

Performance Comparison of Double Exponential Smoothing and Long Short-Term Memory for Population Forecasting

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ABSTRACT

Population forecasting is essential for supporting regional development planning and the effective allocation of public services. However, comparative studies evaluating statistical and deep learning approaches for sub-district population forecasting based on limited historical data are still scarce. This study compares the performance of Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) for forecasting the population of 17 sub-districts in Bireuen Regency using annual population data from 2015 to 2024, with forecasts generated until 2027. The dataset was divided chronologically using a time-based split to preserve temporal dependencies, and forecasting accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). Experimental results show that DES achieved lower forecasting errors in most sub-districts, with MAPE values ranging from 1.61% to 4.48%, whereas LSTM produced MAPE values between 1.56% and 7.55%, outperforming DES only in a few sub-districts, such as Peusangan Selatan. In terms of computational efficiency, DES required approximately 0.0007–0.0008 MB of memory and 0.00–1.48 ms processing time, whereas LSTM required 0.0102–0.0118 MB of memory and up to 162.24 ms processing time. The forecasting results indicate a generally increasing population trend across most sub-districts through 2027. These findings suggest that DES is more suitable than LSTM for forecasting annual population data with relatively stable trends and limited historical observations, whereas LSTM may be more appropriate for larger datasets exhibiting more complex temporal patterns. The developed web-based forecasting system provides visualization and forecasting results to support evidence-based population planning in Bireuen Regency.



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I. INTRODUCTION

Population growth is one of the major demographic factors influencing regional development, public service provision, and the utilization of natural resources. Rapid population growth without proper planning may increase pressure on environmental resources and reduce the effectiveness of public infrastructure and social services. Therefore, accurate population forecasting is essential to support sustainable development planning and government policy formulation. Population forecasting provides estimates of future population conditions based on historical observations and serves as an important tool for planning

healthcare, education, transportation, housing, and other public facilities [1][2].

Population growth is primarily determined by three demographic components, namely birth, death, and migration. An increasing population may contribute positively to economic development through the expansion of the labor force and market demand. However, if population growth is not accompanied by adequate infrastructure and public services, it may create various social and economic challenges. Consequently, governments require reliable forecasting models to estimate future population changes and formulate effective long-term development strategies [1].

Bireuen Regency has experienced continuous population growth during the last decade. According to the Central

Bureau of Statistics (BPS) of Bireuen Regency, the projected population in 2023 reached approximately 453,200 people, consisting of 224,100 males and 229,100 [2]. This population increase has significant implications for the provision of public services, including healthcare, education, transportation, housing, and employment. Therefore, accurate population forecasting is required to support regional development planning and policy decision-making.

Most previous population forecasting studies have focused on aggregated data at the regency or city level, which cannot adequately represent demographic differences among smaller administrative regions. In Bireuen Regency, each sub-district has different characteristics regarding birth rates, mortality, migration, and population growth. These differences influence regional development priorities and public service requirements. Consequently, forecasting population at the sub-district level is expected to provide more detailed and representative information for local governments in planning development programs.

Forecasting is a systematic process of estimating future conditions based on historical data. Various forecasting techniques have been developed, ranging from conventional statistical methods to machine learning and deep learning approaches. Among statistical techniques, Double Exponential Smoothing (DES) is widely applied because it effectively models time-series data containing trend components while maintaining relatively low computational complexity. Previous studies have demonstrated that DES achieves satisfactory forecasting accuracy in several application domains [3][4][5]. However, DES generally assumes relatively stable trends and may not perform optimally when the data exhibit highly nonlinear patterns.

In recent years, deep learning techniques such as Long Short-Term Memory (LSTM) have been increasingly employed for time-series forecasting because of their capability to capture nonlinear relationships and long-term temporal dependencies. LSTM utilizes memory cells and gate mechanisms that enable the model to retain important historical information while learning sequential patterns. Previous studies have reported that LSTM achieves promising forecasting performance in applications such as stock price prediction and inventory forecasting [6][7][8]. Nevertheless, the performance of LSTM depends heavily on the availability of sufficient historical observations and appropriate model configuration.

Although numerous forecasting studies have compared statistical and machine learning methods, comparative studies evaluating Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) for sub-district population forecasting in Bireuen Regency remain limited. In addition, most existing studies emphasize forecasting accuracy without considering computational efficiency, such as processing time and memory consumption, which are important for practical implementation in web-based forecasting systems.

Therefore, this study compares the forecasting performance of DES and LSTM using annual population data

from all 17 sub-districts in Bireuen Regency during the 2015–2024 period. The forecasting results are evaluated using Mean Absolute Percentage Error (MAPE) to measure prediction accuracy, while computational performance is assessed based on processing time and memory usage. Furthermore, a web-based forecasting system is developed to visualize prediction results and facilitate population data management, thereby supporting regional population planning in Bireuen Regency [9].

II. METHODOLOGY

A. Research Framework

This study employed a comparative experimental approach to evaluate the forecasting performance of the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) methods for population prediction in Bireuen Regency. The research consisted of data collection, data preprocessing, model development, forecasting, performance evaluation, and implementation in a web-based application. The overall research workflow is illustrated in Figure 1.

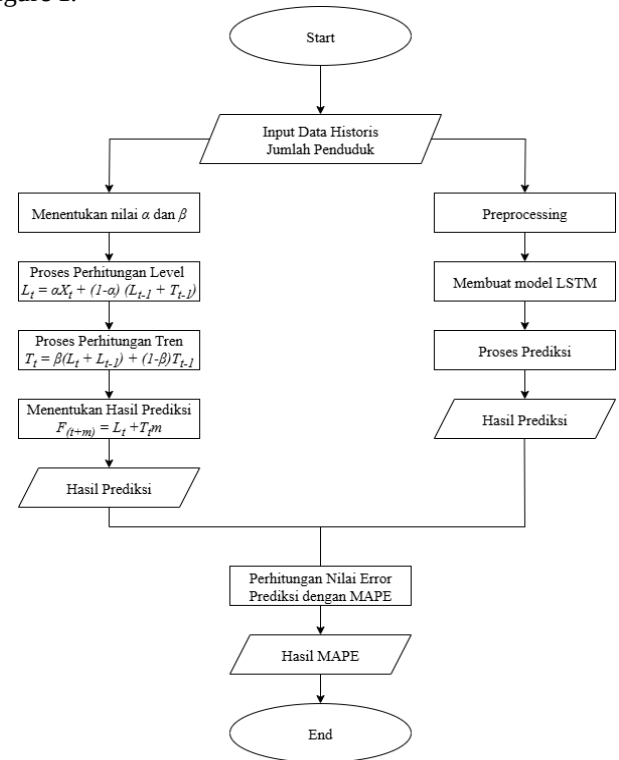


Figure 1. Research Framework

B. Dataset

The dataset used in this study was obtained from the Central Bureau of Statistics (BPS) of Bireuen Regency. It consists of annual population data from 17 districts covering the period from 2015 to 2024. The historical data were used to forecast population values for the years 2025–2027.

Prior to modeling, the dataset was inspected to ensure completeness and consistency. No missing values were found,

allowing the data to be directly utilized in the forecasting process.

C. Preprocessing Data

The preprocessing stage differed according to the forecasting method employed.

For the DES method, the historical population data were arranged chronologically as a time-series dataset without additional transformation.

For the LSTM method, the dataset was normalized using Min-Max Scaling to transform the values into the range of 0–1. The normalized data were then converted into sequential input suitable for the LSTM network. After prediction, the results were transformed back to the original scale through a denormalization process.

To preserve temporal characteristics and avoid data leakage, the dataset was divided using a time-based split approach, where earlier observations were used as training data and later observations were used as testing data.

D. Forecasting Models

Forecasting is the process of estimating future values based on historical observations using statistical or machine learning techniques. In this study, forecasting is performed to predict the population of each sub-district in Bireuen Regency for the upcoming years. Two forecasting approaches are employed: Double Exponential Smoothing (DES), which models trend components in time-series data, and Long Short-Term Memory (LSTM), which learns temporal patterns through a deep learning architecture. The forecasting results produced by both methods are subsequently compared to evaluate their performance.

1. Double Exponential Smoothing (DES)

Double Exponential Smoothing is a statistical forecasting method designed for time-series data exhibiting trend patterns. The method estimates both level and trend components to generate future forecasts.

In this study, DES was applied independently to the population data of each district. The smoothing parameters α (alpha) and β (beta) were determined through parameter optimization by selecting the combination that produced the lowest forecasting error.

The DES equations are expressed as:

$$L_t = \alpha X_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1}$$

$$F(t+m) = L_t + Ttm$$

where:

L_t = Level smoothing value at time t

T_t = Trend smoothing value at time t

X_t = Actual value at time t

$F(t+m)$ = Forecast value for m periods ahead

α = Level smoothing parameter

β = Trend smoothing parameter

The values of α and β were determined experimentally to obtain the lowest forecasting error.

2. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a deep learning architecture derived from Recurrent Neural Networks (RNN) that is capable of capturing long-term dependencies in sequential data through memory cells and gating mechanisms.

The normalized dataset was divided chronologically into training and testing sets using the time-based split approach. The LSTM architecture consisted of an input layer, one hidden LSTM layer, and one dense output layer. Model training employed the Adam optimizer and Mean Squared Error (MSE) as the loss function. Hyperparameters such as the number of neurons, learning rate, batch size, and epochs were optimized experimentally to achieve the lowest prediction error.

After training and evaluation, both the DES and LSTM models were used to forecast population values for the 2025–2027 period. The predicted outputs generated by the LSTM model were then denormalized to obtain the actual population estimates.

E. Performance Evaluation

The forecasting performance of DES and LSTM was evaluated using Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \times 100\%$$

where:

A_t = Represents the actual value

F_t = Represents the predicted value

n = Denotes the number of observations

Besides forecasting accuracy, computational efficiency was also assessed using processing time and memory consumption. These metrics were used to compare the practical performance of both forecasting methods.

III. RESULTS AND DISCUSSION

A. Population Dataset

This study utilized annual population data from 17 districts in Bireuen Regency collected from the Central Bureau of Statistics (BPS) for the period 2015–2024. The dataset exhibits an overall increasing population trend, although the growth rate varies among districts. These differences indicate that each district has unique population characteristics, making comparative forecasting particularly important.

TABLE I
RESEARCH DATASET

Attribute	Description
Data source	BPS Kabupaten Bireuen

Data type	Annual population data
Number of sub-districts	17
Observation period	2015–2024
Total observations	170
Forecast period	2025–2027

Table II presents a representative sample of the historical population dataset for the Samalanga Sub-district. The complete dataset consists of annual population records from all 17 sub-districts in Bireuen Regency covering the period from 2015 to 2024, resulting in a total of 170 observations used in this study. Only one sub-district is presented as an example to illustrate the structure of the dataset, while the complete dataset was used in the preprocessing, model training, evaluation, and forecasting processes for both the DES and LSTM methods.

TABLE II
SAMPLE OF POPULATION DATASET

Sub-district	Year	Population
Samalanga	2015	30617
	2016	31203
	2017	31878
	2018	32476
	2019	33172
	2020	27907
	2021	28086
	2022	28311
	2023	28241
	2024	28241

B. Forecasting Results Using DES

The Double Exponential Smoothing (DES) method was applied to the historical population data of each sub-district in Bireuen Regency to generate population forecasts for the 2025–2027 period. DES models both the level and trend components of time-series data, making it suitable for forecasting datasets that exhibit relatively stable trends.

Before the forecasting process, the smoothing parameters α (alpha) and β (beta) were optimized by evaluating several parameter combinations using the Mean Absolute Percentage Error (MAPE) as the evaluation metric. The optimization results are presented in Table III.

As shown in Table III, the parameter combination of $\alpha = 0.9$ and $\beta = 0.8$ produced the lowest MAPE value of 2.71%. Therefore, these parameter values were selected for all DES forecasting experiments.

TABLE III
OPTIMIZATION RESULTS OF DES PARAMETERS

Alpha	Beta	Lowest MAPE
$\alpha = 0,1$	$\beta = 0,1$	18,35%
$\alpha = 0,2$	$\beta = 0,9$	13,21%
$\alpha = 0,3$	$\beta = 0,8$	7,87%
$\alpha = 0,4$	$\beta = 0,8$	5,87%
$\alpha = 0,5$	$\beta = 0,8$	4,83%
$\alpha = 0,6$	$\beta = 0,8$	4,00%
$\alpha = 0,7$	$\beta = 0,8$	3,42%
$\alpha = 0,8$	$\beta = 0,8$	3,00%
$\alpha = 0,9$	$\beta = 0,8$	2,71%

Using the optimal parameters, the DES model generated population forecasts for all 17 sub-districts in Bireuen Regency for the 2025–2027 period. A representative forecasting result for one sub-district is presented in Table IV, while the complete forecasting results are available in the developed web-based system.

TABLE IV
REPRESENTATIVE DES FORECASTING RESULTS

Sub-district	Year	Actual Population	Forecasted Population
Samalanga	2016	30617	31203
	2017	31203	31789
	2018	31878	32519
	2019	32476	33099
	2020	33172	33836
	2021	27907	24902
	2022	28086	26462
	2023	28311	28151
	2024	28241	28321
	2025	28241	28280
	2026	-	28312
	2027	-	28344

As shown in Table IV, the DES method successfully captured the population trend in Samalanga Sub-district. The predicted values indicate a gradual increase in population and closely follow the historical observations, demonstrating the capability of DES to model annual population data with relatively stable growth patterns.

To further illustrate the forecasting performance of the DES method, a comparison between the actual population values and the predicted values is presented in Figure 2.

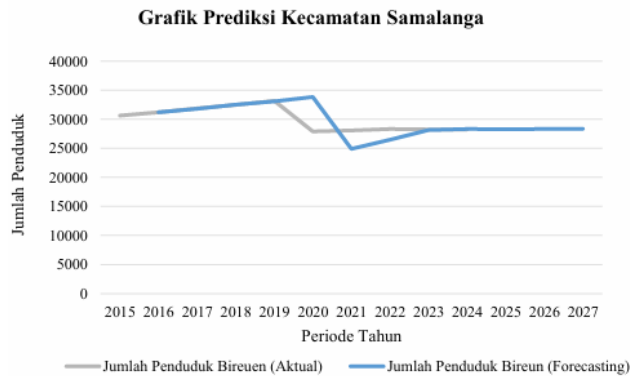


Figure 2. DES Forecast Results Graph

Figure 2 shows that the forecasted values closely follow the historical population trend, indicating that the DES model effectively captures the long-term growth pattern of the population. Although slight deviations are observed in certain years, the overall forecasting results remain consistent with the historical trend, suggesting that DES provides reliable forecasts for annual population data with limited historical observations.

C. Forecasting Results Using LSTM

The LSTM model was trained using normalized historical population data. After the training process, predictions were transformed back into the original population scale through denormalization.

Overall, the LSTM model was able to capture the general population growth trend across the sub-districts. However, because the dataset consisted of only ten annual observations (2015–2024), the forecasting accuracy varied among sub-districts. In several cases, the prediction errors produced by LSTM were higher than those of DES, indicating that the limited amount of historical data constrained the learning capability of the deep learning model.

TABEL V
REPRESENTATIVE LSTM FORECASTING RESULTS

Sub-district	Year	Actual Population	Forecasted Population
Samalanga	2016	30617	28754
	2017	31203	29282
	2018	31878	29635
	2019	32476	29883
	2020	33172	30082
	2021	27907	29593
	2022	28086	29422
	2023	28311	29338
	2024	28241	29272
	2025	28241	29235
	2026	-	29213
	2027	-	29321

Table V shows that the LSTM model successfully generated population forecasts for the 2025–2027 period in all sub-districts. The predicted values generally followed the increasing trend observed in the historical data. Nevertheless, the forecasting performance differed among sub-districts due to variations in population growth patterns and the relatively small number of observations available for model training.

The forecasting performance of the LSTM model is further illustrated through a comparison between the actual population values and the predicted values, as shown in Figure 3.

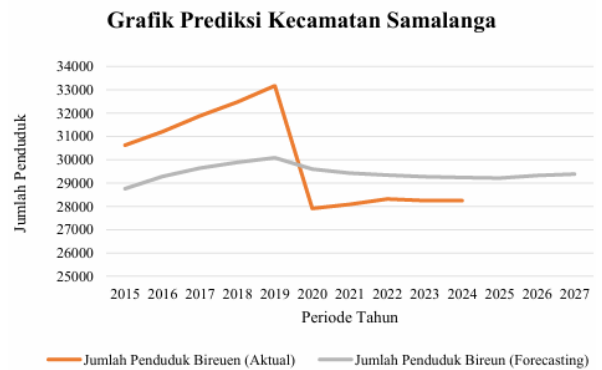


Figure 3. LSTM Forecast Results Graph

Figure 3 illustrates that the predicted values produced by the LSTM model generally followed the overall trend of the historical population data. Although slight deviations were observed in several years, the model was able to preserve the long-term growth pattern. These results indicate that LSTM can effectively learn temporal relationships from historical population data, although its performance is influenced by the limited size of the dataset.

D. Forecasting Accuracy Comparison of DES and LSTM

The forecasting accuracy of the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) methods was evaluated using the Mean Absolute Percentage Error (MAPE). A lower MAPE value indicates higher forecasting accuracy. The comparison results are presented in Table VI.

TABEL VI
COMPARISON OF MAPE VALUES

No	Sub-district	MAPE DES	MAPE LSTM	Best Method
1	Samalanga	4,48%	5,82%	DES
2	Sp Mamplam	2,73%	2,43%	LSTM
3	Pandrah	2,56%	3,17%	DES
4	Jeunieb	2,05%	1,87%	LSTM
5	Peulimbang	1,76%	4,46%	DES
6	Peudada	1,96%	1,56%	LSTM
7	Juli	1,61%	2,20%	DES
8	Jeumpa	3,37%	7,76%	DES
9	Kota Juang	3,85%	3,25%	LSTM
10	Kuala	2,23%	4,35%	DES
11	Jangka	2,42%	2,12%	LSTM
12	Peusangan	3,16%	3,31%	DES

13	Peusangan Selatan	30,52%	2,16%	LSTM
14	Peusangan Siblah Krueng	1,98%	2,33%	DES
15	Makmur	2,23%	2,36%	DES
16	Gandapura	2,69%	3,66%	DES
17	Kuta Blang	2,68%	2,26%	LSTM

The forecasting accuracy of the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) methods was evaluated using the Mean Absolute Percentage Error (MAPE). A lower MAPE value indicates higher forecasting accuracy. The comparison results are presented in Table VI.

Table VI shows that the DES method achieved lower MAPE values in 10 out of 17 sub-districts, while the LSTM method performed better in the remaining 7 sub-districts. Overall, DES produced MAPE values ranging from 1.61% to 30.52%, whereas LSTM produced values ranging from 1.56% to 7.76%.

For most sub-districts with relatively stable population growth patterns, such as Samalanga, Pandrah, Peulimbang, Juli, Kuala, Peusangan, Makmur, Gandapura, and Kuta Blang, DES generated more accurate forecasts than LSTM. This indicates that DES is well suited for annual population data exhibiting consistent trend patterns.

However, LSTM outperformed DES in several sub-districts, including Peusangan Selatan, where DES produced a MAPE of 30.52%, while LSTM achieved a substantially lower MAPE of 2.16%. This significant difference suggests that the historical population pattern in Peusangan Selatan was more difficult to model using the linear trend assumption of DES. The ability of LSTM to learn nonlinear temporal relationships enabled it to produce more accurate forecasts for this particular case.

Overall, the results indicate that DES provides better forecasting accuracy for most sub-districts because the population data generally exhibit stable annual trends with limited fluctuations. In contrast, LSTM performs better in several sub-districts with more complex population patterns.

E. Computational Performance Comparison

Besides forecasting accuracy, the computational performance of the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) methods was evaluated based on processing time and memory usage. These metrics were measured during the forecasting process to assess the computational efficiency of each method.

All experiments were conducted on an HP laptop equipped with an 11th Gen Intel® Core™ i3-1115G4 processor (3.00 GHz), a 500 GB NVMe SSD, and Windows 11 Home Single Language. The forecasting models were implemented using Python with Visual Studio Code as the development environment. Both methods were executed under the same hardware and software environment to ensure

a fair comparison. The comparison results are presented in Table VII.

TABLE VII
COMPARISON OF PROCESSING TIME AND MEMORY USAGE

Sub-district	Method	Memory Usage	Processing Time	More Efficient Method
Samalanga	DES	0.0008 MB	1.0026 ms	DES
	LSTM	0.0103 MB	68.8903 ms	
Sp Mamplam	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0102 MB	7.0014 ms	
Pandrah	DES	0.0007 MB	0.9980 ms	DES
	LSTM	0.0109 MB	56.5336 ms	
Jeunieb	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0111 MB	45.3889 ms	
Peulimbang	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0112 MB	8.3516 ms	
Peudada	DES	0.0007 MB	1.4856 ms	DES
	LSTM	0.0103 MB	63.8921 ms	
Juli	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0103 MB	15.0836 ms	
Jeumpa	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0103 MB	12.1307 ms	
Kota Juang	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0111 MB	20.9713 ms	
Kuala	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0113 MB	8.0013 ms	
Jangka	DES	0.0007 MB	1.0006 ms	DES
	LSTM	0.0118 MB	162.2427 ms	
Peusangan	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0103 MB	0.0000 ms	
Peusangan Selatan	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0108 MB	8.7409 ms	
Peusangan Siblah Krueng	DES	0.0007 MB	0.0000 ms	DES

	LSTM	0.0113 MB	40.1511 ms	
Makmur	DES	0.0007 MB	1.0016 ms	DES
	LSTM	0.0113 MB	138.2842 ms	
Gandapura	DES	0.0007 MB	0.0000 ms	DES
	LSTM	0.0103 MB	119.8967 ms	
Kuta Blang	DES	0.0007 MB	0.2472 ms	DES
	LSTM	0.0107 MB	97.9140 ms	

As presented in Table VII, the DES method consistently required significantly fewer computational resources than the LSTM model across all 17 sub-districts. The memory usage of DES ranged from 0.0007 MB to 0.0008 MB, whereas LSTM required between 0.0102 MB and 0.0118 MB. This difference is due to the relatively simple statistical calculations performed by DES, while LSTM requires additional memory to store neural network parameters during the training and prediction processes.

In terms of processing time, DES also demonstrated superior computational efficiency. DES completed the forecasting process in approximately 0.0000–1.4856 ms, whereas LSTM required between 0.0000 ms and 162.2427 ms, depending on the sub-district. The longest processing time was recorded for Jangka, where LSTM required 162.2427 ms, while DES completed the forecasting process in only 1.0006 ms.

Overall, these results indicate that DES is computationally more efficient than LSTM in terms of both memory usage and processing time. Considering that this study used only ten annual observations (2015–2024), the additional computational cost of LSTM did not consistently produce higher forecasting accuracy. Therefore, DES is more suitable for annual population forecasting with limited historical data and relatively stable trend patterns, whereas LSTM may be more appropriate for larger datasets with more complex temporal characteristics.

F. Discussion

The experimental results indicate that the forecasting performance of each method is strongly influenced by the characteristics of the population dataset. The historical data used in this study consist of annual population records from 2015 to 2024, resulting in only ten observations for each sub-district. In addition, the population trends in most sub-districts are relatively stable and exhibit gradual changes over time.

Under these conditions, the Double Exponential Smoothing (DES) method generally outperformed the Long Short-Term Memory (LSTM) model. DES is specifically designed to capture level and trend components in time-series data and performs well on datasets with limited observations and relatively linear trends. Consequently, DES achieved

lower forecasting errors in most sub-districts while requiring considerably less computational time and memory.

Although LSTM demonstrated superior performance in several sub-districts, such as Peusangan Selatan, its overall performance was less consistent. This may be attributed to the limited amount of historical data available for training the neural network. Deep learning models generally require substantially larger datasets to effectively learn complex temporal patterns and avoid underfitting or overfitting. Therefore, the advantages of LSTM could not be fully utilized in this study.

These findings are consistent with previous studies reporting that Double Exponential Smoothing (DES) performs well on time-series datasets characterized by relatively stable trends and limited historical observations [5]. Similarly, previous research has shown that Long Short-Term Memory (LSTM) generally requires a larger amount of training data to effectively learn temporal patterns and achieve optimal forecasting performance [6]. Therefore, the selection of a forecasting method should consider the characteristics of the dataset rather than assuming that deep learning models always outperform statistical approaches.

Overall, these findings suggest that DES is a more suitable forecasting method for annual population datasets with stable growth patterns and limited historical observations. Meanwhile, LSTM may achieve better performance when applied to larger datasets with more complex and nonlinear temporal characteristics.

This study has several limitations. First, the historical dataset consists of only ten annual observations (2015–2024), which may limit the learning capability of the LSTM model. Second, the study focuses only on population data from Bireuen Regency and does not consider external factors such as migration, economic conditions, or government policies that may influence population growth. Future research may incorporate longer historical records, additional demographic variables, and alternative forecasting methods such as ARIMA, Holt–Winters, or Prophet to provide a more comprehensive evaluation.

G. System Implementation

A web-based forecasting system was developed to implement the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) methods for predicting population growth in Bireuen Regency. The system provides an integrated platform that enables users to manage population data, perform forecasting using both methods, visualize forecasting results, compare prediction outputs, and manage user accounts. By automating the forecasting process, the application improves efficiency and facilitates decision-making for population planning.

The implementation consists of several main modules, including the dashboard, population data management, DES forecasting, LSTM forecasting, method comparison, and user management. Each module is designed to simplify data

processing and provide clear visualization of forecasting results through tables and graphs.

1. Dashboard

The Dashboard serves as the main interface of the web-based population forecasting system. It displays summary information, including the total number of sub-districts, population records, population statistics, and historical population trend visualizations. The dashboard also provides navigation to the Population Data, DES Forecasting, LSTM Forecasting, and User Management modules.

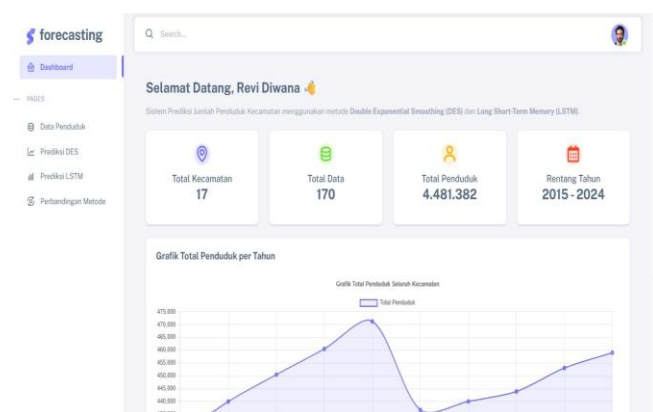


Figure 4. Dashboard View

2. Population Data Management

The Population Data Management module allows users to manage historical population data used for forecasting. It supports viewing, adding, editing, deleting, searching, and importing annual population records for each sub-district. The managed data serve as the primary input for both the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) forecasting methods.

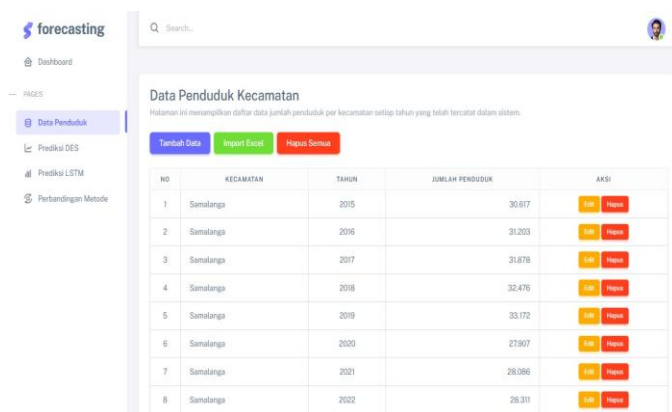


Figure 5. Population Data Management

3. DES Forecasting Module

The DES Forecasting module performs population forecasting using historical data and the selected smoothing parameters. The forecasting results are displayed in both tabular and graphical formats to facilitate trend analysis.

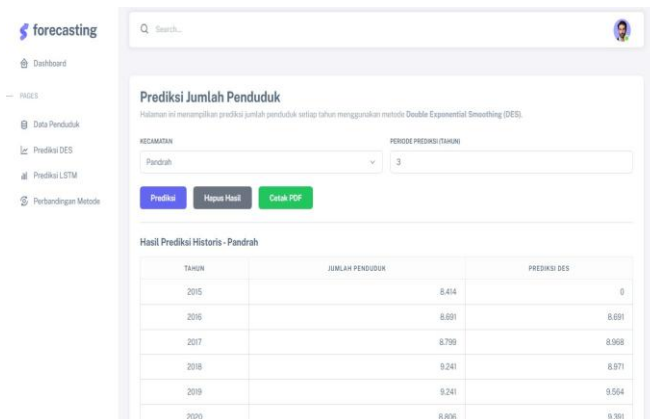


Figure 6. DES Forecasting Module

4. LSTM Forecasting Module

The LSTM forecasting module generates population predictions using a trained Long Short-Term Memory model. The system processes normalized historical data and presents the forecasting results in tables and charts for easier interpretation of population trends.

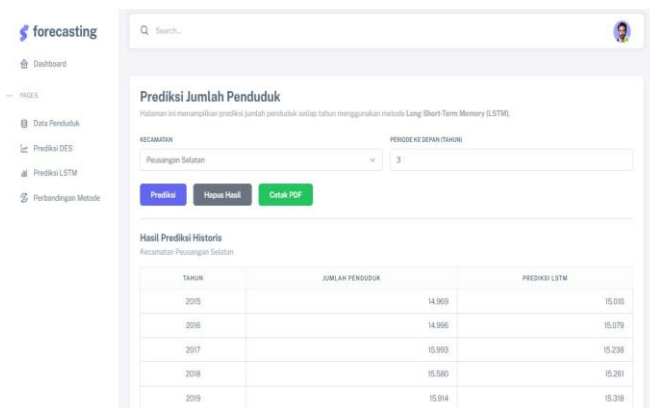


Figure 7. LSTM Forecasting Module

5. User Management

The User Management module enables administrators to manage user accounts within the forecasting system.

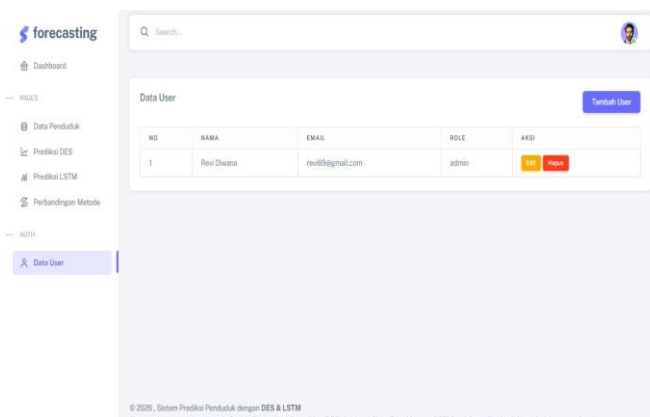


Figure 8. User Management

This module provides functions for viewing, adding, updating, and deleting registered user accounts, as well as managing user access to the system. By controlling user authentication and account administration, the module helps maintain system security, ensures that only authorized users can access forecasting features, and supports the efficient management of the web-based population forecasting system.

IV. CONCLUSION

This study compared the performance of the Double Exponential Smoothing (DES) and Long Short-Term Memory (LSTM) methods for forecasting the population of Bireuen Regency using annual historical data from 2015 to 2024. Based on the experimental results, DES achieved lower MAPE values in most of the 17 sub-districts while requiring significantly less processing time and memory consumption than LSTM. These findings indicate that DES achieve better forecasting accuracy and computational efficiency for annual population datasets characterized by relatively stable trends and limited historical observations.

Although LSTM produced more accurate predictions in several sub-districts, its overall performance was less consistent, which may be attributed to the limited amount of historical data available for training the deep learning model. Therefore, the results of this study suggest that the choice of forecasting method should consider the characteristics of the dataset, and the superiority of DES observed in this study should not be generalized to all population forecasting problems.

The developed web-based forecasting system can assist local governments in estimating future population trends and support evidence-based regional planning and decision-making. Future research is recommended to employ longer historical datasets, incorporate additional demographic variables, and compare DES and LSTM with other forecasting approaches, such as ARIMA, Holt–Winters, and Prophet, to obtain a more comprehensive evaluation.

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