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Customer Churn Prediction in Small and Medium Enterprises Using Gradient Boosting with RFM-Based Behavioral Features

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ABSTRACT

Customer churn prediction is an important task for maintaining customer relationships and supporting data-driven decision-making in micro, small, and medium enterprises (MSMEs). However, customer purchasing behavior is often nonlinear and difficult to characterize using traditional single-model approaches. This study investigates the performance of a gradient boosting model for predicting customer churn in Indonesian fashion MSMEs. A transaction dataset containing 1,240 customer records collected from 24 MSMEs was constructed using three Recency, Frequency, and Monetary Value (RFM)-based behavioral features: recency, frequency, and monetary value. The proposed model was implemented using the Konstanz Information Miner (KNIME) Analytics Platform and evaluated through accuracy, precision, recall, specificity, F1-score, area under the curve (AUC), and stratified five-fold cross-validation. The results show that gradient boosting achieved an accuracy of 87.9%, recall of 84.0%, precision of 65.6%, specificity of 88.8%, F1-score of 73.6%, and AUC of 0.88, outperforming logistic regression, decision tree, and random forest models. The findings indicate that gradient boosting can effectively capture nonlinear patterns in customer transaction behavior and provide predictive information for customer retention analysis in resource-constrained MSME environments. This study contributes empirical evidence on the application of ensemble learning methods for churn prediction in the MSME sector, where predictive analytics remains relatively underexplored.

1. INTRODUCTION

The increasingly widespread use of digital marketing has played an important role in encouraging repeat purchases and maintaining customer engagement. Loyal customers are seen as one of the important factors for micro, small, and medium enterprises (MSMEs) in maintaining a presence in the market and building consumer loyalty in the long term [1]. Customer loyalty is considered to play a role in reducing promotional costs because customers tend to make repeat purchases. Technological developments today are increasingly used to analyze customer loyalty levels and predict repurchase behavior [2]. The use of data-driven analytics and the implementation of digital business models show that the modernization process in the MSME sector in Indonesia is ongoing. Data-driven analytics and digital business models are increasingly being used to understand market behavior and improve the effectiveness of marketing strategies. However, despite the increasingly massive development of digitalization, MSMEs still face significant challenges in predicting customer loyalty. Limited resources capable of analyzing data and the low utilization of predictive methods lead to inaccurate assessments [3]. This phenomenon results in less optimal strategic decision-making for MSMEs.

Customer loyalty is closely related to churn, which is the tendency of customers to end a relationship with a company or switch to another service provider within a certain period [4]. One of the problems that MSMEs still face is the limitation in accurately identifying churn rates. Various previous studies have examined the phenomenon of churn in telecommunications companies and credit card services to evaluate customer loyalty. Research on churn prediction in MSME digital marketing is still relatively limited. This research gap causes the data-driven decision-making process to not be utilized optimally and reduces the ability of MSMEs to develop more targeted and effective customer retention strategies.

One of the most commonly used methods to predict customer churn is the decision tree. This machine learning method models the decision-making process in the form of a tree structure based on predetermined rules [5]. Each branch represents the conditions derived from the predictor variable, while the terminal node shows the customer's classification results. Customers can be grouped into categories that have the potential to stop transacting and those that are expected to remain persistent.

Although widely used in customer churn predictions, the decision tree method still has a number of limitations. These models can leverage historical data to predict customer behavior, but their accuracy is generally lower than ensemble models such as Extreme Gradient Boosting (XGBoost) [6]. Overly simple tree structures tend to result in models that are prone to overfitting; their performance decreases when faced with new data that has not been studied before [7]. Churn prediction models are often evaluated using accuracy-based metrics, even though these measures do not always align with the main business goals [8]. Another limitation is the relatively low ability of decision trees to capture consumer behavior patterns as well as changes in customer preferences that occur over time. The characteristics of consumers in Indonesia are heterogeneous, making churn prediction more difficult if based only on one decision tree model. The implication is that predictive performance tends to decline when models have to deal with high variations in customer behavior.

The decision tree is a single model that is simple to interpret because the decision-making process is represented through logical rules arranged in a hierarchical manner. These characteristics allow decision trees to be used not only as a prediction tool, but also as a means to explore data patterns and understand customer behavior. The simplicity of such structures limits the model's ability to capture nonlinear relationships. This limitation has the potential to increase prediction errors and reduce the model's accuracy, resulting in less optimal churn analysis outcomes and potentially biased conclusions. Currently, a stronger analytical approach is needed to improve churn prediction performance compared to using a decision tree model alone.

A better approach as a solution to the limitations of a simple decision tree is gradient boosting. Each decision tree is trained sequentially to learn from and correct the prediction errors generated by the previous tree. This improvement process is carried out by directing the construction of new trees toward residual values through a gradient-based optimization approach. Gradient boosting produces a much stronger and more accurate model than a single decision tree by combining many simple decision trees.

Gradient boosting overcomes these limitations by repeatedly integrating many simple decision trees into a single unified model. Each decision tree built at the next stage can help reduce prediction errors [9]. These mechanisms result in a more stable and resilient model, especially when faced with heterogeneous customer behavior. Customer churn analysis in digital marketing with a gradient boosting approach tends to be ideal because it can increase the accuracy of predictions. This modeling method is suitable for MSMEs because it offers more reliable predictive capabilities than a simpler single decision tree model.

The gradient boosting algorithm was developed to improve convergence efficiency in predictive modeling. Based on previous studies, empirical evaluations have shown that gradient boosting is capable of achieving high predictive performance [10]. Gradient boosting tends to be less sensitive to parameter shrinkage. Gradient boosting produces more compact ensembles. This is achieved with a smaller number of trees without sacrificing predictive accuracy. Research on the application of gradient boosting in data-driven analytics among MSMEs is still relatively limited, especially in Indonesia. This is caused by resource limitations for conducting research, particularly in the MSME sector. Further research is needed to assess customer churn among MSMEs using gradient boosting to improve the accuracy of customer loyalty projections. Many MSMEs possess large volumes of digital marketing data but have not yet fully utilized advanced predictive algorithms. There are many advantages if insights can be generated as a basis for decision-making. This condition indicates a research gap related to the implementation and effectiveness of ensemble models for churn prediction. Based on this phenomenon, this study aims to analyze the performance of gradient boosting in predicting customer churn among MSMEs.

The main contribution of this study is to examine the effectiveness of gradient boosting in predicting customer churn among MSMEs. Gradient boosting is an approach that remains relatively underexplored. Previous studies have mostly focused on churn prediction in large-scale industries, such as telecommunications and banking services, because these sectors generally have data availability and analytical data infrastructure. MSMEs face limitations in both data availability and analytical capability. The application and effectiveness of advanced ensemble models such as the Gradient Boosted Tree (GBT) have not yet been widely studied in MSMEs. This study employs several behavioral variables based on the Recency, Frequency, and Monetary Value (RFM) framework [11], namely recency, which refers to the number of days since the last purchase; frequency, which indicates the number of transactions; and monetary value, which represents total customer spending. The combination of these variables is used to generate reliable predictions through an ensemble learning approach.

2. METHODOLOGY

This study uses a quantitative approach to analyze data-driven analytics in MSMEs. The analysis is directed at MSMEs in the retail sector in Indonesia by examining customer purchasing behavior using several transaction variables. The dataset used includes total purchases during the last six months, purchase frequency within the same period, and the number of days since the last purchase as an indicator of transaction recency. These three aspects are then processed to build customer behavior patterns that are relevant to churn analysis, as shown in Table 1.

Table 1. Data attributes description

No.	Attribute	Description
1	Total purchase	Total consumer expenditure in the past six months, expressed in Indonesian rupiah.
2	Frequency	Number of purchase transactions made by a consumer within the past six months.
3	Days since last purchase	Number of days elapsed since the most recent transaction before the data collection cut-off.
4	Churn	Status indicating whether a consumer has discontinued making purchases or ceased using the product or service within 90 days.

MSMEs operating in the fashion sector in Indonesia serve as the dataset source in this study. The dataset was compiled from 24 fashion MSMEs operating in Indonesia. Transaction data collected between November 2024 and January 2025 were aggregated at the customer level to construct the RFM variables. After the data preparation process, the final dataset consisted of 1,240 customer records, each representing an individual customer. The use of multiple SMEs was intended to capture a broader range of customer purchasing behaviors within the fashion sector. These transaction records are used as the basis for churn analysis. Purchasing activity within a certain time interval is used as the basis for determining churn status. Customers who made transactions within the last 90 days are assigned a value of 0 and classified as non-churn. Conversely, customers who did not engage in purchasing activity for more than 90 days are assigned a value of 1. This value indicates that the customer belongs to the churn category. The selection of the 90-day threshold is based on previous studies showing that this interval is an appropriate benchmark for defining churn [12]. This coding approach aims to establish the target variable for classification modeling. Churn prediction in fashion retail MSMEs is carried out using data analytics techniques. Data that has been collected from fashion MSMEs is then analyzed using the Konstanz Information Miner (KNIME) data analytics platform. The data processing procedure follows a series of stages to ensure data quality. These stages are intended to enable the model to produce predictive modeling, as shown in Figure 1.

The KNIME Analytics Platform is an analytics platform for machine learning and data science. The platform can facilitate the integration of various heterogeneous analytical tools and platform independence across different operating systems. Data exploration, analysis, and visualization can be performed in KNIME using an integrated data model [13, 14]. The initial stage begins with variable screening using the Column Filter to ensure that only relevant attributes are included in the analysis. Subsequently, the churn target variable, originally in integer format, is converted into a string format so that it can be properly recognized as a class label in the classification process. The data is divided into two parts, 80% as training data (training set) and 20% as test data (test set). This division is carried out to provide an adequate proportion in the model learning process as well as its performance testing. The next stage is the development of a prediction model using the GBT algorithm through the GBT Learner node in KNIME. The trained model is then used to generate predictions for the test data. The prediction results are evaluated using the Scorer node to determine the model's success rate. The evaluation process generates various performance metrics to assess the model's accuracy. The evaluation also assesses the model's ability to predict customers who have the potential to experience churn.

The gradient boosting model was developed using the KNIME Analytics Platform on a computer with an Intel Core i7 processor, 8 GB of RAM, and 512 GB of Solid-State Drive (SSD) storage. The model training process took approximately 18.6 seconds, while the prediction process on the test data was completed in 1.2 seconds. The relatively short computation time indicates that the proposed model requires only modest computational resources, making it suitable for deployment in MSME environments with limited technological infrastructure.

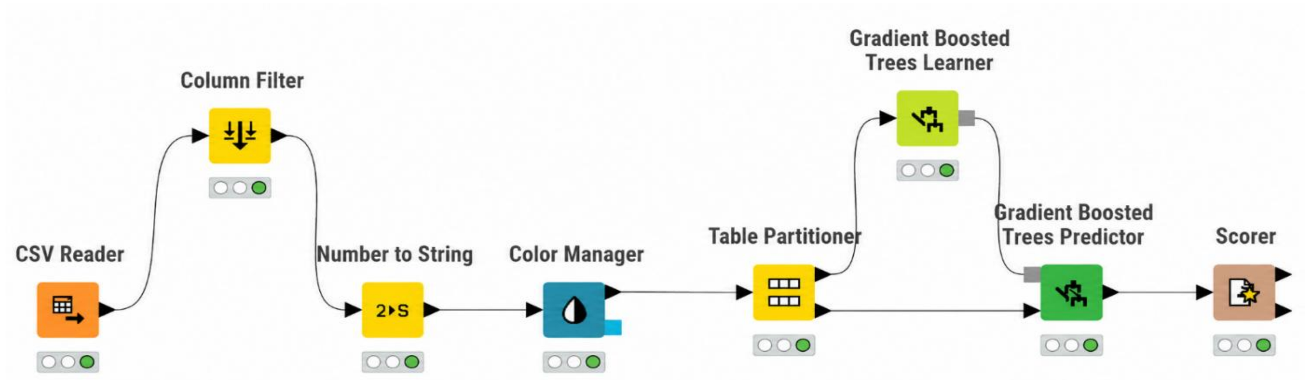

Figure 1. Data analysis process

3. RESULT AND DISCUSSION

This study analyzes descriptive data consisting of total purchase, frequency, and days since last purchase, as presented in Table 2.

Table 2 shows that three main variables, namely transaction value (total purchase), spending intensity (frequency), and recency (days since last purchase), are used to identify customer behavioral profiles. The average customer expenditure, expressed in Indonesian Rupiah (IDR), is IDR 12,283,323, with a very wide range, from IDR 2,141,000 to IDR 25,180,000. This condition indicates a high degree of heterogeneity in purchasing power among different customer segments.

Based on data obtained from MSMEs, the average customer purchase frequency was recorded at 10.31 transactions. The median value indicates that half of the total customers had more than 11 transactions. In the days since last purchase variable, an average of 77.38 days was obtained, with a maximum value of 160 days. The high recency value in the third quartile, which is 109 days, indicates a group of customers who have not purchased for a long time. This condition can be a signal of increasing customer potential to stop transacting (customer churn). The analysis process begins with the data selection stage using the Column Filter feature to ensure that only specific attributes are used in the modelling. The target churn variable, which was originally an integer data type, is converted into a string so that it can be recognized as a class label in the classification process.

Customer churn is an important challenge for business sustainability and therefore requires careful analysis. MSMEs require an accurate predictive model to support effective customer retention strategies. Heatmap analysis plays an important role in descriptive churn prediction. A heatmap depicts customer attributes and purchasing behavior as visual patterns. This is used to describe variables and provide information about customer characteristics and purchasing activity patterns. A heatmap plays an important role in data analysis by visually representing patterns and intensity levels [15]. Heatmaps in predictive modeling help reveal patterns and relationships that may be less apparent when examining numerical summaries. Heatmap analysis aims to improve model interpretability.

Table 2. Descriptive analysis

Classification	Minimum	Maximum	25% Quantile	50% Quantile	75% Quantile	Mean
Total_purchase	Rp 2,141,000	Rp 25,180,000	Rp 4,973,000	Rp 13,584,000	Rp 17,188,500	Rp 12,283, 323
Frequency	1	19	5.5	11	15	10.31
Days since last purchase	1	160	43.5	85	109	77.38

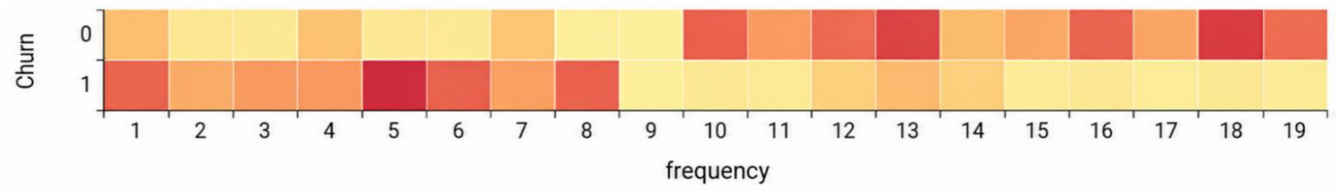

Figure 2. Heatmap

Figure 2 shows the heatmap visualization that reveals a loyalty threshold at the 10th transaction frequency. The heatmap applies an exploratory visualization tool to identify customer behavior patterns. The visualization results show a clear polarity: customers with low transaction frequencies, ranging from 1–9 transactions, have a greater likelihood of experiencing churn. The heatmap visualization also shows that the highest concentration of risk is in the 5th transaction. These results indicate that customers who have exceeded the threshold of 10 transactions exhibit a stable retention rate. This finding illustrates that the initial phase is a very crucial period.

Based on the GBT algorithm in Table 3, the confusion matrix for 248 testing observations shows strong performance. From 50 customers who actually experienced churn, 42 customers were classified as True Positive (TP), and the other 8 customers were classified as False Negative (FN). Furthermore, from 198 the model predicted 176 customers were classified as True Negative (TN), and 22 customers were classified as False Positive (FP). These results had an accuracy rate of 87.9%.

A recall value of 84% showed the model's ability to capture churn signals. The precision value of 65.6% reflected that the model was efficient in prioritizing targeted marketing interventions. An acceptable error rate in False Positive and False Negative classifications shows that the model does not experience overfitting. The model was able to generalize non-linear consumer behavior patterns. This model can also serve as a decision-support tool to help reduce customers' churn risk and improve customers' effectiveness retention programs.

Table 4 shows a comparison of gradient boosting with several classification algorithms to evaluate model effectiveness, namely logistic regression, decision tree, and random forest. The test results show that gradient boosting produced the best performance on the evaluation metrics. This model achieved an accuracy rate of 87.9%, a precision of 65.6%, a recall of 84.0%, and an area under the curve (AUC) value of 0.88. Gradient boosting showed a significant improvement in performance indicators compared to logistic regression and decision tree. The random forest test results produced competitive values with an accuracy of 86.2% and an AUC value of 0.85, but the results were still below the performance of gradient boosting. These findings indicated that the boosting mechanism can improve the model's ability to identify customer behavior patterns.

This study applied stratified 5-fold cross-validation, as shown in Table 5. The results show that the performance difference between the train-test split approach and cross-validation is relatively small. The validation shows 0.3% in accuracy, 0.5% in precision, 0.2% in recall, and 0.01 in AUC, respectively. This finding indicated that the model's performance is relatively consistent across various data splits. The test results also indicated that the model has a good level of stability and reliability in predicting customer churn.

Table 6 shows that the model achieved an accuracy of 87.9%, indicating a high level of agreement between the predicted classifications and the actual customer statuses. These results indicate that the model has a good ability to distinguish between customers who have the potential to experience churn and customers who remain active. The model's ability to recognize customers who do not experience churn is also relatively good. This is reflected in the specificity value of 88.8%, which indicates that most loyal customers can be identified accurately. The model has proven to be effective in detecting churn risks and is able to maintain classification accuracy.

Table 3. Confusion matrix

	Positive	Negative	Total Actual
Positive	42 (TP)	8 (FN)	50
Negative	22 (FP)	176 (TN)	198
Total prediction	64	184	248

Note: TP = True Positive, FN = False Negative, FP = False Positive, TN = True Negative.

Table 4. Performance comparison of churn prediction models

Model	Accuracy (%)	Precision (%)	Recall (%)	AUC
Logistic regression	80.7	56.4	74.5	0.78
Decision tree	81.6	57.8	73.5	0.76
Random forest	86.2	62.6	82.1	0.85
Gradient boosting	87.9	65.6	84.0	0.88

Note: AUC = area under the curve.

Table 5. Cross-validation results

Model	Accuracy	Precision	Recall	AUC
GBT (Train-Test Split)	87.9	65.6	84.0	0.88
GBT (5-Fold CV)	88.2	66.1	84.2	0.89

Note: GBT = Gradient Boosting Tree, AUC = area under the curve.

Table 6. Performance metrics summary

Evaluation Metric	Formula	Result	Interpretation
Sensitivity (Recall)	$\frac{TP}{TP+FN}$	84.0%	Model ability to correctly detect customers who actually churn
Specificity	$\frac{TN}{TN+FP}$	88.8%	Ability to correctly identify loyal customers
Precision	$\frac{TP}{TP+FP}$	65.6%	Degree of accuracy between predicted churn cases and actual churn occurrences
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	87.9%	The model correctly predicts both churn and non-churn cases
F1-Score	$2 \times \frac{precision \times sensitivity}{precision + sensitivity}$	0.736	Balance between precision and sensitivity, reflecting classification effectiveness

Note: TP = True Positive, FN = False Negative, FP = False Positive, TN = True Negative.

The precision value of 65.6% indicates that not all customers predicted to experience churn actually stop transacting. There are still a number of customers who remain active but are classified as churn customers. This condition is acceptable because the model is still able to provide predictive results. This classification error has the potential to cause retention programs to loyal customers. As a result, some of the resources allocated to retain customers are not used optimally. The high recall value indicates that the model is more effective in identifying customers who have potential to experience churn. The F1-score of 0.736 indicates a good balance between the model's ability to detect churn cases and its ability to reduce misclassification errors. These results indicate that the model performs well in terms of accuracy. Based on the test results, the model is reliable to support data-driven decision-making.

The study evaluates model performance using Cohen's Kappa statistics to measure classification reliability. The testing showed a Kappa value of 0.72. Based on the established scale [16], this value showed a substantial agreement level. This finding indicates that high model performance is not the result of class imbalance. Based on the performance testing, this reflected the algorithm's ability to extract valid predictive patterns from customer behavior variables.

This finding showed that gradient boosting has proven effective in predicting customer churn. The GBT model was shown to have achieved the highest accuracy rate of 87.9% among the evaluated models. An AUC value of 0.88 proved to significantly surpass the performance of a single decision tree. A precision rate of 65.6% shows that there are still several false positives, namely customers who are predicted to experience churn but actually remain loyal. This phenomenon is a common challenge in modeling nonlinear human behavior.

The model's ability to find customers who are truly at risk of leaving the company is a very important factor in predicting customer churn. Recall is often used as a key metric in model evaluation. The higher the recall value, the greater the company's chances of recognizing customers who show indications of stopping transactions. This ability is needed by the company before consumers really switch. This condition helps companies reduce risk of customer loss.

The precision value does not always have to be at a very high level to be able to provide benefits for MSMEs. In many cases, precision in the range of 60–70% is still considered adequate. These considerations arise because the costs incurred to provide promotions or incentives to customers who are not actually at risk of churn are generally relatively small. Failure to detect customers who are actually about to leave the company can result in greater losses resulting from lost opportunities to maintain revenue in the future.

The study findings show the advantages of an ensemble learning approach in modeling customer behavior. Compared to conventional classification methods, this approach is better able to capture complex and not always linear relationship patterns. The combination of several learning models allows the process of identifying customer characteristics to be carried out in more depth, so that the relationship between variables can be better understood. These capabilities contribute to improved prediction accuracy and result in more reliable models to support business decision-making.

The confusion matrix analysis results show that each form of misclassification has a different impact on business activities. False positive errors arise when customers who are actually still active are categorized as customers who have the potential to experience churn. This situation can cause companies to run promotional or retention programs for customers that do not require special intervention, resulting in less-than-optimal use of budgets and resources.

A false negative error occurs when a customer who is at risk of leaving company is not successfully detected by the model. Compared to false positives, this type of error has greater consequences. This is because companies lose the opportunity to take retention actions before customers stop transacting. If this condition occurs, the potential income that should still be maintained is at risk of being lost. Based on the test results, the relatively small number of false negatives suggests that the model is able to recognize the vast majority of customers who have a tendency to churn. These findings indicated that the model is effective enough to be applied in support of customer retention programs. Companies can easily determine which customer groups need to be prioritized in maintaining customer relationships.

The findings of this study are consistent with various machine learning studies that explain decision tree model limitations. The model is known to be quite sensitive to small changes in data and prone to overfitting. This happens when the decision tree grows too complex or when the distribution of classes in the dataset is unbalanced. This condition can reduce the model's ability to produce accurate predictions on new data. The GBT approach offers a solution to these weaknesses through a gradual learning process that is carried out iteratively. At each stage, a new tree is built to correct any remaining prediction errors from the previous tree. The model is able to examine the relationships between complex variables, including non-linear patterns. This is done without sacrificing the ability to generalize to data that has never been studied before. The results are in line with previous research that boosting-based methods, such as GBT and XGBoost, tend to produce lower error rates than using a single decision tree model. This advantage can be observed in consumer behavior data in service sector.

MSME transaction data can be analyzed periodically to produce a churn probability score for each customer. This information can be used by management and Customer Relationship Management (CRM) systems to identify customers who are at high risk of leaving the company. Based on the results, companies can develop more targeted retention programs, for example through personalized promotional offers. Special incentive strategies or other marketing approaches can be carried out according to customer characteristics. The developed model allows application to batch-based data processing environments and can be integrated with various business intelligence systems [17]. The integration provides support for faster, data-driven decision-making processes. Integrations help companies anticipate potential churn before it impacts a decline in customer numbers and revenue.

Gradient boosting is more suitable for structured tabular data because it does not require excessive computational resources. Gradient boosting tends to be particularly suitable when the number of input features is relatively limited. The gradient boosting model implementation is feasible in MSME environments that have limited resources. This model can be implemented in batch processing, where transaction data is processed to generate churn predictions.

The development of ensemble boosting models continues to experience significant progress in improving customer churn prediction accuracy. One example is the Enhanced Gradient Boosting Model (EGBM), which uses a Support Vector Machine with a Radial Basis Function kernel (SVM-RBF) as the base learner. The model applies an exponential loss function to improve the learning process in the Gradient Boosting Machine (GBM) [18]. Gradient boosting models are able to produce more accurate predictions than linear models, decision trees, and random forests. This finding strengthens the position of gradient boosting as an effective machine learning approach for capturing relationships in non-linear data [19].

Empirical studies show that XGBoost achieves the highest testing accuracy, while conventional GBM produces more stable generalization ability. Boosting methods produce a simpler and more interpretable leaf-view structure. This is done while still maintaining important information at a higher level. Random forest models tend to produce a denser and more redundant concept lattice [20].

4. CONCLUSION

This study aims to assess the gradient boosting algorithm's ability to recognize customer churn patterns in the MSME sector in Indonesia. Based on the test results, the model produced an accuracy of 87.9%, specificity of 88.8%, recall of 84.0%, precision of 65.6%, and an F1-score of 73.6%. These achievements show that the model is able to maintain a balance between successfully detecting customers who have the potential to leave the company and the ability to reduce misclassification. A high recall value indicates that most customers at risk of churn can be properly identified. There are still several false positive predictions, which are reflected in the precision value, so the efficiency aspect in the retention program implementation still needs to be considered.

The heatmap analysis results provide an overview of the relationship between purchasing behavior and churn tendencies. The findings show that customers with lower transaction frequencies tend to have a greater risk of stopping transactions. This information can be used by MSMEs to carry out early detection of potential churn customers. Marketing strategies and retention programs can be structured more effectively.

Interpretation of the research results should consider the data scope. The analyzed dataset comes from MSMEs in specific regions, so the findings are not able to provide a whole picture the MSMEs' condition in Indonesia. Further research needs to test the model on external datasets from various business sectors to ensure the model's generalizability and evaluate the consistency of its performance outside the current research environment.

This study has limitations because it only used three RFM-based transactional variables: recency, frequency, and monetary value. Although these variables are effective in identifying customer purchasing patterns, they do not fully capture the complexity of customer behavior. Future research could consider adding behavioral and marketing variables, such as customer interaction level, response to promotions, digital activity, and customer satisfaction, to improve churn prediction model generalizability.

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