A Holistic Framework for Predicting and Addressing Donor Churn in NGOs: Insights from Machine Learning and Temporal Analytics

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Abstract—**This research develops a predictive system for donor churn, aimed at identifying and mitigating donor attrition within nonprofit organizations. The system analyzes a large dataset that contains organizational indicators and financial data, including income, expenses, and asset liabilities, by utilizing machine learning techniques. With an emphasis on trends that forecast donor behaviour and churn likelihood based on revenue declines and past donor interaction, the dataset covers several years. The dataset was prepared for model training using data preparation approaches such as feature engineering to generate lagged revenue and churn probability, KNN-based imputation for missing values, and meticulous filtering for consistency. To forecast donor turnover, a number of machine learning algorithms were trained, including as XGBoost, Random Forest, and Logistic Regression. Hyperparameter tuning and cross-validation optimized model performance, while feature importance analysis identified key factors driving churn predictions. The final system offers an interactive, real-time solution that enables nonprofit organizations to monitor donor trends, anticipate churn, and derive actionable insights. By integrating robust data processing with predictive analytics and visualization. This end-to-end solution combines data processing, machine learning, and real-time visualization, enabling organizations to proactively address donor churn and enhance long-term sustainability.**

Index Terms—**Donor churn, machine learning, predictive analytics, feature engineering, hyperparameter tuning, real-time visualization, nonprofit organizations**

I. INTRODUCTION

Donor churn is a critical issue for non-profit organizations, as it directly affects their sustainability and growth. Generally speaking, nonprofits depend on donations to support their operations and programs, and the loss of contributors can have a big influence on their capacity to fulfill their missions. It's important to keep up a consistent flow of donations, but when people stop giving, there's a financial void that can be difficult to close. The phenomenon known as donor churn occurs when contributors stop making contributions for a variety of reasons, including discontent with the organization, shifting financial circumstances, or a lack of participation. Organizations must comprehend the fundamental trends and actions that cause donor churn in order to create measures that effectively stop it. By predicting which donors are at risk of churning, non-profits can take proactive measures to retain them, ensuring continuous support and long-term success.

Traditional methods of analyzing donor behaviour typically rely on basic statistical analysis or manual reviews of donor data. These approaches are frequently inadequate for managing the enormous volumes of data that non-profits gather, even though they can offer some insights. Furthermore, these methods frequently fail to notice minute correlations and trends in the data that can point to early churn indicators. increasingly sophisticated methods are required to precisely forecast donor attrition and improve retention tactics as data volumes and donor behavior become increasingly complex. To tackle these issues, machine learning in particular has become a potent instrument. Machine learning might reveal hidden patterns in donor behaviour that conventional approaches might overlook by employing algorithms that can evaluate massive, multi-dimensional datasets.

This enables organizations to predict donor churn with greater accuracy, allowing them to focus their resources on the donors who are most likely to stop contributing.

This project aims to develop a machine learning-based predictive model to forecast donor churn using a dataset from various non-profit organizations. The dataset includes key donor information such as total revenue, donation frequency, engagement history, and donor demographics. The study aims to determine the key elements affecting donor behavior and churn risk by using this data to train various machine learning algorithms. The ultimate objective is to offer practical insights that non-profits may use to better fundraising efforts, maximize connection with supporters, and strengthen donor retention tactics. Nonprofits can improve relationships with their donors and lower the risk of donor attrition by customizing their communication and engagement methods based on donor churn prediction.

This approach not only improves donor retention but also contributes to the overall financial health and stability of non-profit organizations.

II. LITERATURE REVIEW

The nonprofit sector operates in a complex environment shaped by financial limitations, donor expectations, technology, and regulations. Enhancing donor retention, financial performance, and funding sustainability requires a deep understanding of these factors. Recent studies offer key insights that support the development of data-driven models and strategic frameworks for NGOs and NPOs.

Financial efficiency has emerged as a stronger predictor of nonprofit success than financial effectiveness. A study on U.S. nonprofit sports organizations found that metrics such as the program services ratio and return on assets were reliable indicators of net income (Paper 2). These findings stress the importance of efficient resource allocation and performance monitoring, both of which can be integrated into predictive financial models for NGOs.

Donor retention is another core focus, with machine learning methods like K-Means clustering and RFM modelling proving effective in identifying high-value donors and predicting churn (Paper 3). These techniques enable NGOs to implement targeted engagement strategies, enhancing both fundraising efficiency and long-term donor loyalty—key components in ensuring sustainable operations.

Understanding the grant making landscape is equally important. According to the Global Philanthropy Report (Paper 6), about 260,000 grant making organizations worldwide distribute over $150 billion annually. The COVID-19 pandemic has significantly altered grant making processes, requiring NGOs to adapt their strategies accordingly. Knowledge of different types of grants and the evolving funding landscape can guide NGOs in optimizing proposals and aligning with current donor expectations.

Technological adoption, particularly of Donor Management Systems (DMS), offers promising benefits such as increased donations, reduced costs, and enhanced transparency. However, adoption in nonprofits remains low due to perceived complexity and lack of experience (Paper 7). The Technology Acceptance Model shows that ease of use and prior exposure are critical drivers of adoption. These insights can inform strategies for integrating technology into donor engagement and fundraising systems.

Financial management for NGOs working with vulnerable populations such as the Roma, people with disabilities, and youth in care is complicated by regulatory constraints and limited funding (Paper 8). Understanding these financial challenges can help tailor predictive models that support sustainability and impact. Regulatory reforms may also be necessary to remove barriers and enable more effective service delivery.

Transparency in compensation practices also plays a vital role. Publicly available data from IRS Form 990 provides insight into nonprofit pay structures, which influence donor trust and funding decisions (Paper 9). Fair and transparent compensation aligns with organizational mission and can be linked to improved donor retention and organizational credibility. Incorporating this data into predictive models may uncover valuable relationships between internal governance and external support.

In summary, the literature emphasizes that improving NGO performance requires a multifaceted approach. Financial efficiency, data-driven donor management, grant strategy optimization, technological readiness, and transparent practices all contribute to stronger, more sustainable organizations. Integrating these elements into predictive modelling can help NGOs navigate challenges, strengthen donor relationships, and achieve long-term impact.

III. DATA

The data utilized in this study is derived from the National Center for Charitable Statistics (NCCS) Core Data Series (PC Version), which provides comprehensive annual records of nonprofit organizations in the United States. The dataset encompasses a wide range of financial and operational metrics, including total revenue, public support, expenses, and asset-related variables. For the scope of this research, only nonprofit organizations (NGOs) were retained, and datasets spanning the period from 1989 to 2022 were collected, filtered, and merged based on a common organizational identification number. The consolidated dataset initially comprised 735,499 observations and 230 variables, representing both numerical and categorical data types across multiple years.

To ensure analytical consistency and support longitudinal modeling, the dataset was further filtered to include only those organizations with complete records for the years 2012 to 2022. This step enabled the construction of a balanced panel data structure, where each organization was observed across consistent time intervals. Such a structure is well-suited for both time series analysis and fixed-effects panel modelling, enabling deeper insights into donor behaviour dynamics over time.

IV. DATA PREPARATION AND FEATURE SELECTION

A multi-stage preprocessing pipeline was developed to ensure data quality, address missingness, and optimize the dataset for predictive modeling.

Following the creation of the target variable, a new column named donor_churn was added to the dataset. This was computed by first calculating the percentage change in total revenue for each organization using the formula:

Revenue Change (%) $= \text{Revenue}_t - \text{Revenue}_{t-1} / (\text{Revenue}_{t-1}) \times 100$

If the revenue for an organization dropped by more than 20% compared to the previous year, it was assumed that the organization had experienced donor churn and was labelled as 1; otherwise, it was labelled as 0. This conversion of a continuous revenue change metric into a binary classification problem enabled the application of supervised machine learning models for churn prediction.

Missing value analysis was then performed on key numerical variables to identify both the extent and nature of data gaps. Variables were categorized into high and low missingness groups, and appropriate imputation techniques were applied. For variables exhibiting structured temporal dependencies, K-Nearest Neighbors (KNN) imputation was conducted within each organization's time series grouping, thereby preserving the panel data structure. Less critical variables with lower missingness were imputed using simpler strategies such as mean or mode, depending on data type.

Following imputation, a manual feature selection process was conducted using the dataset's metadata and detailed variable descriptions. From the initial set of 230 features, a subset of 14 variables was chosen based on domain relevance, statistical significance, and interpretability. To address potential multicollinearity, correlation analysis was conducted, and among highly correlated feature pairs, one was systematically removed to enhance model robustness and avoid redundancy.

Finally, given the imbalance in the donor churn classification (with far fewer churned cases), the Synthetic Minority Over-sampling Technique (SMOTE) was employed. This method generated synthetic data points for the minority class, improving the models' ability to detect and generalize churn behavior effectively. This comprehensive preprocessing pipeline ensured the dataset was clean, balanced, and analytically optimized for downstream predictive modeling.

V. METHODOLOGY

Selecting the right model is crucial for building an effective machine learning pipeline, especially when dealing with complex tasks like predicting donor churn. In this study, a range of models were evaluated based on their ability to handle class imbalance, capture non-linear relationships, and provide reliable predictions. The models considered included Logistic Regression, Random Forest, XGBoost, and the Fixed Effects Model, chosen after performing the Hausman test.

A. Logistic Regression is a foundational statistical model commonly used for binary classification problems. It is valued for its simplicity and interpretability, allowing the estimation of probabilities and insights into how predictor variables affect the likelihood of donor churn. Although it assumes a linear relationship between features and the log-odds of the outcome, making it less effective for capturing complex patterns, it served as a useful baseline in this project.

B. Random Forest is an ensemble learning method that constructs multiple decision trees using random subsets of features and samples. It excels at handling high-dimensional and imbalanced datasets, making it particularly suitable for donor churn prediction tasks. During model development, an initial Random Forest model was trained, and the feature importance scores were analyzed to determine the relative influence of each variable. Based on these scores, two features with low predictive importance were excluded from the model. Additionally, multicollinearity analysis revealed one highly correlated feature, which was removed after reviewing the associated metadata to ensure minimal loss of information. The model's ability to handle non-linear patterns and its robustness against overfitting made it a strong candidate for capturing the complexities inherent in donor behavior.

C. XGBoost (Extreme Gradient Boosting) is a highly efficient, scalable implementation of gradient boosting that builds sequential trees, each correcting the errors of its predecessors. XGBoost's strength lies in its ability to model intricate patterns and handle class imbalance using techniques like weighted sampling. Its performance and feature importance visualization make it ideal for donor churn prediction.

D. Fixed Effects Model is a panel data regression technique used to control for unobserved heterogeneity when analyzing repeated measures. In this context, it helped account for donor-specific characteristics not directly observable in the dataset. The Hausman test was conducted to choose between fixed and random effects, with the fixed effects model ultimately selected due to its ability to yield consistent estimates based on time-varying features.

E. These models were selected for their complementary strengths, helping to create a robust, well-rounded prediction pipeline that effectively addressed the challenges posed by donor churn prediction.

VI. HYPERPARAMETER TUNING

After initial model selection, hyperparameter tuning was performed to optimize each model's predictive performance. Hyperparameters such as the number of trees, learning rate, and maximum depth were tuned for Random Forest and XGBoost. Grid Search and Randomized Search techniques were employed—Grid Search exhaustively tested predefined hyperparameter values, while Randomized Search offered a more time-efficient alternative by sampling from a parameter distribution.

A. The tuning process focused on maximizing the model's performance on validation data using metrics like F1 score and ROC AUC. This step was critical to ensure that models generalize well to unseen data while maintaining sensitivity to the minority class (churned donors).

VII. MODEL EVALUATION AND RESULTS

Model evaluation was conducted using a combination of metrics tailored for imbalanced classification tasks. The F1 score was emphasized as it balances precision and recall, providing a clearer view of performance on the minority class. Given the dominance of non-churned donors in the dataset, traditional metrics like accuracy were considered alongside more discriminative metrics such as precision, recall, and ROC AUC score.

Accuracy alone can be misleading in imbalanced scenarios, so emphasis was placed on how well models performed in identifying true churn cases without compromising the precision of their predictions. The ROC AUC score was also used to assess the models' ability to distinguish between the churned and non-churned classes across different thresholds.

TABLE I : COMPARISON OF MODEL PERFORMANCE METRICS

Model	Performance Metrics			
	Accuracy	Precision	Recall	F1 Score

Logistic Regression	0.78	0.66	0.52	0.58
Random Forest	0.85	0.77	0.7	0.74
XGBoost	0.88	0.80	0.75	0.77

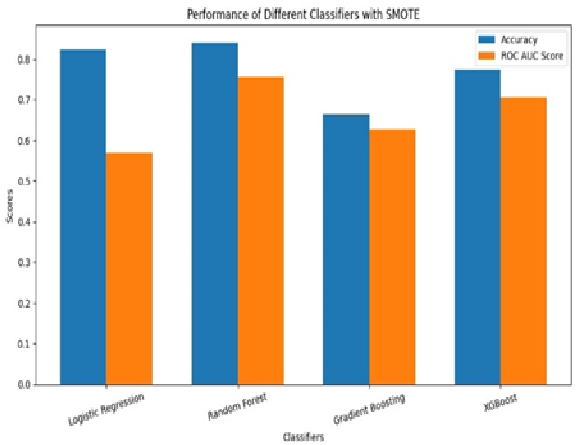

Fig 4.1 Performance of different classifiers with SMOTE

VIII. CONCLUSION

This study presents a comprehensive, data-driven framework for addressing the critical issue of donor churn in non-profit organizations through the application of machine learning and time series modelling techniques. The proposed approach enables accurate identification of high-risk donors and uncovers the key drivers influencing donor retention. The development of an interpretable and scalable predictive model, coupled with ARIMA-based revenue forecasting, equips non-profits with actionable insights to enhance donor engagement and optimize resource allocation. This holistic strategy not only supports sustained revenue streams but also strengthens the long-term impact and operational effectiveness of non-profit initiatives. The findings underscore the value of predictive analytics in driving strategic decision-making and fostering organizational resilience in the philanthropic sector.

IX. LIMITATIONS AND FUTURE ENHANCEMENTS

Despite its effectiveness, the proposed donor churn prediction system presents several limitations. First, model performance is strongly contingent on data quality and completeness. Incomplete or biased records can hinder predictive accuracy and limit generalizability across diverse organizational contexts. Although SMOTE was employed to address class imbalance, predicting churn events typically underrepresented remains a challenge. The computational intensity of training models on large-scale, high-dimensional data may also pose barriers to adoption, especially for smaller non-profits with constrained resources. Incorporating external data sources introduces additional dependencies and potential maintenance complexities.

Integration of external indicators such as macroeconomic trends or donor engagement metrics can enrich feature sets. Advanced models, including Recurrent Neural Networks (RNNs), may be leveraged to capture temporal patterns in donation behavior. Federated learning can be explored to enable collaborative, privacy-preserving model training across organizations.

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