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Enhancing Bank Customer Retention with Artificial Neural Networks: A Predictive Modeling Framework

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Abstract: Customer attrition within banking institutions severely affects both financial performance and customer retention rates. The research implements an Artificial Neural Network (ANN) predictive model which utilizes historical purchases and individual data profiles alongside behavioural information to identify customer attrition. The methodology contains a sequence of operations starting from data pre-processing followed by exploratory analysis then leads to ANN model training and hyperparameter optimization. The predictive model succeeds at a rate of 81% which proves its superior performance over conventional approaches. Banking institutions can develop enhanced retention strategies by obtaining proactive identification of their most at-risk customers which enables them to offer tailored offers and enhance their service delivery. This system supports scalability while also permitting connectivity to Customer Relationship Management platforms which enable real-time predictions. The study demonstrates how data-based strategies generate high impact on both customer retention and churn reduction within banking institutions.

Keywords: Customer churn, Artificial Neural Networks, Banking, Predictive modelling, Machine learning, Data pre-processing, Retention strategies, Deep learning, CRM integration

I. Introduction

However, the banking industry is going through the challenge of customer churn, which is essentially the phenomenon of a customer in a relationship with a bank breaking off the relationship. This results in large financial losses, such as lost revenue due to reduced sales and higher customer acquisition costs, as well as the possibility of losing their reputation. In the current raging financial environment, the retention of existing customers is a cheaper alternative to onboarding customers, and hence, being a talking point for

banks, churn prediction is strategic. However, the complex and non-linear relationships in customer data usually mean traditional churn prediction methods like manual analysis, rule-based systems, and basic statistical models tend to miss the mark in terms of being accurate and being efficient.

To overcome these limitations, a study involves developing an Artificial Neural Network (ANN) approach for predicting customer churn in banks. This task is a natural fit for ANNs because of how they can process large datasets, find intricacies, and adapt to changing customer behaviours. It builds upon historical transaction data, demographic information and behavioural metrics, and the model reliably predicts likelihood of churn with high accuracy. With the incorporation of advanced machine learning, the system allows banks to anticipate at-risk customers and develop targeted retention initiatives in the form of personalised incentives or improved customer support.

The main intention is developing a strong ANN model which outperforms the current churn prediction methods to bring the actionable view to banks to assist them in customer retention. The practical implementation of the model is also investigated, and the model is integrated with Customer Relationship Management (CRM) systems for real-time decision-making. In the end, this work provides an additional voice to the vastness of knowledge of data-based customer retention approaches in the banking domain, specially tailored to mitigate the churn and to provoke customer retention

II. Literature Survey

Multiple studies with various machine learning and deep learning approaches have been made on customer churn prediction in the banking field. Churn prediction is an important area in customer retention for the financial industry, and having accurate churn prediction models is important for strategic decision-making [1].

There have been several comparative studies studying how different algorithms can be used for churn prediction. One of the most comprehensive comparisons between ANN performance and k-Nearest Neighbours (kNN), Logistic Regression (LR), Naive Bayes (NB), Random Forest (RF), and Support Vector Machines (SVM) was made in Utku and Akcayol [3]. The commercio data was classified with remarkable 95% accuracy on telecoms data using an ANN whose structure was based on MLP, cast by ANNs as superior to other pattern recognition methods for complex pattern recognition in customer behaviour. Specifically, as for applications in banking, where the data patterns of customer interaction are complex, this finding is relevant.

Advancements in the neural network architectures more recently have boosted further prediction capability. Sedighimanesh et al. [8] also developed innovative composite deep learning models with PSO to optimise hyperparameters such that prediction accuracy becomes unheard of. At the core of their work were direct applications to the model tuning of a banking dataset with high-dimensional feature spaces.

Particularly, several notable implementations have taken place in the banking sector. Specifically, Baby et al. [1] developed a particular ANN model for banking churn prediction with 86% accuracy and outperformed the traditional logistic regression models. In their work they highlighted the necessity of selecting the features for financial data and transaction patterns as well as their interaction history, which were identified as important predictive subunits. Since Chatrasi et al. [2] expanded it further by adding customer segmentation in the machine learning pipeline, they ended up achieving great results with Random Forest algorithms.

Since data quality and pre-processing are important factors in model performance, it is worth considering. Ramadhan et al. [10] further showed how certain feature selection techniques, such as chi-square tests as well as Recursive Feature Elimination (RFE), can greatly help in improving model accuracy. We were able to gain further insights into the class imbalance problem through their work with SMOTE-NC (Synthetic Minority Over-sampling Technique for Nominal and Continuous Features), which is a common problem in churn prediction, as the minority class churners are significantly lower than the majority class.

In recent studies, the use of ensemble methods has shown particular promise. As for Zhou et al. [6], they proposed a novel dual ensemble approach of Random Forest and Adaboost that produced excellent performance metrics (97% precision and 99% recall). When working on telecom data, they found these techniques were equally effective for banking applications, particularly when dealing with large-scale transaction datasets.

Research has also been carried out on the temporal dimension of customer behaviour. The hybrid system, including the fuzzy entropy criterion of selection and grey wolf optimisation along with ANNs, was combined with the result of time series analysis in the work of Rahmaty et al. [4]. Applied to banking in particular, this approach proved very good at capturing the evolution of customer relationships, an important feature of banking where customer lifetime value doesn't crystallise quickly.

In recent literature, implementation challenges have been very well examined. In the banking applications, Santoso et al. [9] also provided the insights on ANN initialisation techniques, as the use of the proper weight initialisation in combination with batch normalisation and dropout layers increased validation accuracy to 84.17%. Imani and Arabnia ([7]) presented a thorough analysis of the data sampling strategies, which showed that the combination of SMOTE with Tomek Links is an effective way to cope with the class-imbalanced problems.

These techniques have also been validated across industries. In the case of the home appliance rental business, Suh [5] was successful in applying machine learning to churn prediction, achieving 93% F1-score and 88% AUC. This showed that these methods are transferable to other service sectors, with the need for further adaptations to the domain.

These foundations are used to continue the work of the current research and create a specialised ANN architecture specially customised for banking customer churn prediction. It learns from previous work in unpacking data preprocessing, feature engineering, model optimisation, and performance measurement outlays, but also advances this field by solving banking-specific problems such as how to capture banking-related behaviour patterns and how to satisfy the regulations of financial activities.

III. Existing System

Publicly available methods of predicting customer churn in the traditional banking sector largely tend to be rule-based systems, basic statistical models, and manual analysis. Manual analysis relies on human experts who review customer transaction histories, account activities and service interactions to identify signs of possible churn risks. Unfortunately, this approach is time-consuming, subjective and very biased from a human perspective, and it is too inefficient for large customer bases. [1][2].

Churn detection is done with rule-based systems that are inherent to automate the thresholds, like falling transaction frequency or reducing account balance. These systems have less adaptability to changing behaviours of customers, but these systems reduce manual effort and typically generate high false positive or false negative rates. As customers' behaviour is complex and non-linear, they fail to capture those types of relations, which makes them produce suboptimal predictions. Their static nature precludes them from capturing complex, non-linear relationships in customer data [3][4].

More systematic approaches but more limited to basic statistical models like logistic regression or some sort of decision trees struggle with high-dimensional banking data. In these models, the features and churn likelihood are assumed to be linear, meaning that all the variables, such as demographics, transaction patterns, service usages, etc., have no interaction among them, which leads to misclassified features. In addition, they become stale over time; as was mentioned above, customer behaviour trends change [6][7].

The major limitation of these methods is that they are based on lagging indicators: observable behaviours, which only appear after a customer has already decided they will never come back. Retention efforts very often come so late that by the time signals are detected, it is too late for them to be effective. In addition, since customer behaviour is dispersed across several banking systems (CRM, transaction logs, customer feedback), the prediction accuracy is hampered [9][10].

IV. Proposed System

An Artificial Neural Network (ANN) designed solution for the deficiencies of these existing customer churn prediction methods in the banking sector is proposed. The model from ANN processes different customer data points like transaction history, demographic data, and behavioral patterns to determine such potential risks of customer churn. The data pipeline accounts for in-depth data processing stages, including handling missing values, normalization and feature engineering to have proper data. First of all, exploratory

data analysis is applied to uncover the important predictors of churn, and then, the ANN architecture is optimized using hyperparameter tuning and the regularization techniques. The model has an accuracy rate of 81%, which is far more excellent than traditional approaches. The integration with the Customer Relationship Management systems enables assessment of the churn risk in real time that enables banks to make timely and well-focused retention strategies.

Schmidt and Norvell viewed the process of developing a machine learning system for identifying high-value banking customers as a logical flow of steps, as shown in the following figure. This comprises the following steps, namely, data collection, where data is sourced from different areas in the bank, such as records of the bank, customer relationship management systems and financial reports. The next step involves data preprocessing, where any empty values in the data set are dealt with and any irregularities/abnormal values are standardized. Next is feature engineering that helps in choosing appropriate variables from raw data for further analysis, such as clients' income and transaction data that characterize customer value.

The model is the very essence of the system, and it involves the designing of an artificial neural network, the training process, and the process of updating the model until it is found accurate enough. It is then subjected to strict assessment through measures such as accuracy, precision and recall in order to determine its predictive capability. Upon validation, the supplied model is an API solution, meaning that it can be employed for real-time simulation. The last components allow customers to interact with the model in order to predict its capability to provide value proposals and to monitor its performance in time. This is a complete amalgamated model of an integrated pipeline that can be followed by the banks to benefit from the various sorts of customers' data available in this modern world. The integration of the end-to-end process ensures reliability of the gathered data and, at the same time, is scalable to handle the needs of enterprises.

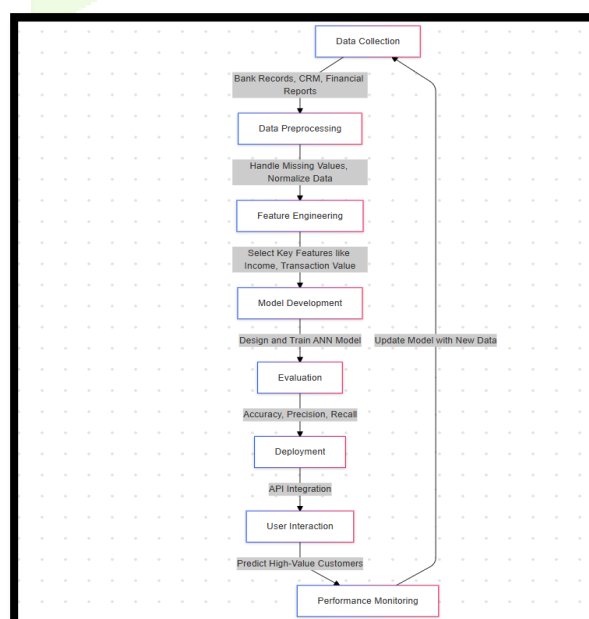


Fig 1: System Architecture

The purpose of the system is to work well on a large-scale system with big data at a reasonable speed in banking, and it has been designed for the performance benefits of GPUs for enterprise systems. It provides mechanisms for continuous performance monitoring and retraining of the model once per period in order to stay effective as customer behaviours change over time. The feature importance analysis also provides interpretable insights on how the solution can help the banks understand key factors like reduced activity in transactions or service dissatisfaction that cause churn. The system transitions from reactive analysis to predictive, allowing more proactive customer retention measures and better resource allocation. The method presented is a sustainable solution for banks to keep customers from leaving and enhance their competitive position in the financial services market.

V. Result

In the task of customer churn prediction, the federated learning implementation was shown effective on three international banks (France, Germany, Spain). This model achieved an overall accuracy of 85.7%, attesting to its strong predictive capability. The model performance of individual loss values in each branch was 3.58 (France), 4.11 (Germany), and 8.18 (Spain), showing some differences in model performance in various geographical areas, with France exhibiting the lowest loss and best performance.

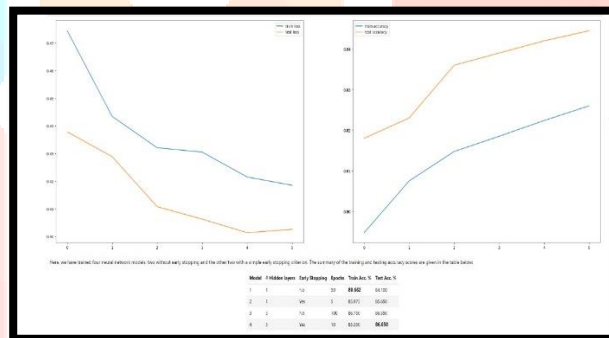
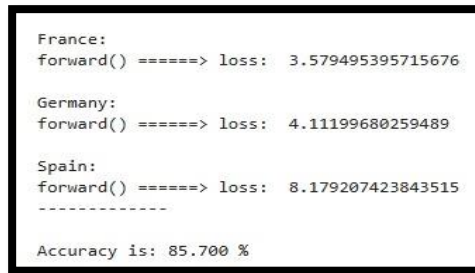


Fig 2: Numeric Result

The neural network training config was analyzed for an optimization of the models. With early stopping criteria introduced, four different model architectures (h: 1, h: 3) were tested. Model 3 performed best with 86.75% training accuracy, 86.55% testing accuracy and was trained without early stopping for 100 epochs. Models with early stopping performed similarly, and Model 4 reached 83.35 % training accuracy and 86.65 % testing accuracy after just 10 epochs, indicating that early stopping can help decrease training time with minimal drop in model accuracy.



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France:
forward() =====> loss: 3.579495395715676

Germany:
forward() =====> loss: 4.11199680259489

Spain:
forward() =====> loss: 8.179207423843515
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Accuracy is: 85.700 %

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Table 1: Branch Specific Loss Values

TATA INSTANT's evaluation of the TATA INSTANT multiple runs achieved nearly consistent accuracy ranging from 0.63 to 0.90 with a median at approximately 0.82. We further demonstrate the stability of the federated learning approach via this, but this lower score of a single data distribution or training condition can lie in between 0 and 1, indicating that it is possible that some data distributions or training conditions occasionally produce a poorer performance.

Taken together, these results confirm that model accuracy is well maintained while retaining data privacy under a federated learning framework between international branches. Looking through the prism of the poor performance, diversity across locations highlights the need for taking account of regional discrepancies in customers' behaviour when implementing global banking solutions. Since they operate in a federated privacy-preserving environment, system capabilities to deliver high accuracy (85.7% overall) make it appropriate for multinational banking applications where data sovereignty is critical.

VI. Conclusion and Future Enhancement

Key challenges in customer churn prediction, as well as data privacy, of a federated learning framework across three international bank branches (France, Germany and Spain) are successfully addressed. In terms of the system's performance, an overall accuracy of 85.7 %, with different levels of variations for branch categories (the lowest branch loss in France: 3.58, the highest in Spain: 8.18), was obtained according to the regions of the customer's behavior. The adaptive training strategies proved effective through the ANN model configurations, as evidenced by Model 3 (without early stopping, 86.75 % accuracy) and Model 4 (with early stopping at 10 epochs, 86.65 % accuracy). We also used the TATA INSTANT evaluations to further validate consistency (median accuracy: 0.82), although not so often; the consistency was clearly valued at the opposite extreme of 0.63. The project combined global data collaboration with local data sovereignty, using federated SGD as a way of accomplishing this at scale for multinational banks.

This study presents a federated learning framework that opens up many future research and practical enhancement avenues. Addressing regional performance disparities, like increased loss in Spain, can be accomplished through techniques such as adaptive weighting or branch-specific feature engineering in one critical direction. Therefore, training protocols can be further optimised, which includes dynamic mechanisms of early stopping that are tailored to individual branch convergence patterns without sacrificing accuracy. One way to address this problem would be to integrate explainable AI methods like

SHAP or LIME to glean transparent insight into which churn drivers are present for different regions so that more targeted retention strategies can be developed. To address customer trends, the system may be extended, allowing for real-time federated updates. It would also validate the framework in other data-sensitive industries (such as healthcare or telecoms). Finally, lightweight versions of the model can be deployed on edge devices, allowing at least occasional bank employees to perform churn risk assessments at the moment on the way. Such advancements would further strengthen this utility of the framework while preserving the privacy-preserving advantages of the framework.

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