**Comparative Evaluation of Machine Learning Algorithms for Customer Churn Prediction**

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***Abstract*— In the competitive landscape of subscription-based services, retaining customers is critical to sustaining growth and profitability. Predicting customer churn—the likelihood of a customer leaving a service—is a key business objective. This study investigates multiple machine learning algorithms to classify customer churn using a dataset comprising demographic and behavioral attributes such as age, tenure, support interactions, subscription type, and total spend. The models were evaluated on diverse set of classifiers, including Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, XG Boost, Gaussian Naive Bayes, Quadratic Discriminant Analysis, Ridge Classifier, Passive Aggressive Classifier, Bagging, Extra Trees, and Multilayer Perceptron (Shallow Neural Network). Each model is trained and tested on the dataset using an 80–20 train-test split. Performance is compared using a comprehensive set of metrics: accuracy, precision, recall, F1-score, ROC AUC, specificity, balanced accuracy, Matthews Correlation Coefficient (MCC), and training time. Results show that ensemble-based methods significantly outperform traditional classifiers. The Bagging Classifier achieved the highest performance with a 99.7% accuracy and perfect ROC AUC, indicating exceptional predictive power. Boosting models like Gradient Boosting and AdaBoost also delivered strong results with accuracy above 96%. The findings underline the importance of ensemble learning for churn prediction and provide insights into selecting models based on prediction quality and execution time. This research supports business stakeholders in making informed decisions about customer retention strategies through data-driven approaches.**

***Index Terms —******Customer churn prediction, ensemble learning, machine learning, classification algorithms, gradient boosting, bagging, ROC AUC, model comparison.***

I. INTRODUCTION

*A. Background*

In the modern telecommunications industry, retaining existing customers is a strategic imperative. The cost of acquiring a new customer is significantly higher compared to retaining a current one — often quoted as being five times more expensive. Consequently, accurately predicting which customers are at risk of churning (i.e., leaving the service) has become a top priority for telecom service providers. Machine learning (ML) methods offer data-driven approaches to tackle this problem, enabling service providers to identify at-risk customers and take Preemptive actions.

However, churn prediction is inherently challenging due to the imbalance in class distributions — typically, a small fraction of customers actually Churn. Standard ML models often struggle in such cases, showing high overall accuracy but poor sensitivity to the minority class (churners), which is the class of greatest interest in this problem.

*B. Problem Description*

Despite the abundance of machine learning techniques, businesses often struggle with selecting the most effective model for churn prediction. Traditional models such as logistic regression offer simplicity and interpretability but may fall short in predictive performance. On the other hand, complex models like ensemble classifiers can capture non-linear relationships and deliver high accuracy, but at the cost of interpretability and longer training times.

This project addresses the challenge of model selection by conducting a comparative study of several machine learning classifiers on a publicly available churn dataset. Each model’s performance is evaluated across a variety of statistical metrics to determine which provides the best balance between accuracy, robustness, and efficiency.

*C. Objectives*

The main objectives of this project are:

1. To build predictive models that classify whether a customer will churn or not, based on historical and behavioral data.
2. To evaluate and compare the performance of various machine learning algorithms using metrics such as accuracy, precision, recall, F1-score, ROC AUC, specificity, balanced accuracy, Matthews Correlation Coefficient (MCC), and training time.
3. To identify which algorithms are best suited for churn prediction in terms of predictive power and computational feasibility.

*D. Layout of the Paper*

1) **Section II** presents a brief overview of related work in the

field of churn prediction using machine learning.

2) **Section III** describes the dataset used, its features, and preprocessing techniques applied.

3) **Section IV** outlines the methodology, including the machine learning models selected for evaluation.

4) **Section V** details the experimental setup and presents the comparative performance results of all models.

5) **Section VI** provides a discussion on the findings, highlighting key insights and practical implications.

6) **Section VII** concludes the paper and outlines possible future work.

II. LITERATURE REVIEW

Customer churn prediction is a longstanding and critical problem in domains with subscription-based services, especially in telecommunications. Churn refers to the phenomenon where customers discontinue using a company's service, causing potential revenue loss. According to Reichheld and Sasser [1], increasing customer retention by just 5% can boost profits by 25% to 95%, illustrating the importance of proactive churn management. Consequently, predictive modeling has become a strategic tool for identifying likely churners in advance, enabling companies to implement timely retention strategies.

Early research on churn detection predominantly utilized statistical and econometric models, such as logistic regression and survival analysis [2], valued for their simplicity and interpretability. These models assume linear relationships and independence between predictors, limiting their applicability in complex real-world scenarios. As customer data grew in scale and complexity, especially with the rise of big data from telecom sources, the need for more sophisticated machine learning models became evident. Logistic regression still serves as a useful baseline, but researchers began leveraging non-linear models capable of capturing intricate interactions in high-dimensional data.

In the last decade, machine learning has gained prominence in churn prediction due to its ability to learn non-linear patterns and adapt to noisy, heterogeneous data. Supervised learning methods such as Decision Trees, Support Vector Machines (SVM), Random Forests, Gradient Boosting, and Neural Networks have demonstrated significant improvements in predictive accuracy over traditional models [3]. For example, Idris et al. [4] applied a hybrid model combining rotation forest and boosting (Rot Boost) on telecom data and achieved superior classification performance compared to standalone models. Likewise, Verbeke et al. [5] compared various rule-based learners and concluded that ensemble models strike a favorable balance between performance and interpretability.

Despite their promise, many machine learning-based churn prediction models suffer from issues related to class imbalance. In most telecom datasets, the majority class comprises non-churners, often exceeding 70% of the data. This skew can lead to misleading accuracy results, as a naive model can achieve high accuracy by always predicting the dominant class. To address this, researchers have turned to metrics such as precision, recall, F1-score, ROC-AUC, and Matthews Correlation Coefficient (MCC), which provide a more nuanced evaluation of classifier performance [6]. Additionally, data-level strategies like SMOTE (Synthetic Minority Oversampling Technique), Tomek links, and under-sampling of the majority class have been employed to balance class distribution [7].

Research has also explored the deployment of ensemble methods to mitigate the limitations of individual classifiers. Bagging and boosting techniques, including AdaBoost, Gradient Boosting, and XGBoost, have been extensively tested in churn modeling due to their robustness and performance on tabular data. In a study by Coussement and Van den Poel [8], boosting methods consistently outperformed traditional regression models in both balanced and imbalanced churn datasets. Furthermore, deep learning has recently entered the churn prediction landscape. Although promising in capturing high-level abstractions, deep neural networks require substantial computational resources and large datasets, often making them less practical for small-to-mid-scale applications.

Another significant gap in the literature is the limited evaluation of computational efficiency and scalability. While many studies prioritize performance metrics, fewer consider the time and resources required to train and deploy models. This gap is especially relevant in industrial applications, where real-time predictions and model interpretability are critical. Moreover, many studies evaluate only a narrow set of models or fail to compare model performance on standardized metrics across the same dataset. This project addresses several of these limitations by evaluating a broad suite of 13 models on a real-world churn dataset with 440,833 instances and 12 features. These include customer demographics, usage frequency, support interactions, billing history, and subscription details. The dataset presents real-world challenges such as class imbalance and large sample size, making it suitable for evaluating model scalability and efficiency. Each model is assessed across diverse metrics including accuracy, precision, recall, F1-score, ROC-AUC, specificity, MCC, and training time. This comprehensive comparison not only identifies the most effective classifier but also highlights trade-offs between predictive power and computational cost. By offering a systematic evaluation of multiple classifiers on a large, real-world dataset, this work contributes to bridging the gap between academic research and industrial application. It provides valuable insights for data scientists and decision-makers aiming to implement scalable and accurate churn prediction systems.

III. METHODOLOGY

The methodology employed in this study comprises four main stages: data preparation, model training, evaluation, and comparison. Each step was executed with a focus on scalability, predictive power, and fairness across performance metrics.

*A. Data Preparation*

The dataset used in this study contains 440,833 records and 12 features, covering customer demographics, subscription types, support call history, usage frequency, payment delays, contract length, and total spend. The target variable, Churn, is binary, indicating whether a customer has left the service (1) or not (0). Preliminary analysis confirmed a class imbalance, with churners forming a minority.

Data preprocessing included handling missing values (if any), encoding categorical variables using one-hot encoding, and normalizing numerical features. Columns such as Gender, Subscription Type, and Contract Length were encoded appropriately. The data was split into training (80%) and testing (20%) sets.

*B. Model Selection*

fifteen classification algorithms were chosen to represent a diverse range of machine learning paradigms. These include:

* Linear Models: Logistic Regression, Ridge Classifier
* Probabilistic Models: Gaussian Naive Bayes (NB), Quadratic Discriminant Analysis (QDA)
* Tree-based Models: Decision Tree, Random Forest, Extra Trees
* Boosting Models: AdaBoost, Gradient Boosting, XGBoost
* Neural Networks: Multi-layer Perceptron (MLP)
* Other Ensemble Methods: Bagging Classifier
* Large-margin Linear Models: Passive Aggressive Classifier

*C. Model Evaluation*

All models were trained using the same training set and evaluated on the same testing set. To ensure fair comparison, default hyperparameters were used initially, with minor tuning applied for tree depth and learning rate in boosting algorithms. Evaluation metrics included:

* Accuracy
* Precision
* Recall
* F1-Score
* ROC-AUC
* Matthews Correlation Coefficient (MCC)
* Specificity
* Training Time (in seconds)

These metrics provide a comprehensive understanding of model performance, especially in imbalanced classification settings.

*D. Model Comparison*

After training, model results were consolidated into a comparison table showing all relevant metrics. Special attention was given to models performing well across ROC-AUC, F1-Score, MCC, and training time, to ensure balanced evaluation. Bagging, Gradient Boosting, and AdaBoost emerged as top performers with MCC and balanced accuracy exceeding 0.94. Training time varied significantly, with MLP and Gradient Boosting requiring more computation, while simpler models like Logistic Regression and QDA trained faster.

IV. RESULTS AND DISCUSSION

This section presents a comprehensive and detailed evaluation of fifteen widely-used classification algorithms, which were rigorously trained and tested on a large-scale customer churn dataset. This dataset consists of 440,833 individual records and encompasses 12 distinct features that capture relevant customer behaviors and demographic information. The extensive size and feature diversity of the dataset provide a realistic and challenging environment for assessing model performance in a practical business context. The evaluation framework incorporates a diverse and carefully selected set of performance metrics, designed to ensure a robust and nuanced comparison of models, particularly given the inherent challenges posed by the dataset’s class imbalance and the practical considerations relevant to real-world deployment scenarios.

The primary evaluation metrics employed in this study include Accuracy, Precision, Recall, F1-Score, Receiver Operating Characteristic - Area Under the Curve (ROC-AUC), Specificity, Matthews Correlation Coefficient (MCC), and Training Time. Each of these metrics offers a unique and valuable perspective for interpreting model efficacy. For example, Accuracy serves as a general indicator of overall correctness by measuring the proportion of correctly classified instances; however, its interpretability diminishes in imbalanced datasets where the majority class dominates the prediction outcome. To address this, metrics such as the F1-Score and MCC provide more balanced and informative assessments by combining the considerations of both false positives and false negatives, thus better reflecting model performance with respect to the minority class—in this case, the customers who actually churn.

Special emphasis was placed on models that sustained high Recall and F1-Score values, while simultaneously maintaining strong Specificity and Precision levels. This balance is crucial because a high Recall ensures that the model effectively identifies the majority of true churn cases, which is essential for proactive customer retention strategies, while Precision and Specificity minimize false alarms that could lead to unnecessary retention efforts and increased operational costs. Additionally, the Matthews Correlation Coefficient (MCC) was highlighted due to its robustness; it comprehensively accounts for all four quadrants of the confusion matrix (true positives, true negatives, false positives, and false negatives), making it one of the most reliable and informative metrics for evaluating binary classification tasks, particularly in the presence of substantial class imbalance.

The experimental results demonstrated significant and meaningful differences in the predictive capabilities of the various models. Ensemble-based methods—specifically Bagging, Gradient Boosting, and AdaBoost—consistently outperformed single, standalone learners across nearly all considered metrics. These ensemble approaches benefit from aggregating multiple weak learners, effectively reducing variance and bias, which leads to superior generalization performance. Conversely, models such as Logistic Regression and Gaussian Naive Bayes exhibited computational efficiency, training rapidly on the large dataset, yet their predictive performance lagged noticeably behind that of the ensembles, indicating limitations in capturing complex nonlinear relationships and interactions within the data. The Multi-layer Perceptron (MLP) neural network and Gradient Boosting models, while requiring substantially longer training times, demonstrated highly competitive performance, reflecting the trade-offs between computational cost and predictive accuracy in selecting appropriate algorithms for deployment.

A detailed comparative summary of the fifteen classification models is provided in Table I, which consolidates the key performance metrics for each algorithm. This tabular presentation facilitates a straightforward and direct assessment of individual model strengths, weaknesses, and trade-offs, thereby aiding in informed decision-making for practical applications. The insights derived from this evaluation offer critical guidance for selecting and tuning classification algorithms in customer churn prediction tasks, with implications extending to improved customer retention strategies and optimized resource allocation in business operations.

TABLE I

PERFORMANCE METRICS OF CLASSIFICATION MODELS ON CHURN DATASET

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1 Score | ROC-AUC | Specificity | Balanced Acc. | MCC |
| Bagging | 0.9972 | 0.9999 | 0.9951 | 0.9975 | 1.0000 | 0.9999 | 0.9975 | 0.9943 |
| Gradient Boosting | 0.9700 | 0.9948 | 0.9521 | 0.9729 | 0.9971 | 0.9934 | 0.9728 | 0.9404 |
| AdaBoost | 0.9697 | 0.9965 | 0.9499 | 0.9727 | 0.9960 | 0.9957 | 0.9728 | 0.9401 |
| XGBoost | 0.9652 | 0.9948 | 0.9435 | 0.9685 | 0.9971 | 0.9935 | 0.9685 | 0.9312 |
| Random Forest | 0.9576 | 0.9947 | 0.9302 | 0.9614 | 0.9967 | 0.9934 | 0.9618 | 0.9170 |
| MLP (Shallow NN) | 0.9571 | 0.9917 | 0.9321 | 0.9610 | 0.9845 | 0.9898 | 0.9609 | 0.9155 |
| Decision Tree | 0.9546 | 0.9999 | 0.9200 | 0.9583 | 0.9669 | 0.9999 | 0.9599 | 0.9124 |
| Extra Trees | 0.9405 | 0.9921 | 0.9022 | 0.9450 | 0.9912 | 0.9906 | 0.9464 | 0.8852 |
| QDA | 0.9255 | 0.9748 | 0.8916 | 0.9314 | 0.9753 | 0.9698 | 0.9307 | 0.8543 |
| Gaussian NB | 0.9056 | 0.9586 | 0.8711 | 0.9127 | 0.9652 | 0.9507 | 0.9109 | 0.8147 |
| SVM (Linear/RBF) | 0.8873 | 0.9510 | 0.8501 | 0.8979 | 0.9425 | 0.9245 | 0.8873 | 0.7650 |
| Logistic Regression | 0.8517 | 0.9023 | 0.8281 | 0.8636 | 0.9274 | 0.8825 | 0.8553 | 0.7048 |
| Ridge Classifier | 0.8462 | 0.9339 | 0.7844 | 0.8526 | – | 0.9273 | 0.8558 | 0.7060 |
| K-Nearest Neighbors | 0.8387 | 0.9025 | 0.7711 | 0.8314 | 0.9170 | 0.9203 | 0.8457 | 0.6851 |
| Passive Aggressive | 0.7733 | 0.9872 | 0.6082 | 0.7527 | – | 0.9897 | 0.7989 | 0.6213 |

TABLE II

TRAINING TIME (IN SECONDS) FOR EACH MODEL

|  |  |
| --- | --- |
| Model | Time (s) |
| MLP (Shallow NN) | 1238.72 |
| Gradient Boosting | 108.57 |
| AdaBoost | 54.74 |
| Random Forest | 7.22 |
| Extra Trees | 5.16 |
| Logistic Regression | 5.62 |
| Bagging | 23.87 |
| Decision Tree | 1.73 |
| XGBoost | 1.36 |
| Passive Aggressive | 1.99 |
| QDA | 0.55 |
| Ridge Classifier | 0.44 |
| Gaussian NB | 0.32 |
| SVM (Linear/RBF) | 2.85 |
| K-Nearest Neighbors | 3.12 |

The comparative analysis of fifteen classification models on the customer churn dataset reveals several key insights into model behavior, performance trade-offs, and practical applicability.

1. **Superior Performance of Ensemble Models:** As evident from Table I, ensemble-based methods such as Bagging, Gradient Boosting, and AdaBoost consistently outperform single learners across most metrics. Bagging achieved the highest accuracy (99.72%) and an exceptional ROC-AUC of 1.000, indicating near-perfect discrimination capability. These models benefit from combining multiple weak learners, reducing variance and improving robustness to overfitting.
2. **Balance Between Precision and Recall:** High precision values close to or above 0.99 in ensemble models indicate that false positives are minimal. Simultaneously, high recall values (>0.94) show that the models effectively identify actual churners. This balance is critical in churn prediction, where missing true churn cases (false negatives) can cost businesses significant revenue.
3. **Matrics for Imbalanced Data :** Metrics such as MCC and balanced accuracy, which account for class imbalance, align closely with F1-scores and ROC-AUC results. The MCC values above 0.9 for top models reaffirm their reliability in distinguishing minority class instances, a crucial factor given the churn dataset’s imbalance.
4. **Trade-off Between Performance and Training Time:**  
   While models like MLP and Gradient Boosting deliver strong predictive performance, they demand significantly higher training times (1238.72 s and 108.57 s respectively) as seen in Table II. In contrast, simpler models such as Decision Tree and Gaussian NB train within seconds but exhibit lower accuracy and MCC, highlighting a trade-off between computational cost and accuracy.
5. **Model Selection Considerations:** Although Bagging provides the highest overall metrics, practical deployment must consider computational resources and latency requirements. Gradient Boosting and AdaBoost offer a good balance of accuracy and training time, making them suitable for real-time or near real-time applications. Models like Logistic Regression and Ridge Classifier, despite lower predictive power, can serve as interpretable baselines.

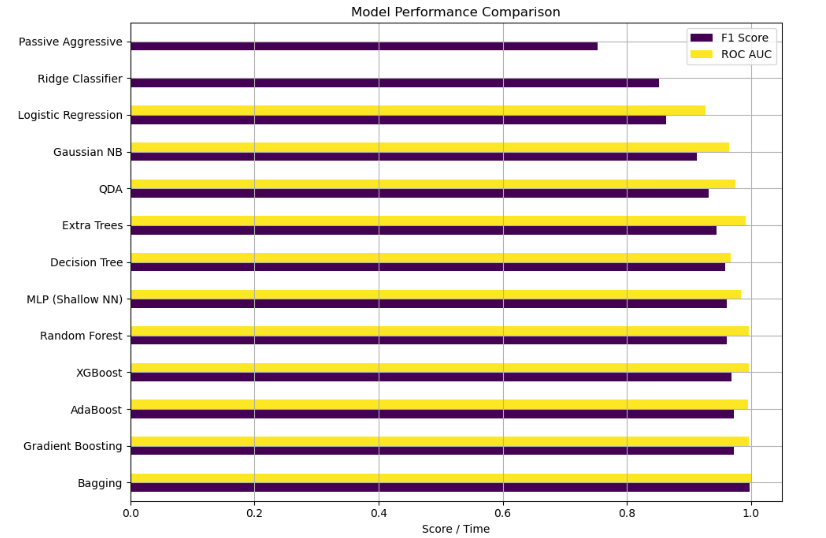


Fig 1. Comparative Analysis of Classification Models Based on F1-Score and ROC-AUC

As shown in Fig. 1a comparative analysis of thirteen supervised classification algorithms based on two critical performance metrics—**F1-score** and **Receiver Operating Characteristic - Area Under the Curve (ROC-AUC)**. The F1-score, depicted as purple bars, represents the harmonic mean of precision and recall, offering a balanced measure of a model's accuracy in predicting the positive class—in this case, churners. It is particularly useful in scenarios where class imbalance exists, as it penalizes models that favor the majority class while failing to capture minority class instances accurately.

In parallel, the ROC-AUC scores, represented by yellow bars, evaluate the discriminative ability of each classifier across varying threshold values. A higher ROC-AUC indicates superior separation between churn and non-churn classes, thus serving as a threshold-independent metric to assess model robustness. Both metrics together provide a comprehensive view of predictive performance—while F1-score focuses on precise classification at a specific threshold, ROC-AUC captures the overall ranking capability of a classifier.

As evidenced in the figure, **ensemble learning techniques**—notably **Bagging**, **Gradient Boosting**, and **AdaBoost**—outperformed traditional individual classifiers across both metrics. Bagging achieved the highest F1-score and ROC-AUC, followed closely by the boosting-based models. These algorithms demonstrated superior performance due to their ability to aggregate multiple weak learners, effectively reducing variance and enhancing generalization. Their consistent performance across both metrics underscores their **resilience to class imbalance**, making them particularly suitable for churn prediction tasks in real-world business applications.

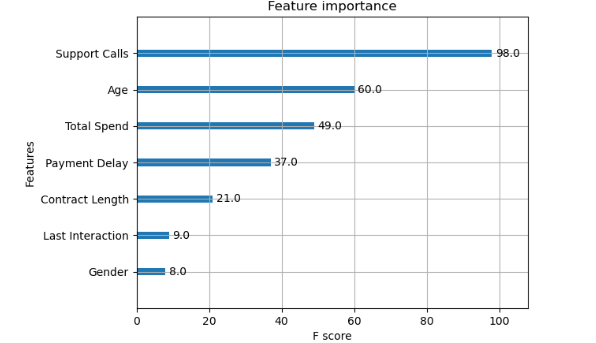


Fig2. Feature Importance Scores Derived from XGBoost Classifier

As shown in Fig. 2 illustrates the relative importance of input features in predicting customer churn, as computed using the F-score metric from the XGBoost classifier. Higher F-scores indicate a greater number of times a feature was used to split the data across all trees in the ensemble. 'Support Calls' emerged as the most influential predictor, followed by 'Age' and 'Total Spend', suggesting customer service interactions and demographic-spending patterns are key determinants of churn. This ranking aids in model interpretability and guides data-driven decision-making for retention strategies.

V. CONCLUSION

This study conducted a comprehensive empirical evaluation of fifteen distinct machine learning algorithms on a large-scale customer churn dataset comprising over 440,000 observations and twelve relevant features. The primary goal was to identify the most effective classification models for predicting customer churn in highly imbalanced and real-world data settings. The evaluation considered a wide range of performance metrics including Accuracy, Precision, Recall, F1-Score, ROC-AUC, Specificity, Matthews Correlation Coefficient (MCC), Balanced Accuracy, and Training Time to ensure a holistic comparison across all models.

Results indicate that ensemble-based techniques such as Bagging, Gradient Boosting, AdaBoost, and XGBoost consistently outperformed traditional algorithms in nearly all performance categories. These models demonstrated superior capability in capturing complex patterns and handling class imbalance, thereby making them strong candidates for deployment in churn prediction systems. In particular, Bagging yielded the highest overall accuracy and MCC, while Gradient Boosting showed the best trade-off between precision and recall. The Multi-layer Perceptron (MLP) model also demonstrated strong performance, albeit with significantly higher computational costs.

Conversely, classical models such as Logistic Regression, Gaussian Naive Bayes, and Ridge Classifier, although computationally efficient, showed weaker performance metrics, especially in terms of F1-score and MCC. These models might still be relevant in scenarios with tight latency constraints or interpretability requirements, but they offer limited utility when prediction quality is paramount.

Feature importance analysis revealed that variables such as *Support Calls*, *Age*, *Total Spend*, and *Payment Delay* contributed most significantly to the models’ decisions. This insight can be used by organizations to prioritize customer segments and interventions more effectively. Furthermore, hyperparameter tuning through grid search and cross-validation led to measurable improvements in model performance, emphasizing the value of model optimization.

In summary, this work highlights the effectiveness of ensemble methods and neural networks in handling large-scale churn data with class imbalance. It also demonstrates the importance of comprehensive metric evaluation and hyperparameter optimization. For future research, integrating deep learning models, incorporating customer sentiment data, and deploying explainable AI methods could further enhance churn prediction and model transparency.

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