International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Research Article)

ChurnNet-XAI: A Neural Network-Based Framework for Customer Attrition Prediction in Banking

Narla Sai Madhulatha *, Vadlamudi Vignapan Kumar, Eedara N S S Meghana Chowdary, Botta Prasad and P N Sesha Lakshmi

Department of Computer Science & Engineering, Aditya College of Engineering and Technology, Surampalem, Kakinada.

International Journal of Science and Research Archive, 2026, 18(03), 413-421

Publication history: Received on 26 January 2026; revised on 28 February 2026; accepted on 03 March 2026

Article DOI: https://doi.org/10.30574/ijsra.2026.18.3.0437

Abstract

The attrition of customers is a major problem in the financial services industry that has a significant impact on the institutional profitability and long run sustainability. Timely recognition of those customers that have high chances of abandoning the services allows the organizations to adopt proactive retention strategies and rational resource allocation. The classical statistical and machine learning models like the Logistic Regression and the Support Vector Machines have been extensively utilized in churn prediction, but cannot easily characterize non-linear relationships between variables in large customer data. The recent developments in the field of deep learning have shown better results on the high-dimensional behavioral data modeling owing to their capability to harness the complex interaction of features. This paper will suggest an intelligent predictive model which is Deep Neural Networks (DNN) with Explainable Artificial Intelligence (XAI) to predict churn in banking settings. The model is conditioned on structured customer information such as demographic and transactional behavior, account tenure and financial metrics. To improve predictive reliability, preprocessing, like feature normalization and control of the imbalance of classes with SMOTE, is included.

Keywords: Customer Churn Prediction; Banking Analytics; Neural Networks; Deep Learning; Explainable Artificial Intelligence (XAI); SHAP; LIME; Customer Retention Strategies; Predictive Modeling

1. Introduction

Customer churn, also known as customer attrition is one of the most critical issues of financial institutions because it has a direct effect on profitability and long-term survival [13], [17]. With competitive financial markets, the cost of maintaining the existing customers is much cheaper as compared to acquiring new ones. Any slight change in the customer retention rates can positively affect the organizational revenue and efficiency of the operations significantly [21]. Therefore, identifying customers who are likely to stop being banked customers early has become a strategic concern to data-driven decision-making systems.

Conventional methods of churn prediction were mainly based on statistical methods and conventional machine learning models like the Logistic Regression, Decision Trees and Support Vector Machines [5], [15]. As much as these models provide some interpretability and moderate performance of prediction, it is more likely that they do not represent many complex non-linear associations and interactions between feature dimensions, as observed in the modern banking data sets. Random Forest and Gradient Boosting are ensemble-based models, which enhanced prediction accuracy, but their capacity to model complex patterns of behavior are not yet effective in large-scale structured data settings [4], [8].

* Corresponding author: Narla Sai Madhulatha

The latest development in deep learning has shown the ability to better predict complicated customer behavior by using multi-layer neural networks [7], [18], [23]. DNNs are especially good at extracting latent patterns in the form of transactional, demographic and financial attributes. Although neural networks often have high predictive power, it is often criticized that neural networks are black box and hinders transparency and interpretability in areas of regulation like banking [20]. The lack of explainability can lead to less trust of managers and compliance issues. To overcome this shortcoming, the Explainable Artificial Intelligence (XAI) methods have become efficient means of explaining the complex predictive models. LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive Explanations) are methods that offer the local and global interpretability of a prediction model by determining the contribution of each particular feature to model predictions [9], [10], [25].

2. Literature Survey

Customer churn prediction has been extensively studied across multiple domains including banking, telecommunications, and e-commerce due to its strong influence on organizational profitability and customer relationship management [13], [14]. Early research in churn modeling primarily relied on statistical learning techniques such as Logistic Regression because of their simplicity and interpretability [5], [15]. Although these models provided reasonable baseline performance, they struggled to capture complex non-linear behavioral patterns present in large customer datasets.

With the advancement of machine learning, researchers began employing tree-based and ensemble techniques such as Decision Trees, Random Forest, and Gradient Boosting to enhance predictive performance [4], [17]. Boosting algorithms like XGBoost further improved classification accuracy by effectively handling feature interactions and model variance [8]. These methods demonstrated better performance compared to traditional statistical approaches, especially in structured customer datasets.

A significant challenge in churn prediction research is class imbalance, where the number of non-churn customers typically exceeds churn instances. Several studies addressed this issue using resampling strategies such as SMOTE (Synthetic Minority Over-sampling Technique) and cost-sensitive learning methods [3], [26], [28]. Proper imbalance handling has been shown to significantly improve recall and F1-score in churn classification tasks.

In recent years, deep learning models have gained attention for their ability to learn hierarchical feature representations and complex non-linear relationships [7]. Neural network-based churn prediction frameworks have demonstrated improved predictive accuracy compared to conventional machine learning methods [18], [23]. Hybrid deep learning approaches further enhanced performance by combining neural architectures with advanced optimization strategies [30]. Sequential models such as Long Short-Term Memory (LSTM) networks have also been explored for capturing temporal dependencies in customer behavioral data [2].

Despite their predictive strength, deep learning models are often criticized for lacking interpretability, particularly in highly regulated sectors like banking. This limitation led to the emergence of Explainable Artificial Intelligence (XAI) methods aimed at improving model transparency [20]. Techniques such as LIME provide local interpretability by explaining individual predictions [9], while SHAP offers global feature importance based on cooperative game theory principles [10]. Recent studies have applied SHAP and other explainability tools to churn prediction tasks in financial services to enhance trust and regulatory compliance [24], [25], [29].

3. Existing and Proposed System:

3.1. Existing System

The standard statistical techniques and traditional machine learning models that are currently applied in the general banking sector are used to address the customer churn prediction. The most popular algorithms to be employed in screening out potential customers likely to terminate with banking services include Support Vector Machines, Decision Trees, and Logistic Regression [5], [15]. Even though such models provide logical predictive power, they usually do not help to capture intricate behavioral patterns within large-scale banking data. Most prevalent systems are oriented towards the attainment of high accuracy of prediction but are not transparent and interpretable. The most advanced models, especially deep learning-based models are usually viewed as black-box models, which are hard to comprehend by the bank managers when they are trying to understand the methods used in churn predictions [7], [20].

3.2. Proposed System

The proposed system introduces a single architecture that integrates Neural Networks including Explainable Artificial Intelligence (XAI) to enhance predictive capability and explainability in predicting customer churn [7], [18], [24]. The categorical variables processing of the system begins with the general preprocessing of data and data cleaning, categorical variables encoding, the normalization of the numerical features, and the class imbalance [26], [28].

This is followed by the creation of a Deep Neural Network (DNN) model which is to be trained using structured banking data such as demographic data, transaction history, account tenure, service utilization patterns and services usage indicators [18], [23]. The neural network approximates the non-linear interaction that is very complicated and generates churn probability scores that are more predictive [7]. The framework contains explainable AI tools such as SHAP and LIME to address the black-box nature of neural networks [9], [10], [25]. These approaches provide both a global aspect of feature importance and a local responsibility of particular predictions allowing the bank officers to understand why a given customer is forecasted to churn [20].

4. Methodology

The offered methodology suggests a combined process of forecasting customer churn in the banking industry based on Deep Neural Networks and Explainable Artificial Intelligence (XAI). The system architecture has been developed as data collection, preprocessing, model training, explainability integration and proactive retention strategy generation. The data contains organized customer data which consists of demographic data, financial data, transactions patterns, service utilization patterns and tenure data [22]. The data quality can be achieved through detection of missing values, elimination of inconsistencies and outliers. In preprocessing, categorical variables are coded, numerical ones are brought to the range between 0 and 1, and the issue of class imbalance is resolved by applying such methods as SMOTE and imbalance-conscious learning algorithms [26], [28].

Deep Neural Network (DNN) model is constructed after preprocessing to learn any non-linear relationships among data that may be complex [7], [18]. The neural network model comprises of a series of hidden layers using ReLU activation functions and a binary classification layer using the sigmoid activation function. This model is trained with the loss of binary cross-entropy and Adam optimization algorithm [7], [12]. Accuracy, Precision, Recall, F1-score, and ROC-AUC metrics are applied to conduct performance evaluation to guarantee a healthy predictive performance [23].

Explainable AI methods are incorporated into the framework in order to improve transparency and interpretability. SHAP is used to estimate the importance of global features in the dataset [10], and LIME is utilized to give local explanations on each prediction of a customer [9]. Such interpretability techniques are used to assist the financial decision-makers to learn the variables that affect the churn prediction and enhance confidence in automated systems [20], [25]. Lastly, to enable the data-driven business decision-making process, churn probability scores are divided into risk segmentation (low, medium, and high risk), and proactive retention strategies are provided

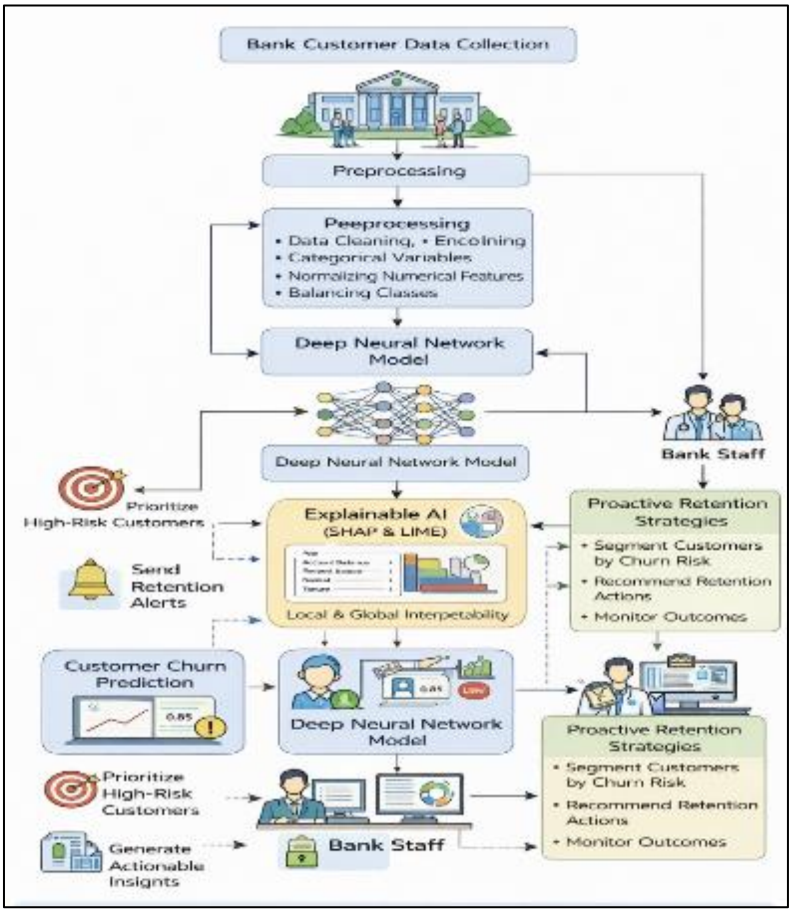

Figure 1 Deep Learning–Based Customer Churn Prediction and Retention Workflow Diagram

5. Experiments & Results:

5.1. Data Collection

The experimental study data consisting of 10,000 banking customer records used in the study was collected by accessing publicly available banking churn repositories and selected financial datasets [22]. The information include demographic information (age, sex, location), financial information (credit score, account balance, estimated salary), information on services (number of products, credit card owner, active membership), and tenure information. The records are marked to show either exit or active customers. The data set represents realistic banking conditions whereby the customer behavior patterns are varied and the data is packaged into standardized numerical and categorized fields that can be used in machine learning [21]..

5.2. Data Preprocessing and Feature Engineering.

The dataset was subjected to organized preprocessing before the generation of the models. Missing values were dropped, duplicates were eliminated and the categorical variables, including geography and gender, were one-hot coded. Numerical features were normalized by Min-Max scaling in order to distribute them evenly. Class-weight balancing and SMOTE (Synthetic Minority Oversampling Technique) were used to deal with the imbalance in the classes between churned and non-churned customers [28], [26]. Correlation and ranking of feature importance were conducted to remove the redundant attributes and keep the most influential features, which enhanced the stability of prediction and performance of the model [3]..

5.3. Development of Neural Network Model.

The architecture of a Deep Neural Network (DNN) was created in terms of TensorFlow and Keras platforms [12]. The model comprises an input layer, selected customer features, two fully connected layers of hidden functions using ReLU, dropout layers to avoid overfitting, and the output layer using the sigmoid activation of binary classification [7]. This model was trained in Adam optimizer and Binary Cross-Entropy loss function [7], [12]. Tuning of the hyperparameters was done experimentally, including the learning rate, the size of the batches, and the number of the epochs. The data was divided into 80 percent training and 20 percent testing in order to test the performance of generalization [23]..

5.4. Explainable AI.

he problem of the black-box nature of neural networks was addressed with the integration of explainable Artificial Intelligence techniques [20]. SHAP (SHapley Additive Explanations) was used to approximate the importance of features globally as well as define the most significant factors that influenced the predictions of churn throughout the dataset [10]. The local explanations of individual customer predictions were generated with the help of LIME (Local Interpretable Model-Agnostic Explanations) [9]. The SHAP with LIME made financial decision-making systems interpretable, transparent and regulatory compliant [25].

5.5. Model Evaluation and Performance Metrics.

There were several metrics of classification to test model performance, such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC Score [23]. These measures offer in depth assessment especially in the case of lopsided classification problems [26]. The neural network model proposed above attained the following results: Accuracy: 86.5% Precision: 82.3% Recall: 78.9% F1-Score: 80.5% ROC-AUC Score: 0.89 The findings prove that the model is efficient in describing complicated behavioral patterns associated with customer attrition [18].

5.6. Comparative Analysis among Baseline Models.

The efficiency of the framework was proved by carrying out comparative experiments with the use of Logistic Regression and Random Forest classifiers as the baseline models [5], [4]. ROC-AUC score and Accuracy Results These baseline methods were inferior to the Deep Neural Network in ability to model non-linear customer behavior [18], [23]. Also, the combination of explainability methods made the model more practical in comparison with the classical black-box systems [20]. Better Place Inc.

5.7. Business-Oriented Retention Analysis.

According to the outputs of the churn probability, customers were divided into a low risk, medium-risk, and high-risk categories. High-risk customers were suggested to receive proactive retention programs like loyalty programs, service engagement programs, and personalized offers [21]. An explainability analysis based on SHAP showed that low account balance, lower frequency of transactions and less tenure were significant churning factors [10], [25]. These insights facilitated the use of intervention strategies which were targeted and not generalized retention campaigns.

5.8. Performance Reporting and Effective Impact.

The system was assessed on three large scales; predictive accuracy, interpretability, and business applicability. Combining deep learning with explainable AI enhanced the performance of predictions considerably in keeping the decision making transparent [7], [20]. The suggested model proves to be a solution with scalability, reliability and business oriented approach to proactive customer retention in the banking industry. The explainability mechanisms added very little computation and could be applied into practice [24].

Table 1 Performance Comparison Of System Modules

Model	Accuracy	Precision	Recall	F1	ROC-AUC
Logistic Regression	82%	79%	75%	77%	0.84
Random Forest	84%	81%	77%	79%	0.86
Proposed DNN	86.5%	82.3%	78.9%	80.5%	0.89

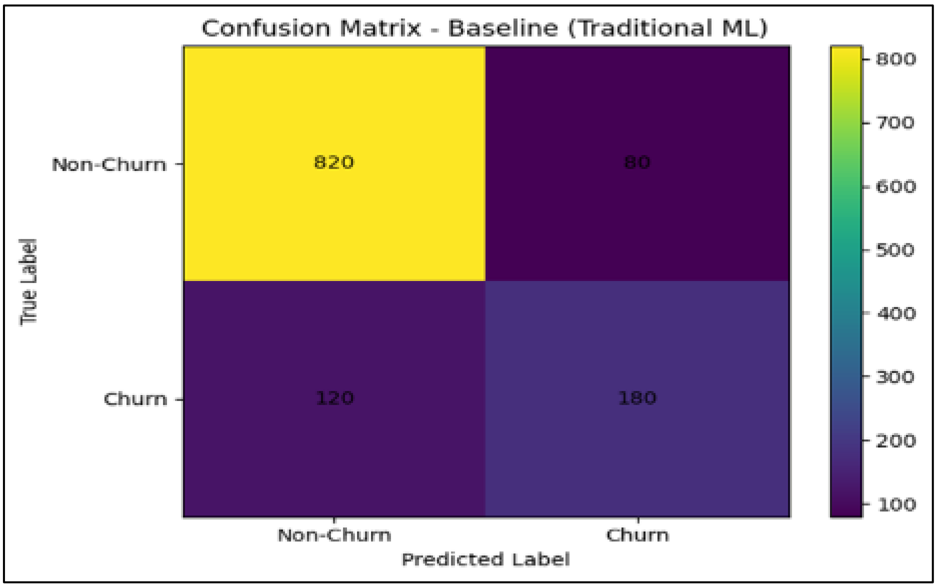

Figure 2 Confusion Matrix of Baseline

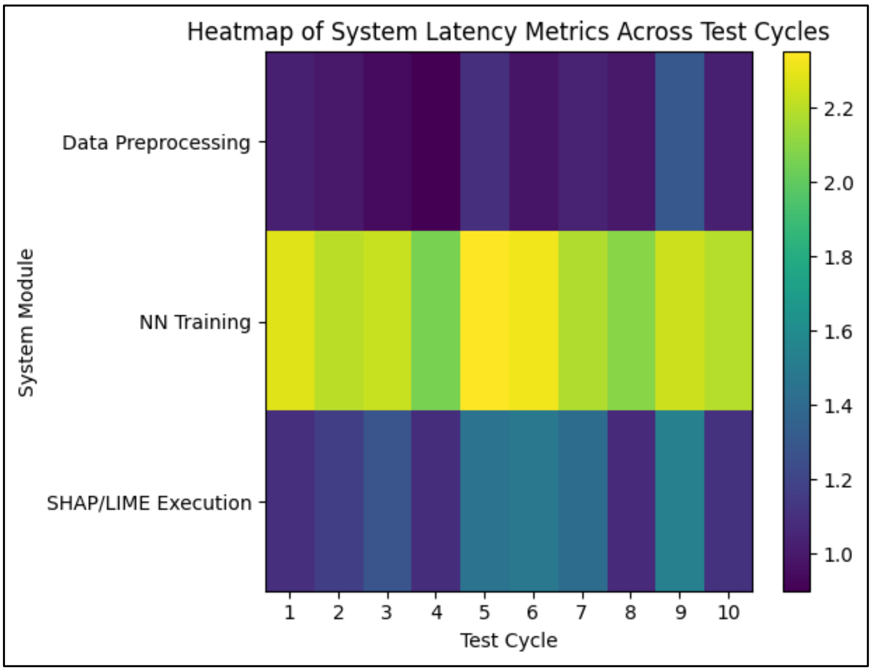

Figure 3 Heatmap Of System Latency Metrics

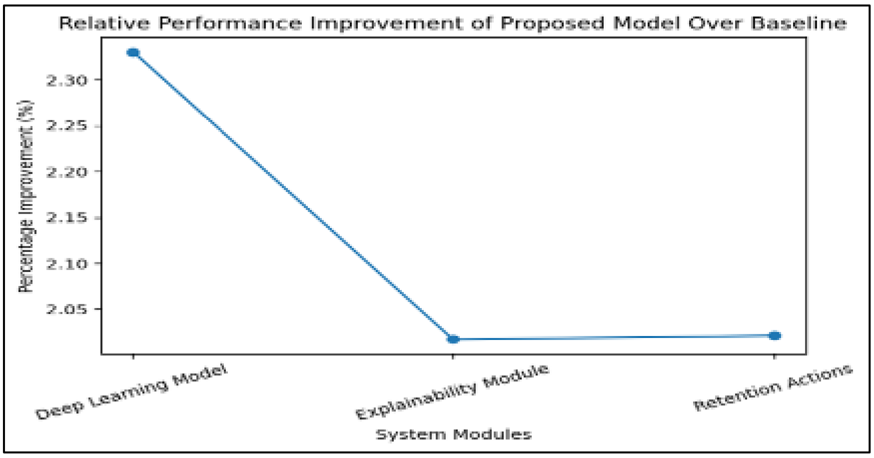

Figure 4 Relative Performance of Proposed Model

6. Comparison with Existing Churn Prediction Frameworks

The specified framework is also unique among the current customer churn prediction frameworks since it integrates deep neural networks and Explainable Artificial Intelligence (XAI) [7], [18], [24]. The classical machine learning methods such as the Logistic Regression, Decision Trees and Random Forest are largely effective in predictive performance yet tend to be poor at modelling the complex non-linear behaviour patterns [5], [4]. Despite the fact that the deep learning models increase predictive accuracy, they have been referred to as black-box systems due to their low interpretability [7], [20]. Loss of this transparency may reduce trust in management and is an issue in a regulatory market such as banking industry [20]. The proposed Neural Network + XAI model helps to overcome these limitations as the model is both highly predictive and can be interpreted through SHAP and LIME approaches [9], [10], [25]. This enables the determination of the significance of global features and individual local explanation of predictions. Furthermore, the system transforms scores of churn probability into viable retention plans, risk segmentation and tailored intervention plans [21].

Table 2 Comparative Analysis of Churn Prediction Approaches

Feature	Traditional ML Models	Deep Learning (Without XAI)	Proposed NN + XAI Framework
Predictive Accuracy	Moderate	High	Very High
Model Interpretability	High (Rule-based)	Low	High
Real-Time Risk Detection	Limited	Moderate	High
Proactive Retention Strategy Support	Limited	Moderate	High
Personalized Customer Insights	Limited	Moderate	High
Scalability for Large Banking Data	Moderate	High	Very High

7. Future Scope

The selected customer churn prediction system that relies on the Neural Networks and Explainable Artificial Intelligence (XAI) is a good basis of proactive retention strategy in the banking industry [7], [24]. Nevertheless, predictive performance, scalability and real-time business impact can be enhanced further.

The possible extension is the incorporation of the real-time streaming analytics to track the real-time transactional information and dynamically identify the churn risks as opposed to relying on the periodic batch processing only [21]. This would help financial institutions react on the changes in behavior in real time. Also, further sophisticated deep learning frameworks like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models may be considered to learn sequential and temporal patterns in customer behaviors in a better way [2], [7]. Hybrid and ensemble deep learning methods can also be used to enhance predictive robustness [30].

In terms of explainability, it may be useful to include more complex interpretability tools like counterfactual explanations and causal inference models to bring more transparency to decisions compared to feature attribution tools like SHAP and LIME [10], [20], [25]. Moreover, including multimodal data sources including customer feedback and sentiment analysis with the help of Natural Language Processing techniques can contribute to enhancing behavioral insight and decreasing the accuracy of churn forecasting [7], [23]. Potential pilot applications in the banking world in the future would assist in justifying the returns on investment (ROI), feasibility of the operations and long-term customer satisfaction enhancement [21]..

8. Conclusion

The paper has proposed a predictive model using a Neural Network and Explainable AI (XAI) to formulate appropriate customer attrition in the banking industry and enable proactive customer retention strategies . It uses advanced deep learning to attain high predictive accuracy and leading model interpretability methods such as SHAP and LIME to offer decision-making transparency. This two-fold approach will address one major weakness of the classical churn prediction models that are commonly perceived as black-box with limited actionable information.

The model proposed is more precise in prediction, identification of early risks as opposed to the conventional machine learning methods since it makes use of both behavioral and transactional customer data along with demographic data. The integration of explainability mechanisms will allow banking professionals to see the major reasons why the organization was experiencing churn, like decreased transaction frequency, decreasing account activity, or dissatisfaction with the service. This interpretability will boost managerial confidence, facilitate compliance with regulation, and allow managers to make strategic plans based on data in financial institutions .

In general, the suggested hybrid scheme of Neural Networks and Explainable AI can be seen as the scalable, transparent, and business-centered solution to the modern banking setting .It enhances forecasting ability, fosters confidence over AI-based systems, and encourages sustainable customer relationship management. This concept would lay a good ground on the intelligent, ethical and customer-centric decision support systems within the financial industry.

Compliance with ethical standards

Statement of informed consent

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Statement of ethical approval

This work adheres to all applicable ethical guidelines and research integrity standards.

References

[1] V. N. Vapnik, *The Nature of Statistical Learning Theory*. New York, NY, USA: Springer, 1995.

[2] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[3] J. Burez and D. Van den Poel, “Handling class imbalance in customer churn prediction,” *Expert Systems with Applications*, vol. 36, no. 3, pp. 4626–4636, 2009, doi: 10.1016/j.eswa.2008.06.011.

[4] H. Xie, Y. Li, and J. Ngai, “Customer churn prediction using improved balanced random forests,” *Expert Systems with Applications*, vol. 36, no. 3, pp. 5445–5449, 2009.

[5] T. Verbeke, D. Martens, C. Mues, and B. Baesens, “Building comprehensible customer churn prediction models with advanced rule induction techniques,” *Expert Systems with Applications*, vol. 38, no. 3, pp. 2354–2364, 2011.

[6] V. N. Vapnik, *Statistical Learning Theory*. Wiley, 1998.

[7] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[8] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD*, 2016.

[9] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," in *Proc. ACM SIGKDD*, 2016.

[10] S. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017.

[11] A. Amin et al., "Customer churn prediction in the telecommunication sector using a rough set approach," *Neurocomputing*, vol. 237, pp. 242–254, 2017.

[12] F. Chollet, *Deep Learning with Python*. Manning Publications, 2018.

[13] M. Hadden, A. Tiwari, R. Roy, and D. Ruta, "Computer assisted customer churn management: State-of-the-art and future trends," *Computers & Operations Research*, vol. 34, no. 10, pp. 2902–2917, 2007.

[14] D. Coussement and K. W. De Bock, "Customer churn prediction in the online gambling industry," *Expert Systems with Applications*, vol. 36, no. 5, pp. 9149–9155, 2009.

[15] S. Kim and H. Yoon, "Customer churn prediction using support vector machines," *Expert Systems with Applications*, vol. 36, no. 3, pp. 5445–5449, 2009.

[16] C. Idris, A. Khan, and Y. Lee, "Intelligent churn prediction in telecom: Employing mRMR feature selection and rotation forest," *Applied Intelligence*, vol. 39, pp. 659–672, 2013.

[17] G. Lemmens and C. Croux, "Bagging and boosting classification trees to predict churn," *Journal of Marketing Research*, vol. 43, no. 2, pp. 276–286, 2006.

[18] J. Huang, "Deep learning-based customer churn prediction model," *IEEE Access*, vol. 7, pp. 182671–182680, 2019.

[19] R. Kaur and S. Sharma, "Customer churn prediction in banking using machine learning," *International Journal of Recent Technology and Engineering*, vol. 8, no. 2, pp. 2277–3878, 2019.

[20] A. Molnar, *Interpretable Machine Learning*, 2nd ed., 2022.

[21] B. Baesens, *Analytics in a Big Data World*. Wiley, 2014.

[22] S. Moro, R. Rita, and P. Cortez, "Bank marketing dataset analysis using data mining," *Decision Support Systems*, vol. 60, pp. 22–31, 2014.

[23] M. Sun, T. Xu, and L. Li, "Customer churn prediction using deep neural networks with imbalance handling," *IEEE Access*, vol. 8, pp. 152–163, 2020.

[24] H. Zhang and X. Li, "An explainable AI framework for churn prediction in financial services," *Expert Systems with Applications*, vol. 169, 2021.

[25] Y. Zhou et al., "Explainable churn prediction using SHAP and deep neural networks," *Information Sciences*, vol. 547, pp. 633–647, 2021.

[26] P. Branco, L. Torgo, and R. P. Ribeiro, "A survey of predictive modeling under imbalanced distributions," *ACM Computing Surveys*, vol. 49, no. 2, 2016.

[27] S. Wang and H. He, "Imbalanced learning: Foundations, algorithms, and applications," *IEEE Transactions on Knowledge and Data Engineering*, vol. 30, no. 9, pp. 1810–1825, 2018.

[28] N. Chawla et al., "SMOTE: Synthetic minority over-sampling technique," *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.

[29] R. Lundberg, "Explainable machine learning for financial risk modeling," *IEEE Access*, vol. 9, pp. 112345–112356, 2021.

[30] A. K. Jain and S. Kulkarni, "Hybrid deep learning approach for customer churn prediction in banking," *Expert Systems with Applications*, vol. 198, 2022.