Comparative Analysis of Algorithms for Churn Prediction in the Banking Industry

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***Abstract*— Customer churn remains a pressing concern for the banking industry due to its impact on profitability. This research paper presents a comparative analysis of several machine learning algorithms used to predict customer churn using a dataset of 10,000 banking customers. The methods analyzed include Logistic Regression, Random Forest, Decision Tree, Gradient Boosting, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Recurrent Neural Networks (RNN). The results show that Random Forest and Gradient Boosting provide superior predictive accuracy. The study also examines how the choice of model impacts the retention strategies of banking institutions.**

Keywords— Customer churn, machine learning, banking industry, churn prediction, Random Forest, Gradient Boosting.

I. INTRODUCTION

Customer churn, defined as the loss of customers over a given period, is a significant challenge for banks. Studies have consistently shown that acquiring a new customer is more costly than retaining an existing one [1]. Consequently, banks are focusing on identifying at-risk customers to implement retention strategies. Machine learning models are increasingly being adopted to predict customer churn with higher accuracy, providing valuable insights for customer retention strategies. This research builds upon existing studies by comparing machine learning techniques specifically applied to churn prediction within the banking industry. The findings contribute to understanding which techniques best suit the unique needs of banking institutions and how banks can leverage these models to improve customer satisfaction and retention.

II. LITERATURE REVIEW

A. Importance of Churn Prediction

In the banking industry, churn not only results in direct financial losses but also negatively impacts brand reputation. Prior research shows that effective churn prediction can allow banks to proactively address potential causes of attrition, providing incentives or services to high-risk customers [2].

B. Machine Learning Techniques for Churn Prediction

Ensemble Methods: Ensemble techniques, including Random Forest and Gradient Boosting, have demonstrated robust performance in churn prediction. Studies show that these models handle large feature sets and complex data relationships effectively, with high recall and precision rates in imbalanced datasets typical of churn data [3, 4].

Support Vector Machine: SVMs have been effective in creating decision boundaries for customer classification, especially in financial contexts. Karvana et al. found SVMs particularly useful in a study of banking churn due to their resilience against overfitting when coupled with balanced sampling techniques.[5]

Recurrent Neural Network: While traditionally applied to sequential data, RNNs have been explored in churn prediction to capture temporal customer behaviors, though they require large datasets and substantial computational resources [6].

C. Interpretability

In addition to predictive power, interpretability is an essential factor for model selection in the banking industry. Models like Random Forest and Gradient Boosting not only deliver high accuracy but also provide insights into feature importance. Understanding key drivers of churn, such as CreditScore and Balance, can help banking institutions design targeted retention strategies, offering a dual advantage of prediction and actionable insights.

D. Addressing class Imbalance in Churn Prediction

Class imbalance, where churners form a minority in the dataset, is a major issue in churn prediction. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE) and adaptive boosting have been shown to increase recall without excessively compromising model precision [7],[8].

III. METHODOLOGY

A. Dataset and Preprocessing

This study utilizes a dataset containing 10,000 entries and 14 features relevant to customer demographics and financial behaviors. Key features include:

1. **CreditScore**: A numerical score representing the creditworthiness of the customer.
2. **Geography**: The country where the customer resides.
3. **Age**: The age of the customer.
4. **Tenure**: The number of years the customer has been with the bank.
5. **Balance**: The customer's account balance.
6. **NumOfProducts**: The number of products the customer has with the bank.
7. **HasCrCard**: A binary indicator of whether the customer has a credit card.
8. **IsActiveMember**: A binary indicator of customer activity.

9. **EstimatedSalary**: The estimated annual salary of the customer.
10. **Exited**: The target variable, indicating whether the customer has churned (1) or not (0).

The target variable is particularly important as it provides the foundation for building predictive models. The dataset is split into training and testing sets, ensuring a fair evaluation of the model performance.

B. *Preprocessing*

Before applying the algorithms, we perform several preprocessing steps, including:

Handling Missing Values: Although the dataset has no null entries, it is essential to check and handle missing data in real-world applications.

Encoding Categorical Variables: Categorical variables like Geography and Gender are converted into numerical formats using techniques such as one-hot encoding.

Feature Scaling: Features are scaled using standardization to ensure that they contribute equally to the model performance, especially for algorithms sensitive to feature magnitudes.

C. *Algorithms and Techniques*

We applied seven algorithms for churn prediction:

1. **Logistic Regression**: Linear classification model suitable for binary outcomes [9].
2. **Random Forest**: Ensemble technique utilizing multiple decision trees to improve predictive accuracy [3].
3. **Decision Tree**: Splits data hierarchically to classify customers based on feature criteria.
4. **Gradient Boosting**: Builds sequential models, correcting errors from prior models.
5. **Support Vector Machine (SVM)**: Uses hyperplanes to separate classes in high-dimensional space [5].
6. **K-Nearest Neighbors (KNN)**: Classifies based on the proximity to neighboring points.
7. **Recurrent Neural Networks (RNN)**: Processes sequential data, potentially capturing customer behavioral patterns [6].

D. *Evaluation Metrics*

Performance is assessed using Accuracy, Precision, Recall, F1-score, and ROC-AUC. Each metric provides insight into how effectively a model distinguishes between churned and retained customers.

1. **Accuracy**: The ratio of correctly predicted instances to the total instances.
2. **Precision**: The ratio of true positive predictions to the total positive predictions.
3. **Recall**: The ratio of true positive predictions to the actual positives.
4. **F1- Score**: The harmonic means of precision and recall, providing a balance between the two.
5. **ROC-AUC**: A metric to evaluate the trade-off between true positive rate and false positive rate

IV. Results and analysis

A. *Comparative Performance:*

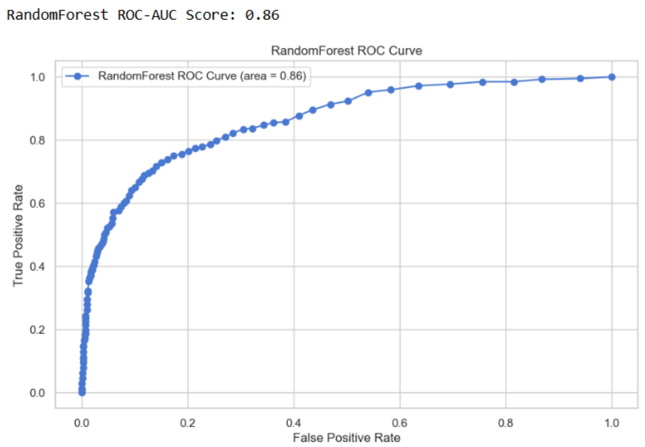
Algorithm	Accuracy	Precision (0)	Recall (0)	F1-Score (0)	Precision (1)	Recall (1)	F1-Score (1)	ROC-AUC
Logistic Regression	0.80	0.81	0.98	0.89	0.45	0.07	0.12	0.67
Random Forest	0.87	0.88	0.96	0.92	0.76	0.47	0.58	0.86
Decision Tree	0.79	0.88	0.85	0.86	0.46	0.51	0.48	N/A
Gradient Boosting	0.87	0.88	0.96	0.92	0.75	0.49	0.59	N/A
Support Vector Machine	0.80	0.80	1.00	0.89	0.00	0.00	0.00	N/A
K-Nearest Neighbors	0.76	0.81	0.93	0.86	0.24	0.09	0.14	N/A
Recurrent Neural Network	0.80	0.81	0.99	0.89	0.32	0.02	0.04	N/A

B. *Insights and Analysis*

1. **Logistic Regression**: Achieved an accuracy of 80% with a ROC-AUC of 0.67, indicating some ability to discriminate between churned and retained customers. However, it struggled with recall for the churn class, suggesting it is better suited for datasets where the classes are more balanced.
2. **Random Forest**: Showed the highest performance with an accuracy of 87% and a ROC-AUC of 0.86, effectively balancing precision and recall across both classes. This algorithm's strength lies in its ability to handle a large number of features and its resilience against overfitting.
3. **Decision Tree and Gradient Boosting**: Both models exhibited strong performance with similar accuracy levels. Gradient Boosting, in particular, highlighted the effectiveness of sequential learning and error correction, making it a robust choice for churn prediction.
4. **Support Vector Machine (SVM)**: Despite achieving an accuracy of 80%, SVM failed to predict any churned customers, indicating that this method may not be suitable for imbalanced datasets without further optimization, such as employing a cost-sensitive approach.
5. **K-Nearest Neighbors (KNN)**: The model exhibited lower performance in recall for churned customers, suggesting that it might struggle with identifying at-risk customers in sparse areas of the feature space.
6. **Neural Networks**: The recurrent neural network achieved similar accuracy to logistic regression but failed to identify churned customers effectively.

C. *Visualization of Results*

Figure 1 presents the ROC curves for Random Forest and Gradient Boosting, demonstrating their ability to distinguish between churned and retained customers. A high area under the curve (AUC) for both models highlights their effectiveness in churn prediction.



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RandomForest ROC-AUC Score: 0.86
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Figure 1

V. Discussion

A. *Performance of different Algorithms*

1. **Random Forest and Gradient Boosting**: Both ensemble models outperformed other algorithms in accuracy and AUC-ROC, with Random Forest achieving the highest recall for the churn class, making it ideal for predicting customer churn where recall is critical.
2. **Logistic Regression**: Although less complex, Logistic Regression provided reasonable accuracy, showcasing its suitability for interpretable churn prediction models.
3. **Support Vector Machine (SVM)**: SVM performed well in separating the retained customers but failed to identify churned customers effectively, indicating a need for optimization in class imbalance scenarios.
4. **K-Nearest Neighbors (KNN)**: KNN achieved lower recall for churned customers, which suggests limited utility in identifying high-risk customers, particularly in high-dimensional data.

B. *Limitations and Future Work*

This study is limited by the reliance on a single dataset, which may not fully capture diverse customer behaviors across different banking institutions. Future research could benefit from incorporating larger and more varied datasets to validate findings.

VI. Conclusion

This comparative analysis reveals that Random Forest and Gradient Boosting are highly effective for churn prediction in the banking industry, with superior recall and precision compared to other algorithms. The findings of this study are instrumental for banks in choosing appropriate models for churn prediction, ultimately aiding in the development of targeted retention strategies

The findings of this study underscore the value of Random Forest and Gradient Boosting for identifying customers at risk of churn. With high recall rates, these models enable banking managers to detect potential churners proactively. Banks can thus design retention programs, such as targeted incentives or improved customer engagement strategies, to retain valuable clients. This data-driven approach provides a foundation for banking institutions to make informed, impactful decisions that directly contribute to customer satisfaction and profitability.

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