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A Comparative Evaluation of Univariate Time Series Forecasting Models for Tourism Operational Indicators at Boom Marina Banyuwangi

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ABSTRACT

Accurate forecasting of a tourism operational indicator is crucial for planning and making informed decisions, but heterogeneity in temporal patterns prevents us from selecting a single optimal model. This research aims to compare univariate time-series forecasting models to identify the best model for each operational index in the Boom Marina Banyuwangi Tourism Area. Data on weekly ticketing_log from PT Pelindo Properti Indonesia covering seven input indicators were used, namely the number of tourists, total income, the number of motorcycles, the number of vehicles, the number of pedestrians, the cash payment amount, and the total parking fee. The flow of this study follows the CRISP-DM framework. It includes (i) data cleansing (using Z-score for winsorization), median imputation, daily-to-weekly aggregation, Robust Scaler normalization, (ii) sliding window formation (4, 8, 12 weeks), (iii) separation into training and test set with a ratio of 80:20. Seven models were used for comparison (BiLSTM, BiGRU, LSTM, GRU, Simple RNN, 1D-CNN, and a Random Forest Regressor) which performance was measured in terms of MAE or RMSE. The findings demonstrate that no single model performed best across all measures. Random Forest Regressor was the best predictor of four indicators: number of tourists (MAE = 0.5053; RMSE = 0.6532) and number of vehicles (MAE = 0.5904; RMSE = 0.7966). In contrast, BiGRU, BiLSTM, and Simple RNN achieved the best performance for total revenue, the number of motorcycles, and the number of pedestrians, respectively. These results imply that tree-based ensemble methods can capture nonlinear patterns, whereas recurrent neural networks are well-suited for indicators with strong temporal dependencies.

Keywords-Time Series Forecasting; Tourism Analytics; Random Forest Regressor; Deep Learning Models; Machine Learning Models; Univariate Prediction; Boom Marina Banyuwangi

I. INTRODUCTION

Tourism is one of the strategic sectors in the international and local economy. This sector contributes in excess of 10% to the world's gross domestic product and generates large numbers of jobs, as reported by UNWTO [1]. In Indonesia, tourism has been a national development priority, as it strengthens the balance of payments (BOP) and enhances community welfare. Banyuwangi Regency, one of Indonesia's prime destinations, attracts dynamic tourists in varying numbers, including visitors to Boom Marina Tourism Area, which is considered a prominent icon of maritime tourism. According to records from local governments in Banyuwangi, there were about 5.4 million visitors per year before COVID-19, which significantly dropped to 2.33 million annually during 2020–2022, then increased to 3.18 million in 2023 [2]. These variations show that the tourism sector is sensitive to external conditions and that prediction systems can influence data-based decision-making, which is especially needed in the case of the Boom Marina Banyuwangi Tourism Area.

In the literature, the classical or traditional (conventional) forecasting techniques, such as ARIMA and SARIMA, are still used. However, these models have limitations in accommodating nonlinear trends and complex dynamics that are often present in tourism time series data [3-5]. Comparisons with traditional models and neural networks also show that Deep Learning (DL) based methods have the best performance, particularly for volatile situations [6, 7]. With the development of DL techniques, models such as LSTM, GRU, and BiLSTM have been developed and demonstrated to capture long-term dependencies and complex seasonal patterns effectively [8-10]. Recent methods such as attention mechanisms, time-series imaging, and hybrid models, provide increasing predictive power [11, 13]. Applications of DL have been further developed across diverse domains, including traffic prediction, crime forecasting, and public policy analysis, demonstrating its strong ability to model nonlinear time-series data [14, 15]. In addition of the number of tourists, the inclusion of additional factors (e.g., transaction data, counts of tourist vehicles, and mobility patterns) also helps enhance the quality of predictions [16, 17]. The adoption of contemporary techniques for tourism analysis is expected to make models more responsive to shifts in structures and demand dynamics [18-20].

Based on these developments, this study aims to compare univariate time-series models utilizing DL methods and ML methods, which are BiLSTM, BiGRU, LSTM, GRU, Simple RNN, 1D-CNN, and Random Forest Regressor. It was applied to predict the tourism indicators in the Boom Marina Banyuwangi Tourism Area. Using the smallest prediction error and a web-based application in this way is promising for making suitable recommendations to manage and develop the tourism destination more effectively and sustainably.

II. METHOD

Time series forecasting has seen much advancement. ML and DL methods work well on modern data patterns compared to classical statistical techniques. Numerous works in transport, economics, and tourism have well established that Recurrent Neural Network (RNN) models, such as LSTM, GRU, BiLSTM, and BiGRU, can yield better predictions than traditional time series forecasting techniques such as ARIMA or SARIMA. In this section, we summarize time-series forecasting studies, by examining DL methods, ensemble models, types of forecasting problems for complex data, and comparative analysis between different models that have been compared in previous works.

A. Deep Learning (DL) for Time-Series Forecasting

For time-series prediction, although DL methods in general, and RNN-based structures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), in particular show prominent performance, among them LSTM has gained a lot of interest for its capacity to capture long-term patterns, it avoids the vanishing gradient problem [8, 21]. A another transportation sectors study [14], it is demonstrated that an LSTM-based model can outperform traditional statistical prediction models for long-term traffic prediction. In the public sector and in crime analysis, other research also supports the conclusion that LSTM and GRU models tend to provide more stable predictive accuracy while accommodating dynamic data [9, 10]. These results suggest that DL models are of growing interest for modeling nonlinear dynamic data, such as tourism indicators.

B. Machine Learning (ML) Ensemble for Forecasting

In addition to DL models, there have been various works using ML algorithms (e.g., Random Forests to Support Vector Machine (SVM) for non-linear time-series data. Random Forest performs better at handling errors, outliers, and changes in system behaviour based on operational data because it can perform non-linear mapping by changing decision-tree structures [19]. The Random Forest provides higher prediction accuracy than traditional regression techniques in many applications, especially when the data exhibit unstable seasonal behavior [4, 22]. In the tourism sector, th findings by [6, 20] indicate that ML models can capture more of the dynamics of visitor demand than classical methods under high volatility. Therefore, an ensemble model such as a Random Forest is a reliable method for predicting tourism indicators.

C. Advances in Modern Time-Series Modeling

Recent studies show the bidirectional RNN models (e.g., BiLSTM and BiGRU) can enhance prediction performance by exploiting both forward and backward temporal dependencies at the same time. It can be effective to learn from seasonal patterns, periodic volatility, and weekly trends commonly observed in tourism demand [9, 10]. In addition, recent technologies such as time-series [11] and attention-based LSTM approaches [12] although not used in this study to develop hybrid models, have also contributed to the development of modern forecasting models. Nonetheless, the developments show that modern architectures are being adapted to remember long-term nonlinear patterns better.

D. Comparative Studies and Research Gaps

A comparison of several algorithms was applied to other research's best-performing algorithm models with specific data properties. Research in [8, 9] indicates that LSTM, GRU, and BiLSTM-based models achieve better performance than ARIMA when forecasting tourism data affected by seasonal variations and non-proportional visit patterns. In a research by [19] shows that was an improved approaches to predicting tourism demand can be achieved by utilizing current techniques, including DL and ML models. However, currently there are relatively few studies that conduct a comprehensive comparative analysis of a wide range of popular models, including BiLSTM, BiGRU, LSTM, GRU, Simple RNN, as well as 1D-CNN and Random Forest, for forecasting univariate tourism indicators. Such a void helps build the robust argumentation of the current work, aiming to propose a verifiable comparison and an optimal selection of models for each tourism indicator.

III. PROPOSED METHOD

This study applies the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework as the workflow guideline to ensure a systematic, structured, and reproducible research [23]. There are six key stages in CRISP-DM: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. Each stage applied iteratively to produce the most effective time-series forecasting model for predicting the tourism indicators in the Boom Marina Banyuwangi Tourism Area.

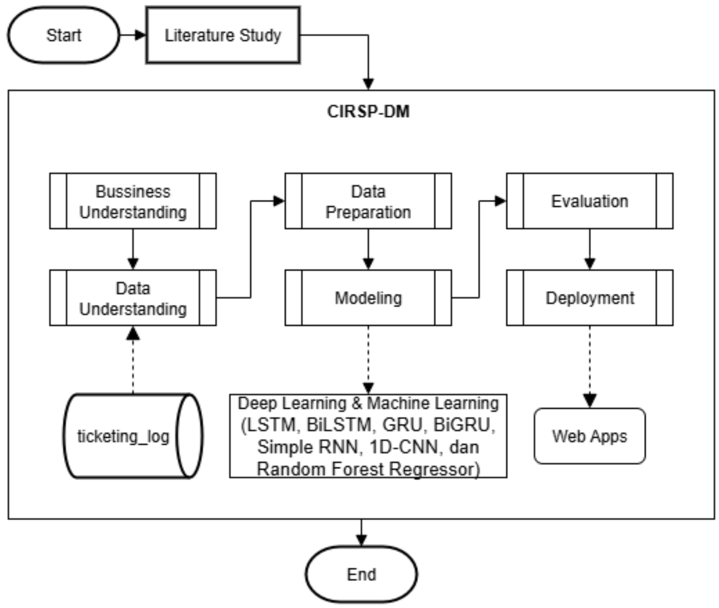

Figure. 1. Research Framework

The diagram in Figure 1 illustrates the proposed research process, which combines the CRISP-DM methodology with the waterfall system development model. This process flow started with executes a literature review and then implements the CRISP-DM phases: Business Understanding, Data Understanding, Transformation of Data, Modeling, and Evaluation. These interact in iterations to assure the quality of data and accuracy of the model. When the best model is found, Workflow proceeds to the Deployment stage based on the Waterfall requirements analysis, system design, implementation testing, and maintenance to obtain a predictive system that can operate accurately, stably, and sustainably. The results are finalized with the conclusions and recommendations in the last part of this work.

A. Business Understanding

The main goal of this research is to enhance the predictive accuracy of seven operational tourism indicators at the Boom Marina Banyuwangi Tourism Area (number of tourists, total revenue, number of motorcycles, number of vehicles, number of pedestrians, total parking, and the amount per individual payment). We cast the problems as a single univariate time-series prediction, requiring models to encode seasonality, volatility, and nonlinearity that are prevalent in real-world datasets. To address this, this research compares several recent model architectures (BiLSTM, BiGRU, LSTM, GRU, Simple RNN, and 1D-CNN, and Random Forect) to determine which classifier achieves the highest accuracy for each indicator. The prediction accuracy will be measured using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which together reflect for precision and stability model to capture the temporal dynamics of tourism indicators.

B. Data Understanding

In this work, ticketing_log data from Boom Marina Banyuwangi Tourism Area, obtained from PT Pelindo Properti Indonesia, were used as the research object. There are seven tourism performance indicators in the dataset: number_of_tourists, total_revenue, number_of_motorcycles, number_of_vehicles, number_of_pedestrians, number_of_cash_payments, and total_parking_fees. Every variable varies in its pattern of change over time, level of volatility, etc. So it is important to have a good understanding of these characteristics when deciding on an appropriate forecasting method. The data are real-world time series that include seasonal peaks or troughs, outliers, and missing data. In turn, it renders them ideal for evaluating the ability of the latest DL and ML models for short-term and long-term forecasting tasks. Detailed explanations of each indicator are included in Table 1.

TABLE 1. DETAILS AND DESCRIPTION OF VARIABLES

Dataset	Variable		Types	Description
log_ticketing Boom Marina Banyuwangi	X_1	week	Numeric	Temporal indicator representing data on a weekly scale; serves as the primary basis for time-series analysis and determining prediction targets for upcoming weeks.
	X_2	number_of_tourists	Numeric	Total number of visitors (people) entering the Boom Marina Banyuwangi Tourism Area.
	X_3	total_revenue	Numeric	Total income generated from all ticketing activities in the tourism area.
	X_4	number_of_motorcycles	Numeric	Total number of two-wheeled vehicles entering the tourism area.
	X_5	number_of_vehicles	Numeric	The combined volume of four-wheeled or larger vehicles (cars, minibuses, buses, trucks) entering the area.
	X_6	number_of_pedestrians	Numeric	Number of visitors entering the area on foot (without recorded vehicle entry).
	X_7	number_of_cash_payments	Numeric	Number of transactions made using cash.
	X_8	total_parking_fees	Numeric	Total revenue obtained exclusively from parking fees for all vehicles.

C. *Data Preparation*

In this stage, the raw of tourism data were transform, varied, and irregular operational into a time-series dataset. There are systematic steps, start from data cleaning, temporal aggregation, numerical normalization, window formation, to the training and testing datasets split. The aim of each step is to ensure the model learns historical patterns optimally, without affected by noise or inconsistencies data.

- *Data Cleaning*

The daily operational data are contain outliers, missing values, and high fluctuations, which require data cleaning before to modeling. Outliers were first detected using the Z-score method, and any extreme values were addressed using winsorization to maintain temporal trends without distortion from outliers. Meanwhile, the missing data were handled using median imputation, as it is both stable and robust to volatility in the time series.

- *Aggregation of Daily Data into Weekly Data*

The clean daily data were subsequently averaged to a weekly data by eliminating noise and stabilizing seasonal patterns. This method is widely used in long-term forecasting research because it can enhance the stability of observed trends [16, 19].

- *Data Normalization*

All numerical variabels were scaled using a Robust Scaler, making the method less sensitive to outliers by using the median and Inter-Quartile Range (IQR) as scaling references. This approach is more appropriate for tourism operational data, which is generally non-normally distributed and contains outliers, it allows the model to learn from more stable standardised data.

- *Formation of Time-Series Windowing*

The sliding-window approach trains a model on a dataset with a given number of previous weeks (lookback, L) to predict the following week. In this study, we used several lookback periods (4, 8, and 12 weeks) to capture the volatility behavior of each indicator.

- *Data Splitting*

The dataset then splited into data training and test by 80:20. This sequential split is to avoid leakage and to assume that the model's performance reflects predictive power on new observations.

D. *Modeling*

The modeling pipeline adopted in this study is shown at Figure 2, detailing all steps of time-series pre-processing and the evaluation phase. Modelling is performed on the processed, transformed, normalized, and windowed tourism dataset. A univariate method is applied, based on historical patterns for each indicator (number_of_tourists, total_revenue, number_of_motorcycles, number_of_vehicles, number_of_pedestrians, number_of_cash_payments, and total_parking_fees), to forecast them individually. The performance is compared with seven algorithms, including BiLSTM, BiGRU, LSTM, GRU, Simple RNN, 1D-CNN, and Random Forest Regressor. We choose the models to provide a comprehensive understanding of effectiveness off DL method based on RNN and CNN comparison to an ensamble-based ML method. The code was implemented using TensorFlow/Keras for DL models and Scikit-learn for a non-neural Random Forest baseline.

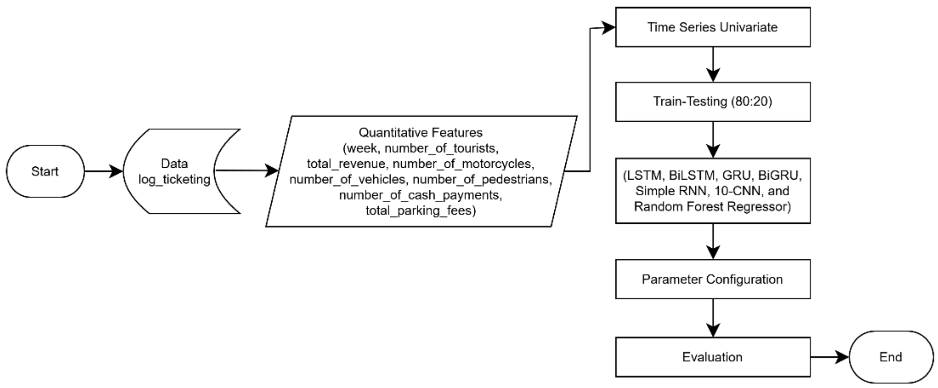

Figure. 2. Univariate Time-Series Modeling Workflow

The training process (see Table 2) were performed under different parameter configurations depending on the architecture: activation functions used, optimizer, lookback length, number of epochs, batch size, and early stopping to prevent overfitting model. After training, each model was validated on test data to evaluate its accuracy and generalization using MAE and RMSE. The model that best performed (lowest error) was chosen as the final one for each of the tourism indicators. This approach makes the modeling procedure systematic and objective, enabling each variable to select the most appropriate forecasting model based on its time-varying pattern and volatility.

TABLE 2. MODEL ARCHITECTURE AND PARAMETER CONFIGURATION IN THE MODELING PHASE

Model	Architecture/Main Parameters	Training	Notes
BiLSTM	Bidirectional LSTM(64), activation='tanh', Dropout(0.2), Dense(1)	optimizer=Adam, loss=MSE, epochs=50, batch_size=8	implemented with TensorFlow/Keras
BiGRU	Bidirectional GRU(64), activation='tanh', Dropout(0.2), Dense(1)	optimizer=Adam, loss=MSE, epochs=50, batch_size=8	implemented with TensorFlow/Keras
LSTM	LSTM(64), activation='tanh', Dropout(0.2), Dense(1)	optimizer=Adam, loss=MSE, epochs=50, batch_size=8	implemented with TensorFlow/Keras
GRU	GRU(64), activation='tanh', Dropout(0.2), Dense(1)	optimizer=Adam, loss=MSE, epochs=50, batch_size=8	implemented with TensorFlow/Keras
Simple RNN	SimpleRNN(64), activation='tanh', Dropout(0.2), Dense(1)	optimizer=Adam, loss=MSE, epochs=50, batch_size=8	implemented with TensorFlow/Keras
1D-CNN	Conv1D(64, kernel_size=2, activation='relu') → MaxPool → Flatten → Dense(32,relu) → Dense(1)	optimizer=Adam, loss=MSE, epochs=50, batch_size=8	implemented with TensorFlow/Keras
Random Forest	RandomForestRegressor(n_estimators=100, random_state=42)	fit in X reshape (samples, timesteps*features)	implemented with Scikit-learn
Preprocessing & Windowing	RobustScaler (median & IQR), winsorize limits=(0.05,0.05), Z-score outlier detection	LOOKBACK test: 4, 8, 12 (choosen by each indicator)	Train-test split time-ordered 80:20

E. *Evaluation*

The performance of the model was evaluated with 20% of test data based on two common time series forecasting metrics. The MAE was used to calculate the average of absolute values of errors between true and predicted outcomes, which indicates directly the accuracy of the model in terms of the same scale as original data. Meanwhile, the RMSE was used to evaluate the error size with more penalty for large differences, indicating a general stability of predictions. This assessment was conducted for each tourism indicator, respectively in order to select the best model that reflects specific temporal patterns of the variable.

F. *Deployment*

While the main contribution of this research is to academia, the forecast framework can be embedded in a tourism decision-making system. For the top performing models in each indicator (high accuracy and stability) can be confidently applied to operational forecasting. By integrating the models on a web-based system, managers of Boom Marina Banyuwangi Tourism Area can have a quick access to data-driven forecasts about potential visitor numbers, revenue, vehicle volume, and transaction activity. Accordingly, predictions may aid management decision for capacity planning, resource allocation, service provision, congestion risk prevention and more agile strategic-planning integrated with tourism dynamics.

IV. RESULT AND DISCUSSION

This section presents the experiments findings of this work and the results explanation using time series forecasting models to seven tourism indicators in Boom Marina Banyuwangi Tourism Area. The review is performed in two principal procedures: exploratory data analysis and the performance evaluations of model.

A. Exploratory Data Analysis

The primary features of each time-series indicator were investigated in an explorative analysis, and Figure 3 is related to visualization of the patterns over time for the seven main variables that was shown in Table 1. In general, all of the indicators exhibit by their high variability, seasonalities and some extreme spikes, reflecting the dynamic nature of tourism activity that can be strongly leaded by weekends, holiday seasons or special events.

The number_of_tourists variabel shows an evident trend, has the peak values of obvious scope in some periods, during long holidays or a large event, especially. This trend shows a clear seasonality and immediately volatility that forecasts model should address. The same behaviour is observed with total revenue, which flows proportionally to tourist quantities but considerably due to the types of activity and levels of spending by tourists. Some spikes in revenue are expected duing high visitation, though occasional unusual increases may result from special events or promotional tourism packages. The number_of_motorcycles and number_of_vehicles actually shows arrived private transport visitors. Both show similar periodic peaks, however motorcycle counts are more unreliable. This trend indicates that private vehicles are dominant transportation in this area. Therefore, these pattern will be very useful for prediction of congestion and operational requirement.

The number_of_pedestrians indicators exhibit significant noise and non-uniform peaks. This one is more difficult to predict due to its instability, which may be influenced by community activities, special events, or other irregular external factors. Also, total parking fees show a similar trend to vehicle counts. However, the nonlinearity is larger, and values increase significantly during spesific periods, which may be due to tarif adjustments, differences in vehicle types, or unusually high visit volumes relative to weekly averages. The number_of_cash_payments also shows a periodic secretory rhythm similar to that observed for tourists, although with more marked peak variations. It implies that payment transactions are significantly dependent on activity intensity in the tourism region and can serve as an auxiliary indicator for a better understanding of visitor behavior.

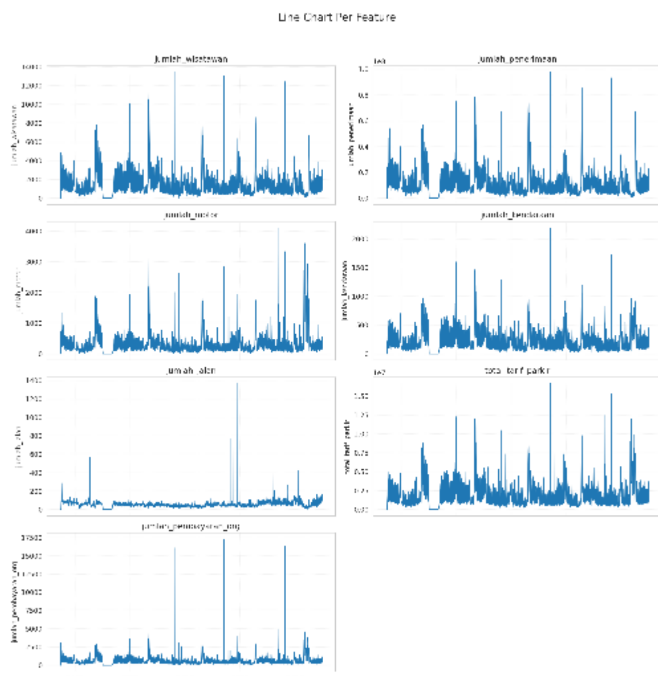

Figure. 3. Time Series Of Indicators Feature

In general, the results show that each indicator has its own characteristics and trends, from a strong seasonality on both tourist and vehicle counts, to a high level of volatility in pedestrian figures and significant nonlinearities in parking revenue. These differences indicate that no single model is likely to be optimal for all variables. So, the relatively comprehensive comparison of several DL and ML models in our study is quite necessary for finding out the best-performed model that aligns with the unique characteristics of each indicator.

B. *Model Performance Evaluation*

The model performance was evaluated by seven models: BiLSTM, BiGRU, LSTM, GRU, Simple RNN, 1D-CNN, and Random Forest. The best results will be used for predict the seven tourism indicators. Each model was tested using the MAE and RMSE with consideration to the lookback window configurations used during the training process.

TABLE 3. PERFORMANCE SUMMARY

Indicator	Best Model	MAE	RMSE	Lookback
number_of_tourists	Random Forest	0.505276	0.653189	4
total_revenue	BiGRU	0.552997	0.735011	4
number_of_motorcycles	BiLSTM	0.880502	1.276617	8
number_of_vehicles	Random Forest	0.590377	0.796585	4
number_of_pedestrians	Simple RNN	0.535168	0.615159	12
number_of_cash_payments	Random Forest	0.625296	0.817408	8
total_parking_fees	Random Forest	0.708757	0.954347	8

The results show that no single model consistently performs best across all indicators. Model performance is sensitive to temporal behavior, e.g., volatility, seasonality, and the degree of complexity in the nonlinear dynamics data. As a result, for each indicator, it is necessary to compare models to determine the best-performing model. In more detail, the best model for each indicator is shown in Table 3. On variables number_of_tourists, number_of_vehicles, number_of_cash_payments, and total_parking_fees, the Random Forest model produces the lowest MAE and RMSE. This indicates that their patterns are better suited to tree-based models, which can capture long-term nonlinear interactions without relying heavily on temporal sequence.

Conversely, total_revenue is the indicator best predicted by BiGRU. This reflects the strength of bidirectional recurrent architectures to capture long-term dependencies from past and future data. For the number_of_motorcycles variabel, the BiLSTM model performs best, suggesting that the LSTM's memory helps capture the dynamic alongside bidirectional information processing. Meanwhile, the number_of_pedestrians variabel are best generated by a Simple RNN model; its patterns are simpler than those of other models and do not require greater RNN complexity. These results confirm that forecasting models cannot be universally applied to all variables. Every indicator must be dealt with individually, based on its historical data patterns. Thus, the in-depth comparison performed is important to assess that the selected model represents the best-performing option based on objective perspective.

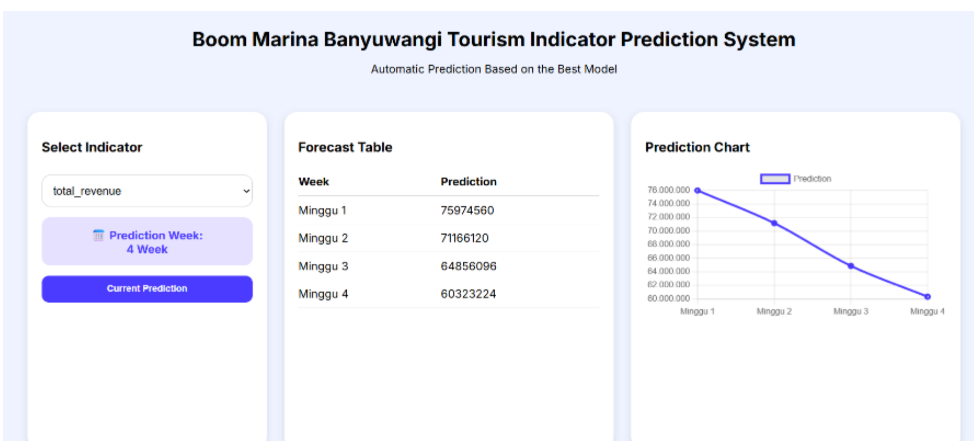

Figure. 4. Implementation of Prediction Website Application Mockup

Figure 4 show the deployment of a web-based forecasting systems using the proposed forecasting model with simple and interactive interface that can easily used by the tourism management in Boom Marina Banyuwangi. The system automatically selects the best prediction model for each tourism indicator and visualises the multi-week predictions both numerically and in a graphic way.

V. CONCLUSION

This research presents a comprehensive comparison analysis of seven time series forecasting model (BiLSTM, BiGRU, LSTM, GRU, Simple RNN, 1D-CNN, and Random Forest) to forecast seven primary tourism indicators in Boom Marina Banyuwangi Tourism Area. With CRISP-DM, the study conducts comprehensive data preprocessing, window-based time-series model development, and model efficiency validation using MAE and RMSE. Experimental results show that no model performs the best across all indicators, which indicates the non-uniform temporal patterns in tourism data. For number_of_tourists, number_of_vehicles, number_of_cash_payments, and total parking fees, Random Forest be best model for non-linearly pattern by ensembling tree-based methods because it provides the most accurate predictions. While BiGRU generates the best performance on total revenue, BiLSTM on number_of_motorcycles, and Simple RNN on number_of_pedestrians which indicate that various degrees of volatility, seasonality, long-term dependence need different model architectures

These results confirm that there is no general model selection template for tourism forecasting, but also selected variable-specific models should be reasonably determined. Modern DL and ML models can improve the accuracy of predictions of traditional statistical models, especially when dealing with real-world tourism data sources which are inherently noisy, seasonal, and highly dynamic. In addition, the deployment of the most accurate models in a web-based forecasting demonstrates the potential value of this research. The systems allows tourism managers of Boom Marina Banyuwangi to receive a solid multi-week forecast for number of visitors, volume transportation, revenue, and payment activity. The predictive capabilities support for better decision-making in terms of operational planning, resource allocation, congestion management, and prospective tourism development.

The paper's research has both theoretical and practical implications by: (1) providing an extensive comparative analysis of multiple forecasting models in forecasting tourism indicators, (2) determining the best model for each variable based on objective performance criteria, and (3) validating real-life application toward system implementation based on forecast outputs. For future work, hybrid approaches (including multi-variate forecasting) may be developed, attention mechanism can also be introduced, or additional external factors such as weather, events, or macroeconomy could be integrated to further optimize prediction accuracy and system reliability.

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