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Research Article

Enhancing Customer Churn Prediction in the Finance Sector through Explainable AI and Machine Learning

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Abstract – Customer churn prediction has emerged as a critical research domain in various industries, including telecommunications, retail, and finance, due to its significant impact on business profitability, customer satisfaction, and long-term sustainability. Churn refers to the rate at which customers terminate their relationship with a company, necessitating the development of accurate predictive models to facilitate effective retention strategies. In this context, machine learning models have demonstrated substantial potential by processing large datasets to identify patterns indicative of customer attrition. However, despite their predictive accuracy, the widespread adoption of these models is often limited by their lack of transparency, commonly referred to as the "black box" problem. This challenge is particularly observed in sectors such as finance and risk management, where customer trust is of paramount importance. Explainable AI (XAI) addresses this limitation by enhancing the interpretability of machine learning models, enabling stakeholders to comprehend the rationale behind predictions while maintaining model performance. This study investigates the integration of XAI methodologies into customer churn prediction models within the financial sector, with a focus on Eminevim, addressing the challenges posed by complex data and the necessity for actionable insights. The performance and interpretability of various machine learning algorithms, such as Random Forest, XGBoost, Light-GBM, and CatBoost are assessed utilizing explainability techniques such as SHAP (Shapley Additive Explanations). The findings demonstrate that XAI-augmented churn prediction models not only preserve high predictive accuracy but also enhance transparency, empowering financial institutions to make informed, data-driven decisions that mitigate customer attrition and promote long-term business sustainability.

Keywords – Customer Churn, Machine Learning, Explainable AI, Explanatory Analysis, Finance

I. INTRODUCTION

Customer churn, defined as the attrition of clients over a specified period, poses a significant challenge for businesses, as it directly impacts revenue generation and long-term growth strategies. In highly competitive markets, retaining existing customers is much more cost-effective than acquiring new ones.

In addition, loyal customers typically have a higher lifetime value and contribute to business growth through word-of-mouth referrals. Consequently, organizations in various industries prioritize churn prevention as a fundamental component of their customer relationship management (CRM) strategies.

In the finance sector, customer retention is critical to sustainable growth, given intense competition, high acquisition costs, and significant investments in customer onboarding. Financial institutions, such as banks, credit card providers, and insurance companies, rely heavily on long-term relationships with their customers to maximize cross-selling, enhance customer lifetime value, and secure customer loyalty. In addition, loss of a customer can lead to reputational damage and lost opportunities in terms of future financial products. Therefore, predicting and mitigating customer churn is essential for financial institutions to maintain their market share and protect against revenue losses.

Customer churn prediction involves estimating the likelihood of customer departure based on historical and behavioral data. Recent advancements in machine learning have significantly improved the accuracy of such predictions by leveraging large datasets encompassing customer demographics, transactional records, and behavioral patterns. However, many of these models, particularly those based on complex algorithms such as ensemble learning and deep neural networks, suffer from a lack of interpretability. The "black box" nature of machine learning models presents a considerable challenge, especially in highly regulated industries such as finance, where accountability and transparency are critical for regulatory compliance and organizational decision-making.

Explainable AI has emerged as a solution to this problem by enhancing the interpretability of machine learning models. XAI techniques offer insights into how specific features impact model predictions, thereby enhancing trust and facilitating informed decision-making. In the context of customer churn prediction, methodologies such as SHAP (Shapley Additive Explanations) enables financial institutions to identify key factors driving customer attrition, ensuring that predictions are not only accurate but also interpretable and actionable. These techniques have proven effective in enhancing the transparency of machine learning models, making them more suitable for application in sensitive industries.

Customer churn prediction has garnered significant attention in recent years, driven by the competitive need to retain existing customers in various sectors, including telecommunications, e-commerce, and, particularly, finance.

Early approaches to churn prediction predominantly relied on statistical techniques such as logistic regression, which were valued for their simplicity [1].

The advent of machine learning has led researchers to increasingly adopt advanced algorithms to enhance the performance of churn prediction models. In particular, decision tree–based ensembles, such as Random Forest (RF) and Gradient Boosting Machines (GBM), have become cornerstone techniques in the field. Their widespread use is primarily due to the attributes such as the ability to handle noisy and high-dimensional data [2].

The availability of big data has driven the widespread use of complex predictive models that excel at analyzing vast amounts of information to capture intricate patterns in customer behavior [3].

Neural networks and deep learning approaches have also been successfully employed for prediction tasks, demonstrating ability to autonomously discover complex, underlying patterns (latent features) directly from raw data on customer behavior and transactions, in order to significantly enhances forecasting accuracy [4].

While these models offer improved predictive performance, their complexity often results in a lack of transparency, posing challenges for organizations where understanding and justifying model decisions is imperative [5].

A distinct research trajectory has emphasized the critical role of incorporating domain-specific expertise and sophisticated feature engineering into machine learning frameworks for churn prediction. Empirical investigations confirm that predictive accuracy is substantially affected by factors, including demographic profiles, transaction frequency, patterns of service utilization, and metrics of customer engagement [6].

The adoption of Explainable AI mainly addresses the transparency challenge associated with complex ML methods in churn prediction, ensuring compliance while maintaining model accuracy. Techniques such SHapley Additive exPlanations have been increasingly adopted to provide insight into individual predictions and overall feature importance [7]. Drawing on concepts from cooperative game theory, SHAP values assign importance scores to each feature, allowing practitioners to understand the contribution of specific features to individual predictions [8].

In the studies conducted by [9][10], it has been shown that XAI techniques like SHAP and LIME can elucidate model decisions, making machine learning models more interpretable without compromising predictive power [11]. These techniques help identify the key factors influencing customer churn, thereby enabling institutions to take targeted action.

Beyond SHAP, other interpretability methods, such as Local Interpretable Model-Agnostic Explanations (LIME) [12], counterfactual explanations [13], and partial dependence plots (PDP) [14], have also been investigated within the context of customer churn prediction in finance. The methodology of counterfactual explanations, which generates insights by suggesting minimal perturbations to input features to alter the prediction outcome, has shown potential in the finance sector, where customer-specific interventions are highly valued [13]. Concurrently, partial dependence plots facilitate the visualization of features' effect on the predicted outcome, providing finance professionals with a comprehensive understanding of feature interdependencies [14]. Although less common than SHAP, these methods contribute to the growing toolkit for explainable churn prediction.

In the finance sector, SHAP has proven especially useful for clarifying the impact of transactional data, credit history, and behavioral features on churn predictions, thereby enabling decision-makers to make informed retention strategies[15]. The interpretability of SHAP has bridged the gap between predictive accuracy and explainability.

Overall, the literature demonstrates a clear evolution from traditional statistical techniques toward more advanced ML and hybrid approaches, with a growing focus on model interpretability.

This paper aims to explore the application XAI in customer churn prediction models, utilizing a dataset gathered from Eminevim's customers. Eminevim, a Turkish savings and financing services company under Emin Group, offers an innovative financing solution known as the "Household Participation System" or "Household Savings System." This approach provides financing options for customers who may not have access to conventional mortgage products.

II. MATERIALS AND METHOD

This research evaluates the predictive performance of multiple machine learning algorithms, including Random Forest, XGBoost, CatBoost, MLP, and etc., while employing XAI methodologies such as SHAP to improve the interpretability of the models. The integration of XAI into churn prediction not only enhances predictive accuracy but also provides valuable insights into the underlying factors contributing to customer attrition, thereby supporting financial institutions in developing more effective, data-driven retention strategies [16].

The effectiveness of churn prediction models largely depends on the quality and accuracy of customer data, as well as the selection of relevant features that capture behavioral and demographic patterns indicative of churn risk [17].

A. *Data Preprocessing*

The features considered in the analysis are detailed in Table \ref{t1}, which consists of customer-level financial and demographic attributes. In this context, financial attributes depict contractual obligations. Here, the OrganizationAmount represents the total payout the client is entitled on a predetermined date as outlined in their contract, whereas the OrganizationFee depicts the service fee the company earns, which depends on the total payout amount and the number of payment installments involved. The InstallmentCount and Amount are predefined contractual values. OrganizationType indicates whether the customer intends to utilize the allocated funds at the end of the contract for the acquisition of a house/car/workplace, and OrganizationSystem refers to the grouping technique of the participants, whether draw (lottery) or individually. Demographic attributes such as AgeGroup at signup, Gender, MaritalStatus, Occupation, and CustomerType (Individual/Corporate) are utilized to identify customer profiles.

Customer payment amounts may fluctuate monthly based on their evolving financial circumstances. These payment dynamics provide crucial insights into customer financial stability, which is instrumental in identifying potential churn risks. Here, the amount, days and months count of delayed payments are taken into consideration in the first 6 and 10 months of the contract, since the churned customers tends to stay in the system up to a year. Also, the count of IncomingCalls and OutgoingCalls indicate the engagement between customer and company.

Table 1. Features of Customer Dataset

Category	Variable
Financial Attributes	OrganizationAmount
	OrganizationFee
	InstallmentCount
	InstallmentAmount
	DownPaymentAmount
	DownPaymentRatio
	RegistrationDate
	PlannedDeliveryPeriod
	Campaign
	OrganizationType
	OrganizationSystem
Demographic Attributes	AgeGroup
	Gender
	MaritalStatus
	Occupation
	CustomerType
Payment Behavior	MonthsDelayed_First6
	DaysDelayed_First6
	AmountDelayed_First6
	MonthsDelayed_First10
	DaysDelayed_First10
	AmountDelayed_First10
Customer Interaction	IncomingCalls
	OutgoingCalls

Data preprocessing is a crucial step in building effective machine learning models, as raw data often exhibits inconsistencies, features on different scales, missing values, and non-numeric categories that must be converted into a suitable format. Inadequate preprocessing directly undermines model performance, potentially leading to biased predictions or slow convergence during training. Standardizing numerical features prevents any single variable from disproportionately influencing the model due to its scale, and encoding categorical variables allows algorithms to process them without error. By implementing effective preprocessing techniques, the stability and accuracy of machine learning leads to more reliable predictions and meaningful insights [18] [19].

To mitigate these risks, a comprehensive preprocessing protocol to the dataset is applied. Preprocessing stages involved parsing registration, planned delivery, and birth dates into machine-readable datetime formats. Temporal fields, such as registration year, month, and quarter were extracted, and customer age at registration was calculated. To facilitate categorical analysis, customers were grouped into age bands. Variables exceeding 80\% missing values were excluded, while missing values in critical fields, such as birth dates, were imputed using auxiliary sources when possible.

Numerical features, especially payment-related variables, were standardized through cleaning and conversion to float, handling various formatting inconsistencies. Derived features were introduced, including the planned delivery period (in months) and the down payment ratio. All numerical attributes were scaled using the StandardScaler to ensure comparability, while categorical variables were preserved in object or category formats. This comprehensive preprocessing pipeline ensured a clean, consistent dataset suitable for both accurate machine learning and transparent, explainable AI (XAI) analysis.

B. Machine Learning Models

To assess the effectiveness of different machine learning approaches for churn prediction, a range of algorithms were implemented, and their respective results were compared.

In this study, the dataset comprises customer records of the company Eminevim, who were registered between 2020 and 2023. Additionally, customers who terminated their contracts within 14 days without making any payments were excluded from the dataset. To handle non-linear patterns and complex interactions, tree-based ensemble methods such as Random Forest, XGBoost, LightGBM, and CatBoost were utilized. These model choices are consistent with recent studies in the financial services sector, where diverse machine learning algorithms have been applied to customer segmentation and churn prediction [20]. For benchmarking purposes, a standalone Decision Tree model was also considered, alongside MLP, Naïve Bayes for its probabilistic learning framework and K-Nearest Neighbors (KNN) to evaluate instance-based performance. Model performance was assessed using three complementary metrics: Accuracy, F1-Score, and ROC-AUC, providing a holistic view of predictive performance.

III. RESULTS

The experimental results are summarized in Table 2. Aligning with expectations, Logistic Regression, while providing a reasonable baseline, has been outperformed by modern ensemble methods. Random Forest and boosting-based models (XGBoost, LightGBM, and CatBoost) achieved substantially higher predictive performance across all metrics, with CatBoost delivering the highest results overall (Accuracy: 0.8215, F1-Score: 0.8105, ROC-AUC: 0.9034). In contrast, simpler models such as Decision Tree and Naïve Bayes showed notably weaker performance, particularly in terms of F1-Score, while KNN demonstrated moderately well performance but was still surpassed by the boosting models. These findings indicate that MLP and gradient boosting methods, CatBoost in particular provide the most effective solution for churn prediction in this context.

Table 2. Performance Comparison of Machine Learning Models

Model	Accuracy	F1-Score	ROC-AUC
CatBoost	**0.8215**	**0.8105**	**0.9034**
XGBoost	0.8176	0.8072	0.9000
MLP	0.8148	0.7999	0.8986
LightGBM	0.8098	0.7984	0.8915
Random Forest	0.8050	0.7912	0.8868
KNN	0.7141	0.7008	0.7809
Logistic Regression	0.7278	0.7156	0.7972
Decision Tree	0.7322	0.7110	0.7307

To improve the interpretability of the predictive models, this study employed SHAP values, which, in simple terms, is a widely adopted framework originating in cooperative game theory that distinctively calculates the contribution of each feature to individual predictions. This method translates complex model outputs into feature-level attributions, revealing a clearer understanding of how demographic, behavioral, and financial variables influence churn likelihood [21].

The result of the SHAP analysis given in Figure 1, highlights that the PlannedDeliveryPeriod exerts the strongest influence on churn prediction, indicating that longer delivery horizons substantially increase churn likelihood.

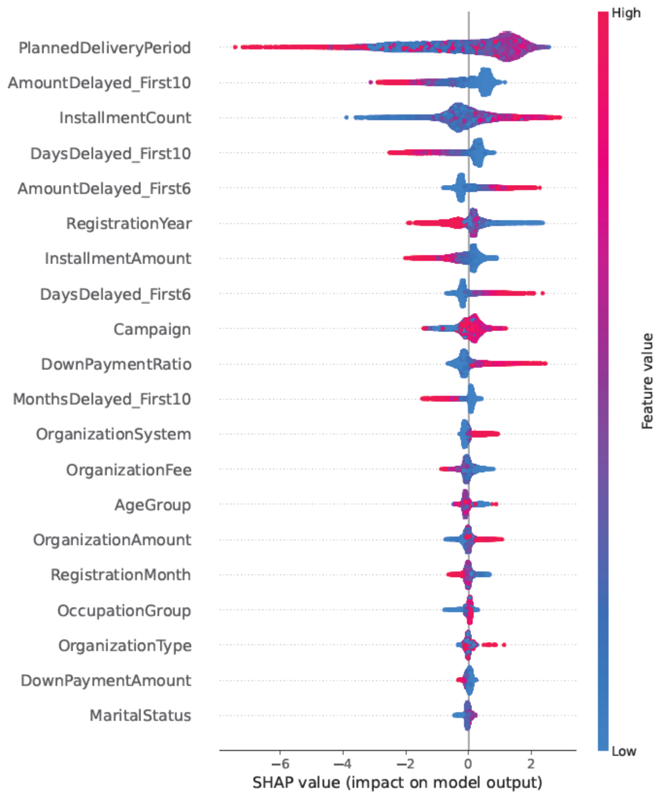

Figure 1. SHAP Result

Financial commitment variables such AmountDelayed in the first 10 and 6 months, also InstallmentCount rank among the most impactful predictors, underscoring the role of early repayment behavior and contract structure in customer retention. Moreover, demographic and organizational attributes (e.g., AgeGroup, MaritalStatus, Occupation, OrganizationSystem) play a secondary but still measurable role, suggesting that while socio-demographic context influences churn, financial structure and payment performance remain the dominant determinants. Interestingly, the down payment ratio shows significant discriminative power, implying that customers who make higher upfront payments are less likely to churn. Overall, the SHAP interpretation confirms that churn is primarily driven by contractual and payment behavior variables, with demographic factors serving as complementary predictors.

IV. CONCLUSION

This study investigated multiple machine learning algorithms for predicting customer churn, including traditional models like Logistic Regression, to advanced ensembles like Random Forest, XGBoost, LightGBM, and CatBoost. The experimental results demonstrated that ensemble-based gradient boosting models outperformed traditional classifiers, achieving the highest accuracy, F1-score, and AUC due to its strength in handling complex data. Among these, CatBoost achieved the best overall performance.

Furthermore, incorporating SHAP analysis enhanced interpretability by identifying the key drivers behind churn predictions and transformed them from black boxes into sources of actionable business insight.

For the future work, integration of hybrid models and the employment of different explainable models will be utilized on the customer dataset. Additionally, various features, mainly extracted from the textual data of the conducted calls, will be utilized.

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