (ANN) is one of the best methods for prediction. ANN is an information processing system that has characteristics similar to the human nervous system that can solve prediction problems by training large data. ANN is able to tolerate errors so that it can produce good predictions. In addition, this method can also be used to model complex relationships between inputs and outputs to find patterns in the data [3].

Artificial intelligence and machine learning have made significant progress over the past two decades. ANN are data-driven models and the training process generally requires proper sampling due to its "black box" nature [4]. To implement machine learning, many use Neural Network algorithms in prediction systems. ANN is chosen because this algorithm is very effective in predicting exchange rate change data and neural networks are useful in predicting market trends [5]. Prediction is used to balance current and future time differences with requirements. ANN can apply forecasting methods well [6].

There are important techniques in determining the best predictive value especially for time series data, one of which is the Windowing technique. Windows size plays an important role in time series data. However, there is no benchmark for the size of the Windows Size itself [7]. A large windows size is very important because it directly determines how much data is given to the ANN classifier [8]. The preprocessing stage is the stage of preparing data before it is processed with certain algorithms. One of the preprocessing steps that need to be done to predict time series data is windowing. Windowing is the formation of a structure from time series data to cross-sectional data. The size of the window affects the accuracy of the prediction results. Window size plays an important role in time series data. Research on this topic is still limited. The results show that the window size affects the accuracy of the prediction method. However, so far, no research has been found on the optimal window size. Mean squared error, often called RMSE, is a measurement method that measures the difference between the predicted value of a model and the

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estimated observed value. The accuracy of the estimation method or measurement error is characterized by a low RMSE value [9]. Researchers have demonstrated various artificial intelligence algorithms used for prediction, classification, clustering in various fields such as agriculture [10], health [11], [12], finance [13], energy [14] and others [15]–[17]. This shows that intelligent algorithms are the choice for researchers to perform analysis.

The results of study before show that the window size affects the accuracy of the prediction method. However, so far, not found any research regarding the optimal window size. In research using data from previous months, inflation can be estimated using ANN methods using a sliding window technique or also called windowing. Windowing creates structure from time series data to cross-sectional data. The size of the window affects the accuracy of the prediction results. The experiments with three window sizes, namely 6, 12 and 18 to find out whether there were differences in the accuracy of the results for different window sizes. Based on experimental results, window size 6 has the best inflation forecasting accuracy with an RMSE of 0.435 [9]. Another research presents a trend analysis of the Covid-19 situation in Malaysia based on data from 25 January 2020 to 30 April 2020. Time series forecasting is also carried out using multiple regression and ANN using the sliding window or lag method. Comparing the results in terms of predictive value of load shedding events on May 1 to 4, 2020, the multilayer perceptron architecture model with lead times of 5 to 14 performed significantly better than the regression model in predicting future trends. A window width of 14 means historical events that occurred two weeks before the next time scale relating to performance. according to Worldometer, as of March 12, the current official estimate of the incubation period for COVID-19 is between 2 and 14 days. Assessment is needed to determine whether the window width or time window size corresponds to the virus incubation period. Sliding window is an easy-to-use method for time series forecasting. The data needs to be restructured so that it can be presented as a classification or temporal regression problem. With time series, historical data is important for determining future trends [11]. Several previous studies using windowing or sliding windows have been carried out with various artificial intelligence algorithm methods used in various fields such as the environment [18]–[20] Aeronautics [21], Data center resources [22], wireless sensor networks [23], Ocean Engineering [24], Data mining [25]–[27], hydrology [28], weather [29] and networking [30]. Prior to this research, there were several other studies that discussed Windows Size optimization but had never been used on data that would be used by researchers. The purpose of this research is to find out whether Windowing optimization affects the ANN method to improve accuracy with the Windows Size and RMSE values obtained in predicting the number of outpatient visits.

Method

A. Research Data

The application of sliding windows to time series with ANN methods involves using moving windows to train and predict time series data using ANN models. The time series is divided into windows of fixed size. The window size can be determined based on the application requirements and the nature of the data. For example, if that is daily data, it can divide into daily or smaller sized windows such as hours or even minutes depending on the level of resolution required. Then each window contains a number of data points from the time series, and these are the input for the ANN model. Additionally, its need a corresponding label for each window, which may be a future value (in the case of prediction) or a category (in the case of classification). These windows are then used to train an ANN model. When training a model, these windows are presented to the model sequentially one by one, and the model learns to understand the patterns and relationships within them. Once training is complete, the model is evaluated using separate validation data to check its performance. This helps to ensure that the model can make good predictions on previously unseen data. Once the model is deemed adequate, that can use it to make predictions on new data. New windows are formed with actual time data, and the model is then used to make predictions based on the information in those windows as in **Figure 1**.

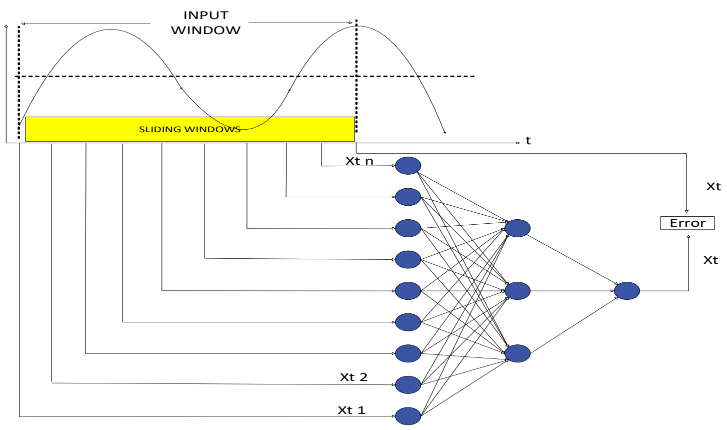

Figure 1. Windowing

The first stage of research carried out was by conducting a literature study. Next, problem identification is carried out by studying the journals obtained. The next stage is data collection. Data is taken from the database and then processed into Excel and graphs. Then data preprocessing is carried out by normalizing the data and continuing with windowing. The prediction process using an ANN is carried out and then results testing and analysis is carried out after getting the final results. The research carried out in several stages can be seen in **Figure 2**.

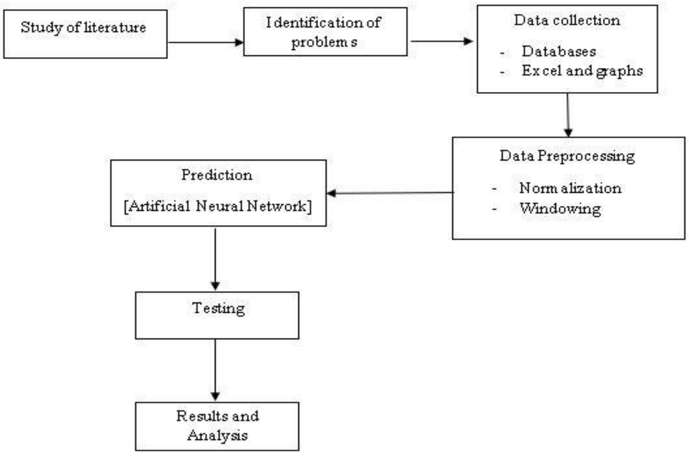

Figure 2. Research Stages

This study uses data taken from the database of the hospital information system of RSUD Dr. Soedirman Kebumen. The data taken is the visit data of all outpatients from 2018 to 2023. The original data amounted to 1058975 rows of data with 14 attributes. The original data is processed into a daily collection of the number of patients so that a time series and total data is formed. The dataset to be processed totals 2016 rows of data with 2 attributes. The data is divided by year to determine the effect of windowing on the ANN method. The data then changes the contents of the Date attribute to Attribute No, which is the sequence number 1 to the end of the year's data.

This research focuses on windowing optimization by providing Windows Size values from smallest to largest with the ANN method on outpatient visit data at RSUD Dr. Soedirman Kebumen. The determination of the Window Size value is determined by making a graph per year and determining every one cycle of the visit graph starting from the beginning of the year. From the resulting data format, a graph is made to determine the cyclical pattern of the data each year. Then on the graph that is produced each year, one cycle of data is found and the value of each continuous cycle is taken. Each cycle finds a value that becomes the Window Size value. The value found is marked with a red line on the graph every year. From the processed graph, 5 values is taken from the No attribute as the Windows Size value in the 2018 to 2023 data. Example in the 2018 patient graph, by looking at the graph visually for one cycle, the second highest peak value is determined, which is data number 16. Then, look for the next closest highest peak or the highest value after the lowest value as in **Figure 3**.

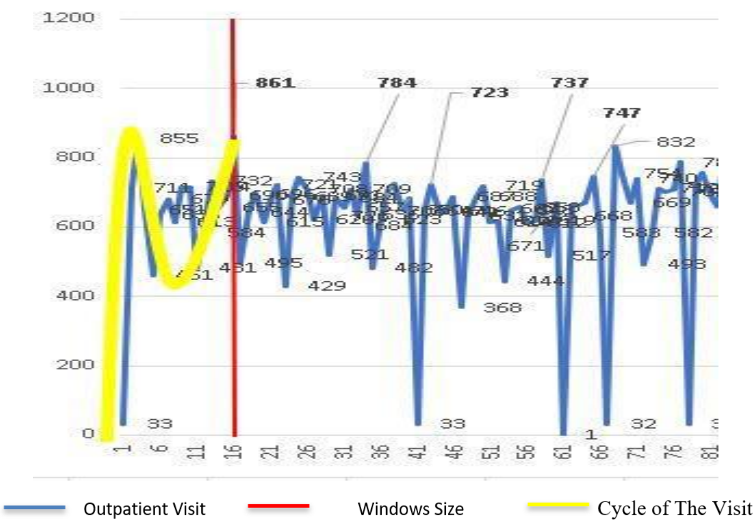

Figure 3. Example Determination of the Window Size Outpatient 2018

In **Figure 3**, an example of determining the first window value through the graph of outpatient visits in 2018 is shown. The x-axis (horizontal) represents the day in 2018, and the y-axis (vertical) represents the number of outpatient visits on the corresponding day indicated by the x-axis. The yellow line represents one cycle of the wave. While the red vertical line represents the number of outpatient visits shows a repeating pattern. The data shows that the first outpatient visit was on the 16th day.

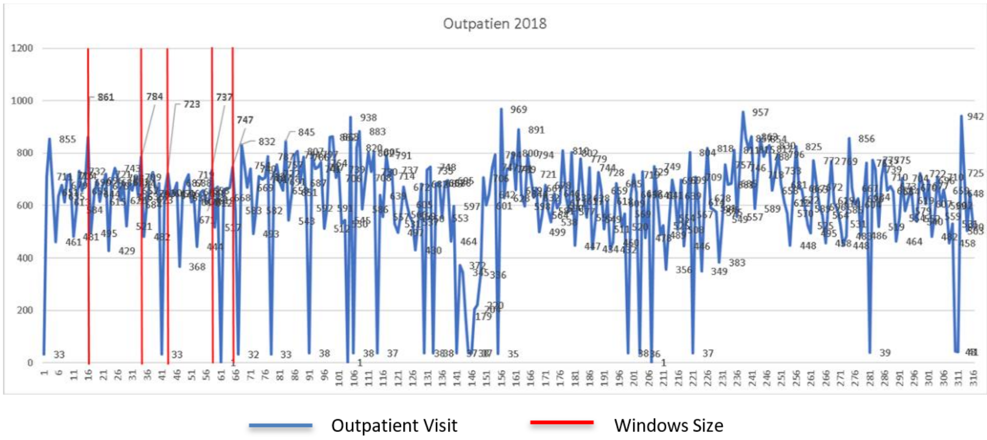

Figure 4. Graph Windows Size 2018

In **Figure 4**, the graph of outpatient visits in 2018 is shown. The x-axis represents the day of the year 2018, and the y-axis represents the number of outpatient visits on the corresponding day indicated by the x-axis. In **Figure 4**, there are five vertical red lines. Each of these vertical red lines marks where the number of outpatient visits shows a repeating pattern. The data shows that outpatient visits repeat on days 16, 34, 43, 58, and 65. To confirm whether outpatient visits indeed repeat on days 16, 34, 43, 58, or 65, testing was conducted using a neural network. The input for the neural network is a sliding window with sizes 16, 34, 43, 58, and 65. Using these five sliding windows, the neural network is trained and tested. The result with the lowest RMSE value indicating that the sliding window produces the best repeating visit pattern.

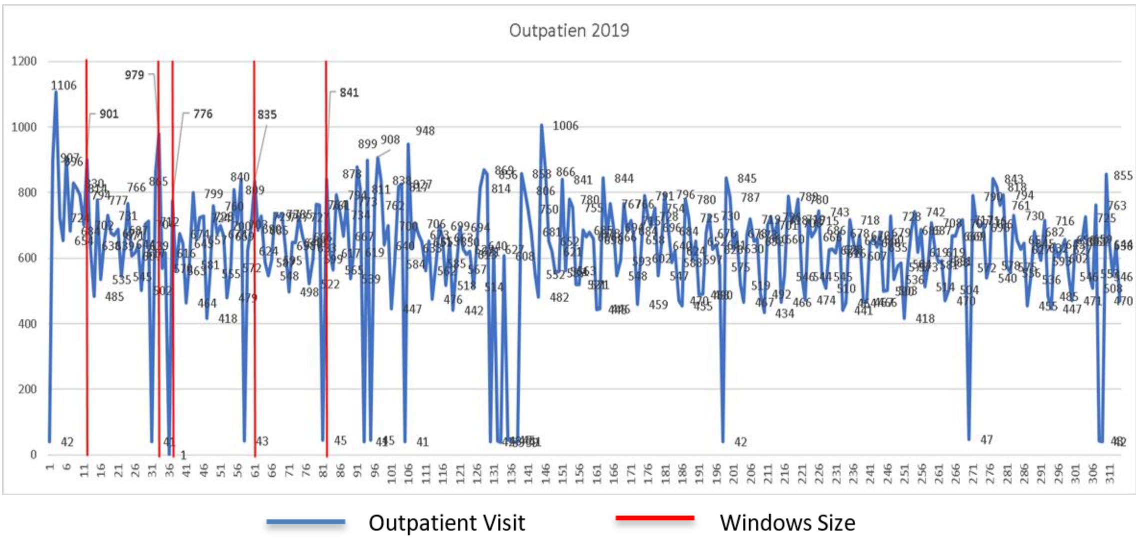

Figure 5. Graph Windows Size 2019

The graph of outpatient visits in 2019 is shown in **Figure 5**. The x-axis represents the days in the year 2019, and the y-axis represents the number of outpatient visits on the corresponding day indicated by the x-axis. There are five vertical red lines in **Figure 5**, each of which marks where the number of outpatient visits shows a repeating pattern. The data shows that outpatient visits recur on days 12, 33, 37, 61 and 82. To confirm whether outpatient visits are indeed recurrent on days 12, 33, 37, 61 and 82, testing is performed using a neural network. The input to the neural network is a sliding window with sizes 12, 33, 37, 61 and 82. Using these 5 sliding windows, the neural network is trained and tested. The result with the lowest RMSE value in 2019 indicates that the sliding window produces the best repeat visit pattern.

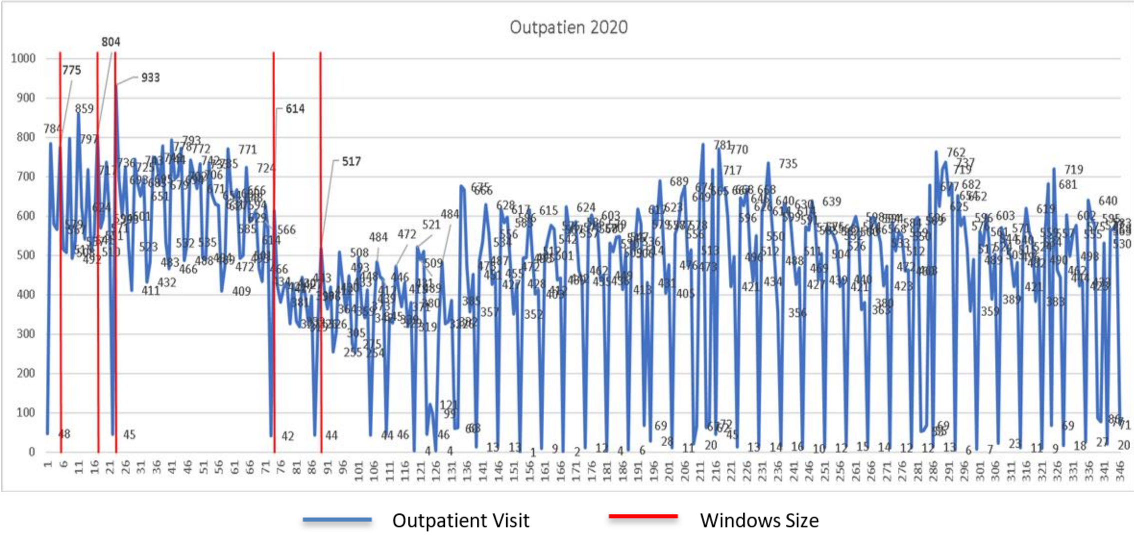

Figure 6. Graph Windows Size 2020

As seen in **Figure 6**, the graph of outpatient visits in 2020 is shown. The x-axis represents the days in 2020, and the y-axis represents the number of outpatient visits on the corresponding day indicated by the x-axis. In **Figure 6**, there are five vertical red lines where each of these vertical red lines marks where the number of outpatient visits shows a repeating pattern on days 5, 17, 23, 74 and 89. Testing is done using a neural network to confirm whether outpatient visits are indeed repeating on days 5, 17, 23, 74 and 89. The input to the neural network is a sliding window with sizes 5, 17, 23, 74 and 89. Using these five sliding windows, the neural network is trained and tested which then produces the lowest RMSE value in 2020. The results show that the sliding window produces the best repeat visit pattern.

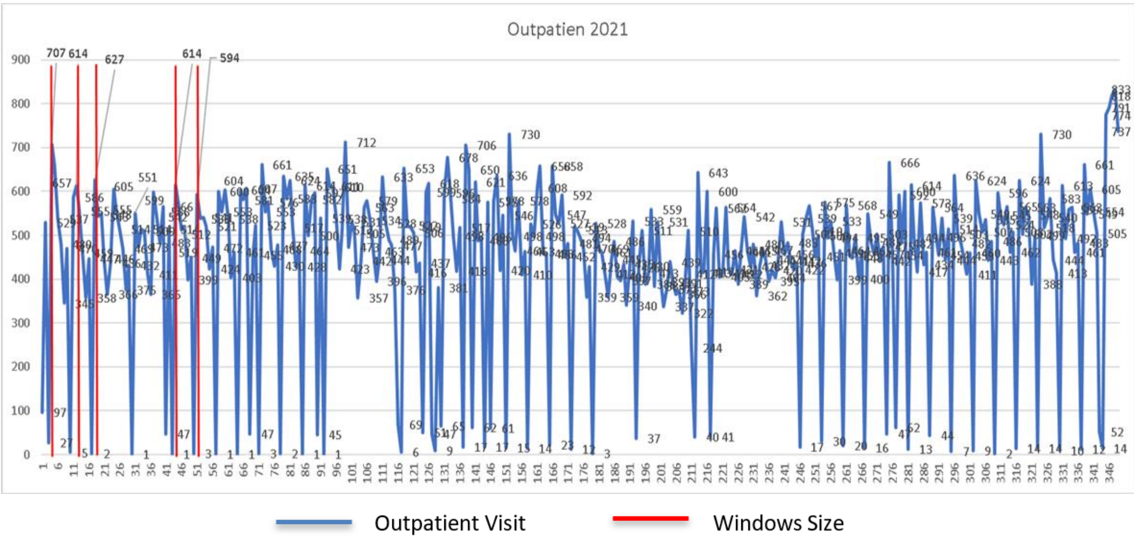

Figure 7. Graph Windows Size 2021

The graph of outpatient visits in 2021 is shown in **Figure 7**. The x-axis represents the days in 2021, and the y-axis represents the number of outpatient visits on the corresponding day indicated by the x-axis. There are five vertical red lines where each of these vertical red lines marks where the number of outpatient visits shows a repeating pattern on days 4, 12, 18, 31 and 44. Indeed, it repeats on days 4, 12, 18, 31 and 44, so testing is carried out using a neural network to confirm whether outpatient visits. The input to the neural network is a sliding window with sizes 4, 12, 18, 31 and 44. Using these 5 sliding windows, the neural network is trained and tested which then produces the lowest RMSE value. The result with the lowest RMSE value in 2021 shows that the sliding window produces the best repeat visit pattern.

In **Figure 8**, the graph of outpatient visits in 2022 is shown in the x-axis represents the days in 2022, and the y-axis represents the number of outpatient visits on the corresponding day indicated by the x-axis. In **Figure 8**, there are five vertical red lines, each of which marks where the number of outpatient visits shows a repeating pattern on days 10, 20, 24, 31 and 34. To confirm whether outpatient visits are indeed repeating on days 10, 20, 24, 31 and 34, testing is carried out using a neural network with sliding window inputs of sizes 10, 20, 24, 31 and 34 . Using these five sliding windows, the neural network is trained and tested. The result with the lowest RMSE value in 2022 indicates that the sliding window produces the best repeat visit pattern.

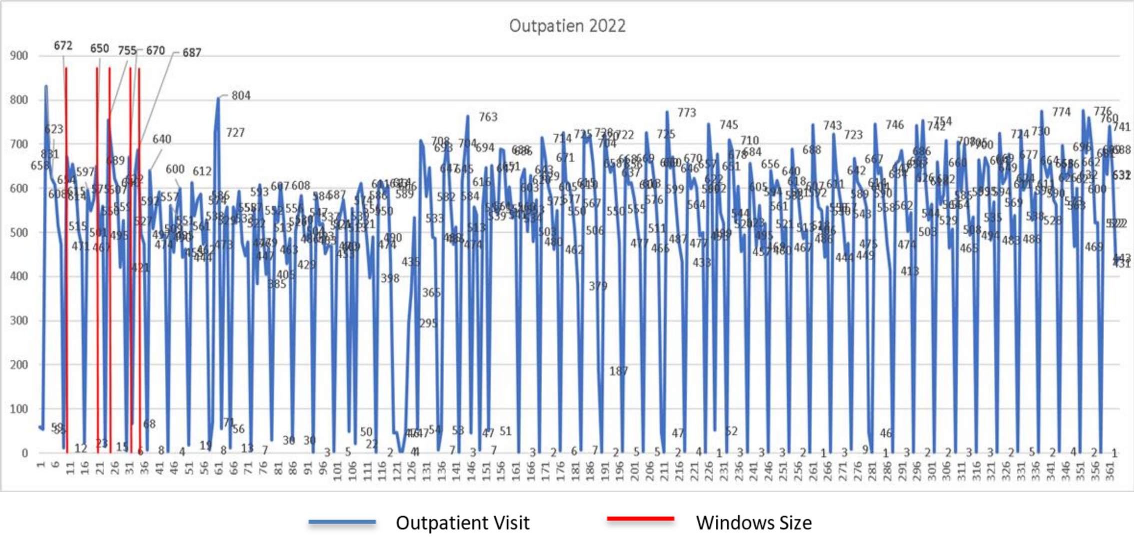

Figure 8. Graph Windows Size 2022

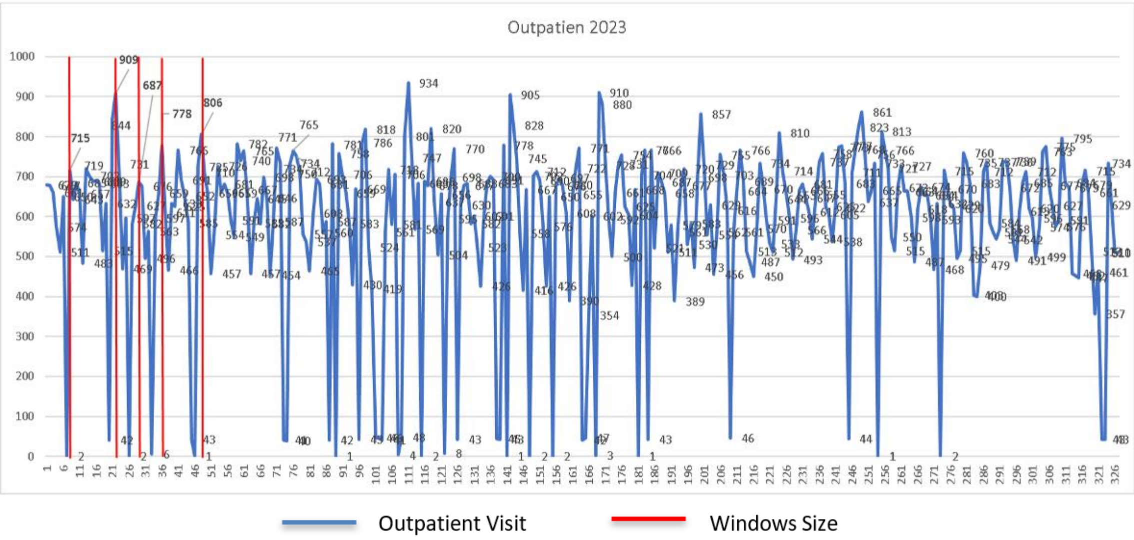

Figure 9. Graph Windows Size 2023

The graph of outpatient visits in 2023 is shown in **Figure 9**. The x-axis represents the days in 2023, and the y-axis represents the number of outpatient visits on the corresponding day indicated by the x-axis. There are five vertical red lines in **Figure 9**, each of which marks where the number of outpatient visits shows a repeating pattern on days 8, 22, 29, 36 and 48. To confirm whether outpatient visits are indeed repeating at these values, a neural network is trained and tested with sliding window inputs of sizes 8, 22, 29, 36 and 48. The result with the lowest RMSE value indicates that the sliding window produces the best repeat visit pattern.

Windows Size values from 2018 to 2023 are as follows in **Table 1**.

Table 1. Window Size Graph Result 2018-2023

Year	Window Size 1	Window Size 2	Window Size 3	Window Size 4	Window Size 5
2018	16	34	43	58	65
2019	12	33	37	61	82
2020	5	17	23	74	89
2021	4	12	18	44	51
2022	10	20	24	31	34
2023	8	22	29	36	48

Table 1 displays statistics on window sizes from 2018 to 2023. Each year, five distinct window sizes from Window Size 1 to Window Size 5 are recorded. 2018 saw the following reported window sizes: 1 window measured 16 by 2; 3

windows measured 34 by 3; 4 windows measured 58 by 5; and 5 windows measured 65 by 6. This demonstrates that, in all categories, 2018 had comparatively large window sizes. In 2018, the window sizes recorded were as follows: window size 1 was 16, window size 2 was 34, window size 3 was 43, window size 4 was 58, and window size 5 was 65. This shows that 2018 had relatively large window sizes across all categories. The year 2019 showed significant variations in window sizes, with window size 1 being 12, window size 2 being 33, window size 3 being 37, window size 4 being 61, and window size 5 reaching its highest value of 82. Although window size 1 was smaller than in 2018, window sizes 4 and 5 increased. In 2020, there was a sharp decline in window sizes 1 and 2, by 5 and 17 respectively. However, window sizes 4 and 5 saw a sharp increase, by 74 and 89 respectively, indicating a significant shift in window sizes this year. 2021 shows an overall trend of smaller window sizes compared to previous years. Window size 1 was 4, window size 2 was 12, window size 3 was 18, window size 4 was 44, and window size 5 was 51. This reflects a significant reduction in window sizes across all categories. In 2022, there is stability in window sizes, although they are smaller compared to 2018 to 2020. Window size 1 is 10, window size 2 is 20, window size 3 is 24, window size 4 is 31, and window size 5 is 34. The year 2023 shows a gradual increase in window sizes from window sizes 1 to 5. Window size 1 is 8, window size 2 is 22, window size 3 is 29, window size 4 is 36, and window size 5 is 48. Despite the increase, these window sizes are still smaller compared to previous years, especially 2018 and 2019. All things considered this table shows how window widths vary from year to year. It may be further examined to identify patterns or other factors that affected window sizes over this time.

B. Prediction Accuracy

Root Mean Square Error (RMSE) is a quadratic evaluation rule that also measures the magnitude of the average error. It is the square root of the mean square difference between the prediction and the actual observation, which is continuous between MSE and RMSE, where the calculation system is the same and the difference is the result of calculating the square of the estimate [5].

$$RMSE = \sqrt{\frac{\sum(x-y)^2}{n}} \tag{1}$$

Where x is actual data value; y predicted data value; n number of data.

C. Prediction Process

Data per year is normalized by giving the value of the filter type attribute and the outpatient attribute is selected. Then the range transformation method was chosen with a minimum value of 0,0 and a maximum value of 1. The normalized yearly data is then optimized using the Windowing feature. The Horizon Attribute value is determined using the No. attribute then the windows size value is determined according to the optimization that has been selected on the data per year.

Data is split into training data and test data using the Split Data feature. The sampling type used is Automatic. The data is then partitioned with a ratio of 70% and 30%. The training data is then entered into the Neural Network method with Training Cycles 200, learning rate 0.01 and momentum 0.9. Next, the training data is entered into the Apply Model feature and added to the test data from the previous Split Data feature. The Apply Model operator functions to apply the model to the dataset.

D. Performance Training

The final process is to test with the Performance feature. This feature is used for performance evaluation. It provides a list of performance criteria values. These performance criteria are determined automatically to match the type of learning task. The final result shows the RMSE value at each Windows Size. Windowing test process is done according to the Windows Size that has been selected on each year's data. In addition to the RMSE, the ANN Architecture that has been improved is obtained.

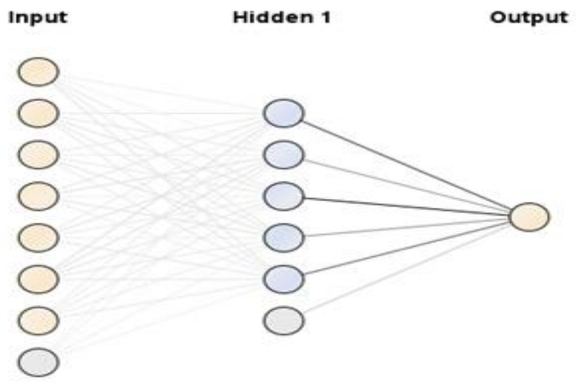

Figure 10. Improved ANN Architecture

Results and Discussion

Cycle visualization is a way to understand recurring patterns in RMSE data related to window size. One way is to visualize visit data in a graphical format, helping us see seasonal patterns and certain days that show anomalies or peaks in visits. By using this method, we can gain better insight into recurring patterns in RMSE data, which can help in improving the accuracy of outpatient visit prediction. Previous studies have never used outpatient visit data, but it can be concluded that improvisation using window size in ANN can help in the accuracy of outpatient visit prediction.The final process is to carry out testing with the Performance feature. This feature is used for performance evaluation. It provides a list of performance criteria values. These performance criteria are determined automatically to suit the type of learning task. The final result displays the RMSE value for each Windows Size. The Windowing testing process is carried out according to the Windows Size that has been selected in the data for each year.The results of tests that have been carried out using Windowing optimization on the ANN method in data per year, the following data is obtained.

Table 2. RMSE value for 2018

Window Size	RMSE
16	1.633 +/- 0.000
34	1.267 +/- 0.000 *
43	1.668 +/- 0.000
58	1.945 +/- 0.000
65	1.916 +/- 0.000

The best RMSE value in 2018 data was achieved on Windows Size 34 that is 1.267 as in **Table 2**.

Table 3. RMSE value for 2019

Window Size	RMSE
12	1.831 +/- 0.000
33	1.577 +/- 0.000
37	1.262 +/- 0.000 *
61	2.468 +/- 0.000
82	3.992 +/- 0.000

The best RMSE value in 2019 data was achieved on Windows Size 37that is 1.262 as in **Table 3**.

Table 4. RMSE value for 2020

Window Size	RMSE
5	1.698 +/- 0.000
17	1.515 +/- 0.000 *
23	1.812 +/- 0.000
74	3.274 +/- 0.000
89	6.270 +/- 0.000

The best RMSE value in 2020 data was achieved on Windows Size 17 that is 1.515 as in **Table 4**.

Table 5. RMSE value for 2021

Window Size	RMSE
4	2.080 +/- 0.000
12	1.880 +/- 0.000
18	1.381 +/- 0.000 *
44	1.907 +/- 0.000
51	1.652 +/- 0.000

The best RMSE value in 2021 data was achieved on Windows Size 18 that is 1.381as in **Table 5**.

Table 6. RMSE value for 2022

Window Size	RMSE
10	1.460 +/- 0.000

Window Size	RMSE
20	1.282 +/- 0.000 *
24	1.990 +/- 0.000
31	2.765 +/- 0.000
34	1.703 +/- 0.000

The best RMSE value in 2022 data was achieved on Windows Size 20, that is 1.282 as in **Table 6**.

Table 7. RMSE value for 2023

Window Size	RMSE
8	1.694 +/- 0.000
22	1.461 +/- 0.000
29	1.263 +/- 0.000 *
36	1.391 +/- 0.000
48	2.009 +/- 0.000

The best RMSE value in 2023 data was achieved at Windows Size 29 that is 1.263 as in **Table 7**.

By looking at the test results from **Table 2** to **Table 7**, it can be seen the effect of Windowing on the data of 2018 and 2019 with Windows Size above 30, which is 34 in 2018 and 37 in 2019. But in 2020 and 2021, there was a significant decrease in the value of Windowing, which is the value of Widows Size under 20 which is 17 and 18. While the value of Windowing in 2022 and 2023 began to rise to 20 and 29. For the achievement of the best RMSE value obtained in 2019, the value was 1.262. While the RMSE in 2020 reached the highest value compared to other years' achievements, which is 1.515.

Table 8. Value of Window Size and RMSE

Year	Window size	RMSE
2018	34	1.267
2019	37	1.262
2020	17	1.515
2021	18	1.381
2022	20	1.282
2023	29	1.263

The achievement of the best RMSE value along with Windows size based on the results of annual data testing from 2018 to 2023 can be seen in the **Table 8**. By comparing the results obtained from 2018 to 2023, the highest Windows size achievement was obtained in 2019 with a value of 37 and the lowest value was obtained in 2020, that is 17. The best RMSE achievement was obtained in 2019 with a value of 1.262 and the worst value was obtained in in 2020 with a value of 1.515.

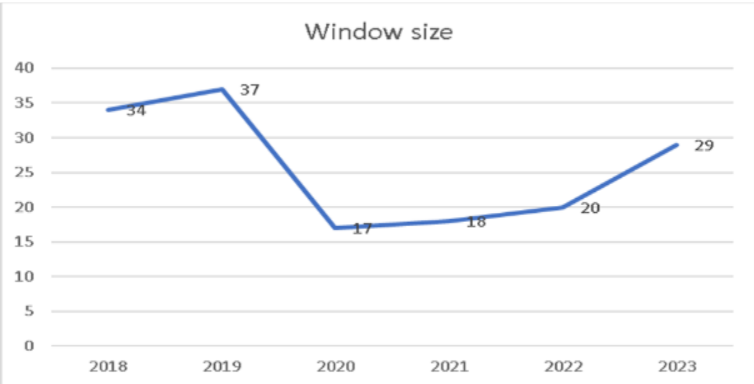

Figure 10. Window Size Graph

The graph of Windows size achievements based on annual data testing results from 2018 to 2023 can be seen in **Figure 10**. In 2018, the window size value was 34, then in 2019 it increased to 37. However, in the following year, namely 2020, it decreased drastically to 17. Then in 2021 it only increased by one point to 18. Meanwhile, in 2022 and 2023, the number of windows increases even more. size 20 and 29. From this graph, the achievement of the value of Window Size experienced the lowest decrease in 2020 with a value of 17.

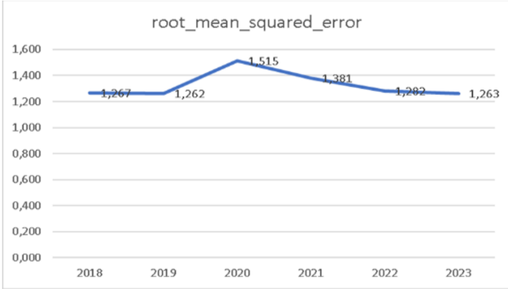

Figure 11. RMSE graph

The graph of the best RMSE value achieved from 2018 to 2023 can be seen in **Figure 11**. RMSE in 2018 obtained a value of 1.267. Then in 2019 the score got even better with an achievement of 1,262. However, in 2020 the score worsened with a score of 1.515. In 2021, the achievement score improved slightly with a score of 1.381. And in 2022 the score improves with a score of 1.282. Then in 2023 the score improves closer to the score achieved in 2019, namely with a score of 1.263.

From the RMSE value achievement graph and the Windows Size graph obtained, it can be seen that in 2020 it has the smallest Window Size value which is 17 with the largest RMSE value which is 1,515. This means that in 2020 it has the shortest visit day, which is 17 days. While the largest RMSE value shows that the most difficult prediction is made in 2020. Which means predicting the number of outpatient visits in 2020 has the highest uncertainty. This happened most likely because of the Covid-19 pandemic that peaked in 2020 in Kebumen Regency. This shows that the widowing method is a method that is easy to use for time series forecasting.

Conclusion

The test results show that the lowest RMSE for 2018 was 1.267 with a window size of 34, for 2019 was 1.262 with a window size of 34, for 2020 was 1.515 with a window size of 17, for 2021 was 1.81 with a window size of 18, for 2022 was 1.282 with a window size of 20, and for 2023 was 1.263 with a window size of 29. These window sizes indicate the cycle of outpatient visits each year. From the research results, it can be concluded that windowing optimization can improve the accuracy of ANN in predicting the number of outpatient visits. Future research needs to be evaluated on larger data to improve results related to testing Windowing using the ANN method. Examination of larger data can provide further validation of the resulting values. With time series, historical data is important for determining future trends.

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