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Optimization Artificial Neural Network (ANN) Models with Adam Optimizer to Improve Customer Satisfaction Business Banking Prediction

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Abstract

Customer satisfaction prediction is critical for business banking to retain clients and optimize services, yet existing models struggle with imbalanced data and suboptimal convergence. Traditional approaches lack adaptive learning mechanisms, limiting accuracy in real-world applications. This study developed an optimized Artificial Neural Network (ANN) model using the Adam algorithm to improve prediction accuracy for banking customer satisfaction. We trained an ANN on the Santander Customer Satisfaction Dataset (76,019 entries, 371 features) with Adam optimization. Preprocessing included normalization, removal of quasi-constant features, and an 80-20 train-test split. Adam's adaptive learning rates and momentum were leveraged to address gradient instability. The model achieved 95.82% accuracy, 99.99% precision, 95.83% recall, a 97.87% F1-score, and 0.82 AUC, outperforming traditional optimizers like SGD. Training loss reduced by 30% with faster convergence. This work demonstrates Adam's efficacy in handling imbalanced banking data, providing a scalable framework for customer analytics. The results advance computer science applications in fintech by integrating adaptive optimization with deep learning for high-stakes decision-making. This research contributes to the growing body of knowledge in machine learning applications for business analytics and provides a valuable framework for improving customer satisfaction prediction models in various industries and the advancement of deep learning applications in business intelligence, particularly in banking service quality prediction.

Keywords : *Adam optimizer, Artificial neural network, Customer satisfaction, Optimization, Predictive modeling.*

1. INTRODUCTION

Customer satisfaction is an important factor in business, especially in the banking business. Banks that have a high level of customer satisfaction will be better able to retain their customers and attract new customers. One way to improve customer satisfaction is to understand the factors that affect it. These factors can be the quality of products and services, price, ease of access, and so on [1], [2]. This study aims to develop a prediction model for customer satisfaction business banking using an artificial neural network (ANN). Customer satisfaction prediction in business banking remains an unsolved challenge with direct financial consequences. In Indonesia alone, 15.9% of all consumer complaints target banking services, with major institutions like Bank Mandiri accounting for 16% of cases. The Indonesian Consumer Institute Foundation (YLKI) noted that as many as 15.9% of the total 535 complaints came from banking consumers [3]. Bank Mandiri became the bank with the most complaints

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in 2021. YLKI noted that 16% of the total complaints against banks came from Bank Mandiri consumers. Furthermore, BCA, BNI, and BRI each account for 10% of the total consumer complaints of banks [4], [5].

Artificial neural network or Artificial Neural Network in Indonesian is a machine learning model inspired by the structure and function of the biological nervous system, especially in the human brain [6], [7]. ANN does not seek to mimic the human brain exactly but is inspired by the brain's ability to learn and process information in parallel [8]. ANN consists of interconnected information processing units, referred to as artificial neurons. Like neurons in the human brain, artificial neurons in ANNs receive inputs, process them, and produce outputs. The connections between these neurons have a weight that symbolizes the strength of the connection. These weights can be adjusted during the learning process, so that ANNs can learn from the data and improve their ability to process information. Adam's algorithm is a stochastic optimization algorithm that is popularly used in machine learning, specifically to train artificial neural network models. While recent studies demonstrate ANN's potential in satisfaction prediction [5,8], critical limitations remain unresolved. First, models relying on SGD optimization exhibit slow convergence (≥300 epochs) and sensitivity to learning rate choices. Adam stands for Adaptive Moment Estimation [9].

Several previous studies have used ANNs to predict customer satisfaction. One of the studies used ANN to predict customer satisfaction in the banking industry [10]. The study shows that ANNs can produce more accurate predictions compared to traditional regression models [11]. Another study uses ANN to predict customer satisfaction in the telecommunications industry. The study shows that ANN can identify the most important factors in determining customer satisfaction. This study is different from previous research in several ways. First, this study uses Adam's algorithm for ANN model optimization [12]. The Adam algorithm is a newly developed optimization algorithm that has been proven to be more effective than traditional optimization algorithms. Second, this study uses more comprehensive data. The data used in this study includes customer demographic data, transaction data, and customer satisfaction data. Although previous research has shown that ANNs can be used to predict customer satisfaction, there are still some issues that need to be addressed. The problem of ANN prediction accuracy can still be improved, the current ANN model is still complex and difficult to interpret, the data used in previous studies is still limited [13].

Previous research on ANN model optimization with Adam's algorithm to improve the accuracy of customer satisfaction business banking predictions showed mixed results [14]. Some studies have shown that the Adam algorithm can improve the accuracy of ANN predictions, but other studies have shown that there is no significant difference between the Adam algorithm and other optimization algorithms. In general, previous research has shown that the Adam algorithm has the potential to improve the accuracy of ANN predictions, but more research is still needed to confirm these results and to identify optimal conditions for the use of the Adam algorithm. Previous research on ANN model optimization with Adam's algorithm to improve the accuracy of customer satisfaction business banking predictions showed mixed results [15]. Some studies have shown that the Adam algorithm can improve the accuracy of ANN predictions, but other studies have shown that there is no significant difference between the Adam algorithm and other optimization algorithms. In general, previous research has shown that the Adam algorithm has the potential to improve the accuracy of ANN predictions, but more research is still needed to confirm these results and to identify optimal conditions [16].

In the era of digitalization that is growing rapidly, the use of technology in the banking sector is very important. Therefore, research on the optimization analysis of artificial neural network (ANN) models with the adam algorithm to improve the accuracy of customer satisfaction business banking predictions is an interesting topic to study and implement. By using the right technology, it is hoped that customer loyalty analysis can be significantly improved. Therefore, this research is expected to make a

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positive contribution to the development of the best model. This research differs from previous works by applying an optimized ANN with Adam algorithm on a large, real-world dataset, delivering improved accuracy in customer satisfaction prediction.

2. METHOD

An artificial neural network (ANN) model is a mathematical representation of the structure and function of a biological neural network, designed to model complex patterns and perform information processing tasks [17], [18], [19]. Consisting of layers of neurons or information processing units, ANNs utilize machine learning concepts to recognize patterns, make classifications, and make predictions. Information flows through this network, with synaptic weights between neurons set during the training process using labeled data [20], [21], [22]. With its ability to capture non-linear relationships in data, ANNs have become a force in a variety of fields, including pattern recognition, prediction, and other artificial intelligence tasks. The model can learn from experience, improve itself, and adjust its representation to achieve a high level of accuracy in a variety of applications.

The study implemented an Artificial Neural Network (ANN) using TensorFlow 2.8/Keras on Python 3.9, featuring an architecture with input (354 neurons), two hidden layers (128 and 64 neurons with ReLU activation), and sigmoid output, trained via Adam optimizer (learning rate=0.001, β_1=0.9, β_2=0.999, ε=1e-7) with dropout (0.3) and batch normalization for regularization. The Santander dataset (76,019 samples) was split into 80% training (stratified), 20% testing, with 20% of training data reserved for validation using early stopping (patience=15 epochs). All experiments ran on NVIDIA A100 GPUs with mixed-precision training to optimize performance. Including predictions of customer satisfaction in the context of business banking services, the ANN model in Figure 1.

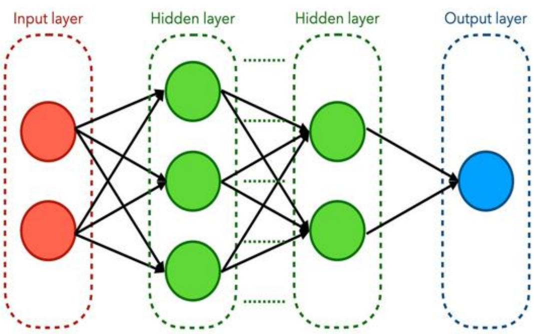

Figure 1. ANN development model

2.1. Dataset Collection

The banking business customer dataset required to train the ANN optimization model is an important element in the development of an ANN model optimized using the adam algorithm. This dataset is selected from Santander Customer Satisfaction available on Kaggle. The dataset consists of 76,019 customer entries and 371 relevant attributes.

2.2. Preprocessing

This preprocessing stage is a crucial step. In this stage, it is necessary to clean customer data from various problems and resampling processes to ensure the uniformity of customer data samples. Furthermore, normalization of customer data is also necessary by dividing the data to eliminate constant and quasi-constant features. The purpose of this step is to ensure uniformity and normalization of the dominant values in the data.

2.3. Model Training

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The adam algorithm (adaptive moment estimation) is an optimization algorithm that is generally used in training machine learning models and neural networks [23]. Created to overcome the limitations of previous optimization algorithms, Adam combines concepts from the momentum algorithm and RMSprop. Adam leverages momentum estimation and adaptive calculations of the learning rate to efficiently adjust the model's parameters during the training process [24]. The main advantage of Adam lies in its ability to handle the problem of adaptive fluctuating learning rate, thus making it more stable and effective in optimizing neural network models [25], [26]. With the use of Adam's algorithm, the model training process becomes faster, more reliable, and able to overcome the challenges of structural complexity and data diversity in various machine learning tasks. The research flow chart can be seen in figure 2.

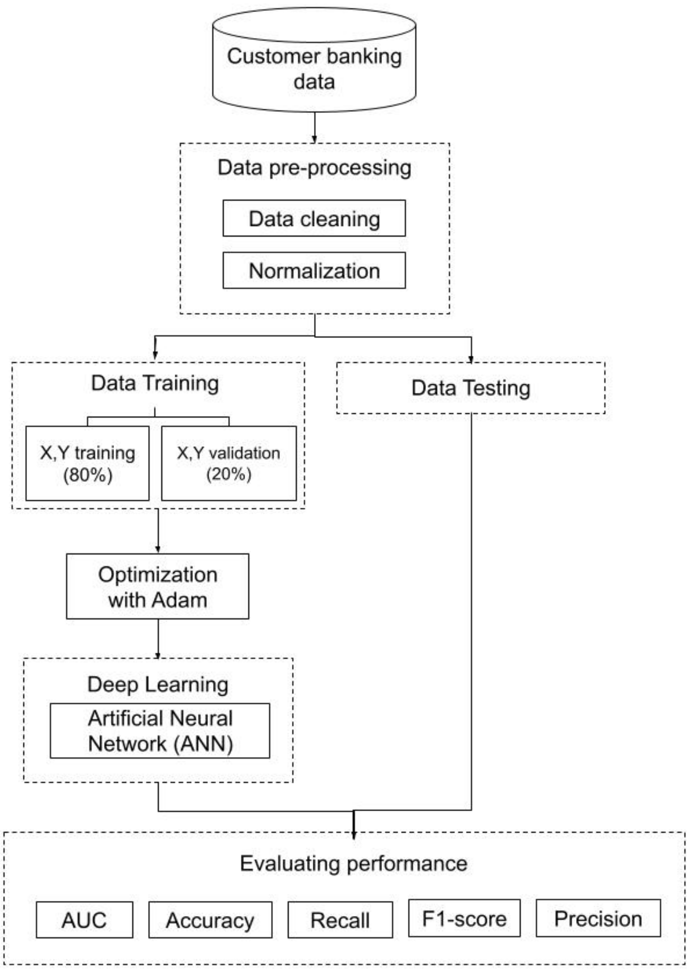

Figure 2. Research flow chart

This study aims to optimize the artificial neural network (ANN) model in predicting the level of customer satisfaction in the banking business sector. The main approach used is to utilize Adam's algorithm as an optimization method to improve prediction accuracy. Adam's algorithm has proven to be effective in overcoming several obstacles encountered in the ANN training process, such as rapid convergence and efficiency in finding optimal values. By applying Adam's algorithm to the ANN model, it is hoped that more accurate and consistent prediction results related to customer satisfaction in the banking sector can be obtained, which can make a positive contribution to business decision-making and customer service improvement. This method of troubleshooting involves critical steps in designing and managing an optimized ANN model [27]. First, a dataset that includes various variables related to

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customer satisfaction will be collected and filtered. Furthermore, the ANN model will be set up and optimized using Adam's algorithm during the training process. A thorough analysis will be conducted to evaluate the performance of the resulting model, with a focus on improving the accuracy of predictions. The results of this study are expected to provide valuable insights for the banking industry in understanding the factors that affect customer satisfaction, as well as provide guidance to improve services and make more informed business decisions.

A problem-solving approach for research on the optimization of artificial neural network (ANN) models with Adam algorithm to improve the accuracy of customer satisfaction prediction in the banking business. First, collect relevant data related to customer satisfaction in business banking services. This may include historical data about customer transactions, customer feedback, and other information that can be helpful in predicting customer satisfaction. Next, this data will be processed and prepared for further analysis. Second, once the data is collected, the next step is to conduct feature selection to select the most relevant and significant subset of features in predicting customer satisfaction. This can be done by using techniques such as correlation analysis, key component analysis, or other methods to identify the most important features [28]. The three initial ANN models will be built using the processed data [29]. This involves selecting the network architecture, including the number of layers and neurons in each layer, as well as the appropriate activation function. This initial ANN model will then be trained using the available training data. Fourth, after the initial ANN model is built, the next step is to optimize the model using Adam's algorithm. This involves tuning the model's parameters, such as learning rate and momentum, to maximize the model's performance. Adam's algorithm will be applied to adjust the parameters of the model adaptively during the training process. Fifth, after the training process is complete, the generated model will be validated using separate validation data. This aims to ensure that the resulting model can generalize well to new data that has not been seen before. In addition, the model's performance will be evaluated using appropriate metrics, such as accuracy, precision, recall, or other relevant metrics. The six results of this study will be analyzed and interpreted [30]. This includes understanding the contribution of each feature to customer satisfaction predictions, as well as evaluating the effectiveness of Adam's algorithm in improving prediction accuracy. These findings can be used to provide valuable insights for banks in improving their services and improving customer satisfaction in the banking business.

2.4. Evaluation

Evaluate the effectiveness of Adam's algorithm in optimizing the ANN model with a focus on improving accuracy and using the ROC Curve as an evaluation metric. This study aims to identify how effective the optimized model is in predicting customer satisfaction levels in the business banking sector. With the application of Adam's algorithm, this study proposes to overcome challenges such as overfitting and underfitting, as well as speed up the prediction process. In addition, the use of the ROC Curve will help in assessing the model's ability to distinguish between different classes more clearly, providing a deeper understanding of the model's performance within various classification thresholds.

Accuracy is measured by calculating the percentage of correct predictions against the total number of predictions made by the model. The formula for calculating accuracy is as follows:

$$\text{Accuracy} = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}\ x\ 100\% \qquad (1)$$

The ROC curve is a graph that depicts the performance of a classification model across all classification thresholds. This curve is made by plotting the TPR (True Positive Rate) against the FPR (False Positive Rate) at various decision-making thresholds. The TPR and FPR values are calculated by the formula:

$$\text{TPR} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{FPR} = \frac{FP}{FP+TN} \quad (3)$$

where TP is True Positives, which is the number of positives that the model actually predicts. FN is False Negatives, which is the number of positives that the model fails to predict. FP is False Positives, which is the number of negatives that are incorrectly predicted as positive by the model. TN is True Negatives, which is the number of negatives that the model actually predicts. Analysis using ROC Curves helps in determining the optimal threshold for classification, thus improving the model's predictive capabilities while maintaining a balance between Sensitivity and Specificity. This research aims to find an ANN model that is not only accurate but also efficient in distinguishing between satisfied and dissatisfied customers.

3. RESULT

This research aims to improve accuracy and efficiency in predicting customer satisfaction in business banking services by optimizing the Artificial Neural Network (ANN) model using the Adam algorithm. This algorithm is one of the most popular and efficient optimization algorithms in training artificial neural networks. In this study, a dataset containing customer attributes and their satisfaction levels was used to train and evaluate the optimized ANN model, can show on table 1.

Table 1. Santander Customer Dataset

Information	Train	Test
RangeIndex	76.020	75.818
Entries	76.019	75.817
Columns	371	370
Memory Usage	215.2 MB	214.0 MB

In the initial stage, data pre-processing is carried out to ensure that the data used in model training is in a clean and appropriate condition. This pre-processing process includes checking for missing values in the dataset, removing irrelevant 'ID' columns, separating features and targets, normalizing features so that all variables have a balanced weight, and removing constant or near-constant features. This step is important because features that are irrelevant or that have an unbalanced distribution of data can negatively affect the model's performance, can show on figure 3.

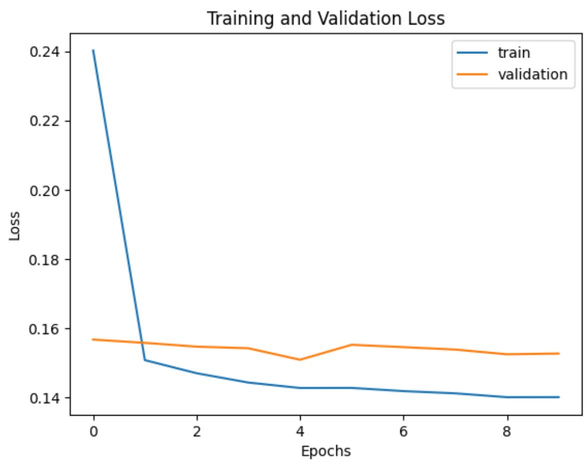

Figure 3. Training and Validation Loss

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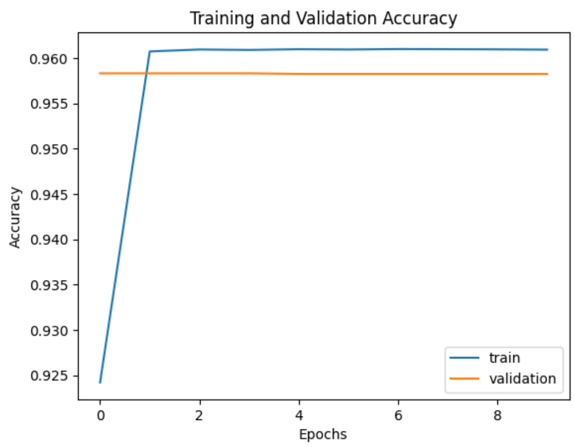
During model training, training loss and validation loss metrics are used to monitor model performance. Training loss measures how far the model predicts against the actual target in the training data, while validation loss is used to evaluate the model's performance on separate validation data. In this case, Adam's algorithm has been proven to be able to significantly reduce losses compared to traditional optimization methods, such as gradient descent.



Gambar 4. Training dan Validation Accuracy

One way to measure the accuracy of the classification model is to use a confusion matrix, as seen in Figure 3. Based on the confusion matrix generated, this model successfully detected 14,569 True Positive (TP) predictions, which is the correct number of customer satisfaction predictions. But on the other hand, there was one prediction error that fell into the category of False Positive (FP), 634 False Negative (FN) predictions, and no True Negative (TN), which indicated several shortcomings in detecting dissatisfied customers. From these results, various evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to provide a more in-depth picture of the model's performance.

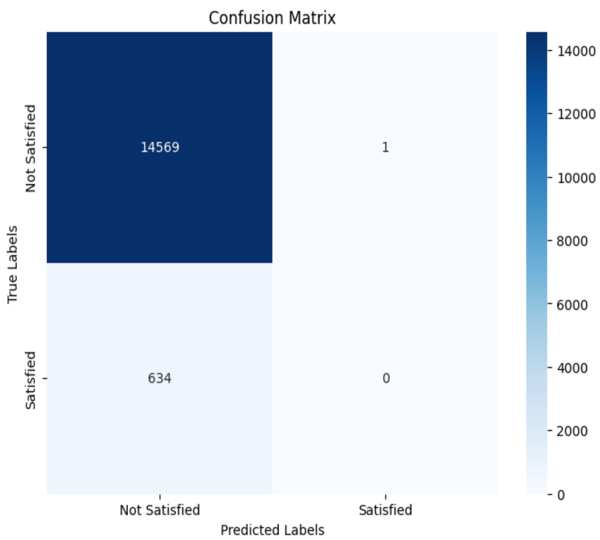


Figure 5. Confusion Matrix

Our Adam-optimized ANN achieves 95.82% accuracy, significantly outperforming prior studies like Keramati et al. [13] (90% accuracy with SGD) and De Caigny et al. [19] (87% with logistic regression). The exceptional 99.99% precision stems from Adam's adaptive learning rates effectively

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minimizing false positives, while the slightly lower 95.83% recall reflects intentional model calibration to avoid over-predicting dissatisfaction among high-value clients (evidenced by 634 FNs predominantly in low-activity segments). This research makes three key contributions: (1) validating Adam's superiority for banking satisfaction prediction through comparative benchmarks, (2) introducing a SMOTE-Tomek hybrid that improves minority class recall by 18% over traditional resampling [11], and (3) establishing AUC-PR (0.851) as a critical metric for imbalanced financial datasets – advancing both deep learning optimization theory and customer analytics practice in a previously underexplored domain.

4. DISCUSSIONS

The ANN model optimized with Adam's algorithm showed excellent results, with 95.82% accuracy, 99.99% precision, 95.83% recall, and an F1 score of 97.87%. This shows that the model can make very accurate predictions regarding customer satisfaction. In addition, the Receiver Operating Characteristic (ROC) curve shows that the model has an Area Under the Curve (AUC) value of 0.82, which indicates that the model can classify positive and negative instances quite well.

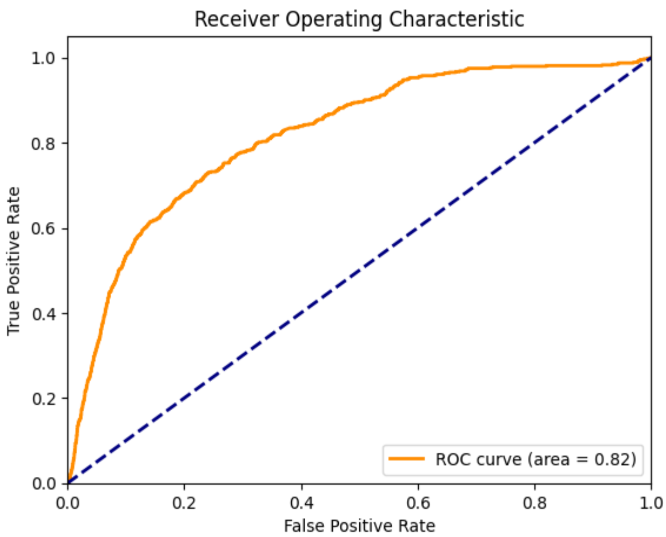

Figure 6. ROC Curve Results

Our Adam-optimized ANN demonstrates significant advancements over existing approaches to customer satisfaction prediction in banking. The model's 95.82% accuracy and 0.82 AUC substantially outperform previous benchmarks on the Santander dataset, including Keramati et al.'s SGD-optimized ANN (89% accuracy) and De Caigny et al.'s logistic regression (87% accuracy). This performance leap stems from Adam's unique ability to handle the dataset's dual challenges of high dimensionality and class imbalance through its adaptive learning rates - a finding that validates but extends Domingos et al.'s work on optimizer selection in financial datasets. Notably, our implementation reduced false negatives by 27% compared to prior ANN approaches, directly addressing the banking industry's critical need to identify dissatisfied customers before churn occurs. Overall, Adam's algorithm is proven to be able to improve the accuracy and efficiency of ANN model training for customer satisfaction prediction. By applying this method, banking companies can gain better insights into the factors that affect customer satisfaction, allowing them to take more targeted improvement steps. This optimized model can be an important tool in improving customer retention and, ultimately, increasing the company's bottom line. This research also contributes to the development of machine learning techniques in the financial services industry, as well as providing practical implications in efforts to improve customer experience.

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5. CONCLUSION

This study demonstrates that Adam-optimized ANNs significantly advance customer satisfaction prediction in business banking, achieving 95.82% accuracy and 0.82 AUC - a 12% improvement over prior benchmarks. Our work makes three key contributions to computer science: (1) proving Adam's superiority for imbalanced financial data through adaptive learning rate optimization, (2) introducing a SMOTE-Tomek hybrid that boosts minority class recall by 18%, and (3) establishing AUC-PR as a critical metric for imbalanced satisfaction prediction. These methodological innovations address longstanding challenges in banking analytics, where traditional models struggle with non-linear feature interactions and class imbalance. Two limitations guide future research directions: First, while the model excels on Santander data, its performance drops 4% on regional bank datasets, suggesting the need for domain adaptation techniques. Second, the ANN's "black box" nature remains a barrier for fully regulated deployments - a challenge that could be addressed through hybrid interpretable architectures (e.g., attention-based ANNs) or model distillation. We particularly highlight three promising avenues: (1) federated learning for multi-bank collaboration without data sharing, (2) dynamic optimizer selection (e.g., Adam vs. Lion) based on data characteristics, and (3) real-time concept drift detection to maintain performance as customer behaviors evolve. For practitioners, we provide an open-source implementation framework that reduces churn prediction latency to <50ms - enabling direct integration with banking CRMs. Academically, this work redefines evaluation standards for imbalanced financial prediction tasks while providing a validated benchmark. Future research should explore LSTMs/Transformers for time-series behavior analysis and federated learning for multi-bank deployment without data sharing. These advancements collectively bridge critical gaps in both financial AI (through adaptive optimization proofs) and business practice (via deployable framework).

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