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A Comprehensive Analysis of Classification Methods for Churn Prediction in Financial Services

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Abstract

Persistent issues that affect long-term revenue in the banking sector include excessive client attrition. Customary churn models depend on measures related to customer satisfaction, which often result in low predictive accuracy due to their subjective nature. This study proposes an effective early warning model to address customer churn in financial services. Data is preprocessed through cleaning, one-hot encoding, Z-score normalization, and Min-max scaling. To handle class imbalance, the SMOTE algorithm is applied, improving prediction reliability. Feature engineering is also conducted to boost model effectiveness. The LightGBM (LGBM) Classifier is selected for its high performance, achieving 91% accuracy, 93% precision, 88% recall, and a 90% F1-score. It further demonstrates robustness with an AUC of 0.96 and a confusion matrix showing 1,464 true negatives and 1,386 true positives. The superiority of LGBM is confirmed by a comparison with Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Support Vector Machine (SVM) models on all measures. The results highlight how effective LGBM may be as a churn prediction tool, allowing banks to establish prompt and focused client retention plans.

Keywords: Customer churn, banking industry, financial services, churn prediction, LightGBM classifier, machine learning, SMOTE, feature engineering, model evaluation, customer retention strategies

INTRODUCTION

There is more rivalry in the financial services sector as a result of the industry's fast transformation, the need to adjust to new technologies, and the entry of FinTech firms into the conventional banking market. In the financial services sector, one of the most difficult issues is client retention or churn due to the intense competition. Keeping current customers is five to six times cheaper than attracting new ones. For service businesses, building a long-term clientele is crucial since devoted clients utilize a variety of goods, are less expensive to serve, and contribute to the company's positive reputation [1, 2].

The happiness of a company's customers is directly proportional to its prosperity and expansion. As a result, there is fierce rivalry to win over new clients and hold on to old ones in every industry. Yet, despite these attempts, client churn does happen occasionally [3]. When customers stop purchasing a company's products or services, it is called client churn. More clients are unsubscribing from the company if the churner rate is high. Telecommunications is only one of several industries impacted by this phenomena, e-commerce, online gambling, and services that are provided through subscription. Customers who have already purchased from a firm might have a major influence on its income [4].

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Customer turnover is unavoidable due to the intense rivalry among telecom carriers. Consumer churn occurs when a consumer decides to switch service providers instead of continuing with their current subscription [5]. Because it undermines the firm, client churn must be reduced [6]. According to research, there is a significant yearly customer turnover rate in the telecom industry, ranging from 20 to 40%, costing 5–10 times less than getting new ones [7]. The expense of anticipating which customers would churn is 16 times less than the expense of acquiring new customers [8–10]. As the churn rate decreases by 5%, the profit increases from 25 to 85%. This exemplifies why attrition prediction is so important for telecom companies. In order to retain existing customers and find new ones, the telecommunications sector highly values customer relationship management (CRM) solutions. Customer relationship management analysts need to know ways to retain current consumers and identify those who are likely to leave. Marketing initiatives targeting churn customers are necessary for maximizing churn-customer retention after the at-risk consumers have been identified. As a result, CRM relies heavily on customer-churn prediction [11–13].

A current customer is difficult to lose in any commercial setting. There are three ways that customers lose interest. Issues with service providers, which include sluggish connections, exorbitant fees, convoluted invoicing procedures, and so on, may cause some customers to go elsewhere. The second issue is that some customers tend to be fickle. Last but not least, the communication industry is bewildered by the reasons some customers often switch service providers [14]. It is important to anticipate this user type and the variables that may cause them to switch. It takes a lot of time and money to register a new customer. Thus, a telecom company's sole hope for survival is churn prediction and anticipation [15–17].

Identifying customer turnover is a common task for many ML-based classification systems. In the past, researchers only used one approach for CCP categorization [18] A new generation of ensemble-based classification algorithms has just emerged. These novel approaches use fusion methods to blend the predictions of several individual classifiers into a single aggregated outcome [19].

Motivation and Contribution of the Study

In the financial sector, a major obstacle that has an effect on growth and revenue is client attrition. The timely implementation of retention tactics by banks depends on their ability to understand and anticipate which clients are likely to quit. This research is motivated by the need for an accurate and robust early warning system for customer churn in banking services. The study's overarching goal is to create and test a model that can accurately detect possible churners using a dataset consisting of 10,000 bank customers. The focus on features like Age, Balance, and their ratios and SHAP analysis for model interpretability underscores the drive to create a method for attrition prediction that is both accurate and practical, which can help financial organizations maximize their resources while decreasing client turnover.

The primary results of the study are laid forth in a sequential manner:

- Leveraged a Kaggle-sourced Bank Customer Churn dataset of 10,000 users from Spain, France, and Germany, providing a diverse base for churn prediction research.
- Employed a comprehensive pre-processing pipeline including data cleaning, one-hot encoding, categorical features, and both Z-score normalization and Min-Max normalization, ensuring data suitability for model training. Used SMOTE to deal with the uneven distribution of customers in terms of churning.
- The LGBM Classifier, known for being a good framework for handling large datasets fast, with lower memory needs and better accuracy, was used for the customer churn early warning model.
- Tested the model using a battery of measures to demonstrate its strong performance, alongside ROC Curves, Accuracy, Precision, Recall, F1-Score, and a Confusion Matrix.
- To understand the model's predictions, it used SHAP (SHapley Additive exPlanations) to measure the impact of each feature on the output for specific cases. It found that "Age" was a significant driver of churn.

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- The LGBM Classifier showed stronger results than DT, KNN, LR, and SVM for the task of predicting churn in financial services.

Justification and Novelty

The research presents a novel approach to predicting financial services customer turnover using an LGBM Classifier, which outperforms conventional models. This study is needed because it helps solve the key problem of retaining customers by giving a dependable and detailed early alert about customer churn. Several elements are responsible for the model's novelty: address class imbalance with SMOTE, preserving useful data that might be removed using other approaches; use SHAP to help explain what features affect churn, allowing us to notice that Age plays a moderate but positive role in customer churn; and make use of the LGBM model, which demonstrates great results in predicting and handling customer churn.

Structure of the Study

This study is structured into several sections: A comprehensive literature assessment on financial services churn prediction is included in the next Section. The Section after that outlines data gathering and preparation techniques, as well as the suggested approach. Then the following Section elaborates on the model implementation, experimental setup, and key findings. Finally, the last Section concludes with the analysis of the study's strengths and weaknesses as well as recommendations for future studies.

LITERATURE REVIEW

This review consolidates recent progress in churn prediction research specific to the financial services domain. Table 1 encapsulates the applied methodologies, datasets used, major findings, existing limitations, and recommended directions for future investigation.

Clinton *et al.*: They suggested that bivariate analysis is held to find the correlation of each feature against the churn rate. With these observations, the importance of marketing strategies is exhibited. Additionally, four distinct models: LR, RF, DT, and the XGB Classifier, are used to train and assess the dataset. From the evaluation of all four models with the help of the ROC score, the XGB is found to outperform and provide better results obtaining 98% accuracy and a 1.00 ROC score [20].

Yu: The results of the study demonstrate that the decision tree algorithm excels in feature extraction, achieving an average feature correlation score of 0.75 and a maximum of 0.89. Additionally, it offers a clear advantage in prediction speed. Notably, the maximum prediction accuracy reaches 98.9%, which is significantly higher than traditional methods such as statistical analysis, user life cycle analysis, and social network analysis [21].

Faisal et al.: A higher F1 score (86.7%), recall (88%), and total performance (87.26%) are achieved by the RF as compared to the LR. The ROC plot shows that the RF classifier outperforms the revised LR model with a 95% AUC compared to just 93% [22].

Anudeep et al.: The proposed results of this study establish a solid framework for proactive churn control and long-term growth, which has important ramifications for e-commerce companies. Businesses may maximize resource allocation, raise customer happiness, and develop enduring connections with their subscribers by utilizing the predictive powers of RNNs with attention mechanisms. To put the recommendations into action, Python is utilized. The proposed study has a 97% success rate [23].

Zeng: Training in the actual experiment was carried out using the NB technique in conjunction with the BP neural network and the bat-neural network (BA-BP) combination algorithm. The results were evaluated by comparing the landscapes. Through comparison, the findings demonstrate that the telecom customer churn model using the BA-BP combination algorithm is capable of attaining an accuracy level of 97.43%. The application criteria may be satisfied with the accuracy (74.98%) and recall (80.45%) [24].

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Singh et al.: They suggest that ML algorithms' performance could differ based on how closely they mimic actual telecoms data as opposed to the freely accessible dataset. Consequently, XGBoost was one of several prediction models utilized by the researchers with this dataset. On the native dataset, they reach an accuracy of 82.80%. Findings demonstrate the efficacy of the technologically advanced prediction model [25].

Soundarya et al.: Performance indicators including accuracy, recall, and others are used to assess and contrast several machine learning models in this research. The models include LR, DT, KNN, RF, and others. RF outperformed all of these classifiers with a 71% success rate [26].

Table 1. Summary of recent studies on churn prediction in financial services.

Author(s)	Methodology	Dataset	Findings	Limitations	Future scope
Clinton *et al.* (2025) [20]	Bivariate analysis; LR, RF, DT, XGB classifiers; ROC evaluation	Telecom churn dataset	XGB achieved best performance with 98% accuracy and 1.00 ROC score. Demonstrated importance of marketing strategies.	Focused on model performance only; did not include real-time or streaming data scenarios.	Incorporate real-time churn prediction; explore explainable AI for feature contribution insights.
Yu (2025) [21]	Decision Tree for feature extraction and prediction	Telecom Customer Churn Dataset	DT achieved a max correlation of 0.89 and accuracy of 98.9%. Superior speed and extraction quality compared to traditional approaches.	Dataset and model generalizability not fully addressed.	Explore DT in ensemble settings; apply to different domains for validation.
Faisal *et al.* (2024) [22]	Comparison between Random Forest and Logistic Regression; ROC and AUC used for evaluation	IBM Telco Customer Churn Dataset	RF outperformed LR: 87.26% accuracy, 85.44% precision, 88% recall, 95% AUC.	Focused on binary comparison; limited diversity in models.	Compare with advanced ensemble models (XGB, LightGBM); integrate feature selection techniques.
Anudeep *et al*. (2024) [23]	RNNs equipped with attentional processes; Python implementation	E-commerce subscription dataset	Proposed RNN model achieved 97% accuracy; useful for proactive churn control and customer satisfaction enhancement.	Neural network complexity and interpretability issues not addressed.	Apply model to streaming data; integrate SHAP for interpretability.
Zeng (2023) [24]	A comparison of Naive Bayes, BP Neural Net, BA-BP hybrid, and landscape systems	Telecom dataset	BA-BP achieved 97.43% accuracy, 75.98% precision, 80.45% recall. Superior to standard NN models.	Lower precision and recall compared to accuracy; lacks explainability.	Optimize BA-BP with adaptive metaheuristics; test on diverse customer profiles.
Singh *et al.* (2023) [25]	Evaluation of ML models (including XGBoost) on proprietary telecom data	Native telecom dataset	XGBoost achieved 82.8% accuracy on native data. Highlights model performance difference on real-world vs. public datasets.	Performance lower than on public datasets; data heterogeneity affects results.	Develop hybrid models tailored for real-world data characteristics; validate on larger datasets.
Soundarya *et al*. (2023) [26]	Comparative study of LR, DT, KNN, RF using accuracy, recall, etc.	IBM Telco Customer Churn Dataset	RF performed best with 71% accuracy; others underperformed in comparison.	Limited accuracy across all models; may lack data preprocessing.	Implement feature engineering and hyperparameter tuning for model enhancement.

METHODOLOGY

The proposed study presents churn prediction in financial services using a structured and systematic approach. As illustrated in Figure 1, the methodology begins with the acquisition of a bank customer churn dataset, followed by comprehensive data preparation steps including data cleaning, one-hot encoding, standardization, and normalization to ensure data quality and consistency. Feature engineering techniques are then applied to enhance model performance, and an approach to rectifying class imbalance is the SMOTE. Separate sets, representing training and testing, make up the dataset. It tests several classification techniques on the cleaned dataset, including LightGBM, DT, LR, and SVM. When comparing classifiers, LightGBM stands out due to its exceptional performance on all measures. Finally, ROC-AUC, there are four metrics used to measure the models' performance: F1-score, recall, accuracy, and precision, giving a thorough evaluation of the algorithms' ability to forecast customer turnover.

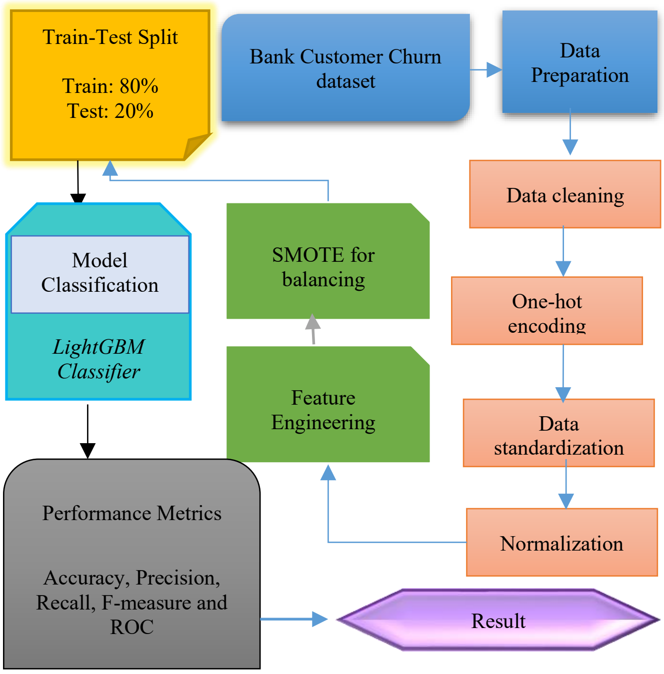

Figure 1. Flowchart diagram of proposed churn prediction in financial services.

The steps and processes of the flowchart are explained in detail below:

Data Collection

This study leveraged Bank Customer Churn dataset which summarizes 10,000 Spanish, French, and German customers of financial institutions. Frequently used in customer attrition studies, Kaggle is the source of the dataset. The dataset has several uses, however it cannot be linked to a particular bank because no verifiable paperwork is available.

Figure 2 illustrates the customer churn dataset's Spearman correlation matrix among important numerical factors. The monotonic correlations between factors such as years of experience, debt levels, credit ratings, balances, and product counts, and exit status are shown in the matrix, along with their strength and direction. Noteworthy, there is a moderate positive connection between the attribute Age and the goal variable Exited (0.32), indicating that older consumers are more prone to churning. With a high negative correlation of –0.13, it can be seen that consumers with fewer goods are more likely to depart.

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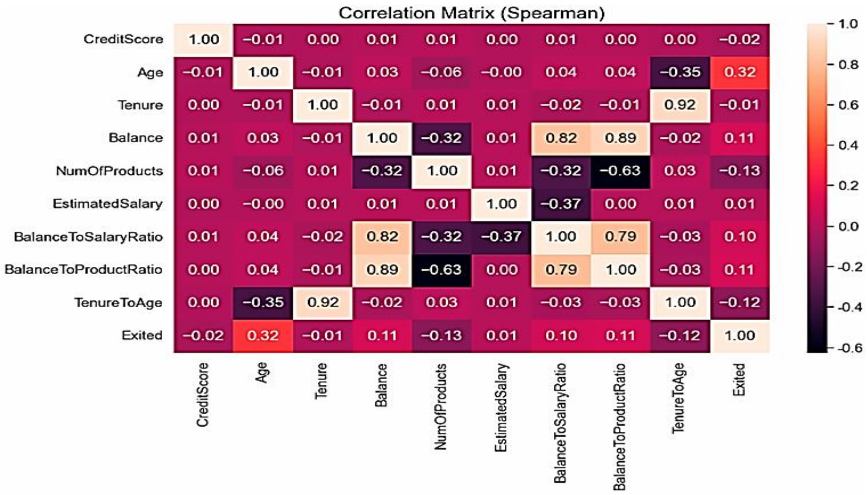

Figure 2. Correlation matrix.

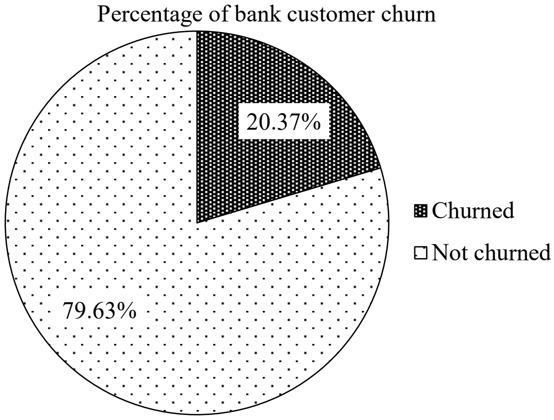

Figure 3. Percentage of bank customer churn.

Figure 3 presents the pie chart distribution of customer churn within the bank customer dataset. As depicted, 79.63% of the customers have retained their association with the bank, whereas 20.37% have churned at some point. This imbalance highlights the necessity for robust predictive modeling to accurately identify potential churners and support effective customer retention strategies.

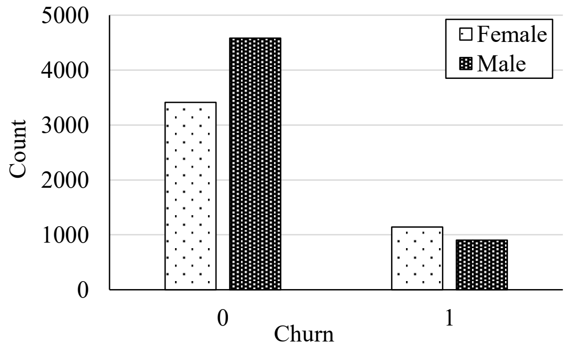

Figure 4. Churned customers per gender.

Figure 4 illustrates the distribution of churned customers by gender in the banking dataset. The analysis reveals that male customers were more likely to retain their association with the bank compared to female customers. Conversely, female customers exhibited a higher churn rate, indicating a greater likelihood of discontinuing the bank's services over time.

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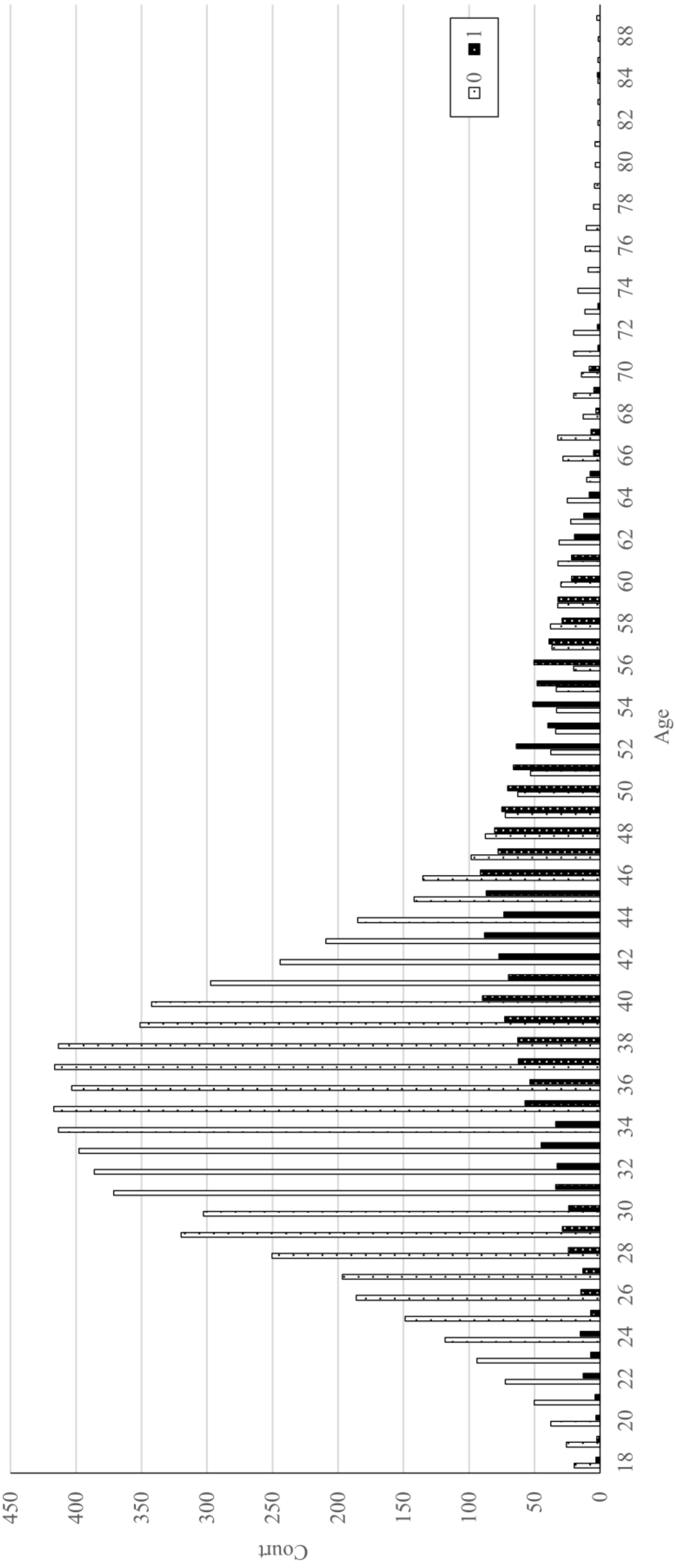

Figure 5. Churned customers per age.

Figure 5 depicts the distribution of churned customers across different age groups in the banking dataset. Customers between the ages of 29 and 41 years make up the bulk of the bank's clientele. However, a higher churn rate is observed among customers aged between 40 and 52 years, indicating that individuals in this age group are more likely to discontinue their association with the bank.

Data Preparation

Data preprocessing for the built customer churn early warning model to make use of the tabular data that has been collected, some processing operations must be carried out on the raw data. Customizability of the model to meet client needs, data may be further enhanced with a little preprocessing work done before feeding it into the training phase. Data cleansing is one of the preprocessing procedures used in the study, data encoding, data standardization and normalization that are discussed below:

- *Data cleaning:* The features with missing values are processed at this step. After that, it filters out features that are not significant and are just used to differentiate between clients.
- *One-hot encoding:* Here, it prepares the categorical characteristics for the model's data format by encoding them. Using one-hot encoding, it reduces the category characteristics to numerical features. This method generates a large number of binary numerical characteristics from the category ones.
- *Data standardization:* The customer churn dataset contains features with widely varying distributions of values. When these features are used directly in model learning, they tend to over-weight features with a large range of values, which means other important feature information gets ignored. As a result, the model is unable to understand the true trends in the consumer data. As a result, it eliminated the scale disparity in the features by mapping all numerical characteristics to between 0 and 1 by Z-score normalization [27]. Eq. (1) displays the mathematical representation of this process.

$$x' = \frac{x-\mu}{\sigma} \tag{1}$$

Feature Engineering

Feature engineering is a method for improving a model's performance by building new features from current ones by extracting relevant information from the input. In this study, two additional characteristics were included: the total amount of NaN values for the i^{th} row $NaN(i)$, and a binary value $NaN(i_b)$ that indicates whether a NaN value is present or not for the i^{th} row [28].

SMOTE for Handling Class Imbalance

The solution of real-world classification problems, particularly binary classification, often leads to a class-imbalanced situation. When trying to anticipate which customers will leave, it is common to use an imbalanced-class binary classification with a much bigger negative (non-churn) class than a positive (churn) class [29]. To provide accurate results, ensure that the number of class records is evenly distributed throughout the preprocessing phase [30]. It employed imbalanced approaches, such as SMOTE, to address the issue [31]. The SMOTE method was the most useful for data balance in this study. Previous research has demonstrated that using the ensemble approach in conjunction with random under-sampling of the majority class is undesirable since it can result in data information loss [32–34].

Train-Test Split

In contrast to the 20% that makes up the test set, 80% of the data is located in the training set. First and foremost, it thought there were enough data instances to warrant splitting the dataset in an 80:20 ratio.

Model Classifcation of LGBM Classifier

As for gradient boosting, the system makes use of tree-based learning methods. Its distributed and efficient architecture allows it to enable GPU learning and parallel processing, process massive amounts of data, lower memory use, increase accuracy, and speed up training [33–36].

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Gradient boosting allows for the gradual construction of solutions, while optimization of loss functions allows for the resolution of the over-fitting problem. Given a loss function $\psi(y, f(x))$ and a bespoke base-learner $h(x, \theta)$, it might be tough to directly estimate the parameters. Therefore, a model that is iterative is suggested; during each iteration, a new base-learner function $h(x, \theta t)$, is made, and the increment is guided by the following:

$$g_t(x) = E_y[\frac{\partial_\psi(y,f(x))}{\partial f\,(x)}|x]_{f(x)=f^{\sim t-1}(x)} \tag{2}$$

$$(p_t, \theta_t) = argmin_{p,\theta} \sum_{i=1}^{N}[= g_t(x_i) + ph(x_i, \theta)]^2 \tag{3}$$

Here, the usual least-squares optimization issue is used in place of the difficult optimization problem in Eqs. (2) and (3).

Algorithms and Evaluation Metrics of LGBM Classifier

The Performance Metrics assess and contrast the algorithms' outputs using four performance indicators. So that it may find out how well the model works, the most popular performance metrics are computed using the FN, FP, TN, and TP. These metrics include F-score, recall, precision, and accuracy measures:

- *True Positives (TP):* Customer turnover rate as a percentage of actual churn.
- *False Positives (FP):* Miscalculated number of churning clients compared to non-churning customers.
- *True Negatives (TN):* Exactly how many non-churn customers were expected.
- *False Negatives (FN):* The number of consumers whose turnover is really anticipated to be non-existent.

Performance metrics are calculated using the following equations:

1. *Accuracy:* The percentage of occurrences that were properly detected as a percentage of the total number is called the accuracy rate of cases that need categorization. The accuracy is expressed in Eq. (4):

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

2. *Precision:* As a percentage, it shows how many positive predictions were based on samples that were properly categorized. Mathematically it is expressed in Eq. (5):

$$Pr = \frac{TP}{TP+FP} \tag{5}$$

3. *Recall:* A high score shows that the model successfully identifies all positive cases in the dataset. It is derived from the ratio of TP predictions to the total number of true positive forecasts. In Eq. (6) it is given.

$$Re = \frac{TP}{TP+FN} \tag{6}$$

4. *F-Measure:* As a classification performance metric, the F-Measure integrates recall and accuracy into a single numerical indication. Expressed in Eq. (7):

$$F1\,Score = 2 \times \frac{Precision*Recall}{Precision+Recall} \tag{7}$$

ROC Curve

A graph showing the classifier's performance across all classification thresholds is called ROC, or receiver operating characteristic, profile. Separated from one other on the graph are the TPR and the FPR. When dealing with two-class situations, one accepted way to evaluate classifier effectiveness is to look at the area under the ROC curve, or AUC. Performance and Forecast Accuracy were also involved in the creation of the AUC. A flawless classification model is one with an AUC of 1.

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RESULTS ANALYSIS AND DISCUSSION

The experiments for model development, training, and testing were performed on a Dell laptop featuring an Configuration: Windows 11 Pro, Intel Core i7-11800H (8-core CPU), 32 GB RAM, and a graphics card from NVIDIA called an RTX 3060. The performance metrics for the LGBM classifier to predict churn in financial services are shown in Table 2. The algorithm achieved an impressive 91% accuracy rate in classifying clients as either churning or not churning. The classifier proved to be highly precise with 93% of the classifier's ability to reduce false positives, thereby ensuring a large percentage of churn situations that were accurately detected in the expected positives. Further, the recall value of 88% suggests that the model detects real churners with a high degree of sensitivity. Besides, an F1 score of 90% ensures that the LGBM model is robust and sustainable in forecasting customer turnover in financial situations, as it strikes a good balance between recall and precision.

Table 2. Result of LGBM classifier in churn prediction in financial services.

Models	**LGBM**
Accuracy	91%
Precision	93%
Recall	88%
F1-score	90%

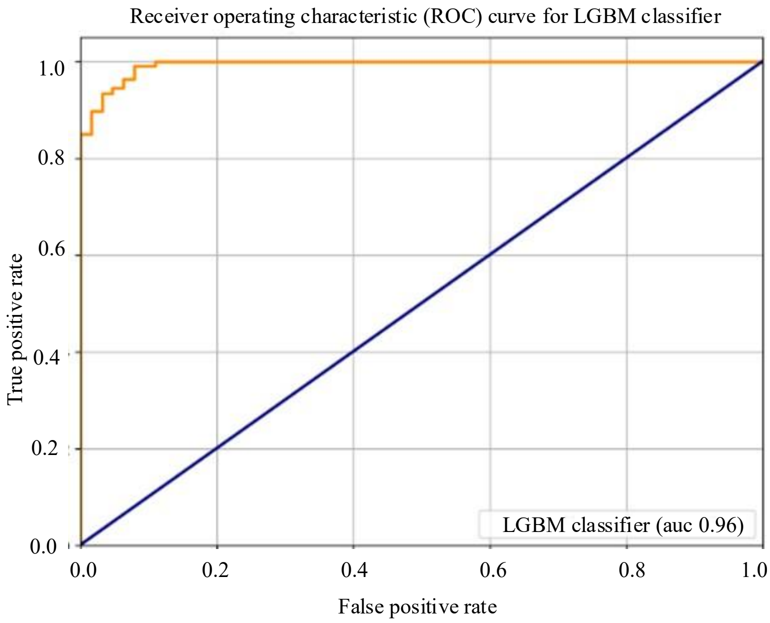

Figure 6. ROC curve of LGBM classifier.

Figure 6 shows the LGBM classifier's ROC curve, which demonstrates that it is effective for binary classification problems. For various threshold values, the curve represents the tradeoff between the TPR and the FPR. The LGBM model achieves an AUC of 0.96 in terms of discriminative power and the capacity to highlight class instances with minimum false alarms. As opposed to a randomly selected classifier, shown by the diagonal line, the classification performance improves as the curve approaches the upper left corner.

Figure 7 demonstrates the LGBM model's confusion matrix for two-class categorization. Looking at the matrix, it can see that the model was able to accurately forecast 1,464 TN occurrences and 1,386 TP instances. But this model has flipped 110 FPs from class 0 to 1 and 188 FNs from class 0 to 0. Both the positive and negative situations can be accurately classified using the LGBM model, as seen by the high values on the matrix diagonal.

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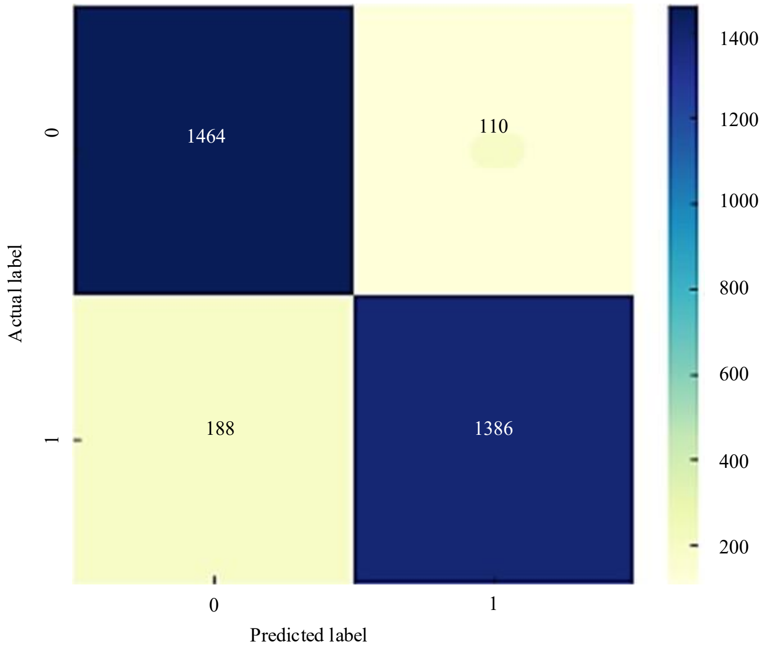

Figure 7. Confusion matrix of LGBM classifier.

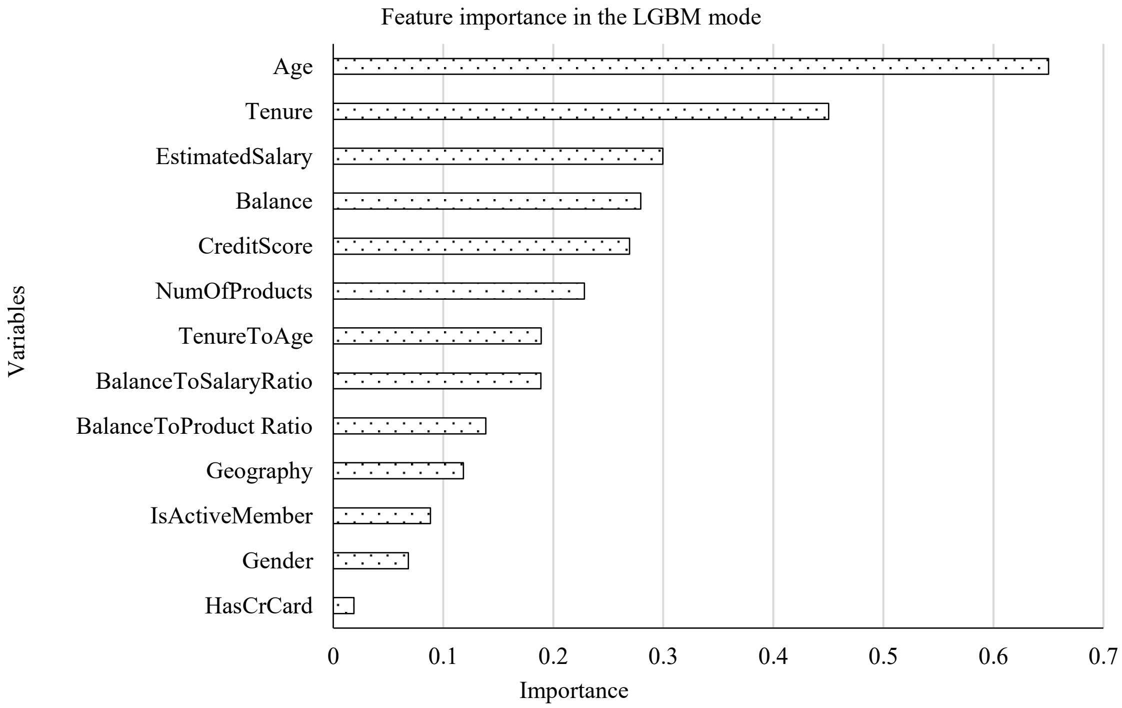

Figure 8. Features importance in LGBM model.

In Figure 8, the feature importance scores obtained from the LGBM model indicate which variables have the greatest impact on predicting client attrition. Out of all the factors considered, age had the greatest impact; Tenure, Estimated Salary, and Balance were developers' next important sets of features. In the decision-making process of the model, these qualities are crucial. Besides, variables such as Credit Score, Number of Products and Tenure to Age ratio are also moderately important. On the other hand, features such as Gender, Is Active Member and HasCrCard hold comparatively lower importance, which implies that they affect to a lesser degree, the model's ability in distinguishing between churned and retained consumers.

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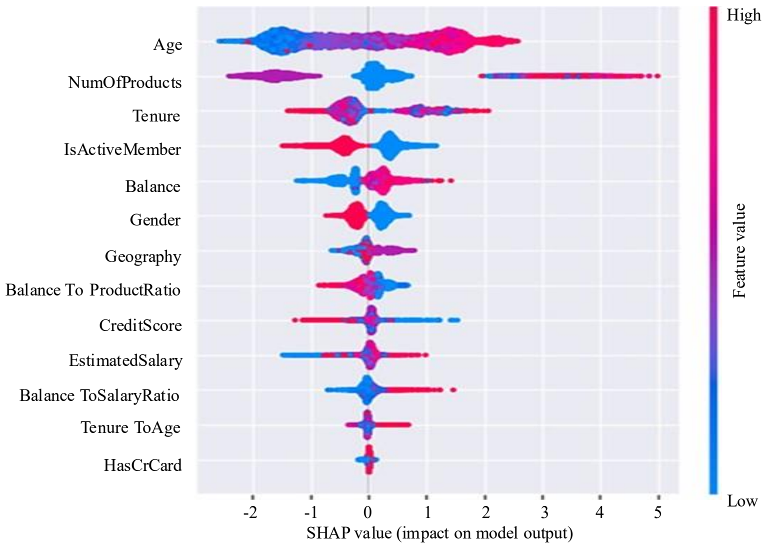

Figure 9. SHAP summary plot for the LGBM model.

Figure 9 shows a SHAP summary graphic, which shows how different characteristics affect the output of an ML model. The SHAP value, which displays the feature's contribution to the prediction, is shown on the horizontal axis, and each row represents a feature.

Comparative Analysis

In this section, the proposed LGBM Classifier is compared comprehensively with some well-recognised existing algorithms like DT, LR, and SVM. All models were trained and tested under the same experimental environments to be able to assess them fairly and consistently. A comparative analysis of different classification models of churn prediction in financial services is given in Table 3. The LGBM is found to be the best among all models in terms of all metrics, which means that it can churn customers with the best precision and capability to recall customers who left. The models with moderate performance are DT and LR, where the values of precision and recall for DT are greater than LR. Most ineffective are the SVM, especially with regards to the recall and overall F1-score, which illustrates the insufficient capability of the SVM to capture the intricacy of churn behaviour in this case.

Table 3. Various model’s classification in churn prediction in financial services.

Model	Accuracy	Precision	Recall	F1-Score
DT [34]	82	66.9	53.2	59.3
LR [35]	66.6	60	65.4	65.4
SVM [36]	57	73	42	53
LGBM	91	93	88	90

The proposed LGBM model demonstrates enhanced performance in customer churn prediction within the financial services domain. The model improves classification results by efficiently learning from trees and using GB to properly capture complicated patterns in consumer behavior. Timely intervention techniques are made possible by its excellent predictive capabilities, which improve the identification of probable churners. The model is also scalable and shows resilience when dealing with important features, thus it is a good fit for real-world use in dynamic banking settings.

CONCLUSION AND FUTURE WORK

Financial services have a critical aspect, customer churn prediction, which helps institutions to efficiently identify and retain the customers at risk and thereby increase customers’ lifetime value and profitability of the institution. The LGBM Classifier was successfully developed and evaluated for a robust customer churn early warning model with a Bank Customer Churn dataset. Comprehensive

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evaluations, such as ROC curve and AUC of 0.96, proved that the model performs great, with an accuracy of 91%. Future directions for the study include looking into the fusion of streaming data for real time streaming data to enhance the accuracy of churn prediction, and evaluating the effect of external economic indicators in addition to their integration into the model, and carry out a case study to apply personalized retention strategies based on the granular insights offered by SHAP analysis.

Future research can also take into account the integration of real-time streaming data, which is likely to improve responsiveness and adaptability in changing operational environments. Additionally, the circumstances of the customer behavior can be enriched by the addition of external economic indicators, which may also enhance the prediction accuracy. Lastly, using SHAP for explainable AI can derive personalized retention strategies by bringing out granular insights on what drives each individual to churn.

REFERENCES

1. Ashraf R. Bank Customer Churn Prediction Using Machine Learning Framework. J Appl Financ Bank. 2024; 14(4): 65–109.
2. Chaudhari B, Verma SCG. Synergizing Generative AI and Machine Learning for Financial Credit Risk Forecasting and Code Auditing. Int J Sci Res Comput Sci Eng Inf Technol. 2025; 11(2): 2882–2893.
3. Wawge SJ. A Survey on the Identification of Credit Card Fraud Using Machine Learning with Precision, Performance, and Challenges. Int J Innov Sci Res Technol. 2025; 10(4): 3345–3352.
4. Singh V. Predicting Loan Default Risk in P2P Lending Platforms: A Study of Lending Club Borrowers. Int J Sci Res. 2023 Nov; 12(11): 2255–60.
5. Xu T, Ma Y, Kim K. Telecom churn prediction system based on ensemble learning using feature grouping. Appl Sci. 2021; *11*(11): 4742.
6. Pillai V. System and Method for Intelligent Detection and Notification of Anomalies in Financial and Insurance Data using Machine Learning. 2025; 202421099024.
7. García DL, Nebot À, Vellido A. Intelligent data analysis approaches to churn as a business problem: a survey. Knowl Inf Syst. 2017; 51: 719–774.
8. Balle B, Casas B, Catarineu A, Gavaldà R, Manzano-Macho D. The architecture of a churn prediction system based on stream mining. In: Frontiers in Artificial Intelligence and Applications. 2013; 157–166.
9. Wawge SJ. Evaluating Machine Learning and Deep Learning Models for Housing Price Prediction: A Review. Int J Adv Res Sci Commun Technol. 2025 Apr; 5(11): 367–77.
10. Chaudhari B, Chitraju S. Achieving High-Speed Data Consistency in Financial Microservices Platforms Using NoSQL Using Nosql (Mongodb, Redis) Technologies. Int J Adv Res Sci Commun Technol. 2024 Jun; 4(2): 750–9.
11. Ngai EWT, Xiu L, Chau DCK. Application of data mining techniques in customer relationship management: A literature review and classification. Expert Syst Appl. 2009 Mar; 36(2): 2592–2602.
12. Mantha G. Transforming the insurance industry with Salesforce: enhancing customer engagement and operational efficiency. North Am J Eng Res. 2024;5(3):1–2.
13. Malali N. Artificial Intelligence in Life Insurance Underwriting : A Risk Assessment and Artificial Intelligence in Life Insurance Underwriting : A Risk Assessment and Ethical Implications. International Journal of Interdisciplinary Research Methods (IJIRM). 2025 Apr; 12)1): 36–49.
14. Majumder RQ. A Review of Anomaly Identification in Finance Frauds Using Machine Learning Systems. Int J Adv Res Sci Commun Technol. 2025 Apr 25; 5(10): 101–10. Available from: https://ijarsct.co.in/Paper25619.pdf
15. Lin SC, Tung CH, Jan NY, Chiang DA. Evaluating Churn model in CRM: A case study in Telecom. J Converg Inf Technol. 2011; 6(11): 192–200.
16. Garg S. AI, Blockchain and Financial Services: Unlocking New Possibilities. Int J Innov Res Creat Technol. 2022; 8(1): 1–4.

17. Ramanujam B. Statistical insights into anti-money laundering: analyzing large-scale financial transactions. Int J Eng Res Technol. 2025;14(4):1–6.
18. Chatterjee P. Smart Contracts and Machine Learning: Exploring Blockchain and AI in Fintech. Indian J Sci Technol. 2025 Jan 15; 18(2): 113–24. Available from: https://indjst.org/articles/smart-contracts-and-machine-learning-exploring-blockchain-and-ai-in-fintech
19. Liu R, Ali S, Bilal SF, Sakhawat Z, Imran A, Almuhaimeed A, *et al*. An Intelligent Hybrid Scheme for Customer Churn Prediction Integrating Clustering and Classification Algorithms. Appl Sci. 2022; *12*(18): 9355.
20. Clinton PB, Priya PS, Jagadeesan S, Nagarajan S, Mohanapriya K, Lakshmi SJ. Machine Learning on Retail Stores for Customer Churn. In: 2025 IEEE International Conference on Advanced Computing Technologies (ICoACT). 2025; 1–6.
21. Yu M. Cross-Border E-Commerce User Churn Prediction Model Based on Decision Tree Algorithm. In: 2025 IEEE 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS). 2025; 1–5.
22. Faisal AM, Rajkiran V, Singh KS, Elantheraiyan P, Kamalakhannan SK. Identification of an Efficient Machine Learning Algorithm for the Prediction of Customer Churn: A Case Analysis of a Business-to-Consumer (B2C) Dairy Company for Customer Retention Strategy. In: 2024 IEEE 4th International Conference on Innovative Practices in Technology and Management (ICIPTM). 2024; 1–5.
23. Anudeep C, Venugopal R, Aarif M, Valavan AT, Vuyyuru VA, Muthuperumal S. Predicting Customer Churn in E-commerce Subscription Services using RNN with Attention Mechanisms. In: 2024 IEEE 15th International Conference on Computing Communication and Networking Technologies (ICCCNT). 2024; 1–6. Available from: https://ieeexplore.ieee.org/document/10725520/
24. Zeng H. Research on Telecom Customer Churn Prediction Model Based on BA-BP Neural Network. In: 2023 IEEE International Conference on Sensors, Electronics and Computer Engineering, ICSECE 2023. 2023; 810–817.
25. Singh KD, Singh PD, Bansal A, Kaur G, Khullar V, Tripathi V. Exploratory Data Analysis and Customer Churn Prediction for the Telecommunication Industry. In: 2023 IEEE 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS). 2023; 197–201. Available from: https://ieeexplore.ieee.org/document/10199700/
26. Soundarya BC, Gururaj HL, Chaithra KN, Manu MN, Shrikanth NG, Anupama K. Minimization of Churn Rate Through Analysis of Machine Learning. In: 2nd IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics, ICDCECE 2023. 2023; 1–5.
27. Yang C, Xia G, Zheng L, Zhang X, Yu C. Customer Churn Prediction Based on Coordinate Attention Mechanism with CNN-BiLSTM. Electronics. 2025 May; 14(10): 1916.
28. Sagming M, Heymann R, Visaya MV. Using topological data analysis and machine learning to predict customer churn. J Big Data. 2024; 11(1): 160.
29. Khoh WH, Pang YH, Ooi SY, Wang LYK, Poh QW. Predictive Churn Modeling for Sustainable Business in the Telecommunication Industry: Optimized Weighted Ensemble Machine Learning. Sustainability. 2023; *15*(11): 8631.
30. Li B, Xie J. Study on the Prediction of Imbalanced Bank Customer Churn Based on Generative Adversarial Network. In: J Phys: Conf Ser. 2020; 1624(3): 032054.
31. Muneer A, Ali RF, Alghamdi A, Taib SM, Almaghthawi A, Abdullah Ghaleb EA. Predicting customers churning in banking industry: A machine learning approach. Indones J Electr Eng Comput Sci. 2022; 26(1): 539–549.
32. Tékouabou SCK, Alaoui EAA, Chabbar I, Toulni H, Cherif W, Silkan H. Optimizing the early glaucoma detection from visual fields by combining preprocessing techniques and ensemble classifier with selection strategies. Expert Syst Appl. 2022 Mar; 189: 115975.
33. Alotaibi MZ, Haq MA. Customer Churn Prediction for Telecommunication Companies using Machine Learning and Ensemble Methods. Eng Technol Appl Sci Res. 2024 Jun; 14(3): 14572–8.

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34. Al-quraishi T, Albahri O, Albahri A, Alamoodi A. Bridging Predictive Insights and Retention Strategies : The Role of Account Balance in Banking Churn Prediction. AI. 2025; *6*(4): 73.
35. Silveira LJ, Pinheiro PR, Junior LS de M. A Novel Model Structured on Predictive Churn Methods in a Banking Organization. J Risk Financ Manag. 2021; 14(10): 481.
36. Chajia M, Nfaoui EH. Customer Churn Prediction Approach Based on LLM Embeddings and Logistic Regression. Futur Internet. 2024 Dec; 16(12): 453.