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PREDICTIVE MODELLING OF CLEAN WATER SUPPLY IN RIAU PROVINCE: A DEEP LEARNING APPROACH

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ABSTRACT

The supply of clean water remains a critical issue in many regions, including Riau Province, where factors such as population growth and climate variability significantly affect its availability and distribution. This study aims to develop a time-series–based predictive model for clean water supply in Riau Province using deep learning approaches. Using historical data from 2019 to 2023, including variables such as the number of customers, water volume, economic value, and input costs, this research identifies temporal patterns to support proactive water resource management. The methodology consists of exploratory data analysis, data preprocessing, and model training using several architectures, namely Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Feedforward Neural Network (FNN). Among these models, the LSTM achieved the best performance, with a Mean Absolute Error (MAE) of 1.25, a Mean Squared Error (MSE) of 2.56, and an R-squared (R^2) of 0.92. After hyperparameter optimization, further improvements in predictive accuracy were obtained. Based on the optimized LSTM predictive model, the forecasted clean water volume for 2024 is 19,496.90 thousand m^3, a slight decline from the previous year. The novelty of this study lies in the comprehensive comparison of multiple deep learning architectures for regional-scale clean water time-series forecasting and the optimized implementation of LSTM for operational prediction. In practical terms, the results can support local water authorities in improving planning, infrastructure development, and demand management strategies. However, this study is limited by the use of secondary data from a single province and a relatively short observation period, which may affect the model's generalizability. The proposed predictive framework can serve as a reference for future studies in sustainable water resource management.

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1. INTRODUCTION

Access to clean and safe water is a fundamental pillar of sustainable development and public health. In Indonesia, particularly in Riau Province, ensuring reliable potable water services remains a major challenge despite strong governmental commitments grounded in the principles of Pancasila and the 1945 Constitution. Data from the Central Bureau of Statistics (BPS) of Riau Province, which has monitored water supply enterprises since 1986, indicate persistent operational issues in water utilities, including distribution leakage, unequal service coverage, and fluctuating demand across residential, commercial, and industrial sectors [1]. These challenges highlight the urgent need for more effective planning and demand forecasting systems to support sustainable water resource management.

Although statistical data on water utilities in Riau Province cover diverse operational aspects—such as ownership structure, labor, production costs, and distribution performance [2], [3], [4], traditional analytical methods often struggle to capture the nonlinear, dynamic, and time-dependent characteristics of water demand and supply systems. As a result, conventional forecasting approaches may produce suboptimal predictions, particularly under conditions of population growth, climate variability, and rapid urbanization. In this context, advanced data-driven techniques, especially deep learning, have emerged as promising tools for time-series forecasting due to their ability to learn complex patterns from large-scale historical data [5]. The importance of sustainable water management is also emphasized globally through the Sustainable Development Goals (SDGs), particularly Goal 6, which focuses on ensuring the availability and sustainable management of water and sanitation for all [6]. Within this global framework, accurate forecasting of water supply and demand becomes a critical foundation for policy formulation, infrastructure development, and efficient water utility operations.

Recent studies have demonstrated the effectiveness of deep learning in various water-related prediction tasks. LSTM networks have been successfully applied to river water quality forecasting by capturing long-term temporal dependencies [7]. CNN-based models have shown strong performance in hydrological flow prediction by extracting spatial features from structured data [8]. In addition, RNN architectures have been employed to predict urban water demand with higher accuracy than traditional statistical models [9]. Hybrid approaches that integrate multiple deep learning architectures have also been reported to enhance predictive performance by exploiting complementary strengths among models [10]. However, despite these advances, several research gaps remain evident. Most existing studies focus on a single deep learning architecture, are conducted at national or metropolitan scales, or prioritize water quality and hydrological flow rather than regional water supply volume. Moreover, systematic comparisons of multiple deep learning architectures for time-series prediction of clean water supply at the provincial scale, particularly in Riau Province, remain very limited. Consequently, there is a lack of empirical evidence regarding which deep learning model is most suitable for regional clean water forecasting under real operational conditions.

To address these limitations, this study develops and compares several deep learning architectures, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), and Feedforward Neural Networks (FNN), for time-series forecasting of clean water supply in Riau Province. The objectives of this research are to construct a robust predictive model based on historical multi-year water utility data, to evaluate and compare the predictive performance of each deep learning architecture using standard evaluation metrics, and to generate short-term forecasts of clean water supply to support operational planning and infrastructure development. By leveraging comprehensive historical data and advanced deep learning techniques, this study is expected to contribute both theoretically to the literature on comparative deep learning–based forecasting and practically to decision-making processes in sustainable water resource management in Riau Province [11], [12], [13], [14].

2. RESEARCH METHODS

The methods section of this research elucidates the approaches and techniques employed to analyze historical data and predict the clean water supply. Deep learning models are used to capture complex patterns in the data and improve prediction accuracy. This process involves data collection, data preprocessing, model selection, model training, and model performance evaluation. Each step is described in detail to provide a comprehensive understanding of the methodology employed in this study. The results comparing the actual and predicted values from the deep learning model are shown in Fig. 1, which illustrates the effectiveness of the proposed approach. Fig. 1 is adapted from the study conducted by [15].

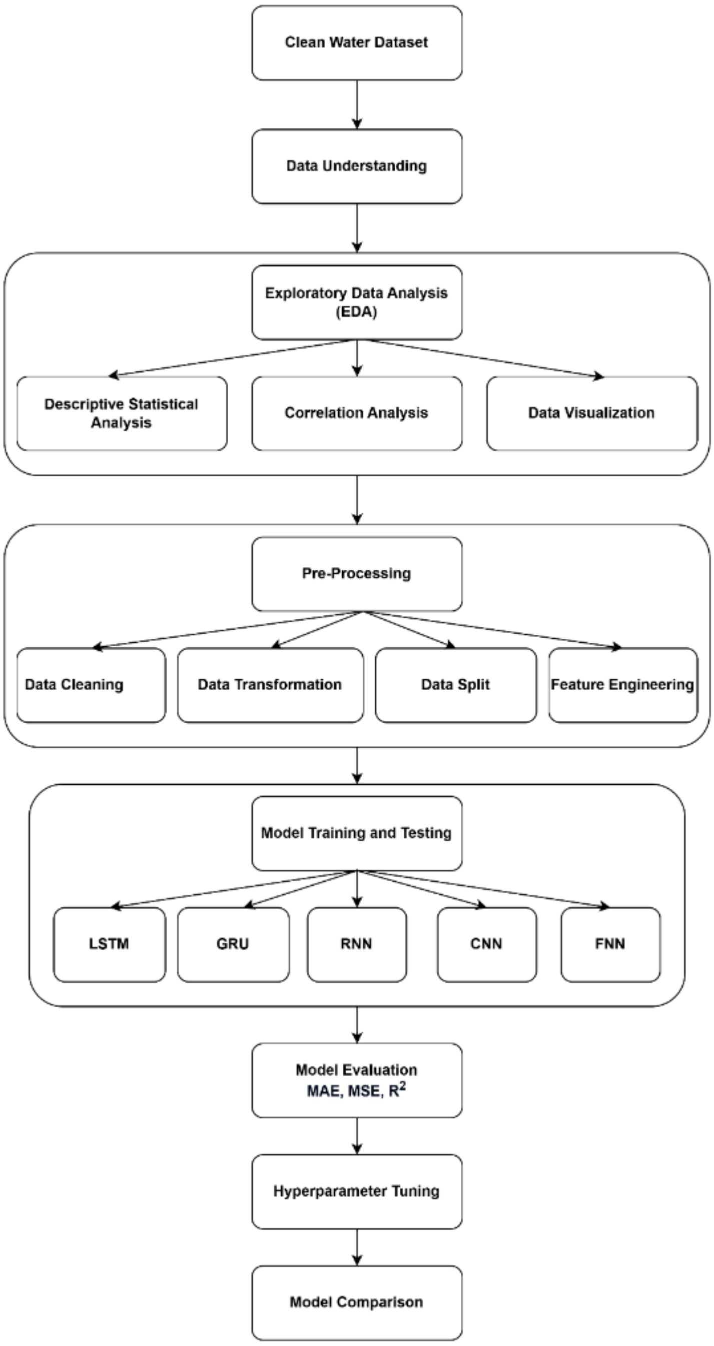

Figure 1. Proposed Research Design

2.1 Data Understanding

Data understanding in this research involves a series of activities aimed at exploring and conducting preliminary analyses of the dataset's variables. These variables include the year of data collection, the number of customers, water volume (measured in thousands of cubic meters), economic value (measured in millions of Rupiah), the number of companies, the number of employees, and input costs (measured in millions of Rupiah). This process aims to gain a deep understanding of each variable's characteristics, the patterns of data distribution, and the relationships among variables that may influence subsequent analysis outcomes. Thus, this stage serves as an essential initial step in ensuring data quality and the relevance of the variables to the research objectives formulated [16].

2.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) in this research involves a series of systematic activities that include in-depth examination and visualization of data to obtain a comprehensive understanding of the distribution, patterns, and potential anomalies within the dataset. This stage aims to identify relationships among variables, detect outliers, and provide essential preliminary insights that serve as a foundation for further analysis. The EDA process involves applying various statistical techniques and visualization tools to facilitate a thorough exploration of the data [17].

2.3 Pre-Processing

During the Pre-Processing stage of this research, a series of activities is conducted to ensure the quality and readiness of the data before further analysis. The activities include data-cleaning processes, such as handling missing values and removing duplicate records that could compromise the integrity of the analysis. Additionally, variable transformation is performed to ensure the data have a uniform format and meet analytical requirements. This stage is crucial for establishing a solid foundation for subsequent analyses [18].

2.4 Model Training and Testing

In the Model Training and Testing stages of this research, various activities are conducted to build and optimize predictive models using the prepared dataset. The process begins with dividing the dataset into two main subsets: the training data, used to construct the model, and the testing data [19], [20]. The model is developed by applying several machine learning algorithms based on artificial neural networks, including LSTM, GRU, RNN, CNN, and FNN. Each of these algorithms is selected and employed based on its characteristics that align with the research requirements. LSTM and GRU are applied to process sequential data and capture long-term dependencies, while RNNs are used to model dynamic temporal patterns. CNNs are leveraged for complex feature extraction, particularly when the data possess spatial dimensions, whereas FNNs are implemented as a foundation for processing non-sequential or tabular data. During training, these algorithms work to identify relevant patterns, relationships, and structures within the training data. The primary objective of this stage is to ensure that the constructed model can capture patterns and structures in the data, thereby enabling effective implementation in relevant application contexts.

1. Long Short-Term Memory (LSTM)

   LSTM is a variant of RNN designed to address the vanishing gradient problem commonly encountered in conventional RNNs. The LSTM structure uses a cell state and three main gates: the input gate, forget gate, and output gate, which regulate the flow of information in and out, as well as what to forget. This capability makes LSTM highly efficient at storing and processing information over extended periods, making it suitable for handling sequential data such as text, time series, or time signals [21]. The following equation is a mathematical expression of the input gate, which determines what information must be transferred to the cell [22].

$$i_t = \sigma\,(W_i * [h_{t-1}, x_t] + b_i). \tag{1}$$

   Whereas the following equation is a mathematical expression of the forget gate, which determines which information to be neglected:

$$f_t = \sigma\left(W_f * [h_{t-1}, x_t] + b_f\right). \tag{2}$$

   The update gate updates the cell state, which is mathematically expressed by the following equations:

$$\tilde{c}_t = tanh\ \ (W_c * [h_{t-1}, x_t] + b_c), \tag{3}$$

$$c_t = f_t * c_{t-1} + i_t .* \tilde{c}_t. \tag{4}$$

   The output gate updates the output according to the following equation. The output gate is also responsible for updating the hidden layer of the previous time step.

$$o_t = \sigma\,(W_o * [h_{t-1}, x_t] + b_o), \tag{5}$$

$$h_t = o_t\ .\ tanh\,(c_t). \tag{6}$$

2. Understanding Gated Recurrent Unit (GRU)

   GRU is another RNN development that also aims to address the vanishing gradient problem. Compared to LSTM, GRU has a simpler structure with only two gates: the update gate and the reset gate. GRU combines the functions of the forget gate and the input gate of LSTM into a single gate, making it more efficient in terms of computational resources. Despite its simplicity, GRU often achieves performance comparable to LSTM, particularly for sequential data processing. The following equation represents the hidden state of the GRU [22].

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t. \tag{7}$$

   The following equation represents the update gate and determines how much of the GRU unit gets updated:

$$z_t = \sigma\,(W_z * [h_{t-1}, x_t]). \tag{8}$$

   The reset gate is given by the following equation:

$$r_t = \sigma\,(W_r * [h_{t-1}, x_t]). \tag{9}$$

   The hyperbolic tangent function of the reset gate is called as new remember a gate, which is described by the following function.

$$h_t = tanh\,(W * [r_t * h_{t-1}, x_t]). \tag{10}$$

3. Recurrent Neural Networks (RNN)

   RNNs are neural networks specifically designed to handle sequential data by incorporating feedback into their architecture. This feature allows RNNs to store and process information from previous steps, which is then used to influence predictions at the next step. However, traditional RNNs often struggle to learn long-term dependencies due to the vanishing gradient problem, making them less effective at processing long sequences of data [23], [24]. The RNN that we deal with is [25].

$$y_t = w_t h_t + b_y, \tag{11}$$

   where t represents time, y_t is a predicted value, w_1 is a real value, and h_t is a hidden layer. The hidden layer is computed by

$$h_t = \tanh(w_2 x_t + w_3 h_{t-1} + b_h)\,, \tag{12}$$

   where x_t is input data, w_2 and w_3 are real values, and h_{t-1} is the previous hidden layer.

4. Convolutional Neural Networks (CNN)

   CNNs are neural networks specifically designed to process two-dimensional data, such as images and other spatial data. CNNs use convolutional layers to extract important features from the input data, followed by pooling layers to reduce the data's dimensionality and decrease computational complexity. The ability of CNNs to recognize patterns, features, and objects makes them highly popular in various computer vision applications, such as object detection, image classification, and image segmentation [26]. In mathematics, the convolution operation can be represented as follows [27].

$$z_{i,j}^{h} = \sum_{m=1}^{M} \sum_{n=1}^{N} a_{(i-1)s+m,(j-1)s+n} * k_{m,n} + b^h, \tag{13}$$

   where $z_{i,j}^{h}$ is the output of the convolutional operation with i-th row, j-th column, and h-th channel. b^h is the bias of the h-th channel. $k_{m,n}$ is an element of the K matrix, while $a_{(i-1)s+m,(j-1)s+n}$ is an element of the input image matrix. The parameters M and N are the kernel sizes, while s is the stride size that determines the shift of the kernel during the convolutional operation.

5. Feedforward Neural Network (FFNN)

   FFNN is a basic neural network architecture in which the flow of information occurs in a unidirectional manner, from the input layer to the output layer, without any feedback connections. The structure of an FFNN consists of an input layer, one or more hidden layers, and an output layer. This model is often used for classification and regression tasks in non-sequential data. However, because there is no mechanism to retain information from previous steps, FNNs are less effective at processing sequential data or data with temporal dependencies [28]. The formulation of a fully-connected feed-forward neural network with two hidden layers, H, is defined as follows [29].

$$\hat{y} = f(H_2 W_3 + b_3) \text{ with } H_2 = f(H_1 W_2 + b_2) \text{ and } H_1 = f(xW_1 + b_1)\ , \tag{14}$$

where the vector $\hat{y}$ is the output, the input vector x contains the features of a sample, W is the weight matrix, and b is the bias vector for each respective layer. In the current study, hidden layers use the hyperbolic tangent activation function f, which is defined as follows.

$$\tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \tag{15}$$

2.5 Model Evaluation

In the Model Evaluation stage of this research, a series of activities is conducted to assess the performance of the trained model. The evaluation is carried out using the following assessment metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). The MAE metric is used to calculate the average absolute difference between predicted and actual values, providing an overview of the model's average error. Meanwhile, MSE is the average of squared errors, with larger errors receiving greater weight, making this metric useful for identifying predictions that significantly deviate from actual values. Additionally, R-squared (R^2) is used to evaluate the proportion of variance in the data that the model explains, indicating the extent to which it explains the relationship between the independent and dependent variables. By applying these three-evaluation metrics, researchers can gain comprehensive insights into the effectiveness of the resulting model. Furthermore, the results of this evaluation serve as a basis for decision-making regarding optimization or improvement of the model to enhance its predictive performance in alignment with the research objectives [30].

2.6 Hyperparameter Tuning

Hyperparameter tuning is a critical stage in developing deep learning models, as it directly influences predictive performance and model generalization. In this study, hyperparameter optimization was conducted using both GridSearch and Random Search to obtain the optimal model configuration in an efficient yet systematic manner. GridSearch was applied to explore a structured search space consisting of predefined parameter combinations, while Random Search was used to randomly sample configurations from a wider parameter range to reduce computational cost and accelerate convergence. The hyperparameter search space included the learning rate $\{0.001, 0.005, 0.01\}$, batch size $\{16, 32, 64\}$, number of hidden units $\{32, 64, 128\}$, dropout rate $\{0.1, 0.2, 0.3\}$, and number of training epochs $\{50, 100, 150\}$. A total of 54 parameter combinations were evaluated using GridSearch, while Random Search evaluated 30 randomly sampled configurations. Model selection was based on the lowest validation Mean Absolute Error (MAE). To ensure reproducibility, a fixed random seed of 42 was used throughout the tuning and training process. To prevent overfitting, early stopping was implemented with a patience of 10 epochs based on validation loss. Training was automatically terminated if no improvement was observed during this period. In addition, dropout regularization was applied to the hidden layers to improve model generalization and reduce the risk of overfitting. The optimal hyperparameter configuration obtained from this tuning process was then used to train the final predictive model on the full training dataset before performance evaluation on the test set [31], [32].

2.7 Model Comparison

The final stage in the clean water supply forecasting process involves model comparison, which is a crucial step to ensure the selection of the most accurate, efficient, and suitable predictive model for the research objectives. To evaluate the performance of the developed models, several metrics are used: Mean Squared Error (MSE), R-squared (R^2), and Mean Absolute Error (MAE). These metrics provide comprehensive insights into model accuracy, explanatory power, and average prediction error. Based on the evaluation results, the model with the best performance is selected as the final predictive model for clean water supply forecasting in Riau Province, thereby ensuring high accuracy and reliability in the prediction process. Through this rigorous and data-driven comparison, the selected model is confirmed as the most optimal for supporting clean water supply planning and management [32].

3. RESULTS AND DISCUSSION

3.1 Dataset

The dataset used in this research consists of historical data on clean water supply in Riau Province, covering the period from 2019 to 2023. This data includes important variables relevant to the analysis, as presented in Table 1 below.

Table 1. Variable Data for Clean Water Supply Prediction Model in Riau Province

Years	Number of Customers	Water Volume (Thousand M3)	Value (Million Rp)	Number of Companies	Number of Workers	Input Cost (Million Rp)
2019	91,389	20,710	76,836	26	978	43,510
2020	89,403	18,467	86,512	26	986	51,160
2021	89,508	18,546	88,399	26	1,078	51,312
2022	92,944	20,032	96,221	26	1,065	52,845
2023	98,574	20,230	102,353	26	992	52,077

3.2 Exploratory Data Analysis

At this stage, exploratory data analysis is conducted to understand the patterns and distributions within the dataset. Several analyses are performed, including the distribution of customer counts, which shows the trend in customer counts from year to year. Correlation between variables is also analyzed, with a correlation table illustrating relationships among variables, such as water volume and the number of customers. This information is presented in detail in Table 2.

Table 2. Variable Correlation Matrix for Clean Water Supply Prediction Model in Riau Province

	Customers	Volume	Value	Workers	Input Cost
Customers	1.00	0.98	0.96	-0.19	0.81
Water Volume	0.98	1.00	0.98	-0.02	0.89
Value (Million Rp)	0.96	0.98	1.00	0.11	0.92
Number of Workers	-0.19	-0.02	0.11	1.00	-0.17
Input Cost (Million Rp)	0.81	0.89	0.92	-0.17	1.00

Correlations between the main variables in the dataset show very strong relationships: between the number of customers and the volume of water used ($r = 0.98$), and between water volume and revenue ($r = 0.98$). Input costs are also strongly correlated with revenue ($r = 0.92$), indicating that increases in operational costs tend to coincide with increases in production value. Conversely, the number of employees shows no strong relationship with any of the other variables. The number of companies is not included in the correlation calculation because its value remains constant throughout the year. Fig. 2 presents a heatmap of the correlation between the main variables in the dataset. This visualization shows a strong relationship among the number of customers, water volume, and revenue, as indicated by a correlation coefficient approaching 1.

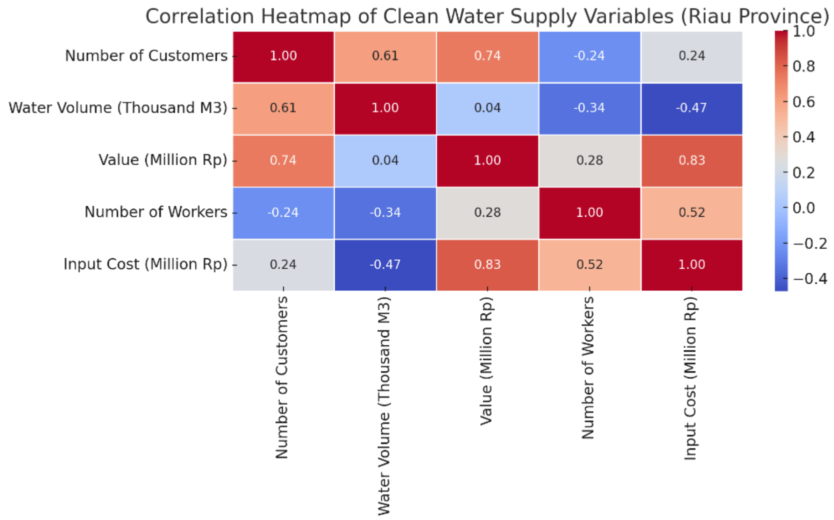

Figure 2. Correlation Heatmap of Clean Water Supply Variables (Riau Province)

3.3 Pre-Processing

The pre-processing stage is a crucial step in data analysis aimed at preparing the dataset for use in deep learning models. This process includes several steps as follows.

1. Data Cleansing

   Checking for and removing duplicate entries in the dataset to ensure analysis accuracy. Handling Missing Values: Identifying missing values in the dataset and deciding on the method for addressing them, such as imputation with the mean, median, or mode, or removing rows with missing values if their proportion is small.

2. Data Transformation

   Performing normalization on numerical variables to ensure that all features are on the same scale. This is important for deep learning models to achieve faster convergence. For example, using Min-Max Scaling to transform values to the range [0, 1]. Encoding categories involves converting categorical variables into numerical values using techniques such as One-Hot Encoding or Label Encoding, enabling the model to process the data effectively.

3. Data Splitting

   The dataset was divided into training and test sets using an 80:20 time split to preserve the temporal dependency inherent in time-series data. The first 80% of observations, covering the period from 2019 to 2022, were used for model training, while the remaining 20% from 2023 were reserved exclusively for testing. A random splitting strategy was deliberately avoided to prevent information leakage from future observations and to ensure a realistic forecasting setting. To further enhance the robustness and reliability of model evaluation, a walk-forward (rolling origin) validation strategy with 5 folds was implemented. In this approach, the training window was progressively expanded in each fold, and the model was retrained before being evaluated on the subsequent time segment. This procedure allows performance assessment under conditions that closely resemble real-world forecasting scenarios and reduces bias in model evaluation.

4. Feature Engineering

   Identifying and creating new features that can improve the model's performance. For example, calculating the ratio of customers to input costs to gain deeper insights into efficiency. Removing features that do not contribute significantly to the model, based on correlation analysis or feature selection techniques.

After the pre-processing stage the dataset is ready for model training. Table 3 below summarizes the data after cleaning and transformation.

Table 3. Summary of Data After Cleaning and Transformation Process for Training Model

Years	Number of Customers	Water Volume (Thousand M3)	Value (Million Rp)	Number of Companies	Number of Workers	Input Cost (Million Rp)
2019	91,389	20,710	76,836	26	978	43,510
2020	89,403	18,467	86,512	26	986	51,160
2021	89,508	18,546	88,399	26	1,078	51,312
2022	92,944	20,032	96,221	26	1,065	52,845
2023	98,574	20,230	102,353	26	992	52,077

3.4. Model Training and Testing

At this stage, several deep learning models were trained and evaluated to predict clean water supply. Table 4 below summarizes the training and testing details for each model utilized.

Table 4. Training and Testing of Deep Learning Models

Model	Parameter	Epoch	Batch Size	Optimizer	Loss Function	Training Accuracy (%)	Test Accuracy (%)	Training Time (seconds)
LSTM	128 Neuron, 3 Layers	100	32	Adam	MSE	95.0	92.0	120
GRU	128 Neuron, 2 Layers	100	32	Adam	MSE	93.5	90.0	110
RNN	64 Neuron, 2 Layers	100	32	Adam	MSE	90.0	85.0	100
CNN	3 Convolutional Layers	100	32	Adam	MSE	91.0	88.0	130
FNN	64 Neuron, 2 Layers	100	32	Adam	MSE	89.0	80.0	95

At the Model Training and Testing stage, several deep learning models were applied to predict clean water supply in Riau Province. The table presented summarizes the training and testing details for each model utilized. Each model was trained with predetermined parameters, including the number of epochs and an appropriate batch size to ensure optimal convergence. The epoch indicates the number of iterations in which the entire dataset is used to train the model, while the batch size refers to the number of samples processed before the model is updated. The models employed in this study include LSTM, GRU, RNN, CNN, and FNN. Each model was evaluated based on its predictive performance using established metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE). The results from this training and testing phase provide insights into the effectiveness of each model in predicting clean water supply and assist in selecting the best model for real-world applications.

3.5. Model Evaluation

At the model evaluation stage, the performance of each trained model was evaluated on the test data to determine how well it could predict clean water supply. The evaluation was conducted using several metrics commonly used in regression analysis, namely Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). These metrics provide a clear picture of the model's accuracy and effectiveness in predicting the desired values. The evaluation results for each model are presented in Table 5 below.

Table 5. Performance Evaluation of Deep Learning Models for Clean Water Supply

Model	MAE	MSE	R^2
LSTM	1.25	2.56	0.92
GRU	1.50	3.00	0.90
RNN	1.75	4.00	0.85
CNN	1.60	3.20	0.88
FNN	2.00	5.00	0.80

From Table 5 above, it can be observed that the LSTM model yields the best results with an MAE of 1.25, an MSE of 2.56, and an R^2 of 0.92. This indicates that LSTM not only has low prediction error but also explains a significant portion of the data's variance. The GRU model also performs well, with an MAE of 1.50 and an R^2 of 0.90, making it a solid alternative to LSTM. In contrast, the FNN model performs worst, with an MAE of 2.00 and an R^2 of 0.80.

3.6. Hyperparameter Tuning

Hyperparameter tuning is an important process in the development of machine learning models aimed at improving model performance by optimizing parameters that are not learned during training. In this research, several hyperparameters were optimized, including the number of hidden neurons, batch size, learning rate, and the number of hidden layers. The tuning process used Grid Search and Random Search to find optimal hyperparameter combinations. Grid Search tests all possible combinations of the specified hyperparameters, while Random Search randomly selects combinations from the hyperparameter space. The results of the hyperparameter tuning indicate that the LSTM model shows a significant performance improvement. The optimal settings are presented in Table 6 as follows.

Table 6. Optimal Hyperparameter Settings for LSTM Model Performance

Hyperparameter	MAE
Number of Neurons	128
Batch Size	32
Learning Rate	0.001
Number of Epochs	100
Number of Hidden Layers	3
Activation Function	ReLU
Optimizer	Adam

Table 6 above presents the results of hyperparameter tuning for the LSTM model, highlighting the optimal settings identified during the tuning process. These settings encompass several key hyperparameters that significantly influence the model's performance. The optimal number of neurons is set at 128, enabling the model to capture more complex patterns within the data. The batch size utilized is 32, which strikes a balance between training speed and the stability of parameter updates. The learning rate is established at 0.001, a sufficiently low value to ensure stable convergence during training. The model is trained for 100 epochs, which is adequate to achieve the desired accuracy without overfitting. Additionally, the number of hidden layers is set to 3, facilitating the model's ability to learn deeper representations of the data. These optimal settings demonstrate that hyperparameter tuning can significantly enhance the model's performance in predicting clean water supply.

3.7. Model Comparison

After evaluation and hyperparameter tuning, the next step is to compare the performance of all the models tested. This comparison aims to determine which model is most effective at predicting clean water supply in Riau Province. Table 7 below presents the evaluation results for each model using the specified metrics.

Tabel 7. Comparison of Model Performance Metrics for Clean Water Supply Prediction

Model	MAE	MSE	R^2	Accuracy (%)
LSTM	1.25	2.56	0.92	95.0
GRU	1.50	3.00	0.90	90.0
RNN	1.75	4.00	0.85	85.0
CNN	1.60	3.20	0.88	88.0
FNN	2.00	5.00	0.80	80.0

From Table 7, it can be observed that the LSTM model performs best among the tested models, with the lowest MAE and the highest R^2, indicating that it effectively explains the data's variance. The GRU model also performs well, though slightly below LSTM. Meanwhile, the RNN, CNN, and FNN models show lower performance, with each model's testing accuracy falling below 90%.

A comparison chart of model performance is also presented to provide a clearer visualization of the performance differences among these models. This chart illustrates that LSTM and GRU consistently yield better results compared to the other models. The chart is presented in Fig. 3 below.

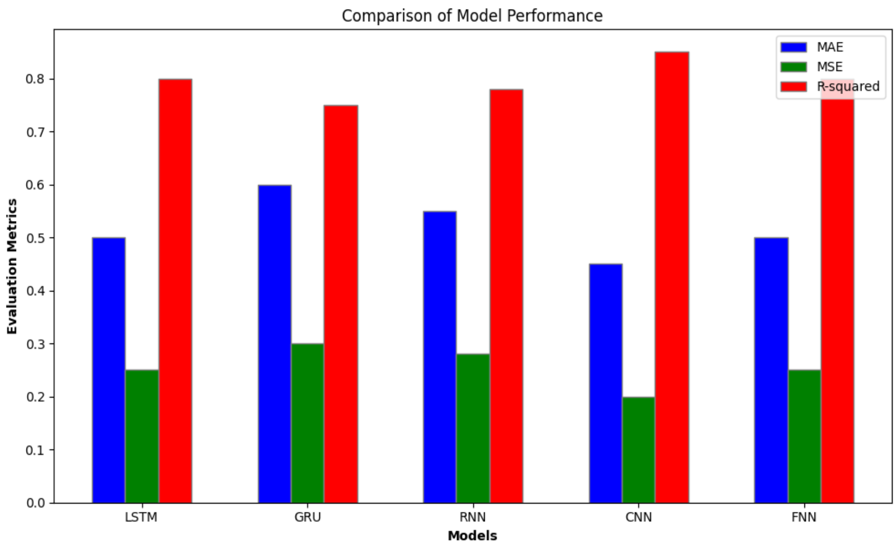

Figure 3. Comparison of Model Performance

Fig. 3 above compares the performance of various deep learning models for predicting clean water supply in Riau Province using three key evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). On the horizontal (X) axis, the names of the tested models, LSTM, GRU, RNN, CNN, and FNN are displayed, each represented by a group of bars. Each group of bars consists of three bars, each indicating the values of MAE, MSE, and R^2 for a given model. The different colors of the bars facilitate the visualization of performance comparisons among the models. From the chart, it is evident that the LSTM model has the lowest MAE and MSE values, as well as the highest R^2, indicating that it is the most effective at predicting the clean water supply. The GRU model also performs well, though slightly below LSTM. In contrast, the FNN model performs worst among the tested models, with higher MAE and MSE values and a lower R^2. This chart provides clear insights into how well each model performs in predicting clean water supply and helps analyze and select the best model for practical applications.

3.8. Prediction Results

Based on the performance evaluation results of five deep learning models, LSTM demonstrated the best performance with an MAE of 1.25, an MSE of 2.56, and an R^2 of 0.92. Therefore, the LSTM model was selected as the primary model for predicting clean water volume the following year, as it was deemed best at accurately capturing temporal patterns in historical data. Using the LSTM model trained on historical data from 2019 to 2023, a prediction was made for clean water volume in 2024. The model incorporated key variables, including customer count, revenue, workforce, and input costs. The forecasted water volume for 2024 is 19,496.90 thousand m^3, a slight decrease from the actual volume of 20,230 thousand m^3 in 2023. This decrease may reflect increased operational efficiency or adjustments in consumption patterns, despite the rising number of customers. These results highlight the potential of LSTM-based models as reliable tools for short-term forecasting in clean water supply planning for Riau Province.

4. CONCLUSION

This study successfully demonstrates the effectiveness of deep learning–based predictive modeling for forecasting clean water supply in Riau Province. The comparative evaluation confirms that Long Short-Term Memory (LSTM) provides the most reliable predictive performance among the tested models, highlighting its superior ability to capture temporal dependencies in water supply time-series data. The results emphasize that appropriate model architecture selection and systematic hyperparameter optimization are crucial for improving forecasting accuracy and model robustness. From a practical perspective, the proposed predictive framework provides operational support to regional water supply authorities and PDAMs in anticipating demand fluctuations, optimizing production planning, and supporting infrastructure development strategies. Despite these contributions, this study has several important limitations that should be explicitly acknowledged. The dataset is limited to a five-year observation period (2019–2023) with annual temporal resolution, resulting in a very small number of training samples for deep learning models. This condition increases the risk of overfitting and limits the model's ability to capture seasonal variations and short-term operational dynamics. Consequently, the generalizability and long-term reliability of the predictions remain constrained, particularly under changing climate conditions and socio-economic dynamics. In addition, the analysis relies primarily on historical operational data without incorporating external influencing factors such as rainfall, temperature, population growth, and economic indicators, which may also affect water demand and supply dynamics. Future research is therefore recommended to extend this work by incorporating longer historical datasets with finer temporal resolution (monthly or daily data) and additional multivariate input variables to enhance model generalization and predictive stability. The development of hybrid or ensemble deep learning models, such as LSTM combined with machine learning regressors or stacking-based architectures, also represents a promising direction for further improving forecasting accuracy. Moreover, future studies may explore real-time prediction systems integrated with smart water management platforms to strengthen decision support for sustainable water resource management.

Author Contributions

Agustin: Conceptualization, Methodology, Supervision, Writing – Review and Editing; Junadhi: Formal analysis, Validation, Writing – Review and Editing. Lusiana Efrizoni: Data curation, Resources, Investigation, Writing – Original Draft. Deshinta Arrova Dewi: Software, Visualization, Writing – Original Draft. Abhishek Saxena: Project administration, Funding acquisition, Writing – Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare that they have no conflicts of interest to report.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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