

Implementation of a Customer Churn Model Using XGBoost and SHAP for Telecommunication Customers

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ABSTRACT

Customer churn is a condition in which customers stop using telecommunications services, potentially reducing revenue and customer loyalty while increasing customer acquisition costs. This study implements XGBoost with Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance and Shapley Additive exPlanations (SHAP) to interpret the factors contributing to churn predictions. The dataset used is the Telecom Customer Churn dataset from Maven Analytics, consisting of 7,043 customer records, with 6,589 records used after excluding customers with Joined status. The optimized XGBoost model achieved a Recall of 77.72%, an F1-score of 77.93%, and a ROC-AUC of 93.73%. SHAP analysis identified the factors contributing to customer churn predictions, while validation using Churn Category and Churn Reason showed that Competitor, Price, and Dissatisfaction accounted for 73.46% of churned customers. The most frequent churn reasons were Competitor had better devices (313 customers), Competitor made better offer (311 customers), and Attitude of support person (220 customers). The results provide analytical support for identifying customers likely to churn and understanding factors associated with churn predictions.

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1. INTRODUCTION

Customer retention is an important factor in maintaining business sustainability [1]. Increasing business competition has made customer loyalty more difficult to maintain, as customers have more alternatives and can switch to other services more easily [2]. Changes in customer preferences, service expectations, and competitive offers can further increase the possibility of customers discontinuing their current services [3]. The ability to identify customers who may discontinue their services is therefore important for businesses that seek to maintain their existing customer base [4].

This condition, known as customer churn, can negatively affect business revenue and increase customer acquisition costs because acquiring new customers generally requires greater resources than retaining existing customers [5]. Customer churn also represents the loss of customers who have already established relationships with a service provider [6]. Early identification of customers with a higher likelihood of churn can provide businesses with information for developing appropriate customer retention strategies [7]. Historical customer data can be utilized to identify patterns related to customer behavior, service usage, and customer characteristics that may be associated with churn [8].

The telecommunications industry is particularly exposed to customer churn due to intense competition, similar service offerings, and a relatively saturated market [9]. Customers can compare service

packages, prices, network services, and additional benefits offered by different providers [10]. The annual customer churn rate in the telecommunications sector has been reported to range from 20% to 40% [11]. The relatively high churn rate indicates the importance of identifying potential churn customers as part of customer retention efforts [12]. These conditions have encouraged the use of machine learning to identify customers who are likely to churn based on historical customer data [13]. Machine learning models can process multiple customer attributes simultaneously and identify patterns that may not be easily recognized through conventional analysis [14].

Customer churn datasets commonly have imbalanced class distributions, with fewer churned customers than retained customers [15]. Such imbalance can limit a classification model's ability to identify the minority class effectively [16]. A model trained on an imbalanced dataset may tend to favor the majority class because it has a larger number of observations [17]. This condition is particularly relevant in churn prediction because correctly identifying churned customers is important for providing information about customers who may require further attention [18]. Synthetic Minority Over-sampling Technique (SMOTE) can be applied to address class imbalance by generating synthetic observations for the minority class within the training data [19].

XGBoost is a machine learning algorithm that can be used for classification tasks involving structured customer data [20]. Its boosting-based approach enables the model to combine multiple decision trees to improve predictive performance [21]. Model performance can also be affected by the selection of hyperparameters, making hyperparameter optimization an important part of model development [22]. Combining SMOTE with XGBoost and optimizing the model parameters can therefore provide an approach for handling class imbalance while improving the model's ability to identify churned customers [23]. Evaluation using metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC provides a more comprehensive assessment of model performance, particularly when the target classes are imbalanced [24].

Validation using actual churn categories and reasons can provide additional information about whether the factors identified by the model correspond to the recorded conditions of churned customers [13]. Such validation does not imply a direct causal relationship between the identified features and customer churn, but provides contextual information for interpreting the model predictions. This study therefore develops a customer churn prediction model using XGBoost with SMOTE and hyperparameter optimization, while SHAP is applied to interpret the model predictions. The identified factors are further compared with the available Churn Category and Churn Reason information to provide additional context regarding the factors associated with customer churn [25].

This study develops a customer churn prediction model for telecommunications customers using XGBoost with Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. SHAP is applied to interpret the model predictions and identify features associated with customer churn. The resulting explanations are further compared with the Churn Category and Churn Reason attributes in the Maven Analytics Telecom Customer Churn dataset. This approach combines predictive modeling with model interpretation and validation using recorded churn information.

The study contributes an evaluation of customer churn prediction using an imbalanced telecommunications dataset and provides an interpretation of the resulting model predictions using SHAP. The comparison with Churn Category and Churn Reason provides an additional validation perspective for examining the factors associated with customer churn. The results are intended to provide analytical information for identifying customers who are likely to churn and understanding factors associated with the model predictions.

2. METHOD

The research was conducted through several stages, including dataset acquisition, data preprocessing, train-test splitting, baseline model development, class imbalance handling using SMOTE, XGBoost modeling, hyperparameter tuning, model evaluation, and SHAP-based interpretation. The overall research procedure is presented in Figure 1.

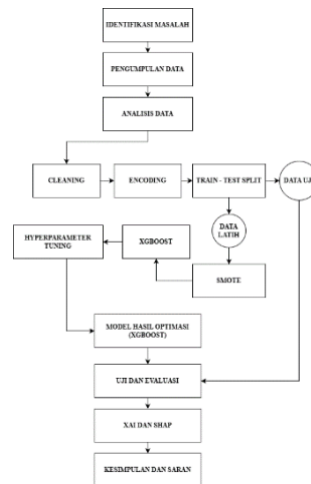


Figure 1. Research Flowchart

2.1. Dataset

The dataset used in this study is the Telecom Customer Churn dataset developed by Maven Analytics and available through Kaggle. The dataset contains 7,043 customer records with 38 attributes covering demographic information, services, contracts, and customer status. Customer Status was used as the target variable with two classes, Stayed and Churned. Records with Joined status were excluded because these customers did not have sufficient service history to be categorized as retained or churned customers.

The Churn Category and Churn Reason attributes were not used as model features because they were reserved for validating the model interpretation results. After target selection, 6,589 records were used for modeling, consisting of 4,720 Stayed customers and 1,869 Churned customers.

2.2. Data Preprocessing

Data preprocessing was performed to prepare the dataset for modeling. The process included checking duplicate records and missing values, removing unused attributes, and applying One-Hot Encoding to categorical attributes. Attributes such as Customer ID, City, Zip Code, Latitude, and Longitude were excluded because they were not required for classification. Customer Status was also removed from the feature set after being used to determine the target variable. Meanwhile, Churn Category and Churn Reason were retained for validating the model interpretation results.

2.3. Train-Test Split

Stratified sampling was used to divide the dataset into training and testing sets while maintaining the class distribution. Four split ratios were evaluated: 70:30, 75:25, 80:20, and 90:10. Each split was tested using the initial XGBoost model without SMOTE or hyperparameter optimization.

The 70:30 split was selected for subsequent modeling based on the comparative evaluation results. This configuration produced 4,612 training records and 1,977 testing records. The larger testing set also provided more observations for evaluating the model compared with the 90:10 split, which contained 659 testing records.

2.4. XGBoost and SMOTE

XGBoost was used as the classification algorithm to predict whether a customer belonged to the *Stayed* or *Churned* class. A baseline XGBoost model was first developed using the selected 70:30 split before applying SMOTE and hyperparameter optimization. The baseline model served as a reference for evaluating subsequent improvements.

SMOTE was then applied to the training data to address class imbalance. The technique generates synthetic observations for the minority class based on existing minority-class samples. SMOTE was applied only to the training data, while the testing data was kept unchanged to provide an evaluation using unseen data.

2.5. Hyperparameter Optimization

Hyperparameter optimization was conducted using Randomized Search followed by Grid Search. Both methods used 5-fold cross-validation, with Recall as the optimization metric because the study focused on identifying customers belonging to the churn class.

The selected XGBoost configuration consisted of subsample = 0.8, n_estimators = 200, max_depth = 4, learning_rate = 0.05, and colsample_bytree = 0.8. SMOTE and XGBoost were incorporated into the

modeling pipeline to ensure that oversampling was performed only on the training portion of each cross-validation fold.

2.6. Model Evaluation

The final model was evaluated using the testing data that was not used during model training or hyperparameter optimization. Five evaluation metrics were used: Accuracy, Precision, Recall, F1-score, and Receiver Operating Characteristic-Area Under the Curve (ROC-AUC).

Accuracy measures the proportion of correctly classified observations. Precision measures the proportion of predicted churn customers that were actually churned. Recall measures the proportion of actual churn customers correctly identified by the model. F1-score combines Precision and Recall into a single measure, while ROC-AUC evaluates the model's ability to distinguish between the *Stayed* and *Churned* classes.

2.7. XAI and SHAP

SHAP was used to interpret the predictions generated by the optimized XGBoost model. The method quantifies the contribution of each feature to individual predictions and provides an overall view of feature importance.

Three SHAP visualizations were used: Feature Importance, Summary Plot, and Waterfall Plot. The Feature Importance and Summary Plot were used to examine the overall contribution of features, while the Waterfall Plot was used to explain the contribution of individual features to a specific customer prediction.

The important features identified through SHAP were compared with the *Churn Category* and *Churn Reason* attributes. These attributes were not used during model training and were only used as supporting information to examine the consistency between the model explanations and the recorded churn information.

3. RESULTS AND DISCUSSION

This section presents the results of the customer churn prediction model and discusses its performance and interpretation. The evaluation covers data preprocessing, train-test split selection, XGBoost modeling, SMOTE application, hyperparameter optimization, and model evaluation using Accuracy, Precision, Recall, F1-score, and ROC-AUC. SHAP is also used to interpret the factors contributing to the model predictions and to compare the identified factors with the available Churn Category and Churn Reason information.

3.1. Dataset and Data Preprocessing Results

The initial dataset contained 7,043 customer records with 38 attributes. After excluding customers with *Joined* status, 6,589 records remained for the classification process. The resulting dataset consisted of 4,720 *Stayed* customers (71.67%) and 1,869 *Churned* customers (28.33%). The difference in class proportions indicates an imbalance between the two target classes.

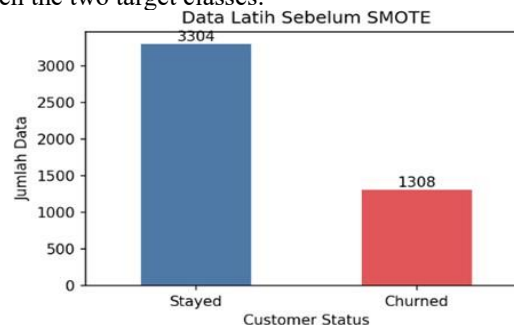


Figure 2. Trainin Data Before SMOTE

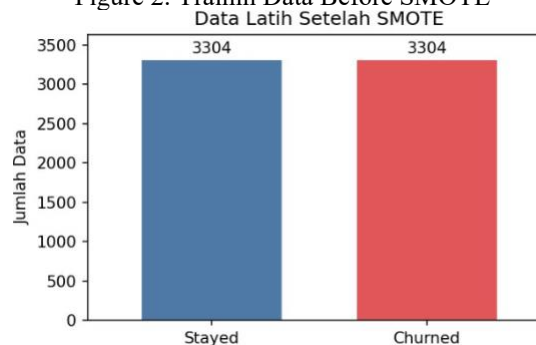


Figure 3. Trainin Data After SMOTE

3.2. Train-Test Split Selection

Four train-test split ratios were evaluated using the initial XGBoost model without SMOTE or hyperparameter optimization. The evaluation results are presented in Table 1.

Table 1. Comparison of Train-Test Split Ratios

Split Ratio	Training Data	Testing Data	Accuracy	Precision	Recall	F1- score	ROC-AUC
70:30	4.612	1.977	85,84%	78,50%	68,98%	73,43%	92,51%
75:25	4.941	1.648	85,44%	77,09%	69,16%	72,91%	91,92%
80:20	5.271	1.318	85,96%	81,19%	65,78%	72,67%	91,72%
90:10	5.930	659	85,89%	79,75%	—	73,04%	91,28%

The 70:30 split produced the highest F1-score and ROC-AUC among the evaluated configurations. This ratio also provided 1,977 testing observations, compared with only 659 observations in the 90:10 configuration. Based on these results, the 70:30 split was used for the subsequent modeling process, resulting in 4,612 training records and 1,977 testing records.

3.3. XGBoost Model Performance

The baseline XGBoost model was developed using the selected 70:30 split without applying SMOTE or hyperparameter optimization. The model was trained using 4,612 records and evaluated using 1,977 testing records. The baseline model achieved an Accuracy of 85.84%, Precision of 78.50%, Recall of 68.98%, F1-score of 73.43%, and ROC-AUC of 92.51%.

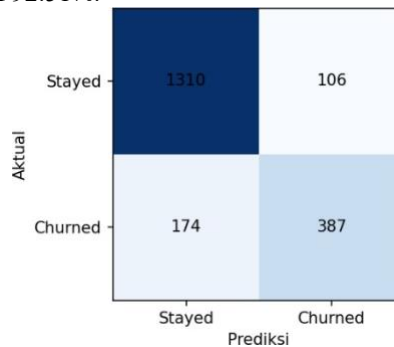


Figure 4. Confusion matrix Model XGBoost Baseline

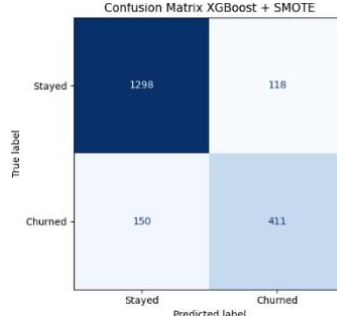


Figure 5. Confusion matrix Baseline After Smote

Figure 5 shows the prediction results of the XGBoost model after applying SMOTE. Predictions for the “Stayed” class are mostly correct, while for the “Churned” class, there are still some data points predicted as “Stayed.” These results were used to calculate Accuracy, Precision, Recall, F1-score, and ROC-AUC.

PERBANDINGAN: XGBoost vs XGBoost + SMOTE

Metrik	XGBoost Baseline	XGBoost + SMOTE	Selisih
Accuracy	85.84%	86.44%	+0.61%
Precision	78.50%	77.69%	-0.81%
Recall	68.98%	73.26%	+4.28%
F1-score	73.43%	75.41%	+1.98%
ROC-AUC	92.51%	92.41%	-0.09%

Figure 6. Comparison of Model Performance

3.4. Hyperparameter Optimization

Hyperparameter optimization was performed after applying SMOTE using Randomized Search and Grid Search with 5-fold cross-validation. Recall was used as the search metric to emphasize the identification

of Churned customers. Randomized Search evaluated 20 randomly selected parameter combinations and obtained a cross-validation Recall of 78.13%, while Grid Search obtained 77.29%.

Table 2. Hyperparameter Search Results

Hyperparameter	Grid Search	Randomized Search
n_estimators	400, 600	200, 400, 600
max_depth	4, 6	3, 4, 5, 6
learning_rate	0,05; 0,1	0,03; 0,05; 0,1; 0,2
subsample	Default (1,0)	0,8; 1,0
colsample_bytree	Default (1,0)	0,8; 1,0

The configuration selected through Randomized Search consisted of n_estimators = 400, max_depth = 4, learning_rate = 0.03, subsample = 1.0, and colsample_bytree = 0.8.

Table 3. Selected XGBoost Hyperparameters

Metode	Recall Rata-rata 5-Fold CV
Grid Search	77,29%
Randomized Search	78,13%

3.5. Final Model Evaluation

The optimized XGBoost model was evaluated using the same 1,977 testing records. The model achieved an Accuracy of 87.51%, Precision of 78.14%, Recall of 77.72%, F1-score of 77.93%, and ROC-AUC of 93.73%. The confusion matrix consisted of 1,294 true negatives, 122 false positives, 125 false negatives, and 436 true positives.

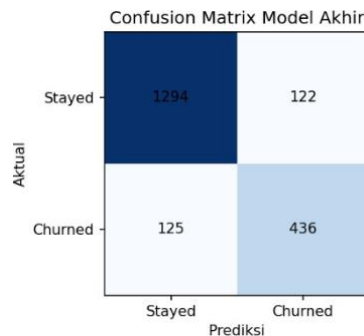


Figure 7. Confusion Matrix of the Optimized XGBoost Model

Compared with the baseline model, the optimized model increased Accuracy from 85.84% to 87.51%, Recall from 68.98% to 77.72%, F1-score from 73.43% to 77.93%, and ROC-AUC from 92.51% to 93.73%.

Precision changed from 78.50% to 78.14%. The results show an improvement in the model's ability to identify Churned customers while maintaining a similar Precision value.

Table 4. Performance Comparison of XGBoost Models

Metrik	XGBoost Baseline	XGBoost After SMOTE	XGBoost Optimasi
Accuracy	85,84%	86,44%	87,51%
Precision	78,50%	77,69%	78,14%
Recall	68,98%	73,26%	77,72%
F1-score	73,43%	75,41%	77,93%
ROC-AUC	92,51%	92,41%	93,73%

The ROC curve of the optimized model produced an area under the curve of 93.73%, indicating its discrimination performance between the Stayed and Churned classes.

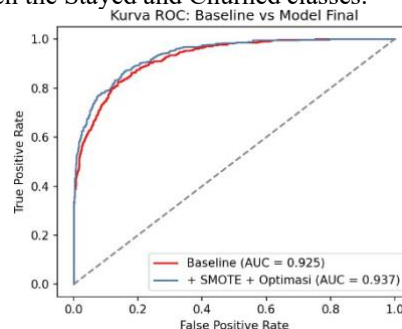


Figure 8. ROC Curve of the Optimized XGBoost Model

3.6. SHAP Interpretation

SHAP was used to interpret the contribution of features to the XGBoost predictions. The SHAP Feature Importance and Summary Plot identified Contract_Month-to-Month, Tenure in Months, Number of Referrals, Number of Dependents, and Monthly Charge as the five features with the highest contributions.

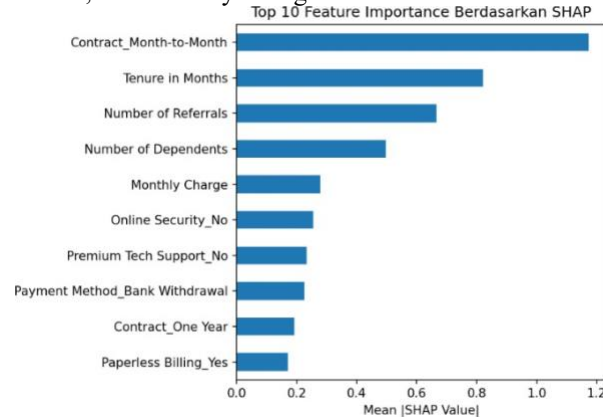


Figure 9. SHAP Feature Importance

The Summary Plot provides information about the direction of each feature's contribution. Higher values of Contract_Month-to-Month tended to contribute toward Churned predictions. Lower Tenure in Months values tended to contribute toward Churned predictions, while higher tenure values tended toward Stayed predictions. Higher Number of Referrals generally contributed toward Stayed predictions, whereas lower values contributed toward Churned predictions. Number of Dependents showed a similar pattern, with higher values tending toward Stayed predictions. Higher Monthly Charge tended to contribute toward Churned predictions.

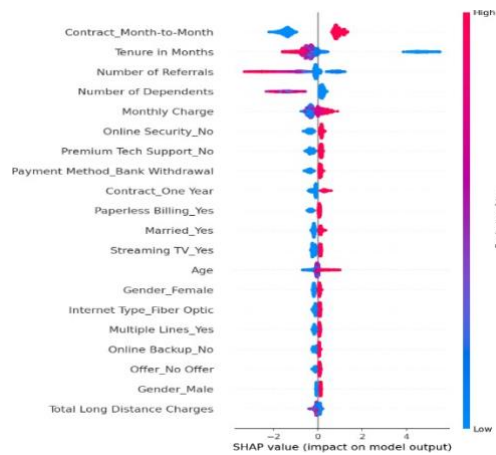


Figure 10. SHAP Summary Plot

The SHAP Waterfall Plot was used to illustrate the contribution of individual features for a single prediction. The example showed contributions from Contract_Month-to-Month, Number of Dependents, Number of Referrals, Monthly Charge, Tenure in Months, and several service-related features. The combined contributions in the example moved the prediction toward the Stayed class.

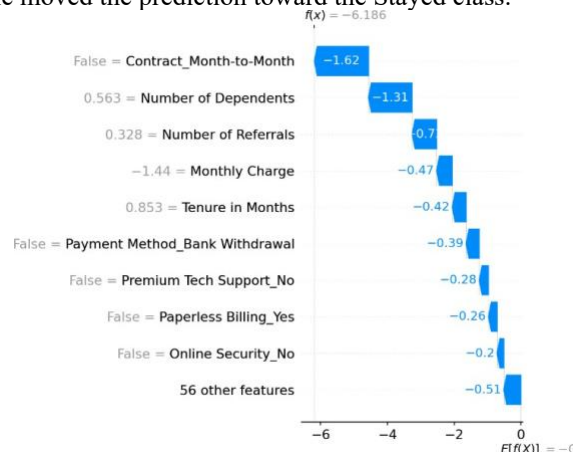


Figure 11. SHAP Waterfall Plot

3.7. Churn Category and Churn Reason Validation

The SHAP interpretation was examined further using Churn Category and Churn Reason, which were not used as model features. Among the 1,869 Churned customers, Competitor was the largest Churn Category with 841 customers (45.00%), followed by Dissatisfaction with 321 customers (17.17%), Attitude with 314 customers (16.80%), Price with 211 customers (11.29%), and Other with 182 customers (9.74%). Competitor, Price, and Dissatisfaction together accounted for 1,373 customers or 73.46% of the Churned records.

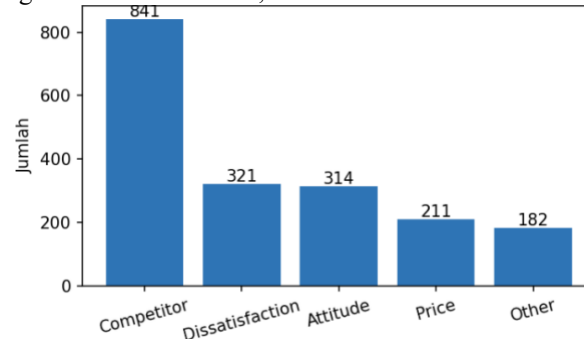


Figure 12. Churn Category Distribution

The Churn Reason results showed that Competitor had better devices was recorded for 313 customers, followed by Competitor made better offer for 311 customers and Attitude of support person for 220 customers. These results provide additional context for the SHAP interpretation by showing the recorded churn reasons associated with the customers classified as Churned.

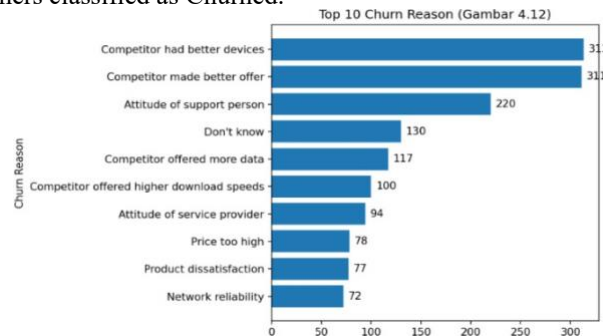


Figure 13. Top Churn Reasons

4. CONCLUSION

This study developed a customer churn prediction model for telecommunications customers using XGBoost with SMOTE and hyperparameter optimization, along with SHAP for model interpretation. The optimized model achieved an Accuracy of 87.51%, Precision of 78.14%, Recall of 77.72%, F1-score of 77.93%, and ROC-AUC of 93.73%. Compared with the baseline XGBoost model, the optimized model improved Recall from 68.98% to 77.72%, F1-score from 73.43% to 77.93%, and ROC-AUC from 92.51% to 93.73%.

SHAP identified Contract_Month-to-Month, Tenure in Months, Number of Referrals, Number of Dependents, and Monthly Charge as the features with the highest contributions to the model predictions. The validation results showed that Competitor, Price, and Dissatisfaction accounted for 73.46% of Churned customers. These results provide analytical support for identifying customers associated with churn predictions and understanding the factors contributing to the model's predictions. Further research can explore other datasets, additional optimization techniques, and alternative explainable artificial intelligence methods to evaluate the consistency of the model and its interpretation across different customer populations.

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REFERENCES

- [1] R. Sinaga and S. Widiyanto, "Understanding Telecommunication Customer Churn: Insights from LightGBM Predictive Modelling and SHAP Feature Interpretation," *ASEAN Mark. J.*, vol. 15, no. 1, 2023, doi: 10.7454/amj.v15i1.1229.
- [2] J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," *J. Mach. Learn. Res.*, vol. 13, pp. 281–305, 2012.
- [3] B. Bischl *et al.*, "Hyperparameter optimization: Foundations, algorithms, best practices, and open challenges," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 13, no. 2, pp. 1–43, 2023, doi: 10.1002/widm.1484.

- [4] E. L. Luma, F. Tat, and Y. Dion, "Hubungan Antara Tingkat Pengetahuan Ibu Tentang Penyakit Pneumonia Dengan Perilaku Pencegahan Pneumonia Pada Anak Di Puskesmas Bakunase Kota Kupang," *CHMK Appl. Sci. J.*, vol. 4, no. 1, pp. 18–28, 2021.
- [5] Y. D. Esdin Lestari Lumaa, Florentianus Tat, "CHM-K Applied Scientific Journals," *Hub. Antara Tingkat Pengetah. Ibu Tentang Penyakit Pneumonia Dengan Perilaku Pencegah. Pneumonia Pada Anak Di Puskesmas Bakunase Kota Kupang*, vol. 4, pp. 18–28, 2021, doi: 10.37792/casj.v4i1.962.
- [6] N. Y. Nhu, T. Van Ly, and D. V. Truong Son, "Churn prediction in telecommunication industry using kernel Support Vector Machines," *PLoS One*, vol. 17, no. 5 May, 2022, doi: 10.1371/journal.pone.0267935.
- [7] C. Kaope and Y. Pristyanto, "The Effect of Class Imbalance Handling on Datasets Toward Classification Algorithm Performance," *MATRIK J. Manajemen, Tek. Inform. dan Rekayasa Komput.*, vol. 22, no. 2, pp. 227–238, 2023, doi: 10.30812/matrik.v22i2.2515.
- [8] H. A. Rasool, K. K. Aljawaheri, and A. A. M. Karram, "Explainable Customer Churn Prediction in Telecom Using Ensemble Learning and SHAP Analysis," *Math. Model. Eng. Probl.*, vol. 12, no. 12, pp. 4373–4386, 2025, doi: 10.18280/mmep.121226.
- [9] L. N. Wakhidah, A. K. Zyen, and B. B. Wahono, "Evaluation of Telecommunication Customer Churn Classification with SMOTE Using Random Forest and XGBoost Algorithms," *J. Appl. Informatics Comput.*, vol. 9, no. 1, pp. 89–95, 2025, doi: 10.30871/jaic.v9i1.8740.
- [10] K. Peng and Y. Peng, "Research on Telecom Customer Churn Prediction Based on GA-XGBoost and SHAP," *J. Comput. Commun.*, vol. 10, no. 11, pp. 107–120, 2022, doi: 10.4236/jcc.2022.1011008.
- [11] I. G. A. R. Astarani and L. A. A. R. Putri, "Klasifikasi Customer Churn Menggunakan XGBoost dengan Optimasi GridSearchCV Berbasis Shapley Additive Explanations," *J. Nas. Teknol. Inf. dan Apl.*, vol. 4, no. November, pp. 1–10, 2025.
- [12] N. Dwi Ramadhanti and R. Nurfitriana Handayani, "Analisis Sentimen Ulasan Pengguna Aplikasi Shopee di Google Play Store Menggunakan Support Vector Machine dengan Teknik SMOTE," *J. Inform. Polinema*, vol. 12, no. 2, pp. 313–322, 2026, doi: 10.33795/jip.v12i2.9073.
- [13] M. Z. Alotaibi and M. A. Haq, "Customer Churn Prediction for Telecommunication Companies using Machine Learning and Ensemble Methods," *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 3, pp. 14572–14578, 2024, doi: 10.48084/etasr.7480.
- [14] J. A. Ilemobayo *et al.*, "Hyperparameter Tuning in Machine Learning: A Comprehensive Review," *J. Eng. Res. Reports*, vol. 26, no. 6, pp. 388–395, 2024, doi: 10.9734/jerr/2024/v26i61188.
- [15] D. Wahyu, K. H. Sakaro, N. Sabrina, E. Ramadhan, and K. Kunci, "Klasifikasi Churn Dengan Algoritma XGBoost Menggunakan Feature Selection Boruta-Shap," *Technol. Sci.*, vol. 7, no. 2, pp. 1193–1201, 2025, doi: 10.47065/bits.v7i2.7965.
- [16] A. Sikri, R. Jameel, S. M. Idrees, and H. Kaur, "Enhancing customer retention in telecom industry with machine learning driven churn prediction," *Sci. Rep.*, vol. 14, no. 1, pp. 1–13, 2024, doi: 10.1038/s41598-024-63750-0.
- [17] A. El Attar and M. El-Hajj, "Explainable AI-driven customer churn prediction: a multi-model ensemble approach with SHAP-based feature analysis," *Front. Artif. Intell.*, vol. 9, no. 1, 2026, doi: 10.3389/frai.2026.1748799.
- [18] H. A. Mengash, N. Alruwais, F. Kouki, C. Singla, E. S. Abd Elhameed, and A. Mahmud, "Archimedes Optimization Algorithm-Based Feature Selection with Hybrid Deep-Learning-Based Churn Prediction in Telecom Industries," *Biomimetics*, vol. 9, no. 1, 2024, doi: 10.3390/biomimetics9010001.
- [19] S. Antoh, R. Herteno, I. Budiman, D. Kartini, and M. I. Mazdadi, "Prediksi Churn Pelanggan Telekomunikasi dengan Optimalisasi Seleksi Fitur dan Tuning Hyperparameter pada Algoritma Klasifikasi C4.5," *J. Sist. Inf. Bisnis*, vol. 15, no. 1, pp. 60–67, 2025, doi: 10.14710/vol15iss1pp60-67.
- [20] B. Prabadevi, R. Shalini, and B. R. Kavitha, "Customer churning analysis using machine learning algorithms," *Int. J. Intell. Networks*, vol. 4, no. April, pp. 145–154, 2023, doi: 10.1016/j.ijin.2023.05.005.
- [21] R. Suguna, J. Suriya Prakash, H. Aditya Pai, T. R. Mahesh, V. Vinoth Kumar, and T. E. Yimer, "Mitigating class imbalance in churn prediction with ensemble methods and SMOTE," *Sci. Rep.*, vol. 15, no. 1, pp. 1–20, 2025, doi: 10.1038/s41598-025-01031-0.
- [22] X. Zhang, A. Ghosh, and D. A. Ali, "Research on Marketing Strategy Management based on Customer Retention," *Acad. J. Manag. Soc. Sci.*, vol. 6, no. 2, pp. 66–70, 2024, doi: 10.54097/rdcx2907.
- [23] O. Rainio, J. Teuho, and R. Klén, "Evaluation metrics and statistical tests for machine learning," *Sci. Rep.*, vol. 14, no. 1, pp. 1–14, 2024, doi: 10.1038/s41598-024-56706-x.
- [24] Z. M. Altukhi, S. Pradhan, and N. Aljohani, "A Systematic Literature Review of the Latest Advancements in XAI," *Technologies*, vol. 13, no. 3, 2025, doi: 10.3390/technologies13030093.
- [25] S. M. Lundberg and S. I. Lee, "A unified approach to interpreting model predictions," *Adv. Neural Inf. Process. Syst.*, vol. 2017-Decem, no. Section 2, pp. 4766–4775, 2017.