



A Random Forest Regression Approach for Predicting Marriage Service Demand at the Office of Religious Affairs

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Abstract

The increasing adoption of digital transformation in the public sector has created opportunities to utilize administrative data for predictive decision-making and service planning. The Office of Religious Affairs (Kantor Urusan Agama/KUA) generates historical marriage service data that can potentially be used to estimate future service demand. However, the application of machine learning, particularly Random Forest Regression, to marriage service demand forecasting in religious administrative services remains limited. This study aims to develop and evaluate a Random Forest Regression model for predicting monthly marriage service demand at KUA Bajenis District, Tebing Tinggi City, based on historical service data. A quantitative approach was employed through several stages, including data preprocessing, chronological feature construction, time-based training and testing, model development, prediction, evaluation, and web-based system implementation. The model utilized year, month, previous-month marriage count, holiday conditions, and Hijri month as predictor variables, while the monthly number of marriage service requests was used as the target variable. The Random Forest model was implemented using 100 decision trees with a random state of 42. Experimental results showed that the model achieved a Mean Absolute Error (MAE) of 1.50, Mean Squared Error (MSE) of 3.7401, Root Mean Squared Error (RMSE) of 1.9339, and Mean Absolute Percentage Error (MAPE) of 37.67%. The model predicted an average demand of 6.49 marriage service requests per month for January–June 2025. These findings indicate that Random Forest Regression can serve as a supporting predictive tool for estimating future marriage service demand and assisting KUA in personnel, resource, and service-capacity planning.

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1. Introduction

Digital transformation in the public sector has driven a shift from predominantly administrative service management toward increasingly data-driven management. Data generated from public service activities no longer serves merely as an administrative record but can also be utilized to identify patterns in public needs and support more proactive decision-making. One form of such utilization is predictive analytics, an analytical approach that uses historical data to estimate

conditions or demands in future periods. In the context of public services, the ability to estimate service demand is important because it can help organizations adjust service capacity, staff scheduling, and resource allocation according to patterns of community needs (Punia & Shankar, 2022; Panda & Mohanty, 2023).

Machine learning approaches are increasingly employed in prediction problems because they are capable of learning complex and nonlinear relationships from historical data. One widely used algorithm is Random Forest, an ensemble learning method that combines multiple decision trees to produce stable predictions. For regression problems, Random Forest generates numerical predictions by aggregating the outputs of multiple decision trees. These characteristics make Random Forest suitable for prediction problems involving nonlinear relationships and historical data (Breiman, 2001; Dudek, 2022). Dudek (2022) demonstrated that Random Forest has competitive performance in short-term load forecasting, while Fan et al. (2022) showed that Random Forest can model multivariable relationships in short-term forecasting problems.

The application of Random Forest has also expanded to various demand forecasting problems. Mbonyinshuti et al. (2022), for example, applied Random Forest to predict the demand for essential medicines in public health facilities based on historical data. Their findings demonstrated that historical consumption data and service characteristics could be utilized to generate predictive information for demand planning. This finding indicates that machine learning can be applied to public service data to support more proactive organizational planning (Mbonyinshuti et al., 2022). Similarly, Punia and Shankar (2022) demonstrated the potential of predictive analytics for demand forecasting and decision support.

Demand forecasting is particularly relevant to services characterized by temporal variations. Panda and Mohanty (2023) demonstrated the application of regression-based and time-series forecasting approaches to model demand patterns, while Kulaczkowski and Lee (2024) showed that Random Forest can be employed for short-term water demand forecasting using historical demand patterns. These findings indicate that information from previous periods can provide important predictive signals for estimating future demand.

The Office of Religious Affairs (Kantor Urusan Agama or KUA) is a government service unit that directly interacts with the community in providing various religious services. KUA performs functions related to marriage services, marriage supervision and registration, and marriage and reconciliation reporting. These activities generate administrative data that can describe the volume of services provided during particular periods.

One important type of data generated by KUA is marriage service application data. Such applications form part of the marriage service process and generate administrative records that can be used to determine the number of service requests during a particular period. When recorded continuously, these data form historical records that can reveal changes in service demand across periods. The historical marriage service data therefore have potential value beyond administrative documentation and can be utilized as a source for predictive modeling.

The number of marriage service requests may vary from one period to another, resulting in different service resource requirements. If demand estimation relies solely on simple observations or staff experience, there is a risk of mismatch between service capacity and actual community needs. Such a mismatch may affect staff allocation, scheduling, administrative preparation, and overall service readiness. Therefore, a computational approach capable of learning patterns from historical service data is required to provide objective and measurable estimates of future demand.

Although Random Forest has been widely applied to forecasting problems, a research gap remains in its application to religious administrative services. Previous studies have focused on medicine demand in public health facilities (Mbonyinshuti et al., 2022), energy forecasting (Dudek, 2022; Fan et al., 2022), supply-chain demand forecasting (Punia & Shankar, 2022; Panda & Mohanty, 2023), water demand forecasting (Kulaczkowski & Lee, 2024), and sales forecasting (Sastrawan et al., 2024). However, the application of Random Forest Regression specifically to predict marriage service demand at KUA based on historical service data remains limited. This gap provides an opportunity to

extend machine-learning-based forecasting from commercial and general public service domains to religious administrative services. A second gap concerns the practical utilization of prediction results. Predictive modeling in public services should not merely focus on statistical performance but should also provide information that can support operational planning. Huslan et al. (2025), for example, demonstrated the application of Random Forest for predicting visitor volume in public services and highlighted its potential to support service planning. Therefore, a predictive model for KUA should ideally provide estimates that can be interpreted as supporting information for future service planning.

Based on these gaps, this study proposes a Random Forest Regression approach for predicting marriage service demand at the Office of Religious Affairs using historical service data. Historical marriage service requests are utilized to construct a predictive model that learns patterns from previous periods and generates estimates for subsequent periods.

The contribution of this study consists of three aspects. First, it applies Random Forest Regression to a specific public-service domain, namely marriage service demand at KUA. Second, it utilizes historical marriage service data as the basis for identifying demand patterns and generating future estimates. Third, it positions the prediction output as supporting information for service planning rather than merely as an algorithmic performance measure.

The study aims to develop and evaluate a Random Forest Regression model for predicting the number of marriage service requests at KUA based on historical service data and to generate estimates that can support service planning in subsequent periods.

2. Research Methodology

This study employed a quantitative approach using a machine learning method to develop a prediction model for the number of marriage service requests at the Office of Religious Affairs (Kantor Urusan Agama/KUA) in Bajenis District. The algorithm used in this study was Random Forest Regression, an ensemble learning method that constructs multiple decision trees using randomly selected data samples and feature subsets, and subsequently combines the predictions generated by all trees through averaging. The research stages consisted of data collection, data preprocessing, predictor variable construction, chronological data splitting, Random Forest Regression model development, prediction, model evaluation, and system implementation.

3.1 Research Stages

The research was conducted systematically to develop a prediction model capable of estimating the number of marriage service requests in subsequent periods. The research stages consisted of:

1. collecting historical marriage service data;
2. performing data inspection and preprocessing;
3. sorting the data chronologically;
4. constructing input and target variables;
5. dividing the data into training and testing sets based on chronological order;
6. developing the Random Forest Regression model;
7. testing the model using testing data;
8. evaluating model performance using MAE, MSE, RMSE, MAPE, and R^2 ;
9. integrating the prediction results into a web-based system.

This approach ensures that the model only learns from information available in previous periods and generates predictions for periods that were not used during the training process.

3.2 Data Collection

The research data consisted of historical marriage service request data obtained from the Office of Religious Affairs (KUA) in Bajenis District. The data were organized according to the service period so that each observation contained information regarding the time period and the number of marriage services recorded during that period. The historical data were used as the basis for developing the prediction model. The target variable (*dependent variable*) was the number of marriage service

requests, while the input variables (*independent variables*) were constructed from available historical information that was considered relevant to the demand pattern. Before being used for model development, the dataset was examined to ensure its completeness, consistency, and format suitability. Missing, duplicate, or improperly formatted data were handled during the preprocessing stage.

3.3 Data Preprocessing

Data preprocessing was conducted to obtain a dataset suitable for the Random Forest Regression algorithm. The preprocessing stage included checking for missing values, identifying duplicate records, standardizing the period format, sorting the observations chronologically, and examining the consistency of marriage service request values. The data were then arranged from the earliest to the latest observation period. This process was particularly important because the study used time-dependent data. Chronological ordering prevented information from future periods from being incorporated into the model during the training process. If invalid or incomplete values were identified, they were handled according to the characteristics of the data and the original data source. After preprocessing was completed, the resulting dataset was used to construct predictor and target variables.

3.4 Variable Construction

The target variable in this study was the number of marriage service requests in a particular period. The predictor variables were constructed from historical information so that the model could learn the relationship between previous demand patterns and demand in the period to be predicted.

Conceptually, the predictor variables can be represented as:

$$X_t = [Y_{t-1}, Y_{t-2}, \dots, Y_{t-k}] \quad (1)$$

where:

- X_t = predictor vector for period t ;
- Y_t = number of marriage service requests in period t ;
- Y_{t-1} = number of marriage service requests in the previous period;
- k = number of historical periods used as predictors.

The target variable is defined as: $y_t = Y_t$. Using this approach, the model learns the relationship between marriage service demand in several previous periods and the number of requests in the period to be predicted. The number of lag periods was determined according to the characteristics of the available dataset. The selection of lag variables considered data availability and historical patterns of marriage service demand.

3.5 Training and Testing Data Splitting

Because the research data were characterized by chronological observations, the dataset was divided using a **time-based split** approach. The data were not randomly shuffled because random splitting may cause information from future periods to be included in the training process, resulting in data leakage. The observations from earlier periods were used as training data, whereas observations from subsequent periods were used as testing data. The data partition can conceptually be expressed as: $D = D_{\text{train}} \cup D_{\text{test}}$. The training dataset can be expressed as: $D_{\text{train}} = \{(X_t, Y_t) | t \leq T_{\text{train}}\}$, while the testing dataset can be expressed as: $D_{\text{test}} = \{(X_t, Y_t) | t > T_{\text{train}}\}$.

The training data were used to develop the Random Forest Regression model, while the testing data were used to evaluate the model's ability to predict observations from periods that had not been used during training. The proportion of training and testing data was determined according to the number of available observations. The selected proportion considered the need to provide sufficient observations for model training and evaluation while maintaining the chronological order of the dataset.

3.6 Random Forest Regression Model Development

Random Forest Regression was selected because of its ability to model nonlinear relationships between predictor variables and the target variable. The algorithm constructs multiple decision trees using data samples generated through bootstrap sampling. At each node-splitting process, a randomly selected subset of features is considered, which helps reduce the correlation among individual trees. Assume that the Random Forest consists of n decision trees. Each tree produces a prediction represented by:

$$\hat{y} = \frac{1}{k} \sum_{i=1}^k f_i(x) \quad (2)$$

where:

- $\hat{Y}$ = final Random Forest prediction;
- k = number of decision trees;
- $f_i(X)$ = prediction generated by the i -th decision tree;
- X = input variables.

The main Random Forest parameters considered in this study included the number of trees ($n_estimators$), maximum tree depth (max_depth), minimum number of samples required to split an internal node ($min_samples_split$), minimum number of samples required at a leaf node ($min_samples_leaf$), and the number of features considered when determining the best split ($max_features$). The model parameters were determined through model testing and configuration selection based on predictive performance. When the number of observations was limited, *walk-forward validation* could be employed to maintain the chronological characteristics of the dataset.

3.7 Prediction Process

After the Random Forest Regression model was trained using the training dataset, the testing dataset was provided to the model to generate predictions of marriage service requests. During the prediction process, historical variables were provided as inputs to all decision trees. Each tree generated an individual prediction, and all tree-level predictions were subsequently averaged to obtain the final Random Forest prediction. The predicted values were then compared with the actual values observed in the corresponding testing periods. The differences between actual and predicted values were used to calculate the model evaluation metrics.

3.8 Model Evaluation

Model evaluation was conducted to determine the ability of the Random Forest Regression model to predict the number of marriage service requests. Five evaluation metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2).

3.8.1 Mean Absolute Error (MAE)

Mean Absolute Error measures the average absolute difference between actual and predicted values.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3)$$

where Y_i represents the actual value and $\hat{Y}_i$ represents the predicted value. A lower MAE indicates a smaller average prediction error and therefore better predictive performance.

3.8.2 Mean Squared Error (MSE)

Mean Squared Error calculates the average squared difference between actual and predicted values. Because the errors are squared, larger prediction errors receive greater penalties.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4)$$

A lower MSE indicates better model performance.

3.8.3 Root Mean Squared Error (RMSE)

Root Mean Squared Error is the square root of the Mean Squared Error.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5)$$

RMSE has the same measurement unit as the target variable, making it easier to interpret in the context of the number of marriage service requests. A lower RMSE indicates better predictive performance.

3.8.4 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error measures the average absolute percentage difference between actual and predicted values.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100\% \quad (6)$$

A lower MAPE indicates a lower relative prediction error and therefore better predictive performance. It should be noted that MAPE cannot be directly calculated for observations with an actual value equal to zero because division by zero occurs. Therefore, if the dataset contains periods with zero marriage service requests, such observations should be handled using an appropriate methodological approach or an alternative evaluation metric.

3.8.5 Coefficient of Determination (R²)

The coefficient of determination (R²) measures the ability of the model to explain the variation in the actual target values.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (7)$$

where $\bar{y}$ represents the mean of the actual values.

A higher R² indicates that the model is able to explain a larger proportion of the variation in the actual data. Unlike MAE, MSE, RMSE, and MAPE, for which lower values indicate better performance, an R² value closer to 1 indicates better model performance.

3.9 System Implementation

The Random Forest Regression model with the selected configuration was subsequently integrated into a web-based information system. The system provides functions for managing historical marriage service data, generating predictions, presenting prediction results, displaying trend visualizations, and presenting model performance information. The database was used to store historical marriage service data, preprocessed data, prediction results, and model evaluation information. Python was used as the implementation environment for the machine learning model, while MySQL was used as the database management system. The general implementation workflow was:

Historical Data → Preprocessing → Feature Construction → Random Forest Training → Trained Model → Prediction Period Input → Prediction → Evaluation/Visualization → Prediction Results

3.10 System Testing

In addition to evaluating the predictive performance of the model, the developed system was tested using the black-box testing method. This testing approach evaluates system functionality based on input and output without examining the internal structure of the program code. The tested functions included login, marriage service data management, data insertion, data modification, data deletion, historical data presentation, prediction processing, trend graph visualization, model evaluation presentation, dashboard functionality, and logout. Each function was tested using predefined input conditions, and the actual output was compared with the expected output. A function was considered successful when the actual system output corresponded to the expected output.

3.11 Implementation Environment

The model was implemented using the Python programming language and machine learning libraries that support Random Forest Regression. Data processing was performed using data manipulation and numerical computation libraries, while visualization libraries were used to present the relationship between actual and predicted values. The developed model was subsequently integrated into the web-based information system and MySQL database. Thus, the proposed research produced not only a predictive model but also a system capable of managing historical data and providing estimates of future marriage service demand.

3. Results And Discussions

4.1 Random Forest Regression Model Results

The Random Forest Regression model was implemented to predict the monthly demand for marriage services at the Office of Religious Affairs (Kantor Urusan Agama, KUA) of Bajenis District, Tebing Tinggi City. The model utilized historical marriage service data and considered five input variables: year, month, the number of marriages in the previous month, holidays, and the Hijri month. The target variable was the monthly number of marriage service requests. The Random Forest Regression approach constructs multiple Decision Trees using randomly selected samples from the training dataset. The prediction generated by the model is obtained by aggregating the predictions from all individual trees through averaging. This approach enables the model to capture relationships among the input variables and the demand for marriage services while reducing the risk of overfitting.

4.2 Data Preprocessing Results

Before model development, the historical data were subjected to preprocessing. The preprocessing stage consisted of data cleaning, data transformation, feature selection, and data partitioning. The data cleaning process was performed to identify missing values, duplicate records, and potential recording errors. Categorical variables were subsequently transformed into numerical representations to enable processing by the Random Forest Regression algorithm. The month variable was transformed into numerical values, where January, February, and March were represented by 1, 2, and 3, respectively. The holiday variable was represented as a binary variable, with 0 indicating no holiday and 1 indicating the presence of a holiday. Similarly, the Hijri month was transformed into numerical values, such as Rajab = 1, Sha'ban = 2, Ramadan = 3, and Shawwal = 4. The selected predictor variables were: Year; Month; Number of marriages in the previous month; Holiday indicator; and Hijri month. The target variable was the number of marriage service requests. After preprocessing, the dataset was divided into training and testing datasets. Eighty percent of the data were used for model training, while the remaining 20% were used for model testing.

4.3 Model Training Results

The Random Forest Regression model was trained using the preprocessed historical data. During the training process, multiple Decision Trees were constructed from randomly selected subsets of the training data through bootstrap sampling. The training data included the year, month, previous-month marriage count, holiday indicator, and Hijri month as predictor variables, while the number of marriage service requests was used as the target variable. The training process consisted of four principal steps.

First, the historical marriage service data were processed as the training dataset. Second, multiple Decision Trees were generated using bootstrap samples. Third, each Decision Tree learned the relationship between the predictor variables and the target variable. Finally, the predictions generated by the individual trees were aggregated to obtain the final Random Forest prediction. In this study, the Random Forest Regression model consisted of 100 Decision Trees with a random_state value of 42. The resulting model was subsequently used to predict marriage service demand on the testing dataset and for future periods.

4.4 Testing and Prediction Results

The performance of the trained Random Forest Regression model was evaluated using the testing dataset. The predicted values were compared with the actual number of marriage service requests for the corresponding periods. The testing results are presented in Table 1.

Table 1. Actual and Predicted Marriage Service Demand

No.	Period	Actual Value	Predicted Value	Absolute Difference
1	September 2024	3	6.49	3.49
2	October 2024	6	6.49	0.49
3	November 2024	7	6.49	0.51
4	December 2024	8	6.49	1.51

The results indicate that the Random Forest Regression model generated a prediction of 6.49 marriage service requests for the testing periods. In September 2024, the actual value was 3 requests, while the predicted value was 6.49 requests. In October 2024, the actual value increased to 6 requests, with a predicted value of 6.49 requests. In November 2024, the actual value was 7 requests, while the model predicted 6.49 requests. Finally, in December 2024, the actual value was 8 requests, compared with a prediction of 6.49 requests. The absolute prediction error was calculated as the absolute difference between the actual and predicted values. The resulting absolute differences were 3.49, 0.49, 0.51, and 1.51 for September, October, November, and December 2024, respectively. The results demonstrate that the prediction error varied across the testing periods. The smallest absolute difference occurred in October 2024, with an error of 0.49, whereas the largest difference occurred in September 2024, with an error of 3.49.

4.5 Future Marriage Service Demand Prediction

After testing the model, the trained Random Forest Regression model was used to estimate marriage service demand for the subsequent six months. The prediction results are presented in Table 2.

Table 2. Predicted Marriage Service Demand for Future Periods

No.	Period	Predicted Value
1	January 2025	6.49
2	February 2025	6.49
3	March 2025	6.49
4	April 2025	6.49
5	May 2025	6.49
6	June 2025	6.49

The model estimated a marriage service demand of 6.49 requests per month for the six subsequent periods from January to June 2025. Since marriage service demand is represented as a count variable, the predicted value can be rounded to approximately six marriage service requests per month for practical planning purposes. These predictions can provide supporting information for KUA management in planning personnel, administrative resources, and service capacity according to the estimated monthly demand.

4.6 Model Performance Evaluation

The performance of the Random Forest Regression model was evaluated using four commonly used regression metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The MAE measures the average absolute difference between the actual and predicted values. A lower MAE indicates a smaller average prediction error. Based on the testing data, the model obtained an MAE of 1.50. This indicates that the average absolute deviation between the predicted and actual marriage service demand was 1.50 requests. The MSE measures the average squared difference between actual and predicted values and assigns greater weight to larger prediction errors. The resulting MSE was 3.7401, indicating the average squared prediction error produced by the model on the testing dataset. The RMSE is the square root of the MSE and expresses the prediction error in the same unit as the target variable. The resulting RMSE was 1.9339. This value indicates the magnitude of the prediction error in terms of the number of marriage service requests. MAPE measures the average absolute percentage error between the actual and predicted values. It is expressed as a percentage and can therefore be used to assess prediction error relative to the actual observations. The resulting MAPE was 37.67%, indicating that the average percentage deviation between the predicted and actual values was 37.67%.

4.7 Summary of Model Evaluation

The overall evaluation results are summarized in Table 3.

Table 3. Performance Evaluation of the Random Forest Regression Model

No.	Evaluation Metric	Result
1	MAE	1.50
2	MSE	3.7401
3	RMSE	1.9339
4	MAPE	37.67%

The evaluation results show that the Random Forest Regression model achieved an MAE of 1.50, an MSE of 3.7401, an RMSE of 1.9339, and a MAPE of 37.67%. The MAE indicates that the model's predictions differed from the actual values by an average of 1.50 marriage service requests. Meanwhile, the MSE and RMSE quantify the prediction error based on the squared differences between the actual and predicted values. The MAPE of 37.67% indicates an average relative prediction deviation of 37.67%.

4.8 Overall Findings

Overall, the experimental results demonstrate that Random Forest Regression can be applied to estimate the demand for marriage services at KUA Bajenis District, Tebing Tinggi City. The model used historical information consisting of year, month, previous-month marriage count, holiday conditions, and Hijri month to generate monthly demand predictions. The testing results show that the model produced predictions close to the actual observations in several testing periods, particularly in October and November 2024. The model subsequently generated an estimated demand of 6.49 marriage service requests per month for January–June 2025. From the evaluation results, the model achieved an MAE of 1.50, MSE of 3.7401, RMSE of 1.9339, and MAPE of 37.67%. These findings indicate that the developed Random Forest Regression model can serve as a supporting predictive tool for estimating future marriage service demand and assisting KUA in service planning and resource allocation.

4. Conclusion

Based on the research findings and implementation of the marriage service demand prediction system at the Office of Religious Affairs (KUA) using the Random Forest Regression algorithm, the developed system was successfully implemented as a web-based application integrating user authentication, dashboard, user management, marriage data management, prediction, visualization, and system settings. The historical marriage service demand data from KUA Tebing Tinggi were successfully processed and visualized through historical trends, actual-versus-predicted comparisons, and future

projections. The Random Forest Regression model achieved an MSE of 3.7401 and an RMSE of 1.9339, indicating that the model can be used as a supporting approach for estimating future marriage service demand. In addition, black-box testing showed that the system functions according to the specified requirements, from data input and management to prediction and model evaluation. The developed system can therefore support more measurable service planning at KUA by providing estimates of future marriage service demand. For future development, it is recommended to compare Random Forest with other machine learning algorithms, such as Support Vector Machine (SVM) and XGBoost, and to incorporate additional external variables, including social, cultural, and government policy factors, as well as a larger historical dataset, to improve the model's accuracy, robustness, and adaptability to real-world conditions.

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