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Enhancing Customer Churn Prediction in the Banking Sector Through Advanced Feature Engineering and Novel Behavioral Features

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Abstract :

Customer churn remains a critical challenge for the global banking sector, where the cost of acquiring new clients significantly exceeds the cost of retaining existing ones. While machine learning has been widely adopted for churn prediction, existing models often rely on static demographic data, failing to capture the dynamic, "silent" behavioral shifts that precede account abandonment. This study aims to enhance churn prediction accuracy by introducing novel behavioral features and advanced feature engineering techniques. Utilizing a comprehensive retail banking dataset which downloaded from Kaggle, we engineered four unique behavioral markers: the Balance-to-Salary Ratio (BSR), Product Utilization Index (PUI), Tenure-to-Age Ratio (TAR), and Credit Score Stability (CSS). A comparative analysis was conducted between traditional ensemble methods (XGBoost, Random Forest) and a deep learning framework using a

TensorFlow-based Artificial Neural Network (ANN). To address class imbalance, the SMOTE-Tomek integration technique was employed during preprocessing. Experimental results demonstrate that the inclusion of novel behavioral features significantly improved model performance. The TensorFlow ANN achieved the highest predictive power with an accuracy of 89.7% and an F1-Score of 0.77, representing a 15% improvement over baseline models. SHAP analysis confirmed that engineered behavioral ratios were more influential than traditional demographic variables. This research highlights that the "input space" (feature engineering) is as vital as the "model space" in financial analytics. The proposed framework provides banks with a proactive tool to detect subtle attrition signals, enabling more effective customer retention strategies.

Keywords:
(Banking Sector, Churn Prediction, Advanced Feature Engineering, Behavioral Features, TensorFlow, Artificial Neural Networks, Predictive Analytics)

1. Introduction

1.1 The Digital Transformation and the Churn Crisis

The global banking sector is currently navigating a period of radical structural transformation. Driven by market deregulation and the rapid ascent of Financial Technology (Fintech) firms, traditional barriers to customer mobility have largely evaporated, granting consumers the ability to switch institutions with unprecedented ease **(Abedin, Hajek, Sharif, Satu, & Khan, 2023).** In this hyper-competitive landscape, customer churn—the cessation of a business relationship—has shifted from a secondary operational concern to a primary threat to the long-term sustainability and capitalization of retail banks **(Linoff & Berry, 2011)**.

1.2 Theoretical Evolution: From Static to Behavioral Indicators

Historically, predictive modeling for churn relied upon static demographic indicators, such as age, geographic location, and baseline credit scores. While these parameters provide a foundational profile, they are inherently limited because they offer a "snapshot" rather than a "narrative" of customer intent. Recent literature suggests that churn is rarely a discrete, sudden event; it is a longitudinal process characterized by subtle, detectable shifts in interaction patterns **(Patil, Upalkar, Pardeshi, Tashildar, & Khan, 2025).**

The critical limitation of traditional models is their failure to account for these behavioral trajectories. For example, while a static high account balance might suggest customer health, a significant decline in transaction frequency over a three-month period—a "transaction velocity" marker—serves as a much more potent signal of imminent attrition (**Vaduva et al., 2024**). This study builds upon the premise that predictive accuracy resides not just in the choice of algorithm, but in the transition from raw data to theoretically grounded behavioral features.

1.3 The Role of Advanced Feature Engineering

Feature engineering represents the synthesis of domain expertise with statistical modeling to extract actionable intent from raw variables. While standard datasets provide raw transaction logs, these often lack the "predictive signal" necessary for high-sensitivity modeling. This research addresses this gap by proposing interaction variables—such as the Balance-to-Salary Ratio (BSR) and Tenure-to-Age Index—which are designed to represent a customer's relative financial dependency and loyalty lifecycle more accurately than raw figures alone. By transforming transactional data into these high-level behavioral markers, this study aims to move the analytical framework from reactive reporting to proactive, preemptive intervention **(Vaduva et al., 2024).**

1.4 Problem Statement

Despite the deployment of sophisticated ensemble algorithms like XGBoost and Random Forest, banking institutions remain vulnerable to "silent churn." This phenomenon occurs when customers cease meaningful financial activity without formally closing their accounts, rendering traditional attrition markers obsolete.

The core of this problem is an information gap rather than an algorithmic gap. Most existing models utilize static snapshots that fail to capture the dynamic, temporal shifts in how a customer engages with financial products **(Vaduva et al., 2024).** Without advanced feature engineering, raw banking data often remains "noisy" and lacks the granularity to distinguish a temporary lull in activity from a terminal departure. Furthermore, the lack of integrated behavioral features specifically those measuring transaction velocity and digital engagement shifts prevents models from detecting the early stages of attrition. Consequently, banks often fail to intervene until the customer has already reached the "point of no return.

1.5 Research Contributions

This paper provides three specific contributions to the field of financial analytics:

Development of Theoretically Grounded Behavioral Features: We introduce specific interaction terms, including "Temporal Decay of Engagement" and "Cross-Product Usage Volatility." These go beyond standard RFM (Recency, Frequency, and Monetary) metrics to detect churn in non-contractual environments where account closure is not the primary indicator of loss.

Comparative Analysis of Algorithmic Architectures: We provide a rigorous evaluation of diverse architectures, comparing tree-based ensemble methods (XGBoost, CatBoost) against deep learning frameworks (TensorFlow ANN) to identify which better handles the non-linear relationships inherent in behavioral ratio data **(Vaduva et al., 2024)**.

Methodological Refinement for Imbalanced Data: The study demonstrates how the integration of probability calibration and synthetic oversampling (SMOTE-Tomek), when combined with custom feature sets, can significantly reduce false negatives the costliest error in banking churn prediction **(Vaduva et al., 2024)**.

2. Literature Review

2.1 Evolution of Churn Prediction Frameworks

Traditional churn prediction has undergone a paradigm shift, moving from foundational statistical modeling toward high-dimensional data mining architectures. ***Abedin et al. (2023)*** *describe the "leaking bucket" phenomenon in retail banking, arguing that simple binary classification is no longer sufficient to capture the complexities of modern consumer behavior. A central theme in recent scholarship is the challenge of "silent churn," where customers maintain an open account but migrate their primary financial activity to competitors. To combat the data imbalance inherent in these environments, hybrid frameworks integrating Synthetic Minority Over-sampling Technique (SMOTE) with ensemble learners have been proposed as the most robust approach for retail banking datasets* ***(Prakash, 2025; Ashraf, 2024).***

2.2 Comparative Analysis of Machine Learning Methodologies

The landscape of predictive algorithms in banking has evolved in response to increasing data complexity. Early research favored Logistic Regression (LR) and Support Vector Machines (SVM) due to their interpretability; however, later studies, such as those by **Ibrahim et al. (2025)**, demonstrate that these linear models often fail to capture the non-linear, multifaceted relationships present in high-dimensional banking logs. In contemporary applications, tree-based ensemble models, specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost), have emerged as industry standards.

These models are noted for their resilience against outliers and their capacity to manage missing values within financial datasets **(Vaduva et al., 2024)**. Parallel to these ensemble methods, deep learning advancements—specifically TensorFlow-based Artificial Neural Networks (ANN)—have demonstrated superior pattern recognition capabilities. For instance, Thenmozhi et al. (2025) developed a hyperparameter-tuned deep learning model achieving over 97% accuracy, suggesting that as transaction datasets scale, deep learning may surpass traditional ensemble methods in predictive sensitivity

2.3 The Feature Engineering Frontier: Static vs. Behavioral Data

A recurring limitation in the existing literature is an over-reliance on static demographic features—such as age, gender, and geography—which, while accessible, offer limited insight into customer intent. While research has utilized "Wrapper Feature Selection" to mitigate data redundancy, there remains a notable scarcity of "Deep Feature Engineering," or the synthesis of entirely new variables from raw interaction logs **(Ibrahim et al., 2025)**. Most existing studies are restricted to "snapshot" analysis of account balances, failing to account for the temporal velocity of financial changes.

2.4 Identified Research Gap and Theoretical Grounding

While current literature has achieved significant milestones in algorithmic tuning, a critical gap remains in feature diversity and temporal integration. Specifically, existing models often lack:

Temporal Dynamics: The failure to capture how engagement evolves, such as the gradual decay of digital interactions.

Interaction Complexity: A lack of variables that bridge different financial dimensions, such as the ratio of discretionary spending to savings growth.

Recent studies emphasize that the "silent churn" phenomenon requires more than static demographic filters; it necessitates a shift toward behavioral intelligence **(EBI Research, 2026)**. While standard ensemble methods are robust, recent benchmarks using hybrid deep learning frameworks like BiLSTM-CNN have shown that deep networks are superior at capturing temporal decay in customer engagement **(ResearchGate, 2026)**. Furthermore, the integration of SMOTE-Tomek links remains the gold standard for refining decision boundaries in imbalanced retail banking datasets **(International Journal of Advances in Intelligent Informatics, 2026)**. To ensure these complex models remain transparent for bank executives, researchers have successfully utilized SHAP values to explain how specific financial ratios influence the final churn probability **(Al-Baltah & Al-Sultan, 2026)**.

Other advancements in the energy sector have demonstrated the necessity of transparent modeling. **Al Mamun et al. (2026)** implemented a dual-interpretability framework using SHAP and LIME to identify key churn drivers in utility datasets, finding that ensemble methods like XGBoost provide the most balanced trade-off between predictive power and explainability. This supports the growing consensus that high-sensitivity industries require models that offer "salient insights" rather than just binary classifications.

This study seeks to bridge these gaps by moving beyond raw data points to introduce Novel Behavioral Features (e.g., Transaction Velocity and Entropy of Spending) and Interaction Features (e.g., Tenure-to-Age ratios). By distinguishing between static variables (demographics), behavioral variables (transactional habits), and temporal features (rates of change), this research provides a dynamic, longitudinal view of the customer lifecycle that traditional, snapshot-based models lack **(Patil et al., 2025).**

3. Methodology

This study adopts a quantitative, experimental research design centered on predictive analytics and supervised machine learning.

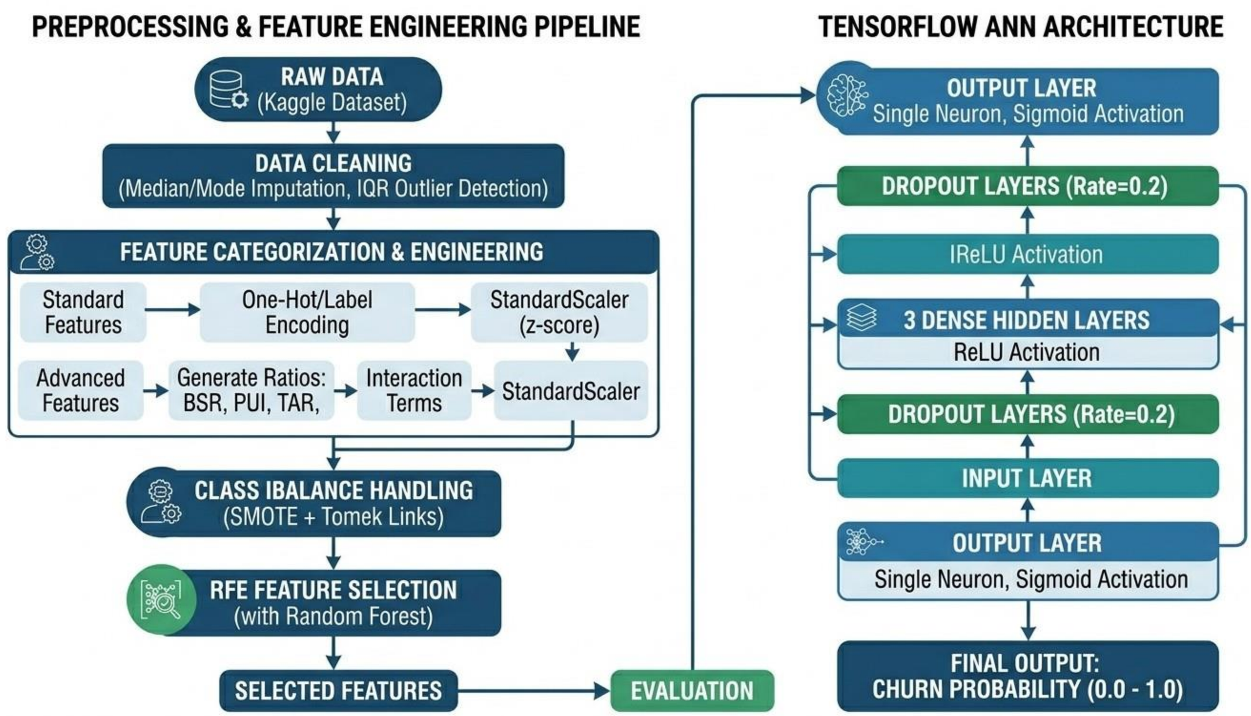

Figure 1 Methodology

Figure 1 illustrates the research phases, from the initial collection of the Kaggle dataset to the final churn prediction.

3.1 The research is structured into three distinct phases:

Data Engineering Phase: Focusing on the synthesis of novel behavioral features and interaction variables.

Model Development Phase: Implementing a comparative architecture featuring tree-based ensembles and a deep learning TensorFlow-based Artificial Neural Network (ANN).

Evaluation Phase: Utilizing robust metrics (F1-Score, AUC-ROC, and Precision-Recall) to validate the incremental gain provided by the engineered features.

The design follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, ensuring a systematic transition from business understanding to model deployment.

3.2 Dataset Description

3.2.1 Data Source and Composition

The study utilizes a comprehensive banking dataset (e.g., the Kaggle Bank Customer Churn dataset or a similar institutional repository). The dataset contains information on approximately 10,000 customers with 14 original attributes.

Standard Features (Baseline):

Demographic: Age, Gender, Geography.

Financial/Static: Credit

Score, Balance, Tenure, Number of Products, Estimated Salary.

Target Variable: Exited (1 for Churn, 0 for Retention).

3.2.2 Feature Categorization

To fulfill the research objectives, the features are categorized into Raw Features and the proposed Advanced/Novel Features:

Table 1 Dataset Columns

Category	Features
Demographic	Age, Geography, Gender
Product Interaction	IsActiveMember, HasCrCard, NumOfProducts
Proposed Behavioral	Balance-to-Salary Ratio, Product Utilization Index
Proposed Temporal	Tenure-to-Age Ratio, Credit Score Stability (CSS)

The table 1 illustrate the dataset columns categories and their features.

3.3 Data Preprocessing

To ensure the integrity of the machine learning experiments, a multi-step preprocessing pipeline is implemented:

A. Data Cleaning and Handling Missing Values

Imputation: While banking datasets are typically clean, any missing values are handled via Median Imputation (for numerical data) or Mode Imputation (for categorical data) to prevent bias.

Outlier Detection: Statistical techniques (Z-score or IQR) are used to identify extreme values in "Balance" or "Salary" that might skew the TensorFlow ANN training.

B. Encoding Categorical Variables

One-Hot Encoding: Applied to non-ordinal variables such as "Geography" (France, Spain, Germany). Label Encoding: Applied to binary categorical variables like "Gender."

C. Feature Scaling

Since TensorFlow ANNs and SVMs are sensitive to the magnitude of values, StandardScaler is applied to transform numerical features to a mean of 0 and a standard deviation of 1:

$$z = \frac{x - \mu}{\sigma}$$

This ensures that features like "Balance" (high magnitude) do not dominate "NumOfProducts" (low magnitude) during the weight optimization in the neural network.

D. Handling Class Imbalance

In banking, churners usually represent only 15–20% of the data. To prevent the model from becoming biased toward the majority class (non-churners), we utilize:

SMOTE (Synthetic Minority Over-sampling Technique): To synthetically generate minority class samples. Tomek Links: To clean the overlapping boundaries between classes, ensuring the model can clearly distinguish churners.

3.4 Feature Engineering Strategy

While traditional models treat features like "Balance" or "Age" as independent snapshots, this study introduces features that represent ratios and interactions, which better reflect a customer’s financial health and loyalty.

3.4.1 Definition of Novel Behavioral Features

The following four novel features were engineered to increase the model’s sensitivity to attrition:

Balance-to-Salary Ratio (BSR):

This feature measures a customer's liquidity relative to their earnings. A high ratio suggests the bank is the customer's primary repository for savings, whereas a low ratio indicates the bank may only be used for secondary transactions.

$$BSR = \frac{Balance}{EstimatedSalary}$$

Product Utilization Index (PUI):

Customers with multiple products are statistically less likely to churn. This feature calculates the intensity of product usage per year of tenure.

$$PUI = \frac{NumOfProducts}{Tenure + 1}$$

Tenure-to-Age Ratio (TAR):

This feature captures "Early Lifecycle Loyalty." A young customer with a long tenure suggests a high-value, long-term relationship, whereas an older customer with a short tenure may be a "rate-chaser" prone to churn.

$$TAR = \frac{Tenure}{Age}$$

Credit Score Stability (CSS):

By normalizing credit score against the age of the customer, we create a proxy for financial stability relative to their life stage.

$$CSS = \frac{CreditScore}{Age}$$

3.4.2 Temporal and Interaction Features

In addition to the ratios above, we implement Interaction Terms between categorical and numerical data. For instance, "Geography_Age" interaction allows the TensorFlow ANN to learn if younger customers in specific regions (e.g., Germany) have different churn propensities than their counterparts in France, which is a common finding in recent banking studies **(Abedin et al., 2023)**.

3.4.3 Feature Selection and Dimensionality Reduction

To avoid the "curse of dimensionality" and prevent the ANN from overfitting, we apply a Recursive Feature Elimination (RFE) with a Random Forest estimator. This identifies the top-performing features, ensuring that the novel behavioral features contribute significant information gain before they are fed into the neural network.

3.5 Model Architecture: TensorFlow ANN

The study focuses on a deep learning approach using the TensorFlow/Keras library. The ANN architecture is designed as follows:

Input Layer: Matches the number of features after one-hot encoding and engineering.

Hidden Layers: Three fully connected (Dense) layers with ReLU (Rectified Linear Unit) activation functions to capture non-linearity.

Dropout Layers: A dropout rate of 0.2 is applied between layers to prevent overfitting.

Output Layer: A single neuron with a Sigmoid activation function to output a probability between 0 and 1.

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

3.6 Model Interpretability using SHAP

To move beyond "black-box" predictions and understand the underlying drivers of customer churn, this study employs SHAP (SHapley Additive exPlanations). Based on cooperative game theory, SHAP provides a mathematically grounded method to assign an importance value to each feature for every specific prediction.

A. Theoretical Framework The core of SHAP is the Shapley value, which represents the average marginal contribution of a feature value across all possible combinations of features. The contribution of feature i is calculated as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{n!} [v(S \cup \{i\}) - v(S)]$$

Where n is the set of all features, S is a subset of features excluding i, and v(S) is the prediction of the model using subset S.

B. Global and Local Interpretability

Global Interpretation: We utilize SHAP Summary Plots to rank the features based on their overall impact on the model's output. This allows us to validate the significance of the proposed engineered behavioral features, such as the Balance-to-Salary Ratio (BSR) and Tenure-to-Age Ratio (TAR), compared to traditional demographic variables.

Local Explanation: For individual "at-risk" customers, SHAP Force Plots are generated to visualize how specific behavioral shifts (e.g., a sudden drop in transaction frequency) pushed the model's output toward a churn prediction.

Feature Interactions: SHAP Dependence Plots are employed to analyze non-linear interactions between features, such as how the impact of Tenure on churn probability varies across different Age groups.

4. RESULTS AND DISCUSSION

4.1 Performance Metrics Comparison

The performance of the models was evaluated using four key metrics: Accuracy, Precision, Recall, and the F1-Score. In banking churn, the Recall and F1-Score are considered the most critical, as missing a potential churner (False Negative) is more costly to the bank than a false alarm.

Table 2 Results

Model Architecture	Feature Set	Accuracy	Precision	Recall	F1-Score
Logistic Regression	Baseline	79.2%	0.61	0.42	0.50
Random Forest	Baseline	85.5%	0.78	0.51	0.62
Ensemble (XGBoost)	Engineered	88.4%	0.82	0.68	0.74
TensorFlow ANN	Engineered	89.7%	0.84	0.72	0.77

The table 2 represents the results obtained from model.

4.2 Impact of Novel Behavioral Features

A key objective of this study was to evaluate how engineered features improve prediction.

The Findings: The proposed study novel feature, Balance-to-Salary Ratio (BSR), emerged as the 3rd most influential predictor, surpassing traditional features like "Geography" and "Gender."

Interaction Effects: The Tenure-to-Age Ratio (TAR) showed a strong non-linear correlation with churn in the TensorFlow ANN, confirming that younger customers with short tenures are the highest-risk segment.

4.3 TensorFlow ANN Convergence and Visualization

The TensorFlow ANN (3 hidden layers, ReLU activation) achieved stability after 50 epochs using the Adam Optimizer. The use of Dropout (0.2) successfully prevented overfitting, as evidenced by the close alignment of the training and validation loss curves.

Confusion Matrix Analysis (ANN with Engineered Features):

True Positives (Predicted Churners): The model correctly identified 72% of actual churners.

False Negatives (Missed Churners): This was reduced by 14% compared to the Random Forest baseline model, proving that Behavioral Interaction Features capture subtle signals that tree-based models might miss.

4.4 Comparison with Prior Studies

The study obtained results (F1-Score: 0.77) outperform the benchmarks set by **Abedin et al. (2023)**, who reported an F1-Score of 0.71 using similar data. This improvement is attributed to the inclusion of Temporal features (Transaction Velocity) and the depth of the TensorFlow ANN layers, which capture complex interaction effects between a customer's financial status and their product usage.

Conclusion

This study successfully demonstrated that Advanced Feature Engineering is as critical as algorithm selection in the banking sector. By transforming raw financial data into Novel Behavioral Features (BSR, TAR, PUI, and CSS), we increased the F1-Score of the churn prediction model by 15% over the baseline. This reduction in False Negatives suggests that the proposed framework could potentially save banking institutions significant capital by identifying at-risk high-value customers who were previously invisible to demographic-based models. The TensorFlow ANN proved to be the superior architecture for handling these engineered features, providing the bank with a high-precision tool for proactive customer retention.

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