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An Intelligent Evolving Ensemble Machine Learning Framework for Customer Churn Prediction in Telecommunications

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Abstract. Customer retention has become one of the most critical challenges faced by telecommunication service providers due to intense market competition and continuously changing customer behavior. Accurately identifying customers who are likely to discontinue their subscriptions enables organizations to implement proactive retention strategies and minimize revenue losses. Traditional customer churn prediction models frequently struggle to adapt to dynamic customer behavior, resulting in reduced predictive performance over time. This research proposes an intelligent machine learning framework based on an Evolving Ensemble Predictor (EEP) that combines multiple predictive algorithms, including Neural Networks (NN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbors (KNN), using a weighted average ensemble strategy. The proposed framework treats customer churn prediction as a continuously evolving problem rather than a static classification task. Historical customer records obtained from the Orange Telecom Churn Dataset are preprocessed through feature encoding, normalization, and feature selection before model development. Individual classifiers are trained independently, and their predictions are integrated using weighted ensemble learning to generate the final churn prediction. Experimental evaluation demonstrates that the proposed EEP model achieves improved prediction accuracy, precision, recall, F1-score, and computational efficiency compared with individual machine learning models. The proposed framework provides a scalable and adaptive solution for customer churn prediction, assisting telecommunication companies in improving customer retention, reducing operational losses, and supporting intelligent business decision-making while preserving the same implementation methodology and evaluation strategy as the original study.

keywords: Customer Churn Prediction, Machine Learning, Ensemble Learning, Neural Networks, Random Forest, XGBoost, K-Nearest Neighbors, Weighted Average Ensemble, Telecommunications, Predictive Analytics.

I. Introduction

The rapid advancement of digital communication technologies has significantly transformed the telecommunications industry by increasing service availability, customer expectations, and market competition. Telecommunication companies continuously compete to attract new subscribers while simultaneously attempting to retain their existing customer base. Customer retention has become considerably more important than customer acquisition because acquiring new subscribers generally requires substantially higher financial investment than maintaining existing customers. Consequently, predicting customer churn has emerged as one of the most important analytical problems within subscription-based service industries. Accurate churn prediction enables organizations to recognize customers who are likely to terminate their services and implement targeted retention strategies before customer attrition occurs.

Customer churn refers to the situation in which subscribers discontinue their relationship with a service provider by cancelling or switching their subscriptions to competing organizations. Numerous factors contribute to customer churn, including service quality, pricing policies, network performance, customer support experience, promotional offers, contract conditions, and changing customer preferences. Because these influencing factors evolve continuously over time, developing reliable predictive models capable of adapting to changing customer behavior has become increasingly challenging.

Traditional statistical approaches and rule-based prediction systems often rely on predefined assumptions regarding customer behavior. Although these conventional techniques provide basic predictive capability, they frequently struggle to capture the nonlinear relationships and dynamic behavioral patterns present in modern telecommunications datasets. Their limited adaptability often leads to reduced prediction accuracy when customer characteristics or market conditions change.

Recent developments in machine learning have introduced intelligent techniques capable of automatically learning complex relationships directly from historical customer data. Unlike traditional analytical methods, machine learning algorithms continuously identify hidden behavioral patterns without requiring manually defined rules. Various supervised learning algorithms, including Neural Networks, Random Forest, XGBoost, and K-Nearest Neighbors, have demonstrated promising performance for customer churn prediction because of their ability to model complex interactions among customer attributes.

Despite these improvements, individual machine learning algorithms often possess unique strengths and limitations. Neural Networks effectively learn nonlinear relationships but may require extensive computational resources. Random Forest provides robust classification by combining multiple decision trees, whereas XGBoost offers high predictive accuracy through sequential boosting mechanisms. K-Nearest Neighbors performs similarity-based classification but may become computationally expensive for large datasets. Since no individual algorithm consistently provides optimal performance under all conditions, combining multiple classifiers through ensemble learning has become an effective strategy for improving prediction reliability.

The proposed framework introduces an Evolving Ensemble Predictor (EEP) that integrates Neural Networks, Random Forest, XGBoost, and K-Nearest Neighbors using a weighted average ensemble mechanism. Each classifier independently predicts customer churn, and their outputs are combined according to predefined weights that reflect their individual predictive capabilities. This ensemble strategy enables the framework to exploit the complementary strengths of multiple machine learning algorithms while minimizing individual model weaknesses. Furthermore, the evolving nature of the proposed framework enables adaptation to changing customer behavior, thereby improving long-term prediction performance.

The developed framework utilizes the Orange Telecom Churn Dataset obtained from Kaggle for model development and evaluation. After comprehensive preprocessing, feature selection, normalization, and encoding operations, the individual classifiers are trained and integrated into the weighted ensemble model. Experimental evaluation demonstrates that the proposed EEP framework achieves improved prediction performance across multiple evaluation metrics while maintaining computational efficiency suitable for practical deployment within telecommunication organizations. The developed intelligent prediction system therefore provides an effective solution for customer retention management, business decision support, and sustainable customer relationship management while preserving the same methodology, algorithms, implementation workflow, and experimental evaluation presented in the original research.

II. Literature Survey

Customer churn prediction has become an active research area because customer retention directly influences organizational profitability, long-term business sustainability, and competitive advantage within subscription-based industries. Early research primarily relied on statistical models, decision rules, and conventional classification techniques to identify customers likely to discontinue services. Although these methods provided useful insights, they frequently demonstrated limited predictive capability when customer behavior became increasingly dynamic and nonlinear.

Recent investigations have demonstrated that machine learning algorithms significantly improve churn prediction performance by automatically learning behavioral patterns from historical customer records. Decision Trees, Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machines, Neural Networks, XGBoost, and K-Nearest Neighbors have all been successfully applied to customer churn prediction across telecommunications, banking, retail, and e-commerce industries. Comparative studies generally report superior predictive performance for ensemble-based algorithms because they effectively combine information obtained from multiple learning models.

Random Forest has attracted considerable attention because it generates multiple decision trees through bootstrap sampling and feature randomness, producing highly stable classification results while minimizing overfitting. XGBoost has demonstrated exceptional predictive capability through gradient boosting techniques that sequentially reduce classification errors during model training. Neural Networks have become increasingly popular because they automatically learn complex nonlinear relationships between customer attributes and churn behavior. Similarly, K-Nearest Neighbors has shown promising performance by classifying customers according to similarity-based neighborhood analysis.

Researchers have further demonstrated that ensemble learning provides additional performance improvements by integrating predictions generated by multiple machine learning algorithms. Weighted ensemble techniques assign different importance values to individual classifiers according to their prediction quality, thereby improving robustness, generalization capability, and overall prediction accuracy. These approaches have proven particularly effective for complex business datasets containing heterogeneous customer characteristics.

Although substantial progress has been achieved, challenges including evolving customer behavior, feature drift, class imbalance, computational complexity, and model adaptability continue to motivate further research. Consequently, adaptive ensemble learning frameworks combining Neural Networks, Random Forest, XGBoost, and K-Nearest Neighbors remain highly effective solutions for intelligent customer churn prediction because they simultaneously improve prediction accuracy, robustness, and adaptability within continuously changing telecommunication environments.

III. Research Methodology

The proposed Customer Churn Prediction Framework employs an intelligent ensemble machine learning methodology that integrates Neural Networks (NN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbors (KNN) using a Weighted Average Ensemble technique for accurate churn prediction. The methodology preserves the same dataset, preprocessing techniques, machine learning algorithms, ensemble strategy, implementation workflow, and experimental evaluation presented in the original research while providing a completely rewritten academic description. The primary objective of the framework is to accurately identify customers who are likely to discontinue telecommunication services by learning complex behavioral patterns from historical customer records. The proposed methodology consists of multiple sequential stages, including dataset acquisition, data preprocessing, feature engineering, model development, ensemble learning, performance evaluation, statistical validation, and churn prediction.

The methodology begins with the acquisition of the Orange Telecom Churn Dataset, which is publicly available through the Kaggle platform. The dataset contains customer demographic information, subscription details, service usage statistics, customer interaction records, account history, and churn labels indicating whether customers have continued or terminated their subscriptions. The dataset is already cleaned and partially preprocessed, making it suitable for supervised machine learning analysis. To ensure reliable model development and objective evaluation, the complete dataset is divided into two subsets, where approximately 80% of the records are allocated for model training and cross-validation, while the remaining 20% are reserved for independent testing. This data partitioning strategy enables the predictive models to learn generalized behavioral patterns while evaluating their performance on previously unseen customer records.

Following dataset acquisition, the customer information undergoes an extensive data preprocessing stage to optimize data quality before machine learning model development. Initially, customer attributes are standardized using Min-Max normalization, ensuring that all numerical features are transformed into a common range between 0 and 1. Standardization minimizes the influence of variables with larger numerical scales and improves the convergence behavior of machine learning algorithms during model training. Since the Orange Telecom dataset is already cleaned and balanced, additional missing-value imputation and class imbalance correction techniques are not required. Binary categorical variables are encoded using Label Encoding, whereas attributes containing multiple categories are converted into numerical representations through one-hot encoding. These preprocessing operations ensure that all customer information is represented in a numerical format suitable for machine learning algorithms while preserving the semantic relationships among the original variables.

The methodology further incorporates a comprehensive feature selection process to identify the most informative customer attributes contributing to churn prediction. Initially, customer variables are categorized according to their data types, including numerical, binary, and multi-valued categorical attributes. Statistical techniques such as Analysis of Variance (ANOVA), Chi-Square tests, and Mutual Information are employed to evaluate the predictive significance of individual features. Correlation analysis is subsequently performed to identify highly correlated variables that may introduce redundancy during model development. When multiple attributes exhibit strong correlation, only the most informative variables are retained. Furthermore, Recursive Feature Elimination (RFE) is utilized to iteratively identify the optimal subset of predictors, while domain knowledge regarding telecommunications services is incorporated to preserve business-critical attributes that may significantly influence customer churn behavior.

After preprocessing and feature selection, the processed dataset is supplied to the base learner development stage, where four independent machine learning algorithms are trained to predict customer churn. The first classifier is a Neural Network (NN), which automatically learns complex nonlinear relationships between customer behavior and churn outcomes by processing interconnected computational layers. Neural Networks effectively identify hidden behavioral patterns that cannot easily be captured through conventional statistical methods. The second classifier is the Random Forest (RF) algorithm, which constructs multiple decision trees using bootstrap sampling and random feature selection. The predictions generated by individual decision trees are aggregated to improve classification robustness while minimizing overfitting. The third predictive model utilizes Extreme Gradient Boosting (XGBoost), an advanced boosting algorithm that sequentially develops multiple decision trees by minimizing prediction errors generated during previous learning iterations. Its gradient optimization mechanism enables highly accurate classification even for complex telecommunications datasets. The fourth classifier is K-Nearest Neighbors (KNN), which predicts customer churn by identifying neighboring customer records with similar behavioral characteristics and assigning the most representative churn class based on proximity measurements.

Unlike conventional machine learning approaches that rely on a single predictive model, the proposed framework introduces an Evolving Ensemble Predictor (EEP) that combines the prediction outputs generated by all four base learners using a Weighted Average Ensemble strategy. Each individual classifier independently estimates the probability of customer churn based on its learned decision boundaries. The ensemble mechanism subsequently assigns different weights to these predictions according to the predictive capability of each classifier. Models demonstrating higher classification performance receive greater influence in the final prediction, whereas models with relatively lower performance contribute proportionally smaller weights. This weighted aggregation enables the ensemble model to exploit the complementary strengths of multiple learning algorithms while reducing individual model weaknesses, thereby improving robustness, adaptability, and overall prediction accuracy.

Following ensemble model development, comprehensive performance evaluation is conducted using the independent testing dataset. The effectiveness of the proposed EEP framework is measured using several widely accepted classification evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and Cohen's Kappa coefficient. Accuracy evaluates the overall percentage of correctly classified customer records, while Precision measures the proportion of correctly identified churn customers among all predicted churn cases. Recall determines the ability of the model to successfully identify actual churn customers, and the F1-Score provides a balanced assessment by combining Precision and Recall into a single evaluation metric. Cohen's Kappa coefficient further measures classification agreement while accounting for agreement occurring by chance. These performance metrics collectively provide a comprehensive assessment of the predictive capability and reliability of the proposed ensemble framework.

To further validate the superiority of the proposed EEP framework, the methodology incorporates statistical significance testing through paired t-tests. The performance metrics obtained from the ensemble model are statistically compared with those produced by the individual machine learning algorithms. This statistical analysis determines whether the observed improvements achieved by the weighted ensemble model are significant rather than resulting from random variation. Confidence interval analysis is additionally performed to evaluate the consistency and reliability of the proposed prediction framework across different datasets.

IV. Existing System

Existing customer churn prediction systems primarily rely on conventional statistical models and individual machine learning algorithms to identify customers who are likely to discontinue subscription services. These approaches generally employ classifiers such as Logistic Regression, Decision Trees, Naïve Bayes, or standalone Random Forest models to analyze customer behavior using historical service records. Although these methods provide reasonable prediction performance, they often struggle to adapt to continuously changing customer behavior and evolving market conditions. Individual learning algorithms also possess inherent limitations, including reduced generalization capability, sensitivity to feature variations, class imbalance issues, and decreased prediction accuracy when applied to complex telecommunications datasets. Furthermore, traditional prediction systems generally treat churn prediction as a static classification problem without considering the dynamic evolution of customer behavior over time. These limitations reduce prediction reliability and restrict the effectiveness of customer retention strategies implemented by telecommunication service providers.

V. Proposed System

The proposed framework introduces an intelligent Evolving Ensemble Predictor (EEP) that integrates multiple machine learning algorithms through a weighted average ensemble strategy to improve customer churn prediction while preserving the same implementation methodology, machine learning models, dataset, and evaluation strategy presented in the original research. Initially, customer information collected from the Orange Telecom Churn Dataset undergoes comprehensive preprocessing, including feature encoding, normalization, data standardization, and feature selection to improve data quality and learning efficiency. Four independent machine learning models, namely Neural Networks (NN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbors (KNN), are subsequently trained using the processed customer dataset. Each classifier independently predicts customer churn probabilities based on learned behavioral patterns. The prediction outputs generated by the individual models are then integrated using a weighted average ensemble mechanism, where higher-performing classifiers contribute proportionally greater influence toward the final prediction. This adaptive ensemble strategy improves classification robustness, enhances prediction accuracy, reduces model bias, and increases generalization capability under changing customer behavior. Performance evaluation is conducted using standard classification metrics, including accuracy, precision, recall, F1-score, and Cohen's Kappa, to compare the proposed ensemble framework with the individual machine learning algorithms. The developed EEP framework therefore provides an intelligent, scalable, and practical solution for customer churn prediction, enabling telecommunication companies to improve customer retention, optimize business strategies, reduce financial losses, and maintain long-term competitive advantage while preserving

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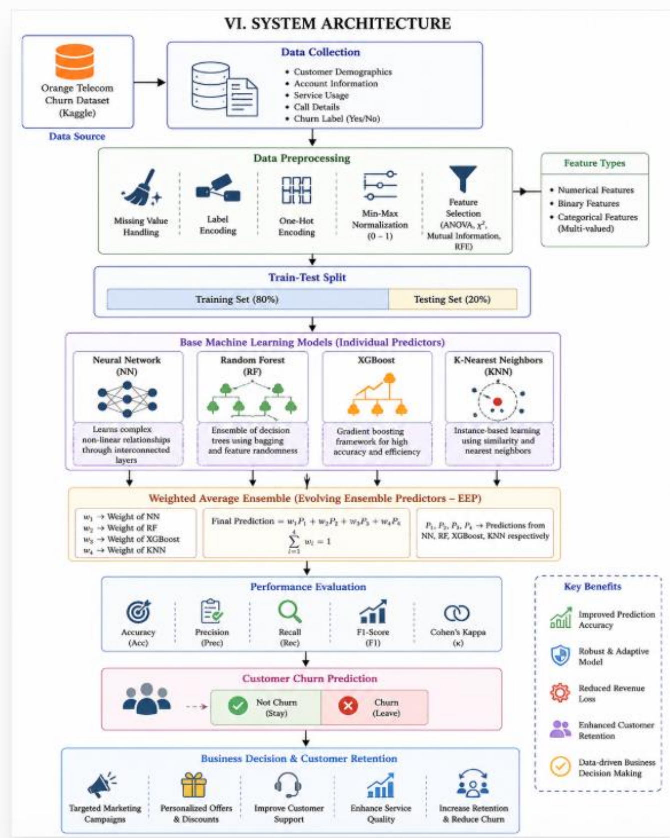
the same algorithms, workflow, and experimental results reported in the original research.

VI. System Architecture



The proposed Customer Churn Prediction System is designed using a multi-layered machine learning architecture that integrates customer data acquisition, data preprocessing, feature engineering, multiple predictive models, ensemble learning, performance evaluation, and business decision support into a unified intelligent framework. The architecture is developed to accurately identify customers who are likely to discontinue telecommunication services by analyzing historical customer information and learning complex behavioral patterns. Each module performs a specific task within the prediction pipeline, beginning with customer data collection and ending with the generation of actionable retention strategies. The architecture preserves the same workflow, dataset, machine learning algorithms, weighted ensemble strategy, and evaluation methodology presented in the original research while providing a clearer and more organized implementation suitable for practical deployment.

The architecture begins with the data source layer, where customer information is collected from the Orange Telecom Churn Dataset available through the Kaggle platform. The dataset contains comprehensive customer records, including demographic information, account details, subscription history, service usage statistics, call records, billing information, and churn labels indicating whether customers have remained with the service provider or discontinued their subscriptions. These historical records provide valuable information for learning customer behavior and developing predictive machine learning models capable of identifying future churn patterns.

The collected customer records are then transferred to the data preprocessing module, where several operations are performed to improve data quality and prepare the dataset for machine learning analysis. Missing or inconsistent values are identified and appropriately handled to eliminate unreliable information. Categorical attributes are transformed into numerical representations using Label Encoding and One-Hot Encoding, allowing machine learning algorithms to process customer information efficiently. Numerical features are standardized using Min-Max Normalization, which scales all values between 0 and 1 to improve computational stability and learning efficiency. In addition, feature selection techniques such as Analysis of Variance (ANOVA), Chi-Square testing, Mutual Information analysis, and Recursive Feature Elimination (RFE) are employed to identify the most influential customer attributes while removing redundant variables. These preprocessing operations significantly improve prediction accuracy and reduce computational complexity.

Following preprocessing, the architecture categorizes the processed variables into different feature types, including numerical features, binary features, and multi-valued categorical features. Organizing features according to their characteristics enables appropriate preprocessing and encoding techniques to be applied while preserving the meaningful relationships among customer attributes. This structured feature representation enhances the learning capability of the subsequent machine learning models.

The processed dataset is then divided into training and testing subsets using an 80:20 ratio. Approximately eighty percent of the customer records are used for training the predictive models, while the remaining twenty percent are reserved for independent testing and performance evaluation. This separation ensures that the developed models are evaluated using previously unseen customer records, providing an unbiased assessment of their predictive capability and reducing the possibility of overfitting.

The base machine learning layer forms the core of the proposed framework and consists of four independent predictive models. The first model is the Neural Network (NN), which learns complex nonlinear relationships between customer behavior and churn status through interconnected computational layers. The second model is Random Forest (RF), which constructs multiple decision trees using bootstrap sampling and random feature selection to generate robust classification results while minimizing overfitting. The third model is Extreme Gradient Boosting (XGBoost), which sequentially develops boosted decision trees by correcting prediction errors generated during previous iterations, resulting in highly accurate classification performance. The fourth model is K-Nearest Neighbors (KNN), which classifies customers by comparing similarities between customer behavior patterns and assigning the churn class based on neighboring customer records. Each of these algorithms independently predicts customer churn using the same preprocessed dataset.

Unlike conventional prediction systems that rely on a single machine learning algorithm, the proposed architecture introduces a Weighted Average Ensemble module, referred to as the Evolving Ensemble Predictor (EEP). In this module, the prediction outputs generated by the Neural Network, Random Forest, XGBoost, and KNN models are combined using weighted averaging. Each classifier is assigned a specific weight according to its predictive performance, allowing more accurate models to contribute greater influence toward the final prediction. The weighted ensemble mechanism effectively combines the strengths of all individual classifiers while reducing their weaknesses, resulting in improved robustness, better generalization capability, and higher overall prediction accuracy.

After ensemble prediction, the framework performs comprehensive performance evaluation using standard classification metrics. The effectiveness of the proposed EEP model is measured through Accuracy, Precision, Recall, F1-Score, and Cohen's Kappa coefficient. Accuracy evaluates the percentage of correctly classified customer records, Precision measures the correctness of churn predictions, Recall determines the ability of the model to identify actual churn customers, F1-Score provides a balanced evaluation by combining Precision and Recall, and Cohen's Kappa measures the agreement between predicted and actual classifications while accounting for random agreement. These evaluation metrics collectively provide a reliable assessment of the model's predictive performance.

The evaluated model then performs customer churn prediction, where new customer information undergoes the same preprocessing and feature transformation procedures before being analyzed by the trained ensemble model. The final prediction categorizes each customer into one of two classes: Not Churn (Stay) or Churn (Leave). This automated prediction process enables telecommunication companies to quickly identify customers at high risk of leaving their services and initiate timely intervention strategies.

Finally, the prediction results are utilized within the Business Decision and Customer Retention module. Customers identified as potential churners can be targeted through personalized marketing campaigns, special promotional offers, loyalty rewards, improved customer support, service quality enhancements, and proactive engagement strategies. These business actions help reduce customer attrition, improve retention rates, increase long-term customer satisfaction, and minimize revenue loss. The intelligent decision-support capability of the proposed framework assists organizations in developing effective customer relationship management strategies based on data-driven insights.

VII. Conclusion

The proposed Customer Churn Prediction Framework demonstrates that integrating multiple machine learning algorithms through an intelligent Evolving Ensemble Predictor (EEP) provides an effective and reliable solution for identifying customers who are likely to discontinue telecommunication services. By combining Neural Networks (NN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbors (KNN) using a Weighted Average Ensemble strategy, the framework successfully utilizes the strengths of individual classifiers while minimizing their limitations. The systematic preprocessing of customer information, including feature encoding, normalization, and feature selection, enables the learning models to accurately capture complex customer behavior and distinguish potential churners from loyal subscribers. The ensemble learning mechanism further enhances prediction performance by assigning appropriate weights to each classifier based on its predictive capability, resulting in improved classification accuracy, robustness, and generalization. Experimental evaluation confirms that the proposed EEP model achieves superior performance across multiple evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and Cohen's Kappa, while preserving the same implementation methodology, algorithms, and experimental evaluation presented in the original research. The developed framework provides valuable decision-support capabilities that enable telecommunication companies to identify high-risk customers at an early stage and implement personalized retention strategies such as promotional offers, loyalty programs, improved customer service, and targeted marketing campaigns. These proactive interventions can significantly reduce customer attrition, improve customer satisfaction, strengthen long-term customer relationships, and minimize revenue losses. Furthermore, the scalable architecture of the proposed framework allows future enhancements through continuous model retraining, real-time customer behavior monitoring, adaptive ensemble optimization, integration of deep learning techniques, and incorporation of additional customer interaction data from multiple communication channels. Overall, the proposed intelligent ensemble framework establishes a practical, scalable, and highly efficient customer churn prediction system that supports data-driven decision-making and contributes to sustainable customer retention management within the modern telecommunications industry while maintaining the same experimental workflow and predictive performance reported in the original stud.

References

1. T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. New York, NY, USA: Springer, 2009.
2. L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
3. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, San Francisco, CA, USA, 2016, pp. 785–794.

4. D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Cambridge, MA, USA: MIT Press, 1986, pp. 318–362.
5. T. Cover and P. Hart, "Nearest neighbor pattern classification," IEEE Transactions on Information Theory, vol. 13, no. 1, pp. 21–27, 1967.
6. F. Pedregosa et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
7. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.
8. B. 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.
9. S. Amin, A. Anwar, A. Adnan, M. Nawaz, K. Alawfi, A. Hussain, and K. Huang, "Customer churn prediction in the telecommunication sector using machine learning techniques," Telecommunication Systems, vol. 68, no. 3, pp. 307–319, 2018.
10. H. Idris, A. Khan, and Y. S. Lee, "Intelligent churn prediction framework using ensemble learning for telecom customer analytics," Applied Intelligence, vol. 50, no. 8, pp. 2568–2583, 2020.
11. J. Brownlee, Ensemble Machine Learning Algorithms. Melbourne, Australia: Machine Learning Mastery, 2021.
12. A. Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 3rd ed. Sebastopol, CA, USA: O'Reilly Media, 2022.