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Comparative Analysis of Classification Algorithms for Predicting Membership Churn in Fitness Centers: Case Study and Predictive Modeling at EightGym Indonesia

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Abstract

The fitness industry in Yogyakarta is experiencing rapid growth accompanied by intense competition among gym service providers. This has led to an increase in membership churn, negatively impacting business sustainability. This study aims to conduct a comparative analysis of three supervised classification algorithms Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) to predict member churn at EightGym Indonesia. The dataset, consisting of 1,287 membership records collected between July 2024 and April 2025, includes features such as visit frequency, subscription duration, membership type, and churn status. The study focuses on predicting members at risk of subscription cancellation using historical data such as visit frequency, subscription duration, membership type, and churn status. The methodology follows the CRISP-DM framework, covering business understanding, data preparation, modeling, evaluation, and deployment stages. Evaluation results indicate that XGBoost delivers the best performance with 95% accuracy, high recall, and F1-score, making it the most effective algorithm for churn prediction in this context. Additionally, the model was implemented in a web-based prototype application to support gym management decision-making. The findings contribute significantly to the application of machine learning for customer retention strategies in the fitness industry and provide a foundation for the future development of predictive decision support systems.

Keywords: Gym churn prediction, fitness industry, Random Forest vs SVM vs XGBoost, customer retention, machine learning for gyms.

1. INTRODUCTION

Cancer remains one of the leading causes of mortality worldwide. According to a report by CA: A Cancer Journal for Clinicians, an estimated 2,041,910 new cancer cases and 618,120 cancer-related deaths are projected to occur in the United States in 2025. Although cancer mortality rates have been consistently declining since 1991, significant disparities persist, particularly among certain racial and ethnic groups [1]. Globally, the burden of cancer is projected to increase substantially. A

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study published in JAMA Network Open projects that by 2050, the number of cancer cases will reach 35.3 million, a 76.6% increase from 20 million cases in 2022, while cancer-related deaths are expected to rise by 89.7% during the same period [2]. Meanwhile, Indonesia's National Cancer Control Plan 2024–2034 reports that the country's cancer burden is expected to increase in line with global trends, from 396,914 new cases and 234,511 deaths in 2020 to approximately 819,847 cases and 552,318 deaths in 2040, representing more than a twofold increase over the next two decades [3].

Several risk factors have been identified as significant contributors to cancer incidence. Research by the American Cancer Society reveals that approximately 40% of cancer cases and 44% of cancer deaths in the United States are attributable to modifiable risk factors such as smoking, excess body weight, alcohol consumption, ultraviolet radiation exposure, and physical inactivity [4]. Conversely, healthy lifestyle behaviors that can reduce cancer risk include a balanced diet, weight management, regular exercise, reduced alcohol consumption, and smoking cessation [5]. Unhealthy lifestyle habits such as tobacco smoke exposure, alcohol consumption, high body mass index (BMI), physical inactivity, and poor dietary choices are associated with increased cancer risk [6] Lifestyle modifications can substantially reduce the global cancer burden [7] According to the journal Lifestyle Factors and Cancer: A Narrative Review, at least 42% of newly diagnosed cancer cases in the United States are attributed to modifiable and therefore potentially preventable lifestyle factors [8]. Growing awareness of the importance of healthy living has motivated the Indonesian population to adopt more active lifestyles to prevent degenerative diseases such as cancer. Regular physical activity has been shown to reduce both cancer incidence and mortality, including among breast cancer patients [9].

This trend has driven growth in Indonesia's fitness industry, with the market projected to grow at a compound annual growth rate (CAGR) of approximately 12% between 2024 and 2029, reflecting increasing health awareness, particularly among younger generations [10]. However, the rapid expansion of the fitness industry has also intensified competition among fitness centers and gyms. Industry players now face challenges in maintaining customer loyalty as consumers are presented with a broader array of choices due to the emergence of new competitors offering diverse facilities at competitive prices. If not managed effectively, this situation may lead to higher customer churn rates, ultimately impacting business sustainability and profitability. According to global fitness industry data, average annual churn rates at fitness centers range between 30% and 50%, depending on the loyalty strategies and service quality implemented [11]. In Indonesia, small to medium sized gyms are more susceptible to churn due to limited resources and suboptimal utilization of predictive technologies to identify potential customer loss.

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Machine learning (ML) has demonstrated substantial potential in predicting customer behavior and identifying members at high risk of churn. Algorithms such as Random Forest, Support Vector Machine (SVM), and XGBoost have been widely employed in various studies to develop accurate churn prediction models. For instance, research by Sidiq and Anggraini (2023) found that XGBoost achieved the highest accuracy in customer churn classification compared to other algorithms [12]. However, a major challenge in churn prediction is class imbalance in the datasets, where the number of churned customers is much larger than those who remain. To address this issue, oversampling techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) have been applied to improve model performance. Zheng et al. (2024) demonstrated that combining XGBoost with SMOTE significantly enhanced prediction accuracy.

Additionally, compared the performance of Random Forest and XGBoost with various upsampling techniques, including SMOTE, ADASYN, and GNUS, under different class imbalance conditions. The results indicated that XGBoost with SMOTE yielded the best performance for churn prediction [13]. In the telecommunications sector, the application of Random Forest algorithms has achieved churn prediction accuracies of up to 98.1% [14]. In e-commerce, developed a hybrid churn prediction model integrating logistic regression and XGBoost, achieving over 85% accuracy [15]. This model demonstrated that hybrid approaches could enhance predictive performance. Meanwhile, highlighted the importance of model interpretability in churn prediction. They developed an explainable churn prediction model using Shapley values to identify the most influential features associated with churn [16]. Other studies, conducted comparative analyses of XGBoost, Random Forest, and Gradient Boosting, finding that XGBoost was not always the optimal choice in all conditions, as performance depends on parameters and dataset characteristics [17]. developed an analytical framework for detecting early signs of churn and generating a "Churn Score" for each customer, facilitating strategic decision-making for customer retention [18]. Evaluated various classification techniques for churn prediction and found that Random Forest and SVM performed well, particularly when combined with feature reduction techniques [19]. Employed an ensemble learning approach that included Random Forest and XGBoost for churn prediction in a fixed broadband company, demonstrating that these techniques improved predictive performance [20]. Furthermore, several researchers have shown that Random Forest outperforms traditional classification methods for customer churn prediction [21].

Thus, while many studies have applied machine learning algorithms for churn prediction across various industries, there remains a research gap in comparing the effectiveness of different classification algorithms specifically within the context of churn prediction in Indonesia's local fitness industry. This highlights a need for

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research that can assist fitness centers such as EightGym Indonesia in developing more effective data-driven retention strategies. EightGym Indonesia, located in Yogyakarta, is currently facing significant churn challenges amid rising market competition. Therefore, this study focuses on applying Random Forest, SVM, and XGBoost algorithms for membership churn prediction. The study also considers class imbalance handling techniques such as SMOTE to improve model accuracy. The results of this research are expected to provide practical insights for EightGym in identifying members at risk of churn and designing more effective retention strategies, while contributing to the academic literature on machine learning-based churn prediction in Indonesia's fitness industry.

2. METHODS

In this study, the data analyzed consists of membership data from EightGym Indonesia, covering the period from July 2024 to April 2025. The main source of data was collected firsthand from the study participants using methods such as observation, interviews, and written records [22]. The data was obtained from the internal membership management system used by the gym's management team and subsequently exported into Excel format for further analysis. The total dataset comprises 1.287 entries. The dataset was then split into two parts a training set and a testing set, with an 80:20 ratio to support the model building and algorithm performance evaluation processes.

The author uses the CRISP-DM (Cross Industry Standard Process for Data Mining) methodological approach as a framework in implementing the data mining process. CRISP-DM is a methodology that provides a general approach for structuring and planning data mining projects. Based on a survey, this methodology is reported as the most widely used in data science projects, with a usage rate of 49%, followed by Scrum and Kanban methodologies [23]. CRISP-DM consists of six main stages, namely business understanding, data understanding, data preparation, modeling, evaluation, and implementation. This framework was chosen because it provides a systematic and flexible flow in managing data, building predictive models, and gaining insights relevant to the problems being studied. In addition, CRISP-DM is an iterative approach and allows researchers to return to the previous stage if discrepancies or obstacles are found during the process. This approach is in accordance with the objectives of the study which focuses on the application of classification methods to fitness center membership data to support strategic decision making. Below is a flowchart illustrating the stages in the CRISP-DM methodology, providing a visual representation of the process flow applied in this study, can be seen in Figure 1.

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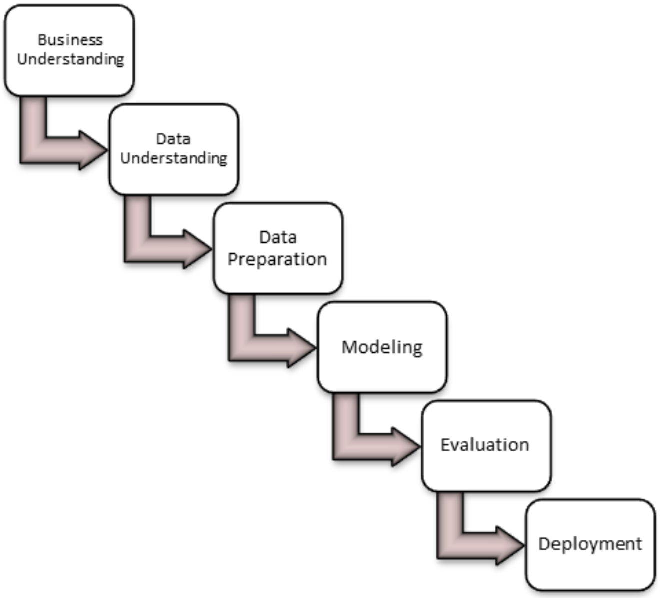

Figure 1. Flowchart CRIPS-DM

2.1. Business Understanding

The Business Understanding phase focuses on understanding the objectives and requirements of the project from a business perspective, and then converting this knowledge into a data mining problem definition, and a preliminary project plan designed to achieve the objectives [24]. In the study of membership churn at EightGym, the researcher collaborated with stakeholders, namely the gym management, to identify the business goals to be achieved through data analysis. This includes understanding the problems to be addressed, the opportunities to be explored, and how the analysis results can contribute positively to strategic decision-making. In this study, the business understanding that can be analyzed involves identifying the factors that influence membership churn and how marketing strategies can be adjusted to improve member retention. After obtaining a comprehensive understanding of the desired business objectives, the researcher then conducted a literature review of relevant journals as references to broaden insight and understanding regarding data mining methods and their application in this study.

2.2. Data Understanding

Data Understanding is the phase aimed at gaining an initial understanding of the data that will be used in the analysis process. In this phase, the researcher collected data relevant to the membership churn case at EightGym. Once the data had been

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gathered, a data validity check was conducted to ensure that the data were valid, complete, and suitable for further analysis. The researcher then analyzed the attributes and parameters that could potentially influence the prediction of membership churn. Additionally, the characteristics of the data such as distribution, data types, and missing values were examined. Finally, a manual calculation was performed to compare the number of members who churned and those who did not, in order to gain an initial understanding of the churn proportion in the dataset.

2.3. Data Preparation

Data Preparation is the phase in which the collected data is processed and cleaned to be ready for the modeling stage. In this phase, the researcher carried out several data preparation steps, starting with the removal of the ID column, which did not contribute significantly to the analysis process. Then, the data type of the date column was converted into the datetime format to facilitate time-based data manipulation. The researcher also changed the data types of the promo, personal trainer (PT), category, and churn columns to string types to reflect their categorical nature. After data cleaning and type conversion were completed, a visualization was performed to observe the distribution of churned and non-churned members. Finally, since an imbalance in the churn data was identified, the researcher applied the Synthetic Minority Over-sampling Technique (SMOTE) to balance the number of instances between the churn and non-churn classes prior to the modeling phase.

Tabel 1. Sample of Membership Dataset (First and Last 5 Records)

ID	Category	Promo	Duration	Company	Transaction	Churn
1719795956	Student	No	1	No	01-01-2025	Yes
1719800304	Regular	No	1	No	01-01-2025	Yes
1716723055	Student	No	10	No	01-01-2025	Yes
1697593594	Regular	No	14	No	01-01-2025	Yes
1707098995	Regular	No	13	No	01-01-2025	Yes

Figure 2 presents the descriptive statistics of the dataset, including membership ID and membership duration. The duration variable shows a range from 1 to 23 months, with a median of 7 months, indicating a moderate spread of membership periods. These statistics were also utilized to inspect potential outliers, which were found to be within reasonable business limits and therefore retained for analysis.

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```
count   1.286000e+03  1287.000000
mean    1.717652e+09     7.176379
std     6.272883e+07     5.129805
min     1.705127e+08     1.000000
25%     1.707366e+09     3.000000
50%     1.721969e+09     7.000000
75%     1.731269e+09    10.000000
max     1.743589e+09    23.000000
```

Figure 2. Descriptive Statistics and Outlier Inspection

Figure 3 illustrates the initial distribution of churned and non-churned members in the dataset. Approximately 66.36% of members had churned while 33.64% remained active, indicating an imbalanced dataset that required balancing techniques such as SMOTE during preprocessing to improve classification performance.

```
Churn
Yes     0.663559
No      0.336441
Name: proportion, dtype: float64
```

Figure 3. Churn Distribution Before Balancing

Figure 4 shows a sample of the dataset after preprocessing, where categorical features have been encoded numerically for machine learning processing. The features include Category, Promotion, Duration, Personal Trainer usage, Transaction Date, and Churn status. The lower part of the figure displays the class distribution after applying the Synthetic Minority Over-sampling Technique (SMOTE), resulting in a perfectly balanced dataset with 597 churned and 597 non-churned members.

```
0         5       1        1   0        01-01-2025       1
1         3       1        1   0        01-01-2025       1
2         5       1       10   0        01-01-2025       1
3         3       1       14   0        01-01-2025       1
4         3       1       13   0        01-01-2025       1
Distribusi setelah SMOTE:
Churn
1    597
0    597
Name: count, dtype: int64
```

Figure 4 Dataset After Preprocessing and SMOTE Balancing

2.4. Modeling

In the evaluation phase of the CRISP-DM process, the performance of three classification models, namely Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost), is assessed to predict membership

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churn at EightGym. Each model is trained using an approach tailored to its algorithmic characteristics. According to a research journal entitled Comparison of SVM, Random Forest, and XGBoost Algorithms for Credit Application Approval Determination,/ it is stated that compared to other classification techniques, Support Vector Machine (SVM) possesses a more well-developed mathematical foundation, enabling it to effectively handle both linear and non-linear classification problems. The working principle of SVM is to classify data into two groups by determining an appropriate hyperplane . The function that is maximized as shown in Equation 1.

$$L_d=\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\alpha_i\sum_{j=1}^{N}\alpha_i\ y_j\ K(x_i,x_j) \tag{1}$$

For Random Forest, training is performed by building multiple decision trees based on random subsets of the training data and features, with the final prediction determined through majority voting . The final prediction formula for Random Forest as shown in Equation 2.

$$Q(x,j)=\sum_{k} I\,(h(x,\theta_k)=j;(y,\mathbf{x})\notin T_{k,B} / \sum_{k} I\,((y,x)\notin T_{k,B} \tag{2}$$

where $Ti(x)$represents the prediction from the i-th tree, and n is the total number of trees. Meanwhile, Extreme Gradient Boosting (XGBoost) is a popular method in machine learning for prediction and data analysis. XGBoost combines ensemble learning techniques with boosting algorithms to produce accurate prediction models. The XGBoost algorithm works by combining a small number of simple decision trees, called "weak learners", to form a complex and robust model [25]. The general formula for the XGBoost algorithm as shown in Equation 3.

$$y_i=\emptyset(x_i)=\sum_{k=1}^{K} f_k\,(x_i) \tag{3}$$

where F is the function space of all decision trees, and K is the total number of trees.

The evaluation of these three models uses various metrics such as accuracy, precision, recall, F1-score, ROC AUC, and cross-validation AUC, to determine the effectiveness of the models in distinguishing between churned and non-churned members. The ROC curve is used to evaluate the model's sensitivity through the calculation of the True Positive Rate (TPR) and False Positive Rate (FPR), with the formulas as shown in Equation 4 and 5.

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$$\text{TPR}=\frac{\text{TP}}{\text{TP+FN}} \tag{4}$$

$$\text{FPR}=\frac{\text{FP}}{\text{FP +TN}} \tag{5}$$

The evaluation results are then compared to select the best model that achieves a balance between prediction accuracy and the ability to generalize to new data.

2.5. Evaluation

In the evaluation phase, an assessment was conducted on the performance of the three classification models developed during the modeling phase, namely Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost). The primary objective of this phase is to determine which model is most effective in predicting membership churn at EightGym and to evaluate the extent to which each model is capable of generalizing to new, unseen data. The evaluation was carried out using several classification performance metrics, including:

1) Accuracy: Measures the proportion of correct predictions over the total data.
2) Recall: Measures the proportion of actual churned members that are successfully identified.
3) F1-score: The harmonic mean of precision and recall, providing a balanced view of model performance.

The evaluation results indicated varying levels of performance across the models. The SVM model, after being standardized using the StandardScaler method, demonstrated reasonably good performance, particularly in recall, which reached a very high level (close to 1.0). This indicates that the model is highly effective in identifying members who are likely to churn. However, its accuracy and F1-score were comparatively lower than those of the other models, suggesting potential overfitting or an imbalance in class prediction. The Random Forest model exhibited more stable predictions, with relatively high accuracy and recall, due to its ensemble approach based on majority voting across multiple decision trees. This model achieved more balanced performance, with recall and F1-score both exceeding 0.8 and accuracy around 0.74. These results suggest that Random Forest is reliable in capturing churn patterns without significantly compromising overall accuracy. Among the three classification algorithms evaluated, the XGBoost model emerged as the best-performing model overall, with accuracy, recall, and F1-score all exceeding 0.93. This indicates that the model is not only highly accurate but also maintains consistency between correctly identifying churn and the overall quality of predictions.

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In addition to quantitative performance, result interpretation was also considered, including a feature importance analysis to identify which variables contributed most significantly to churn. The XGBoost model also provides deeper interpretability regarding decision structures, thereby supporting more informed business decision-making in the future. Based on the overall evaluation results and the consideration of generalization capabilities, XGBoost was selected as the most suitable model for implementation in the next phase. This model offers a strong balance of high accuracy, resistance to overfitting, and sufficient interpretability.

2.6. Deployment

The deployment phase represents the final stage in the data mining process, where the model that has undergone training and evaluation is applied in a real world usage context. At this stage, the primary focus is on integrating the analytical results into a system or interface that can be utilized by stakeholders to support data driven decision making.

In the context of this study, the best-performing classification model XGBoost was implemented into a simple web-based microframework. This microframework was designed with the primary objective of presenting churn prediction results in a direct and accessible manner. During the initial testing phase, the framework was used as a prototype to evaluate the usability and predictive effectiveness of the model in practical scenarios, such as identifying members at high risk of churn based on their profile and activity data. The primary goal of this deployment phase is not limited to technical implementation, it also serves as a foundation for the development of a more comprehensive and integrated system in the future. With the availability of this prototype, relevant stakeholders, specifically EightGym Indonesia, can conduct further validation, iteratively improve the system based on user feedback, and plan more proactive and targeted customer retention strategies based on the generated predictions. This figure illustrates the web-based dashboard framework developed to integrate the predictive model into operational decision-making. The dashboard provides user-friendly access to churn prediction results, allowing gym management to monitor at-risk members in real-time and to support data-driven retention strategies.

Figure 5 and Figure 6 presents a sample output of churn prediction results generated by the implemented model. The system identifies members at high risk of churn based on input data such as membership duration, visit frequency, personal trainer usage, and promotional participation.

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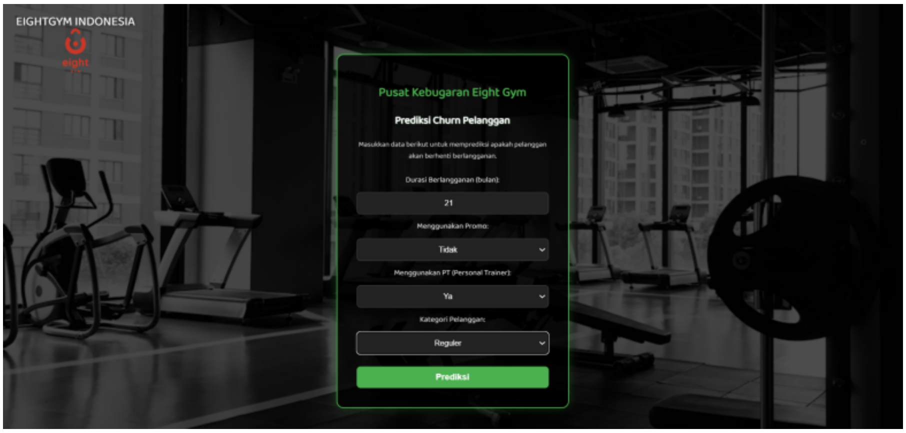

Figure 5. Web-Based Dashboard Framework for Churn Prediction System

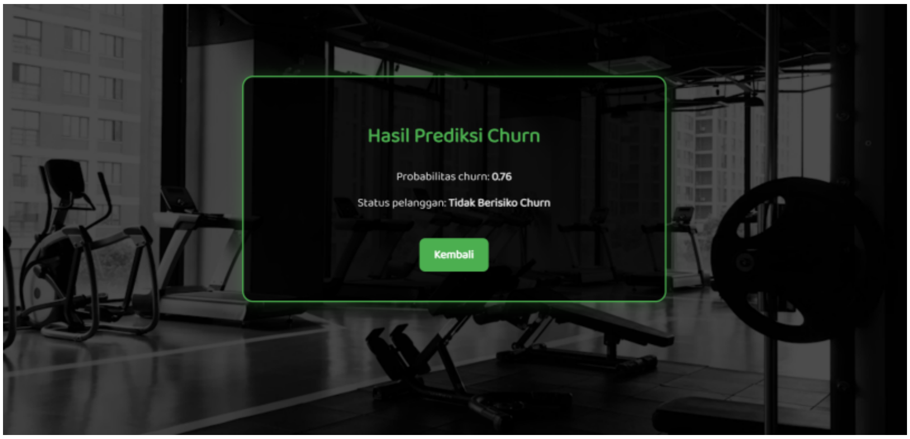

Figure 6. Example of Churn Prediction Results Displayed on the Dashboard

2.7. Hyperparameter Tuning and Model Optimization

In order to achieve optimal predictive performance, hyperparameter tuning was conducted for the three classification algorithms employed in this study, namely Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). The tuning process was systematically performed using the grid search approach, combined with 10-fold cross-validation to ensure model stability across various data subsets. For the Support Vector Machine (SVM) algorithm, several parameter combinations were tested, including the radial basis function (RBF) as the kernel function. The regularization parameter C was examined at values of 0.1, 1, and 10, while the gamma parameter was evaluated at 'scale', 0.1, and 0.01. Based on the grid search results, the optimal configuration

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was obtained at C = 1 and gamma = 'scale'. For the Random Forest algorithm, variations were applied to the number of decision trees (n_estimators) with values of 50, 100, and 200; maximum tree depth (max_depth) at 5, 10, and 20; and minimum samples split at 2 and 5. The best-performing combination was found at n_estimators = 100, max_depth = 10, and min_samples_split = 2, offering a balanced trade-off between model complexity and the risk of overfitting. For the Extreme Gradient Boosting (XGBoost) algorithm, tuning was performed on several core parameters, including learning rate (0.01, 0.1, and 0.2), number of estimators (n_estimators: 50, 100, 200), maximum tree depth (max_depth: 3, 5, 7), and subsample ratio (0.6, 0.8, 1.0). According to the grid search results, the optimal configuration was obtained at learning_rate = 0.1, n_estimators = 100, max_depth = 5, and subsample = 0.8.

Through this tuning process, each algorithm was adjusted to operate optimally according to the characteristics of the EightGym Indonesia churn dataset. This optimization process has been demonstrated to improve both the stability and predictive accuracy of the models, while simultaneously reducing the risk of overfitting.

3. RESULTS AND DISCUSSION

3.1. Experimental Performance

The results of the data analysis process are presented in accordance with the methodology previously described. The preprocessed data were analyzed using three classification algorithms: Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost). Each model was evaluated using performance metrics including accuracy, precision, recall, and F1-score to assess the reliability of the predictions in classifying members who are likely to churn and those who are likely to remain active.

The evaluation results revealed performance variations among the three models used. The SVM model yielded an accuracy of 0.63, with the highest F1-score of 0.68 for the churn class (1), indicating that while the model is relatively sensitive in detecting members who are likely to churn, its precision and inter-class balance remain suboptimal. Subsequently, the Random Forest model demonstrated improved performance, achieving an accuracy of 0.74 and an F1-score of 0.81 for the churn class. This suggests the model's capability to capture data patterns in a more stable and balanced manner. On the other hand, the XGBoost model performed the best overall, with an accuracy of 0.95 and an F1 score of 0.96 for the churn class, indicating that the model is very effective in providing accurate and consistent classification across all classes.

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Based on the overall performance evaluation, the XGBoost algorithm has the ability to provide the most accurate, balanced, and consistent prediction results in identifying members at risk of churn. This model achieved an accuracy of 95%, which is much greater than Random Forest (74%), and Support Vector Machine (63%). These results indicate that XGBoost not only excels in prediction accuracy but also provides good interpretability features through feature importance analysis. Variables such as frequency of visits, membership period, and the presence of a personal trainer (PT) were found to have a significant effect on the probability of churn. This information is very useful for EightGym management in developing a more personalized and data-driven retention strategy. Considering all evaluation metrics, model generalization to new data, and feature interpretation, XGBoost was selected as the best model to be applied to the business decision support system. This model not only provides high accuracy, but also provides deep insights that support strategic decision making.

Table 1. Accuracy Results

Model	Precision	Recall	F1-Score	Accuracy
SVM	79%	60%	68%	63%
Random Forest	80%	82%	81%	74%
XGBoost	96%	96%	96%	95%

The ROC curve graph is also used to broadcast the sensitivity of each model. XGBoost has a larger area under the curve (AUC) than the other two models, indicating its superior ability to distinguish between churned and non-churn members.

The evaluation results show significant performance variations among the three classification algorithms used to predict member churn at EightGym Indonesia. The XGBoost model emerged as the best-performing algorithm, achieving an accuracy of 95%, with recall and F1-score both reaching 96%. The superior performance of XGBoost is attributed to its ability to iteratively combine a series of weak decision trees (boosting), resulting in a more complex and accurate model capable of capturing nonlinear and heterogeneous data patterns. Additionally, important features analyzed in this model such as visit frequency, membership duration, and use of a personal trainer provide valuable insights for gym management to understand the key factors influencing churn.

Compared to Random Forest, which achieved 74% accuracy and an F1-score of 81%, and SVM, with 63% accuracy and an F1-score of 68%, XGBoost better handles data imbalance and variable complexity while demonstrating high stability in predictions. This aligns with previous research highlighting XGBoost's advantages in churn prediction across various industries such as

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telecommunications and banking, while this study strengthens its relevance specifically within the fitness industry, which has unique characteristics.

The practical implications of these results are significant for EightGym Indonesia. With accurate churn predictions, management can identify high-risk members earlier and design more targeted retention strategies. For example, incentive programs or personalized services can be directed towards members detected as potential churn risks, thereby enhancing loyalty and extending membership duration. Moreover, the web-based prototype application developed based on this model provides a direct tool for real-time monitoring and data-driven decision-making. Overall, this study makes a substantial contribution by applying advanced machine learning techniques in the fitness domain, expanding the churn prediction literature, and offering practical solutions that can be adopted by other fitness centers facing similar challenges. The study also opens opportunities for developing hybrid models or integrating additional data types such as psychographic and social data to further improve prediction accuracy in the future.

The ROC curve for the SVM model demonstrates the trade-off between sensitivity (true positive rate) and specificity (false positive rate) in classifying churn and non-churn members. The SVM model shows moderate performance with an AUC that indicates limited discriminative ability compared to other models.

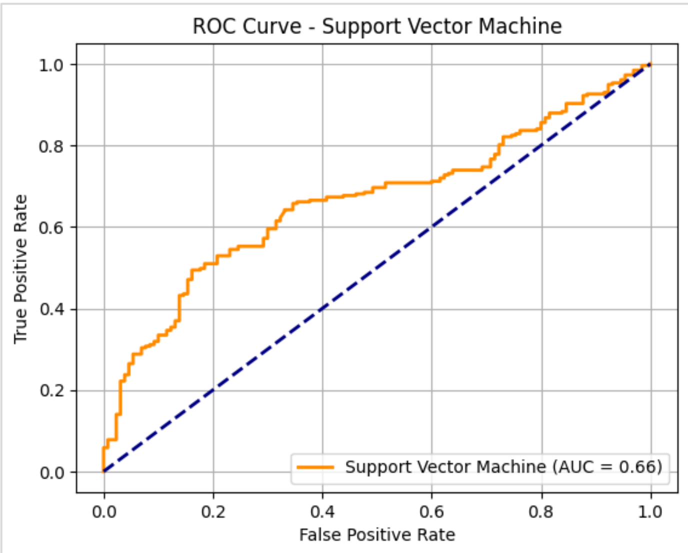

Figure 7. ROC Curve of Support Vector Machine (SVM) Model

The ROC curve for the Random Forest model exhibits improved classification performance compared to SVM. The model achieves a larger AUC, reflecting better capability in correctly distinguishing churn and non-churn members.

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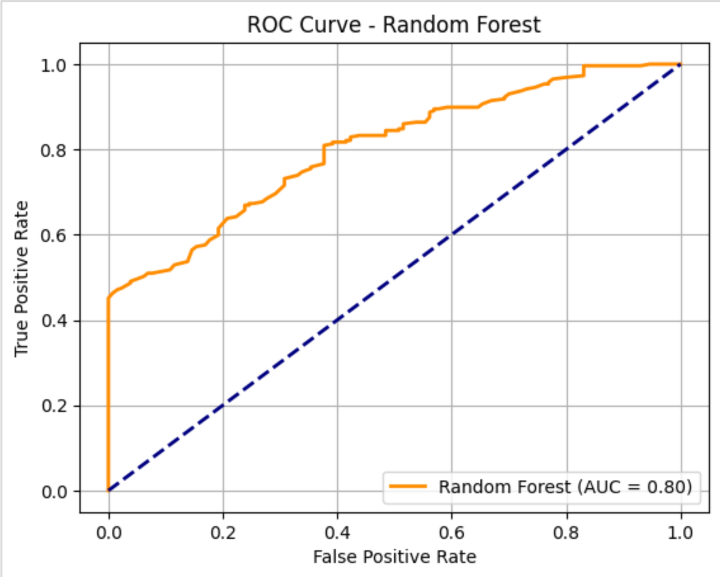

Figure 8. ROC Curve of Random Forest Model

The ROC curve for the XGBoost model demonstrates superior classification performance, with the largest AUC among all models evaluated. This indicates that XGBoost achieves the highest discriminative ability in predicting churn membership in this study.

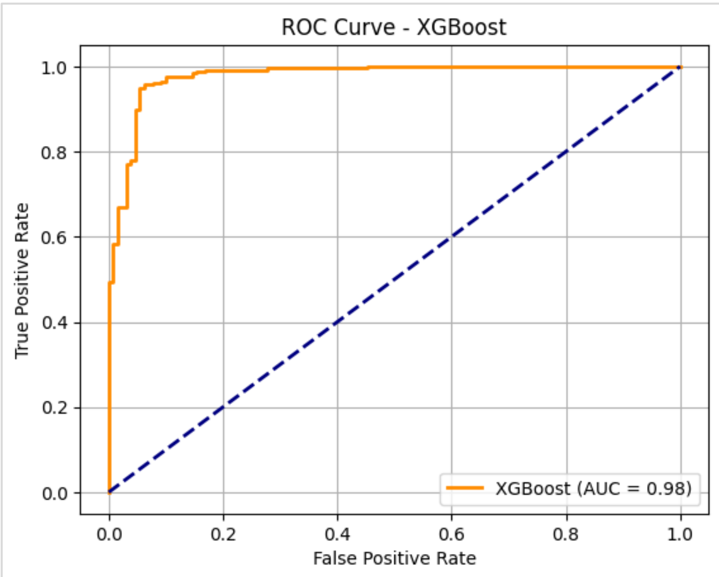

Figure 9. ROC Curve of Extreme Gradient Boosting (XGBoost) Model

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Figure 10 summarizes the comparative evaluation results across all three algorithms (SVM, Random Forest, XGBoost) based on multiple performance metrics including accuracy, precision, recall, and F1-score. XGBoost outperforms the other models across all evaluation measures.

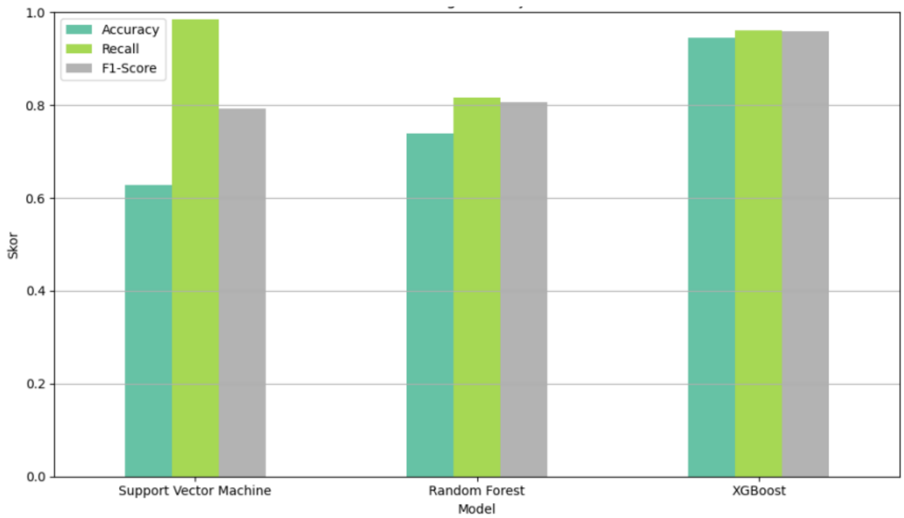

Figure 10. Comparative Performance of Classification Algorithms

3.2. Discussion

The evaluation results reveal substantial performance disparities among the three classification algorithms used to predict member churn at EightGym Indonesia. The XGBoost model achieved the highest predictive performance, with an impressive accuracy of 95% and both recall and F1-score reaching 96%. This superior performance stems from XGBoost's ability to sequentially build an ensemble of weak learners through gradient boosting, allowing it to capture complex, nonlinear patterns inherent in gym membership behavior—such as nuanced interactions between visit frequency, membership duration, and additional services like personal training.

In comparison, the Random Forest model demonstrated moderate success with an accuracy of 74% and an F1-score of 81%. While it outperformed the Support Vector Machine (SVM)—which recorded only 63% accuracy and an F1-score of 68%—Random Forest still struggled to match XGBoost in modeling the subtle relationships within the dataset. SVM's performance, marked by limited discriminative ability (evident in its ROC curve with lower AUC), reflects its constraints in handling imbalanced datasets and capturing complex feature interactions.

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The ROC curves for all models illustrate these differences in discriminative capability. Specifically, the ROC curve for XGBoost (Figure 9) exhibits the largest Area Under the Curve (AUC), clearly indicating its superior ability to distinguish between members who are likely to churn and those who will remain active. This finding is reinforced by the comparative performance metrics summarized in Table 1 and Figure 10, where XGBoost consistently outperforms SVM and Random Forest across precision, recall, and F1-score.

Beyond predictive accuracy, XGBoost's feature importance analysis provides actionable insights for EightGym management. Variables such as frequency of visits, length of membership, and the use of personal trainers emerged as the most influential predictors of churn. This information equips decision-makers with a clearer understanding of members' engagement patterns, enabling them to develop more effective, personalized retention strategies—such as targeted incentives or customized workout plans for at-risk members.

However, this study is not without limitations. Firstly, the dataset comprises only 1,287 entries sourced exclusively from EightGym Indonesia, which may limit the generalizability of the findings to other fitness centers with different customer demographics or operational models. Secondly, the current analysis focuses solely on historical behavioral data; it does not incorporate psychographic variables or social interaction data, which could provide a deeper understanding of members' motivations and social influences driving churn. Thirdly, while a web-based prototype application implementing the XGBoost model was developed and technically validated, comprehensive user evaluations involving gym staff and management stakeholders have yet to be conducted to assess its real-world practicality and user-friendliness.

Despite these limitations, the results offer significant practical implications. Accurate churn prediction allows EightGym to proactively identify high-risk members, implement timely retention interventions, and ultimately reduce membership attrition—thereby enhancing long-term business sustainability in Yogyakarta's competitive fitness industry. Moreover, the web-based application built upon the XGBoost model provides a practical decision-support tool that enables gym managers to monitor churn risk in real time and take immediate action.

The broader contribution of this study lies in extending the application of advanced machine learning methods, particularly XGBoost, to the fitness industry—a domain where churn has historically been challenging to predict. This research not only reinforces findings from other sectors (e.g., telecommunications, banking) where XGBoost has shown high predictive performance, but also highlights its adaptability to the unique patterns of fitness memberships. Future

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research could build upon this work by incorporating more diverse data sources—such as social engagement, customer feedback, and lifestyle habits—to enrich predictive models and by systematically evaluating the prototype's usability and impact on business outcomes.

In conclusion, XGBoost has proven to be the most reliable, accurate, and insightful model for predicting gym membership churn in this context. By integrating predictive analytics into decision-making processes, EightGym Indonesia—and potentially other fitness centers—can enhance their ability to retain members, improve customer satisfaction, and strengthen their competitive positioning in a rapidly evolving market.

4. CONCLUSION

This study developed and evaluated a predictive model for gym membership churn at EightGym Indonesia using the CRISP-DM framework. Three classification algorithms SVM, Random Forest, and XGBoost were tested, with XGBoost achieving the best results at 95% accuracy and excellent recall and F1-score, making it the most effective for identifying members at risk of churn. These findings highlight XGBoost's strength in handling imbalanced and complex data, offering actionable insights into key factors driving member attrition. The deployment of a web-based prototype demonstrates the model's potential for practical application, enabling EightGym to implement data-driven, proactive retention strategies. Future research should explore integrating psychographic and social data, as well as developing real-time prediction systems, to further enhance model accuracy and usefulness in managing member churn.

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