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Comparison of Random Forest and XGBoost for Lead Conversion Prediction to Improve Sales Forecasting Accuracy in CRM Systems

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ABSTRACT

This study aims to compare the performance of Random Forest and XGBoost algorithms for customer lead scoring classification within a Customer Relationship Management (CRM) system for a CCTV business in Palembang City. The dataset consisted of 500 customer records collected from 2023 to 2025 and classified into three lead-scoring categories: Hot, Warm, and Cold. The research process involved data preprocessing, an 80:20 training–testing split, model development, and performance evaluation using Accuracy, Precision, Recall, and F1-Score. The results showed that Random Forest achieved an Accuracy of 88.00%, Precision of 89.31%, Recall of 88.00%, and F1-Score of 87.68%. In comparison, XGBoost achieved superior performance, with an Accuracy of 90.00%, Precision of 90.48%, Recall of 90.00%, and F1-Score of 89.89%. These results indicate that XGBoost outperformed Random Forest in classifying customer lead scores and was therefore identified as the best-performing model for the dataset. In addition, product prediction analysis indicated that CCTV Outdoor had the highest predicted sales potential for 2026, with 112 predicted occurrences (22.4%). Overall, the findings demonstrate that machine learning can support customer prioritization, product potential analysis, and data-driven sales strategies within CRM systems.

1. Introduction

The development of information technology and data mining has encouraged companies to transform customer data into meaningful information that can support marketing, sales, and decision-making activities [1]. The utilization of technology enables customer data to be analyzed to identify customer characteristics, activities, and potential. One of the applications of this technology is Customer Relationship Management (CRM), which helps companies manage customer data, interaction histories, and prospective customers in an integrated manner [2]. In marketing and sales activities, Lead Scoring can be used to classify prospective customers according to their level of potential, enabling companies to determine follow-up priorities more effectively [3].

The implementation of Lead Scoring is important because prospective customers exhibit different characteristics

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and behaviors [4]. Companies therefore require an approach capable of processing customer data to identify prospects with a higher likelihood of making a transaction. By utilizing Machine Learning, customer classification can be performed automatically based on patterns identified in historical data [5]. The resulting classification can assist companies in prioritizing prospective customers, thereby enabling marketing and sales activities to be conducted in a more targeted and efficient manner [6]. CCTV Palembang City is a company engaged in the sale and installation of surveillance cameras (CCTV), serving prospective customers with diverse characteristics and behaviors [7]. These variations create a need for an analytical method that can identify customer potential levels based on data available in the company's CRM software. The application of Machine Learning to the Lead Scoring process can provide a solution for classifying prospective customers into specific categories, thereby assisting the company in determining which customers should receive priority during the sales follow-up process [8].

This study employs the Random Forest and XGBoost algorithms to perform Lead Scoring classification. Random Forest generates predictions by combining multiple decision trees through an ensemble learning approach, while XGBoost employs a boosting approach that sequentially builds decision trees to improve predictive performance. The performance of both algorithms is evaluated and compared using Accuracy, Precision, Recall, and F1-Score to determine the algorithm that provides the best classification performance. Based on these problems, this study aims to compare the performance of the Random Forest and XGBoost algorithms in classifying customer Lead Scoring within CRM software. The results are expected to identify the algorithm with the best classification performance and provide recommendations that can support the company's marketing and sales processes by enabling more effective prioritization of prospective customers based on their potential.

2. Method

The research method employed in this study is a machine-learning-based classification approach using the Random Forest and XGBoost algorithms to perform Lead Scoring classification within a CRM system. The research began with the collection of customer and sales data from CCTV Palembang City, followed by a preprocessing stage to clean, transform, and prepare the data for analysis. The processed dataset was then divided into training and testing sets for model development and evaluation. Subsequently, the performance of the Random Forest and XGBoost algorithms was compared using Accuracy, Precision, Recall, and F1-Score to determine which algorithm achieved the best classification performance.

In this study, the Random Forest algorithm was configured using several hyperparameters for the construction of the classification model. These hyperparameters control important aspects of the decision-tree construction process and influence the predictive performance of the model for Lead Scoring classification [9]. The hyperparameters used in the Random Forest model are presented in Table 1.

Table 1 - Random Forest Algorithm Parameters

No.	Parameter	Value
1	n_estimators	100
2	max_depth	10
3	min_samples_split	2
4	min_samples_leaf	1
5	max_features	sqrt
6	random_state	42

The XGBoost algorithm was configured using several hyperparameters to control the classification process. These hyperparameters regulate important aspects of the boosting process, including the number of boosting rounds, tree depth, learning rate, and the proportion of data and features used during model training [10]. The XGBoost hyperparameters used in this study are presented in Table 2.

Table 2 - XGBoost Algorithm Parameters

No.	Parameter	Value
1	n_estimators	100
2	learning_rate	0.1
3	max_depth	6
4	subsample	0.8
5	colsample_bytree	0.8
6	objective	binary:logistic
7	random_state	42

The hyperparameters of both algorithms were configured as part of the modeling process. The Random Forest algorithm was configured with 100 decision trees and a maximum tree depth of 10, while the XGBoost algorithm was configured with 100 boosting rounds, a learning rate of 0.1, and a maximum tree depth of 6. Both models were subsequently trained using the training dataset and evaluated using the testing dataset. The performance of the two models was then compared based on Accuracy, Precision, Recall, and F1-Score to determine which algorithm achieved the best classification performance for Lead Scoring.

3. Result and Discussion

Lead Scoring classification was performed using the Random Forest and XGBoost algorithms on 500 customer records from CCTV Palembang City covering the period from 2023 to 2025. Following data preprocessing, the dataset was divided into 400 records for training and 100 records for testing. The Lead Scoring classification consisted of three categories: Hot, Warm, and Cold (Table 3).

Table 3 - Lead Scoring Class Distribution

Category	Number	Percentage
Hot	122	24.40%
Warm	286	57.20%
Cold	92	18.40%
Total	500	100%

Following the preprocessing stage, the dataset was divided into training and testing sets using an 80:20 stratified split. From the total of 500 customer records, 400 records (80%) were allocated to the training set, while the remaining 100 records (20%) were allocated to the testing set. Stratified splitting was applied to maintain the distribution of the three Lead Scoring categories—Hot, Warm, and Cold—in both datasets. This approach was used to ensure that each category was adequately represented during the model training and evaluation processes. The training set was used to develop the Random Forest and XGBoost classification models, while the testing set was used to evaluate their predictive performance on previously unseen data. The use of separate training and testing sets also helps reduce the risk of evaluating the models on the same data used for training, thereby providing a more reliable assessment of their classification performance.

Model evaluation was performed using the testing dataset based on four classification performance metrics: Accuracy, Precision, Recall, and F1-Score (Table 4). Accuracy measures the proportion of correctly classified instances among all testing instances. These evaluation metrics were used to provide a comprehensive assessment of the performance of the Random Forest and XGBoost models in classifying prospective customers into the Hot, Warm, and Cold Lead Scoring categories.

Table 4 – Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	88.00%	89.31%	88.00%	87.68%
XGBoost	90.00%	90.48%	90.00%	89.89%
Model	Accuracy	Precision	Recall	F1-Score

The table presents the performance comparison between the Random Forest and XGBoost algorithms for Lead Scoring classification based on Accuracy, Precision, Recall, and F1-Score. The Random Forest model achieved an Accuracy of 88.00%, Precision of 89.31%, Recall of 88.00%, and F1-Score of 87.68%. In comparison, the XGBoost model achieved higher performance across all evaluation metrics, with an Accuracy of 90.00%, Precision of 90.48%, Recall of 90.00%, and F1-Score of 89.89%. These results indicate that XGBoost outperformed Random Forest in classifying prospective customers into the Hot, Warm, and Cold Lead Scoring categories. The higher F1-Score achieved by XGBoost also indicates a better balance between Precision and Recall, suggesting that XGBoost provides more consistent overall classification performance for the dataset used in this study.

Following the data-splitting process, the resulting distribution of the dataset is presented in Table 5.

Table 5 – Training and Testing Data Distribution

No.	Data Type	Percentage	Number of Data
1	Training Data	80%	400
2	Testing Data	20%	100
Total	Overall Data	100%	500

The training dataset was used for model training and development, while the testing dataset was used to evaluate the model's classification performance on previously unseen data. This separation ensures that the models are evaluated using data that were not involved in the training process, providing a more reliable assessment of their predictive performance.

3.1 Random Forest Evaluation Results

Following the evaluation of the Random Forest model, further evaluation was conducted using the XGBoost algorithm with the same training (Table 6).

Table 6 – Random Forest Evaluation Results

Metrics	Value
Accuracy	0.8800
Precision	0.8931
Recall	0.8800
F1-Score	0.8768

These results indicate that the Random Forest model achieved good performance in Lead Scoring classification on the testing dataset.

3.2 XGBoost Evaluation Results

Following the evaluation of the Random Forest model, further evaluation was conducted using the XGBoost algorithm with the same training and testing datasets. The use of identical datasets ensures a fair and consistent comparison between the two algorithms. The XGBoost model was evaluated using four classification performance metrics: Accuracy, Precision, Recall, and F1-Score. The resulting performance metrics are presented in Table 7.

Table 7 - XGBoost Evaluation Results

Metrics	Value
Accuracy	0.9000
Precision	0.9048
Recall	0.9000
F1-Score	0.8989

These results indicate that XGBoost achieved good performance in Lead Scoring classification on the testing dataset, with higher evaluation scores across all four metrics than the Random Forest model.

3.3 Prediction of the Most Potential Product Categories

In addition to Lead Scoring classification, this study also presents prediction results based on the product categories preferred by customers (Figure 1). The prediction results are visualized using a bar chart to illustrate the distribution of predicted customer preferences across the different product categories. Based on the prediction results, CCTV Outdoor had the highest number of predictions, with 112 records (22.40%), followed by CCTV Camera with 109 records (21.80%), DVR with 100 records (20.00%), CCTV Package with 95 records (19.00%), and CCTV Indoor with 84 records (16.80%). These results indicate that CCTV Outdoor was the most frequently predicted product category, while CCTV Indoor had the lowest number of predictions among the five categories.

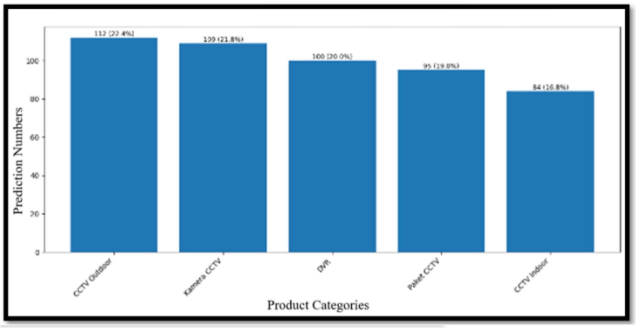

Fig. 1 - Prediction of the Most Potential Product Categories in 2026

Based on these results, CCTV Outdoor was the product category with the highest number of predicted records, while CCTV Indoor had the lowest. These findings provide an overview of the distribution of predicted product categories based on the customer data used in this study. The information can support the company in identifying product categories that may warrant greater attention in marketing and promotional activities, as well as in planning product inventory priorities for 2026.

3.4 Discussion

Based on the research results, the Random Forest and XGBoost algorithms were able to classify CCTV Palembang City customers into three Lead Scoring categories: Hot, Warm, and Cold. The models were evaluated using 100 testing records after being trained on 400 training records. The evaluation results showed that Random Forest achieved an Accuracy of 88.00%, Precision of 89.31%, Recall of 88.00%, and F1-Score of 87.68%, while XGBoost achieved an Accuracy of 90.00%, Precision of 90.48%, Recall of 90.00%, and F1-Score of 89.89%. These results indicate that both algorithms were capable of identifying patterns in the customer data for Lead Scoring classification [11].

Random Forest demonstrated good performance in classifying customers. The algorithm constructs multiple decision trees and combines their predictions to determine the final classification [12]. Based on the evaluation results, the Accuracy of 88.00% indicates that 88% of the testing records were correctly classified. The Precision of 89.31% indicates that a high proportion of the records predicted as a particular class were correctly classified, while the Recall of 88.00% indicates that the model was able to correctly identify a high proportion of the relevant records. Meanwhile, the F1-Score of 87.68% indicates a relatively balanced performance between Precision and Recall [13].

XGBoost achieved higher performance than Random Forest across all four evaluation metrics. XGBoost obtained an Accuracy of 90.00%, Precision of 90.48%, Recall of 90.00%, and F1-Score of 89.89%. These results indicate that XGBoost achieved better classification performance on the research dataset. The boosting approach employed by XGBoost sequentially builds decision trees and focuses on reducing prediction errors from previous iterations, which may have contributed to its higher evaluation scores compared with Random Forest in this study [10].

The comparison of the two algorithms shows that XGBoost outperformed Random Forest, with differences of 2.00 percentage points in Accuracy, 1.17 percentage points in Precision, 2.00 percentage points in Recall, and 2.21 percentage points in F1-Score. Therefore, XGBoost achieved the best overall classification performance on the research dataset [14]. However, this finding does not necessarily indicate that XGBoost will outperform Random Forest on all datasets, as algorithm performance can vary according to dataset characteristics, feature distributions, and classification problems. Therefore, comparing multiple algorithms is important for identifying an appropriate model for a particular application [15].

In addition to the classification results, this study also generated predictions of product categories with potential demand for 2026. Based on the prediction results, CCTV Outdoor had the highest number of predicted records, with 112 records (22.40%), followed by CCTV Camera with 109 records (21.80%), DVR with 100 records (20.00%), CCTV Package with 95 records (19.00%), and CCTV Indoor with 84 records (16.80%). These results provide an overview of the distribution of predicted product categories and indicate that CCTV Outdoor had the highest predicted demand among the five product categories. This information can serve as supporting evidence for CCTV Palembang City in determining marketing priorities, promotional activities, sales strategies, and product inventory planning for 2026 [16].

4. Conclusion

Random Forest and XGBoost can be applied to classify customer lead scores in Customer Relationship Management (CRM) software. The evaluation results indicate that Random Forest achieved an accuracy of 88.00%, precision of 89.31%, recall of 88.00%, and F1-score of 87.68%. In comparison, XGBoost achieved an accuracy of 90.00%, precision of 90.48%, recall of 90.00%, and F1-score of 89.89%. These results demonstrate that XGBoost outperformed Random Forest across all evaluation metrics and was therefore identified as the best-performing algorithm in this study. Furthermore, the product category prediction results show that Outdoor CCTV had the highest number of predicted records, with 112 records (22.4%). This finding may serve as a consideration in determining marketing and sales strategy priorities for 2026.

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