CHAPTER V
CONCLUSION & ADVICE

5.1. Conclusion

Based on the results of research that has been carried out regarding the prediction of the number of tourist visits in East Java Province using the Gated Recurrent Unit (GRU) method, the following conclusions can be drawn:

1. The application of the GRU method has succeeded in building an integrated prediction model for 38 districts/cities.

   The Gated Recurrent Unit (GRU) method was successfully applied to build a prediction model of the number of tourist visits per district/city in East Java Province based on monthly data from the Central Statistics Agency for the 2019–2025 period. The model was built with an integrated panel data approach that combines the time dimension (84 months) and the spatial dimension (38 regions) simultaneously, so that only one single model is needed to serve the entire district/city. The model architecture consists of an input layer with a window size of 12 months, a GRU layer with 64 units, a dropout layer with a rate of 0.8, and a dense layer with one neuron. The model training process showed good convergence with a train loss value of 0.015233 and a best val loss of 0.014702 at the 49th epoch, as well as a stable learning curve with no indication of overfitting. Thus, the formulation of the first problem and the first research objective have been answered and achieved.

2. The performance of the GRU model results in a good level of accuracy with the best RMSE of 95,216.35.

   Based on the evaluation using the Root Mean Square Error (RMSE) metric on the test data for the January–December 2025 period, the GRU model developed showed good performance. Through a hyperparameter test scenario that included six groups of variations (GRU units, window size, learning rate, dropout, epoch, and batch size), the optimal configuration was obtained in the S4-C scenario with the best RMSE of 95,216.35. Scenario S4-C is part of the Scenario 4 group that focuses on dropout rate variations, where S4-C uses the highest dropout rate value of 0.8. In full, the configuration of the best scenario of S4-C uses GRU units of 64, a window size of 12 months, a learning rate of 0.001, a dropout rate of 0.8, an epoch of 100, and a batch size of 32.

This configuration excelled over the other 18 scenarios because the dropout rate of 0.8 which deactivated 80% of neurons at random during training proved to be the most effective regularization mechanism to prevent overfitting of tourist visit data that was volatile but not too temporally complex. This phenomenon can be explained by the fact that the tourist visit data has a repetitive and relatively regular seasonal pattern, so that models with strong regularization are forced to study generalizable general patterns, rather than memorize the details of the noise in the training data. These findings are also confirmed by comparisons between dropout scenarios, where S4-A with a 0.1 dropout results in the worst overall RMSE of 161,600.35, S4-B with a dropout of 0.4 results in an RMSE of 98,612.98, and S4-C with a dropout of 0.8 being the best with an overall RMSE of 95,216.35. Thus, the formulation of the second problem and the second research objective have been answered and achieved.

3. The results of the prediction of the number of tourist visits for each district/city in East Java Province show variations in the performance of the GRU model between regions.

   The model is able to predict well in areas with stable patterns and low visit volumes such as Mojokerto City (RMSE 18,434), Probolinggo City (RMSE 23,410), and Blitar City (RMSE 28,325) which are far below the overall RMSE average of 104,414 people per month. On the other hand, areas with extreme fluctuations such as Surabaya City, Malang Regency, and Malang City recorded the highest RMSE because the visit pattern was very dynamic and influenced by external factors that were not captured by the univariate model. Overall, the GRU model developed is quite reliable for regions with stable visit patterns, but still requires further development for regions with complex visit characteristics. Thus, the formulation of the third problem and the third research objective have been answered and achieved.

5.2. Suggestions

Based on the limitations and findings during the study, here are suggestions for further development:

1. Addition of exogenous (multivariate) variables to improve prediction accuracy at super priority destinations.
2. Exploration of GRU hybrid architecture with attention mechanisms or other models.
3. Data usage on a weekly or daily basis.
4. Comparison with other deep learning methods such as LSTM, BiLSTM, or Transformer.