



## Forecasting Pneumonia Toddler Mortality Using Comparative Model ARIMA and Multilayer Perceptron

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### Abstract

*Pneumonia is an inflammatory lung disease that causes the second largest number of deaths in Indonesia after Dengue Hemorrhagic Fever (DHF). In 2021, there was an increase in cases of 7.8% compared to the previous year, and was exacerbated by the Covid-19 pandemic. Predictive methods were needed to predict and compare the ARIMA and MLP methods, where the results of the best methods were selected for long-term forecasting. The research data used was from January 2014 – December 2021, with a total of 96 data. In choosing the best method, the basic error calculations used were Mean Absolute Deviation, Mean Squared Error, and Mean Absolute Percentage Error. This study aims to build a predictive model for the next period of pneumonia under-five mortality. These results can be used for government policy-making related to mortality prevention for the next period. The results showed that the MLP method was superior to ARIMA. Testing 28 mortality rate data using the final test result showed that the best method was MLP, with a hidden layer value of 2.2, a learning rate of 0.3, and an error percentage of 1.27%. The prediction results of the overall mortality rate of pneumonia under five in 2022 was predicted to be 136 people.*

*Keywords: Pneumonia, Forecasting, ARIMA, Multilayer Perceptron*

### 1. Introduction

Pneumonia is an inflammatory lung disease with the second death rate in Indonesia after Dengue Hemorrhagic Fever (DHF) [1]. Bacteria and viruses cause acute inflammation of the lung tissue called pneumonia [2]. The chance of death from pneumonia in children under five is even greater if the risk factors are 0-5 years old. Pneumonia is still a death case that has claimed the lives of toddlers to date, therefore this should get more attention from the Government, especially in the Province of Bali. Basic Health Research (Riskesdas) proves that in 2007, 15.5% of pneumonia patients died or 83 children under five died every day, making pneumonia the number 2 cause of all deaths of children under five in Indonesia. The Indonesian Basic Health Survey (IDHS) found that between 2002 and 2007, the incidence of pneumonia in children under five increased from 7.6% to 11.2%. Bali was the second highest pneumonia case in Indonesia in 2007 (11.1%), besides that Denpasar City was also the city with the fourth highest pneumonia incidence in Bali (18.73%) with the highest pneumonia coverage of 15.93% in 2012 [3].

Under-five deaths due to pneumonia are now expected to increase along with the worsening of the Covid-19 pandemic. Based on these problems, one way to monitor and predict spikes in the next period is to apply data mining techniques. The procedure for finding information contained in several data is called data mining [4] this is intended to produce better conclusions and make accurate decisions [5]. The data mining method uses a forecasting method (forecasting), which is a technique in assuming the amount of time in the future based on data in the past to know the situation in the future adulthood [6]. Forecasting is carried out to reduce the uncertainty of an event that may occur in the future period, an effort to reduce this impossibility is called the forecasting method. This study was conducted to compare the prediction results of each method used to obtain predictive results with the best accuracy values to be used for long-term forecasting of pneumonia mortality data, especially in children under five.

One of the existing research and widely used by professional experts in building predictive models is called data mining. A time series study is a quantitative method to identify patterns of past data collected in a

structured manner [7]. The most widely used method is ARIMA. One of the meanings of ARIMA is an analysis method that is carried out on certain time series data, namely a set of structured observations made, usually quantitative, over a certain period [8]. Deep learning has many types of algorithms that focus on learning multi-level (non-linear) data representations. One of the deep learning algorithms that have been used to predict time series data is the Multilayer Perceptron algorithm derived from artificial neural networks (ANN). The approach chosen for this research prediction is ARIMA and Multilayer Perceptron (MLP) where this method is one of the successful methods and applies the best algorithm.

Several studies have proven that the ARIMA and MLP methods can predict. One of them is the research of Munandar, D, et al, regarding the prediction of solar radiation using the MLP and ARIMA methods. This study requires numerical weather data with several measurement parameters such as wind direction, wind speed, temperature, humidity, solar radiation, and rainfall at the LIPI weather station. The results showed that the Multilayer Perceptron (MLP) deep learning model performed better with an RMSE of 8.68 W/m<sup>2</sup> [9].

Another study was conducted by Masngut et al., a study on the Multilayer Perceptron (MLP) and ARIMA methods that have been applied to predict the daily rainfall comparison of a case study at Simpang Ampat, Pulau Pinang, Malaysia. The results showed that the Multilayer Perceptron neural network model had superior results compared to the ARIMA model. The results also show that ANN has an under-forecast of daily rainfall data of 2.21% compared to ARIMA with an over-forecast of -3.34%. From this study, it shows that the Multilayer Perceptron neural network model (6,4,1) produces MAE (8,4208), MFE (2,2188), RMSE (34,6740) and R (0,9432) results better than the previous model. ARIMA. The results prove that the Multilayer Perceptron neural network model has outperformed the ARIMA model in predicting daily rainfall values [10].

In a subsequent study by Bhargavi K, et al, ARIMA, MLP, and RNN (Recurrent Neural Networks) methods were used to predict the US dollar exchange rate. The US dollar exchange rate data is the data used in his research. The conclusion from the test results shows that ARIMA shows a much better prediction than the MLP and RNN models [11].

The ARIMA method has been used to predict the price of grain and rice in Indonesia by Fitri Ramadhani, et al. In his research, it was shown to determine the appropriate ARIMA model in predicting the price of grain and rice at the farmer, wholesale, and international levels. The ARIMA model is selected through the lowest AIC and SC accuracy values. The results show

the ARIMA model (1.1.2) on the price of rice at the farmer and mill level, the ARIMA model (1.1.3) at the wholesale price of unhulled rice, and the ARIMA model (3.1.7) on the international price of rice. price lists at different levels of market share require different ARIMA models in making predictions [12].

The following is another study by Siti Soraya, et al, who in their research used the ARIMA method in predicting foreign tourist visits to West Nusa Tenggara. Data were collected from January 2010 to June 2019 and obtained from the Central Statistics Agency (BPS). The test results show that ARIMA (4.1.1) is the best model to be applied, this model is suitable for predicting the number of foreign residents or tourists visiting NTB because this model provides the lowest SSE and MSE values compared to other models [13].

Another study was also conducted by Haslina, et al, where this study used the ARIMA Box Jenkins method to predict the increase in the number of Javanese transmigrants to Bali in Sukamayu Regency, South Sulawesi. Data is collected on a monthly basis which was collected in the Sukamayu Regency area from 2000-2015. The results showed that the best model obtained for predicting the number of transmigrants was ARIMA (0.1.1)(1.0.0)<sup>12</sup> [14].

The ARIMA method was also used by Widodo, et al, in predicting the total death of tuberculosis in the Malang area in 2017. ARIMA-ARCH is the method used in this test. The data used are data with the total incidence of tuberculosis in Malang Regency from 2007–2015. Prediction results of total tuberculosis cases in Malang Regency using the ARIMA-ARCH model provide MAPE accuracy of 1.88% which shows a good level of accuracy. When predicting the total tuberculosis cases in the Malang area between October 2016 and December 2017 using ARIMA training (0,1,3) ARCH (1). Prediction results obtained: in October 2016 – December 2017, the number of tuberculosis cases was 79 cases per month, with a total of 948 cases [15].

The use of the ARIMA method has also been used by Kurniasih, et al, in predicting child mortality in China by comparing the methods used including indicators a-Sutte, ARIMA, and Holt-Winters. This research was conducted using data from 1992–2017, with a total of 1323 data. This data is divided into two of them 1316 training data and as many as 7 test data. To see the accuracy of the predictions produced, the researchers compared the accuracy values with the method by examining the MSE and MAPE values. Based on the results of the study, it was found that the a-Sutte indicator had lower MSE and MAPE values when paired with other models (ARIMA and Holt-Winters). This is supported by MSE data from the a-Sutte indicator which is smaller than ARIMA (2,2,2) and Holt-Winters, which is 0.03; 3.06; and 3.15 [16].

The next study that is still related to forecasting using the ARIMA method is by B. Devaney, et al. A study on the prediction of total passengers and cargo at Juanda International Airport and Tanjung Perak Port using the Hybrid ARIMAX method and the DLNN (Deep Learning Neural Network) Model. The data in this study uses monthly data from January 2001-December 2019 on airport data, port data uses January 2006 data. The results of the ARIMA-DLNN hybrid modeling study have proven to have good abilities in interpreting various patterns of information and producing good predictions for data training. This can be seen with lower RMSEP with other models, but DLNN modeling has good skills to predict test data. The best modeling for the eight variables applied is seven, with the best modeling being DLNN and the other is the hybrid ARIMAX-DLNN model [17].

Another study also used the ARIMA method to predict the Malaysian ringgit exchange rate against the dollar by H. Hatta, et al. The data used in his research was drawn from January 2015-December 2017, with weekly data sets collected every Friday, bringing a total of 161 data over three years. The results showed that ARIMA is the best model for forecasting exchange rates in this study. In the results of his research, the R studio application was used to build a model and get the best-recognized model using the ARIMA model [18].

The Multilayer Perceptron method has been used to compare the performance accuracy of the Multilayer Perceptron, ID3, and C4.5 methods in cases of typhoid fever by Adeymo, et al. The data in this research are patient data collected by the Nigerian Hospital, the ID3 method, C4.5 Decision tree, and Multilayer Perceptron (MLP) Artificial Neural Network implemented in the WEKA data mining software. This study was conducted to predict typhoid fever patients. Observations show that the performance of Multilayer Perceptron (MLP) has more accuracy when compared to the other two classification methods. The Multilayer Perceptron (MLP) classification applied to the attribute has a classification accuracy of 83.6299% but in terms of speed, the C4.5 algorithm is the best because it requires 0.01 seconds to train the data [19].

A study conducted by Steven Sen, et al, in this study, used the MLP and LSTM comparison method to predict rice prices. The period of rice price data used in the study starts from 2016-2019 which was obtained at PT. Food Station, with a total of 1307 data, 1123 training data, and 184 test data. The results showed that LSTM outperformed MLP with an RMSE value of 0.49 for training data and an RMSE value of 0.27 for test data. The ideal LSTM model from the three tests applied is the model with 16 hidden layers and 150 epochs [20].

Pratiwi, et al, also conducted another study using the Multilayer Perceptron (MLP) method to predict the

number of suspected drug abusers. The data used is a collection of data on the number of suspects in 2007 - 2018, which is divided into training, and test data. The total data for suspects in 2007-2015 is training data, while the total data for suspects for 2016-2018 is test data. The network model used for evaluation is eight models. The results of the study stated that the best network model with model 2, hidden level 3.2 and learning rate 0.1, found the smallest error. The MAD value generated by modeling two is 326.33 with an error rate of 3.7% [21].

The next study by Harun Mukhtar, et al, focuses on the Multilayer Perceptron (MLP) method, which is used to predict the arrival of foreign tourists to Indonesia based on nationality per month. The data used is the monthly visit of foreign tourists to Indonesia with a data range of January 2019 - December 2020. The test results show an accuracy of 82% obtained for tourism forecasts in September 2020, and for forecast accuracy results - 97% in December 2020, and the forecast results received for January 2021 are expected to have 7,106 tourists. The number of epochs in the MLP algorithm calculation is 2000 epochs, and the resulting error value is 0.0003. Based on these results, predictions are accurate [22].

The next study that is still related to forecasting is the study of Isman Kurniawan et al, regarding the implementation of CNN (Convolutional Neural Network) and MLP (Multilayer Perceptron) for forecasting air temperature in the city of Padang. The data collection of air temperature with a range of January 2015 - December 2017 measured at the LIPI meteorological measurement station in Muaro Anai, Padang is the data used in the study. The test results show that the CNN model gives the best results with an R2 value of 0.9965, indicating that the CNN model is the best modeling applied in this study, namely in predicting air temperature [23].

Based on several studies that have been described previously, it is concluded that the ARIMA (Autoregressive Integrated Moving Average) and MLP (Multilayer Perceptron) methods are considered capable of implementing accurate and best results for forecasting data. Comparison is a way that can be done to compare the two methods in obtaining the best.

In this study, researchers applied two forecasting methods, including ARIMA and Multilayer Perceptron (MLP). This study will compare or compare the prediction results of each method used to get prediction results with good accuracy values by comparing the smallest error values using prediction accuracy scores. The measure of accuracy applied in this study is determined by comparing the values of MAD, MSE, and MAPE, where the accuracy validation process has differences from previous studies. The three accuracy measurement tools will later provide an accuracy value

that is compared to find out which method gives the smallest and best prediction error. The mortality data for pneumonia toddlers provided by the Denpasar General Hospital, in which the pneumonia under-five mortality data has never been used for related research, has been confirmed to be different from the data used in other studies. The process for the data preprocessing stage applies excel and the ARIMA method process is carried out with the help of Minitab19 tools, for the MLP method uses Weka as research support tools from the author. The results of the comparison are obtained by comparing the modeling generated by the ARIMA method including the estimation of the ARIMA model parameters and then testing the white noise assumption and determining the accuracy of each ARIMA model. The MLP includes estimating the architectural modeling of the MLP model to get a model with good accuracy later the best modeling of each method will be compared or compared to choose the smallest accuracy value for long-term forecasting.

In this study, we aim to applying the ARIMA and MLP comparison method is to compare the predictive results of each method used to obtain prediction results with the best accuracy value to produce the best method that can be applied in predicting the mortality rate of pneumonia under five in the future. The results of the research on forecasting the mortality rate for children under five with pneumonia can be used as a reference as a decision-making strategy for the local government related to the prevention of mortality in the next period.

## 2. Research Methods

The research method is a sequential procedure for the sake of research. The method used to assist this research with the title Forecasting Toddler Death Due to Pneumonia Using Comparative Model ARIMA and Multilayer Perceptron by going through five stages of the research process including the process of data selection, visualization, forecasting, forecasting accuracy, and forecasting results. The results of the forecasting will produce knowledge and information regarding the long-term forecasting results in forecasting the mortality rate of pneumonia under five. Figure 1 is an overview of the applied assessment processes.

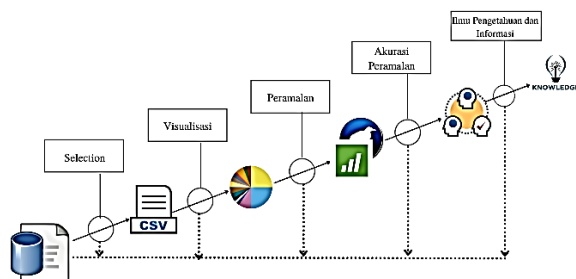


Figure 1. Research Method Flow

### 2.1 Data Selection

The collection and selection of data on under-five mortality due to pneumonia were carried out to collect the data needed in data mining. The data collected is used as material in conducting research on forecasting infant mortality due to pneumonia using the ARIMA and Multilayer Perceptron comparison methods.

The data used in the study were deaths from pneumonia in children under five from January 2014 – December 2021. The data received were monthly data, so the total data received was 96 data. Data on total under-five mortality due to pneumonia were obtained in the form of death reports. The number of deaths was grouped by age and sex. This data is then used as the basis for the forecasting process. The data is a summary of Excel report data, consisting of one folder containing eight documents each containing a summary of monthly death data. The data is prepared at the data pre-processing stage, in this case, the data is divided into two, namely training data and testing data with a percentage ratio of 70%:30%. Data on the number of under-five deaths due to pneumonia predicted in this study were only based on the category of the number of deaths. Understanding the data from the collected data aims to be able to sort the data needed to carry out the next forecasting process.

### 2.2 Data Visualization

Data visualization is provide a general understanding of the data used in forecasting. The form of the graph is a visualization used in presenting the data in this study.

Data graphs were created using Microsoft Excel. The data graph is formed based on the number of under-five deaths due to pneumonia in the category of the number of pneumonia under-five deaths under study. The data graph is made to determine the distribution pattern of the initial data before forecasting.

### 2.3 Forecasting

Forecasting is an estimate of the measurement of the magnitude of the future based on data held in the past, the purpose of which is to determine future conditions [24]. Forecasting is done in the study of the number of under-five deaths due to pneumonia using two forecasting methods including ARIMA and MLP.

ARIMA prediction in this study uses several testing steps, including model identification, evaluation, and diagnostics. The identification stage is mainly aimed at seeing patterns in the data, especially the results of autocorrelation and partial autocorrelation, as well as seeing whether the original data needs to be distinguished or not. The evaluation and diagnostic steps of this process are carried out simultaneously with the Minitab19 prediction tool, the model is suggested by comparing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), which creates

an evaluation mode, but the model is also directly diagnosed by looking at the error rate in the model. When choosing the right model, the probability value (p) in the final estimation equation must be taken into account. The correct model is a model that has a probability value of  $<0.05$ . The most important part of the diagnostic process is the statistics generated. In this case, the Mean Square Error (MSE) value must be taken into account. The MSE value will be compared with the MSE number in other ARIMA models. The AR, MA, and ARIMA models use a stationary time series estimate. Time series data are mostly non-stationary [25]. Below is a flow chart of the ARIMA model, which is shown in Figure 2.

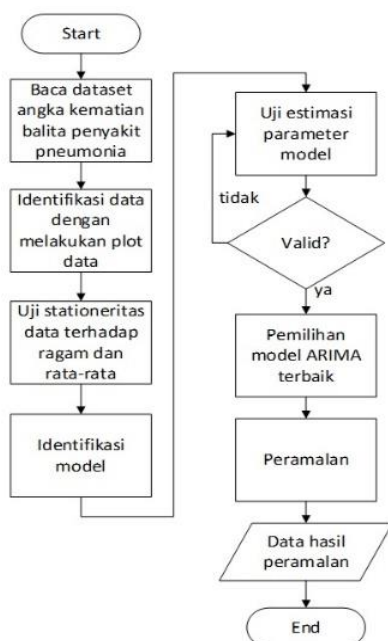


Figure 2. ARIMA Model Flowchart

Figure 2 is the process flow of the ARIMA algorithm, where the process flow ARIMA algorithm describes how the ARIMA algorithm works. The process flow of the ARIMA algorithm begins by reading the dataset on mortality due to pneumonia that has been saved using the .csv file format and then the data is identified using a data plot to determine the distribution of the data and visualize the data. The identification stage has been successfully carried out, the next stage is to test the stationarity of the data. The stationarity test is divided into two stages, the stationarity test stage for variance (variance) and the stationarity test stage for the mean (mean). The data that results from the stationarity test for variance can be viewed using a time series plot that fluctuates from period to period, so the un-stationary can be eliminated by transforming the data to stabilize the variance. Stationary non-stationary data in variation can be done by transforming power by looking at what is called the transformation parameter (optimal lambda). The following is the value of (optimal lambda)

which is commonly used in forming the transformation in Table 1 [26].

Table 1. Transformation Form

| Value $\lambda$ | Transformation          |
|-----------------|-------------------------|
| -1              | $\frac{1}{Z_t}$         |
| -0,5            | $\frac{1}{\sqrt{Z_t}}$  |
| 0               | $\ln Z_t$               |
| 0,5             | $\sqrt{Z_t}$            |
| 1               | $Z_t$ (not transformed) |

where  $Z_t$  is the initial data. If the data has been stationary after the transformation with optimal lambda ( $\lambda=1$ ) then the data can be continued in the next stage. The data that has been tested for stationary data is used to identify the resulting model, if the test results are valid then the stages can be continued with the selection of the best ARIMA model, if the test results are not valid then the parameter estimation test other models are carried out to obtain valid test results. The ARIMA model that passed the test and the best can be used for prediction, predictions are made using the best ARIMA model to get good prediction results. The prediction results are received, then the data mining process using the ARIMA algorithm is complete.

MLP is a pure part of perceptron modeling which was discovered by Rosenblatt in 1950. MLP is the most commonly used neural network model. A multilayer perceptron has one or more hidden layers between the input and output layers [27]. An algorithm that has often been applied in multilayer perceptron training is called backpropagation. This algorithm is carried out in two steps, namely forward computing to calculate the error/loss function that exists in the actual and target outputs, and backward computing to propagate the error back as a correction of sympathetic weights for all existing neurons [28].

Multilayer Perceptron is trained with the backpropagation algorithm, which is used in data mining. Multilayer Perceptron has characteristics including, having several inputs, having one or more hidden layers with several units, using a sigmoid activation function on the hidden layer, and having connectivity between the input layer and the first hidden layer, between the undisclosed layer, and between the last hidden layer and the hidden layer, output layer.

The training of the Multilayer Perceptron method with Backpropagation consists of three stages including, Phase I: forward propagation in which each input receives and receives a signal and forwards it to each hidden layer. The hidden layer calculates its activation and sends a signal to the output. The output will then calculate the activation value in response to the input is



given to the network, Phase II: backpropagation and weight changes where each output will update its bias and weight values with each hidden. Hidden will also affect the value of the bias and its weight with each input [29]. Figure 3 below is a flow chart of the MLP in the study.

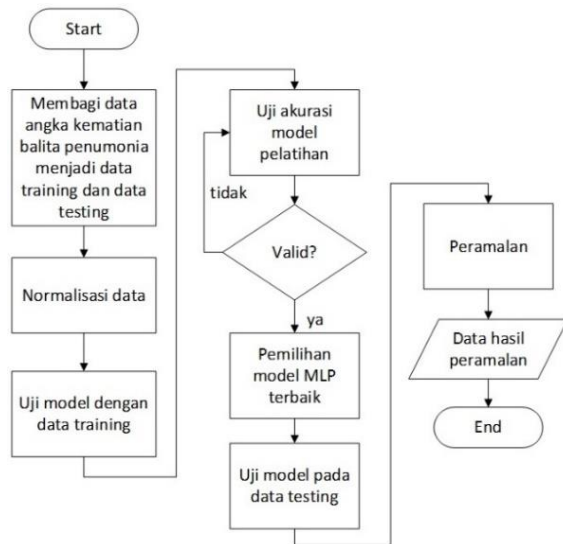


Figure 3. MLP Model Flowchart

The picture above is the flow of stages of the MLP algorithm, where the process flow of the MLP Algorithm describes the workings of the MLP algorithm. The flow of the MLP algorithm begins by separating the infant pneumonia mortality rate data into training data and testing data. The training data is used to determine the best MLP modeling and the test data is used to test the resulting model against the training data. After the data is split, the data is normalized, and data normalization or data scaling is called between 0 to 1 using Equation 1[30].

$$x' = \frac{0,8(x-a)}{(b-a)} + 0.1 \quad (1)$$

where  $x$  is the denormalized data or initial data,  $x'$  is the data resulting from normalization,  $a$  is the lowest data value, and  $b$  is the highest data value.

The data were normalized and then tested in the training model, if the test results are valid then the steps can be continued with the selection of the best MLP model, on the contrary, if the test results are not valid then another model parameter estimation test is carried out to obtain valid test results. The MLP model that passed the test and the best can be used for prediction, predictions are made using the best MLP model to get good predictive results. The prediction results are obtained, then the data mining process with the MLP algorithm is complete.

## 2.4 Forecasting Accuracy

Forecasting carried out will have varying error rates. Forecasting results are then selected which has the

lowest error value using a measure of forecasting accuracy. The measure of accuracy used in the study was determined by analyzing the calculation of Mean Absolute Deviation (MAD) Equation 2, Mean Squared Error (MSE) Equation 3, and Mean Absolute Percentage Error (MAPE) Equation 4 [30].

$$MAD = \sum \left| \frac{A_t - F_t}{n} \right| \quad (2)$$

$$MSE = \sum \frac{(A_t - F_t)^2}{n} \quad (3)$$

$$MAPE = \left( \frac{100}{n} \right) \sum \left| \frac{A_t - F_t}{A_t} \right| \quad (4)$$

where  $A_t$  is the actual value in the  $t$ -time range, the  $F_t$  value is the predicted value in the  $t$ -time range, and the value of  $n$  is the number of predictions involved.

The lower the prediction accuracy value obtained by the three predictive measuring instruments, the better the prediction method applied.

## 3. Results and Discussions

The data used in the study is a collection of data on the mortality rate of pneumonia under five in the form of an excel file. The data received is monthly data, so the total data received is 96 data consisting of two fields, namely month/year which states the time or month of death, and the number of deaths which states the total number of deaths that occurred in that month, starting from January 2014 until December 2021. Normalization is carried out on the data to minimize errors by changing the actual data into values in the 0-1 interval range. Table 2 shows the details of the distribution of data on the mortality rate of under-five pneumonia.

Table 2. Dataset Sharing

| Data Training            | Data Testing                |
|--------------------------|-----------------------------|
| 68 data                  | 28 data                     |
| January 2014 – July 2019 | August 2019 – December 2021 |

The data is divided into training and testing data. Training data is data from January 2014 to July 2019. Testing data is data from August 2019 to December 2021.

### 3.1 Data Flow

The data flow in this study was used to determine the distribution of data and visualization or distribution of data on under-five mortality due to pneumonia to determine the distribution of data and visualization of under-five mortality in pneumonia under-five mortality data.

The data flow is also used to determine the correct forecasting method. The graph of the monthly dataset of deaths due to pneumonia in children under five from 2014 to 2021 each month is shown in Figure 4.

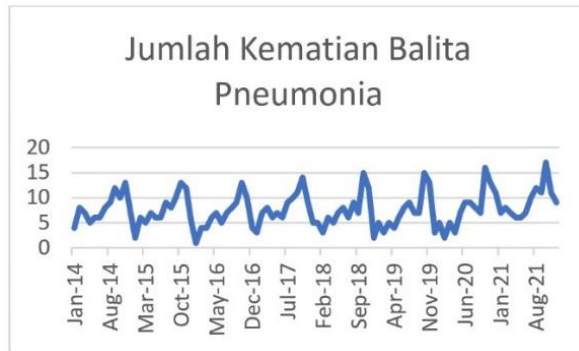


Figure 4. Pneumonia Toddler Mortality Data Graph

The illustration above shows that the data plot of the under-five mortality rate in 2014 – 2021 displayed in this study is a recurring or seasonal mortality data plot every month. The data outage, which is called the amount of data that is closely monitored with other data, appears in the graph in September 2021 with a total death of 17 people, while the total death rate for pneumonia under-five children tends to decrease at the beginning of the year, while the total death rate for pneumonia under five tends to decrease at the beginning of the year. The information that can be concluded in the data plot is that at the beginning of the year pneumonia under-five mortality tends to decrease, and in the middle, to the end of the year pneumonia under-five mortality tends to increase.

### 3.2 ARIMA Models

ARIMA modeling was estimated using the Minitab19 tool which resulted in the estimation of ARIMA modeling parameters described in Table 3.

Table 3. ARIMA Model Estimation Results

| Model         | Type | Coef   | P     |
|---------------|------|--------|-------|
| ARIMA (0.1.1) | MA 1 | 0.379  | 0.056 |
| ARIMA (0.1.2) | MA 1 | 0.504  | 0.014 |
|               | MA 2 | 0.381  | 0.040 |
| ARIMA (0.1.3) | MA 1 | 0.425  | 0.053 |
|               | MA 2 | 0.228  | 0.291 |
|               | MA 3 | 0.286  | 0.185 |
| ARIMA (0.1.4) | MA 1 | 0.434  | 0.144 |
|               | MA 2 | 0.240  | 0.269 |
|               | MA 3 | 0.394  | 0.103 |
|               | MA 4 | -0.144 | 0.525 |
| ARIMA (1.1.0) | AR 1 | -0.204 | 0.290 |
| ARIMA (1.1.1) | AR 1 | 0.465  | 0.029 |
|               | MA 1 | 0.952  | 0.000 |
| ARIMA (1.1.2) | AR 1 | 0.325  | 0.536 |
|               | MA 1 | 0.762  | 0.186 |
|               | MA 2 | 0.144  | 0.730 |
| ARIMA (1.1.3) | AR 1 | 0.299  | 0.578 |
|               | MA 1 | 0.752  | 0.141 |
|               | MA 2 | 0.221  | 0.545 |
|               | MA 3 | 0.253  | 0.527 |
| ARIMA (1.1.4) | AR 1 | -0.866 | 0.210 |
|               | MA 1 | -0.535 | 0.161 |
|               | MA 2 | 0.677  | 0.108 |
|               | MA 3 | 0.365  | 0.226 |
|               | MA 4 | 0.356  | 0.176 |

The model significant if the value of all the resulting variables is less than 0.05, the results show that all modeling parameters 1,3,4,5,7,8, and 9 are not significant because the resulting P value is 0.05. Parameters of models 2 and 6 show that all of the results of the parameter values are significant. Because models 1,3,4,5,7,8 and 9 have all parameters that are not significant, the model is excluded from the tests carried out and there are only 2 models namely ARIMA(0.1.2) and ARIMA(1.1.1) which are then Diagnostic tests were carried out to ensure that the model obtained from the estimation results using the white noise presumption applying the Ljung-Box Test is shown in Table 4.

Table 4. White Noise Test Results

| Model         | Lag | Chi-Square | DF | P-Value |
|---------------|-----|------------|----|---------|
| ARIMA (0.1.2) | 12  | 15.16      | 10 | 0.126   |
|               | 24  | 31.27      | 22 | 0.091   |
| ARIMA (1.1.1) | 12  | 13.59      | 10 | 0.042   |
|               | 24  | 29.72      | 22 | 0.025   |

Based on the table above, it is known that the overall Q statistics on lag 12, and 24 on model one are not significant, which means that model 1 is white noise. Model 2 produces a value of P = 0.042 at lag 12 and a value of P = 0.025 at lag 24 which indicates a significant model, which means that model 2 is not white noise. The next stage is to determine the best model by analyzing the accuracy value of each model, and by comparing the MAD and MSE values. The results of the ARIMA model accuracy test are presented in Table 5.

Table 5. ARIMA Model Accuracy Test Results

| Model         | MAD   | MSE  |
|---------------|-------|------|
| ARIMA (0.1.2) | 1.81  | 1.05 |
| ARIMA (1.1.1) | 0.086 | 0.54 |

Determination of the best model is applied by monitoring the comparison of MAD and MSE accuracy values. The results of MAD and MSE show that model 2 produces smaller MAD and MSE values compared to model 1 so that the ARIMA model chosen with model 2 is ARIMA (1.1.1).

### 3.3 MLP Models

The MLP modeling was estimated using the WEKA tools which resulted in the estimation of the MLP modeling parameters described in Table 6.

Table 6. Results of Architectural Analysis of the MLP Forecasting

| Learning Rate | Hidden Layer | Epoch | MAD  | MSE  | MAPE |
|---------------|--------------|-------|------|------|------|
| 0.1           | 2.2          | 1000  | 0.82 | 0.64 | 2.54 |
| 0.1           | 3.2          | 1000  | 0.47 | 0.70 | 2.32 |
| 0.2           | 2.2          | 1000  | 0.68 | 0.99 | 2.15 |
| 0.2           | 3.2          | 1000  | 0.61 | 0.69 | 1.96 |
| 0.3           | 2.2          | 1000  | 0.11 | 0.16 | 1.27 |
| 0.3           | 3.2          | 1000  | 0.32 | 0.56 | 1.68 |
| 0.4           | 2.2          | 1000  | 0.99 | 0.41 | 2.65 |
| 0.4           | 3.2          | 1000  | 0.96 | 0.78 | 2.68 |

The results of the architectural analysis of the MLP forecasting model show the accuracy of forecasting the number of pneumonia under-five deaths. Hidden layers 3.2 and 2.2 are applied in this study. The learning rate used is between 0.1 and 0.4. Each learning level is tested on each tested architecture. The results of the accuracy show that the best MLP architecture model with a hidden layer level = 2.2 and a learning rate = 0.3 has the smallest error value of 1.27% compared to other architectures. The graph of the MLP prediction results on the pneumonia mortality training data for toddlers on the training data is presented in Figure 5.

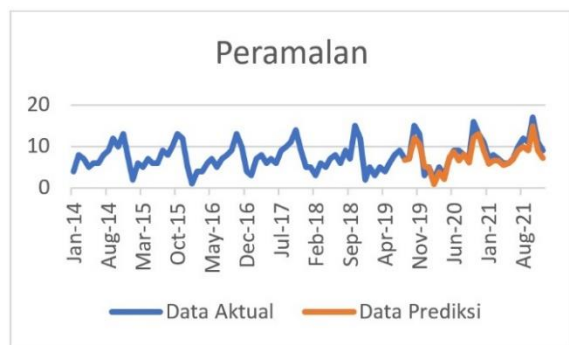


Figure 5. Graph of MLP Prediction Results on Training Data

Forecasting results using the MLP method are superior to ARIMA with the resulting error value of 1.27. Forecasting that was done using the pneumonia under-five mortality dataset on the training data resulted in a data pattern predicting the number of under-five deaths due to pneumonia with the results of the training being predicted to tend to be the same as the data pattern generated in the predictive data which almost followed the actual data pattern in the actual data. This is due to seasonal factors that lead to forecasting results using training datasets according to current conditions or conditions that are happening at this time. It is proven in the comparison results with actual data, the predictions produced are not too far from the actual results. The prediction results of the training data are used to determine the resulting prediction model, which will later be used to test the infant mortality rate data set against test data to obtain long-term predictions of pneumonia mortality in children under five. The MLP (Multilayer Perceptron) method will then be used to test the test data using the training model obtained from the training data.

### 3.4 ARIMA and MLP Analysis Results

The results of the analysis of mortality datasets with MLP precision were better than ARIMA with MAD, MSE, and MAPE values of 0.11, 0.16, and 1.27. The MLP error value is proven to be lower than ARIMA, which is 1.27%. Table 7 shows the results of the comparison of the best model accuracy.

Table 7. ARIMA and MLP Accuracy Comparison Results

| Forecasting Method                          | MAD   | MSE  | MAPE |
|---------------------------------------------|-------|------|------|
| ARIMA (1.1.1)                               | 0.086 | 0.54 | 1.58 |
| MLP (hidden layer= 2.2, learning rate= 0.3) | 0.11  | 0.16 | 1.27 |

Table 7 shows the results of the accuracy of forecasting the number of under-five deaths from pneumonia. The results show that the forecasting method that has the lowest MSE value is the MLP forecasting method with a value of 0.16. The MLP method also has the lowest MAD and MAPE values, namely 0.11 and 1.27%. The results of this accuracy are then used as the basis for selecting the MLP forecasting method, which is determined as the best forecasting method for the number of under-five deaths due to pneumonia.

### 3.5 Long-Term Forecasting Results

The best MLP modeling with a hidden layer level of 2.2 and a learning rate of 0.3 is the best modeling because it has the smallest MAD and MSE values compared to other models. This model is then used to forecast pneumonia under-five mortality for the next 12 months or a decade from January 2022 to December 2022. Forecasting results are shown in Table 8.

Table 8. Long-Term Forecasting

| Month     | Prediction |
|-----------|------------|
| January   | 9.18       |
| February  | 10.5       |
| March     | 9.57       |
| April     | 7.83       |
| May       | 7.26       |
| June      | 9.05       |
| July      | 13.1       |
| August    | 14.4       |
| September | 15.7       |
| October   | 16.8       |
| November  | 15         |
| December  | 12.7       |

Based on Table 8, shows that the largest number of pneumonia under-five deaths occurred in October with a total of 16 deaths, the total number of pneumonia under-five deaths in 2022 is predicted to increase by 136 people. The total number of pneumonia under-five deaths in 2022 is predicted to increase by 136 people. Forecasting in February - May 2022 has decreased with a total of 33 deaths, in June - October 2022 there has been an increase of a total of 67 deaths and in November - December has decreased with a total of 27 deaths. The results of this forecast indicate that the number of under-five deaths with pneumonia has increased following the data in the previous year, as evidenced by the pattern of the data increase shown which at the end of the year became the highest peak of the data produced. The following is a visualization of the long-term forecasting results shown in Figure 6.



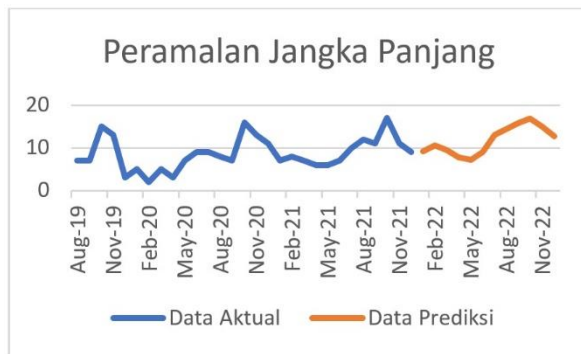


Figure 6. Long-Term Forecasting Results

#### 4. Conclusion

Based on the results of experiments carried out according to the ARIMA method, the ARIMA (0.1.2) and ARIMA (1.1.1) models passed the parameter significance testing stage, which met the overall value of the variable 0.05, but the lowest variable value and the lowest forecasting accuracy value were found on the (1,1,1) model. Based on these results, ARIMA (1,1,1) modeling is the best model that allows it to be used to predict mortality in children under five due to pneumonia. The results of the tests carried out using the Multilayer Perceptron method, the model architecture obtained by testing hidden layers 2.2 and 3.2, and testing a learning rate of 0.1-0.4 resulted in the best Multilayer Perceptron architecture having a learning rate of 0.3 and a hidden layer 2.2. This architecture shows the smallest average error value compared to other architectures with a value of 0.11 and an MSE value of 0.16. The comparison results show that the best method used is Multilayer Perceptron. The MLP method has the lowest error percentage rate of 1.27%. The results of forecasting the mortality rate of pneumonia under five in February - May 2022 decreased by a total of 33 deaths, in June - October 2022 there was an increase of a total of 67 deaths and in November - December decreased of a total of 27 deaths. Forecasting the long-term pneumonia under-five mortality rate shows that the number of pneumonia under-five deaths in 2022 is predicted to increase by 136 people.

The use of comparative forecasting methods ARIMA (Autoregressive Integrated Moving Average) and MLP (Multilayer Perceptron) have never been used to predict the mortality rate of pneumonia under five, it's just that the two methods have been used to compare using datasets or variables studied differently from research on forecasting mortality rates pneumonia under five, other differences were found in the year of the study, as well as the research instrument used. The results of this research for forecasting the mortality rate of children under five with pneumonia can be used as policy decisions for the local government regarding the prevention of mortality in the following years.

Further research can be done by developing forecasts using the latest datasets, and the data used can be more detailed, such as using daily or weekly data because of the limited data obtained in this study, so this can be used as a recommendation for other researchers. The development of forecasting results can be done by conducting research on a larger scale, such as when conducting case studies in a province. Other developments can be made by adding other death characteristics. The use of forecasting methods used must be more diverse to obtain prediction results with better accuracy values.

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