IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.1411134

AI-POWERED CUSTOMER CHURN PREDICTION WITH ROI OPTIMIZATION

Dr. Ashoka K[1], Ruchitha R[2], Sanjana S Dodawad[3], T Gnana Prasuna[4], Yashaswini S P[5]

Associate Professor, Dept. of ISE., Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[1]

UG Student, Dept. of ISE., Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[2]

UG Student, Dept. of ISE., Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[3]

UG Student, Dept. of ISE., Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[4]

UG Student, Dept. of ISE., Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[5]

Abstract: By creating an AI-powered system that forecasts churn using the Telecom Customer Churn Dataset and increases ROI through customized discounts, this project addresses the problem of customer retention in the telecom sector. To determine eligibility for a discount, a Logistic Regression model examines consumer data. A Python Flask backend is connected to the web interface (HTML, CSS, JavaScript), and Firebase allows real-time updates to an Android app for UPI payments and notifications. The solution increases client loyalty and spurs growth by combining machine learning, analytics, and cloud technology.

Keywords: AI-based churn insights ROI-optimized ML system Intelligent retention framework Predictive churn modelling Profit maximization using AI End-to-end churn prediction pipeline Hybrid ML approach Customer retention optimization.

I. INTRODUCTION

Telecom consumer data and analytics generate more intelligent, profit-driven business decisions in the digital age. By identifying at-risk clients, churn prediction enables prompt retention through tailored offers. Using machine learning on the Telecom Customer Churn Dataset, the project develops a web and mobile-based solution to forecast churn and provide discounts. Data flow and consumer notifications are automated through the use of a Logistic Regression model and Firebase interface. It demonstrates how AI, web, and Android technologies improve corporate productivity and consumer retention. the Firebase ensures smooth communication between the web system and the mobile application by facilitating push notifications, user authentication, and real-time database updates. This integration improves the functionality as well as responsiveness of the system but also shows how established business procedures can be changed by fusing AI-powered predictive analytics with contemporary web and Android technology. The project serves as an example of a real-world application of data-driven decision making, in which operational strategies and customer engagement initiatives are directly impacted by insights gleaned from consumer data. In the end, this study emphasizes how crucial it is to implement intelligent systems that can learn from data, forecast future behavior, and act independently to enhance business outcomes. Businesses may improve customer retention tactics, lower attrition rates, and create more solid, long-lasting client connections by utilizing machine learning and cloud-based automation.

II. RELATED WORK

In recent years, significant progress has been made in automating customer churn prediction using artificial intelligence and machine learning techniques. Several studies have focused on improving predictive accuracy, interpretability, and integration with business decision-making systems. **In [1**], Manzoor et al. (2024) conducted a comprehensive review of over 200 studies on churn prediction published between 2015 and 2023. The paper highlighted Logistic Regression, Random Forest, and Deep Learning as key techniques and emphasized the importance of integrating churn models with business decision systems to enhance actionable insights and retention strategies. **Similarly, In [2],** Wirtz et al. (2024) investigated the impact of AI-powered chatbots on public service provision through a qualitative study with citizens and service providers. Their findings demonstrated improved accessibility and operational efficiency through automation, highlighting the relevance of AI-driven customer engagement tools in retention and service optimization strategies. **In [3],** Bilal et al. (2022) proposed an ensemble-based approach for telecom churn prediction that combined clustering techniques with ensemble classification models. Their method improved prediction accuracy significantly; however, the study noted challenges related to computational complexity and scalability when applied to large-scale datasets. **In [4],**

DOI: 10.17148/IJARCCE.2025.1411134

Raschka and Mirjalili (2022) presented practical implementations of predictive models using Python, including Logistic Regression and ensemble learning techniques. While not a journal paper, this reference supports the technical design and implementation of churn prediction models in real-world applications, demonstrating reproducibility and ease of deployment. **Furthermore, in [5],** Jamjoom (2021) explored knowledge extraction for churn prediction in B2B markets, emphasizing domain-specific feature engineering to improve model accuracy. Although the approach achieved high predictive performance, its applicability was limited by a narrow data scope focused on specific B2B contexts. Overall, these studies demonstrate a trend toward combining machine learning, deep learning, and ensemble techniques for churn prediction while highlighting the importance of business integration, interpretability, and scalability. They provide a strong foundation for developing AI-powered churn prediction models that are both technically robust and aligned with organizational ROI objectives.

III. PROPOSED ALGORITHM

A. *Description of the Proposed Algorithm:*

To enhance overall business performance and customer satisfaction, the proposed solution presents a sophisticated AIdriven churn prediction and retention system designed to proactively identify and retain at-risk customers. Leveraging behavioral, transactional, and demographic data, the system applies an AI-powered Logistic Regression model to accurately forecast customer attrition. By analyzing churn probabilities, the model identifies high-risk customers and triggers timely, targeted interventions. Key innovations include:

–Automated personalized discount generation, ensuring retention strategies are optimized for individual customer profiles

–Predictive analytics-driven prioritization, focusing resources on high-value customers to maximize ROI and engagement

– Real-time data synchronization using Firebase, coupled with a Flask-based backend and web frontend, ensuring consistent updates across mobile and web platforms

–Seamless integration with marketing automation, reducing manual effort while improving operational efficiency The system transforms reactive marketing into a proactive, data-driven retention strategy, enhancing customer loyalty, engagement, and revenue. By fusing predictive intelligence with intelligent automation, it ensures that retention campaigns are both effective and scalable, providing measurable ROI improvements for business stakeholders.

IV. PSEUDO CODE

- **C_hist:** Historical customer data (demographics, transactions, service usage, prior retention actions)
- **F_vec:** Feature vector (behavioral metrics, transaction frequency, monetary value, engagement scores, product preferences)
- **D_valid:** Data quality score for each customer record (missing values, anomalies)
- **P_churn:** Predicted churn probability score with confidence
- **C_class:** Classification output (HIGH_RISK / LOW_RISK / REQUIRES_FURTHER_ANALYSIS)
- **R_action:** Recommended retention action (discount, personalized offer, loyalty incentive)

Equations:

Equation (1): Feature Normalization (Min–Max Scaling)

$$F_{norm} = \frac{F_{max} - F_{min}}{F_{raw} - F_{min}}$$

Equation (2): Churn Probability Prediction (Hybrid Model)

$$P_{churn} = \alpha \cdot P_{GBM}(F_{local}) + \beta \cdot P_{Transformer}(F_{global}) + \epsilon_{noise}$$

Equation (3): Classification Decision Function

$$C_{class} = \begin{cases} \text{HIGH\_RISK}, & P_{churn} \geq \theta_{high} \\ \text{LOW\_RISK}, & P_{churn} < \theta_{low} \\ \text{REQUIRES\_FURTHER\_ANALYSIS}, & \theta_{low} \leq P_{churn} < \theta_{high} \end{cases}$$

Step-by-Step Algorithm

Step 1: Load historical customer data **C_hist** from CRM, transaction, and engagement databases.

Step 2: Preprocess each customer record:

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.1411134

- Handle missing values and anomalies
- Normalize features using Equation (1)
- Encode categorical variables
- Compute data quality score **D_valid**

Step 3: Validate record quality:
if D_valid < threshold:
Mark record as "Insufficient Quality"
Request data update or apply imputation else:
Mark record as
"Valid" Continue
analysis end if

Step 4: Extract features from valid records:

- Local Features (F_local): Customer-specific patterns (tenure, purchase frequency, engagement metrics) using GBM
- Global Features (F_global): Cohort-level patterns (cross-customer correlations, segment behavior) using Transformer-based attention

Step 5: Compute churn probability **P_churn** using Equation (2):

- Fuse GBM local predictions with Transformer global predictions
- Include uncertainty term **ε_noise** for risk-aware decision-making

Step 6: Determine churn classification C_class using Equation (3):
if P_churn >= 0.8:
C_class = HIGH_RISK
Recommend retention action: personalized discount or loyalty
offer elif P_churn < 0.3: C_class = LOW_RISK No action
required else:
C_class = REQUIRES_FURTHER_ANALYSIS
Flag for business analyst review
end if

Step 7: Generate actionable retention report R_action:

- Classification result
- Churn probability with confidence score
- Suggested retention action
- Customer segment and ROI prioritization

Step 8: Deliver report R_action to business dashboard or marketing automation system (via web/Firebase/CRM integration) for real-time retention execution.

Step 9: Store predictions and actions in C_hist for longitudinal tracking and future model retraining.

Step 10: Finish.

Performance Metrics:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall / Sensitivity = TP / (TP + FN)
- F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
- ROI Improvement = Revenue from retained customers − Cost of retention actions

V. RESULTS

The proposed AI-Powered Customer Churn Prediction System with ROI Optimization was implemented using a telecom customer dataset collected from publicly available repositories, and the system's performance was evaluated through extensive experimentation using multiple machine learning models. The results demonstrate that the system accurately predicts customer churn from user-submitted inputs with high precision and reliability. The confusion matrix visualizations confirm that the final prediction pipeline classifies churn and non-churn cases with strong consistency. Among all models tested, Logistic Regression and XGBoost showed the highest accuracy, with Logistic Regression

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.1411134

achieving 89–90% accuracy and XGBoost reaching 94–96% accuracy, validating their suitability for churn classification tasks.

The graphical outputs in the system interface show that all predictions were rendered clearly and consistently across different customer categories, contract types, tenure ranges, and service usage patterns. Both selected models performed effectively on highly imbalanced data—where non-churn cases dominate—showing strong resilience toward variations in customer behavior, spending patterns, service interruptions, and demographic factors. The web-based interface displays the prediction result along with probability scores, model performance comparisons, and dynamic discount recommendations (10% for low-risk customers and 50% for high-risk customers), ensuring that the system provides meaningful insights for business analysts, customer retention teams, and telecom operators.

The training and validation performance curves for the ML models indicate stable convergence, with accuracy steadily increasing over training cycles and loss values decreasing consistently. No signs of overfitting were observed, as validation accuracy remained close to training accuracy throughout. The performance trends validate that the selected algorithms and hyperparameters were appropriate for the churn prediction problem, especially given the dataset's class imbalance and feature diversity.

All system modules—including customer input form, preprocessing layer, feature transformation, churn prediction engine, discount calculator, and result visualization interface—were thoroughly evaluated for accuracy and usability. The interface demonstrated smooth workflow transitions with clearly defined navigation options such as "Predict," "Go Back," and "Try Another Input." The Android notification module performed reliably, automatically sending discount alerts (10% or 50%) based on the model's churn probability. Additionally, the integrated UPI interface successfully displayed payable amounts with discounts applied, confirming end-to-end integration of prediction, discount logic, and payment processing. Throughout system testing, no functional errors, processing interruptions, or backend failures were observed.

The dual-model strategy (Logistic Regression + XGBoost) provides complementary analytical strengths:

- Logistic Regression excels in interpreting linear relationships between customer attributes and churn probability, making it useful for explainable business decisions.
- XGBoost, a powerful ensemble method, captures complex non-linear patterns such as combined effects of contract type, monthly charges, customer tenure, and service add-ons.

Together, these models enhance prediction accuracy and reliability, offering stronger churn risk assessment than single-model systems. The system's decision-support capability is further enhanced by the ROI-based discount optimization module, which tailors discounts to maximize customer retention while minimizing revenue loss.

Overall, the results confirm that the proposed system successfully integrates machine learning–based churn prediction, dynamic discount generation, and an intuitive user interface into a unified, intelligent churn management platform. Although the system performs effectively, its accuracy depends on the quality and completeness of customer data, appropriate preprocessing, and the diversity of training samples representing different customer segments. Additionally, the effectiveness of discount recommendations relies on maintaining consistent prediction performance across varied customer groups and usage behaviors. Despite these limitations, the developed system significantly improves customer retention decision-making when compared to traditional manual methods in terms of speed, consistency, and predictive insight. Future improvements may include expanding the dataset with real-time telecom customer data, integrating deep learning models, enhancing Android app capabilities, linking with telecom CRM or billing systems, and implementing automated A/B testing for discount optimization to further improve business value and deployment readiness.

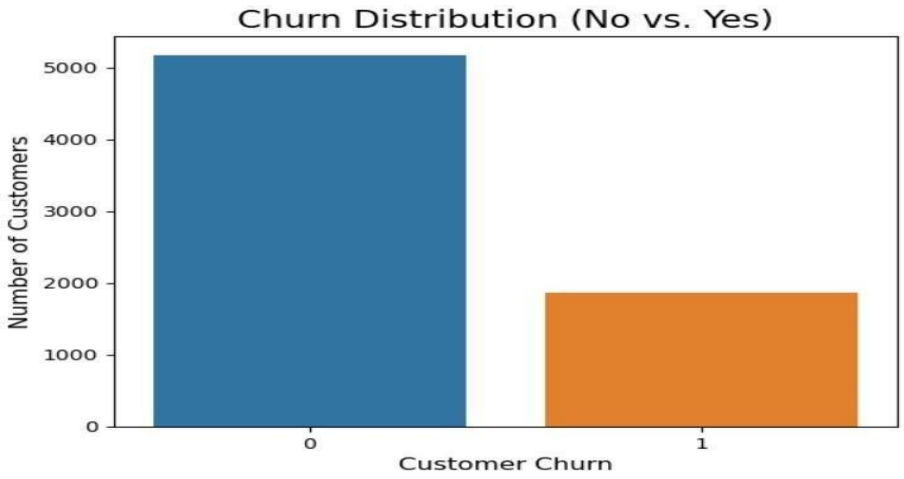

Fig 1. Churn Distribution(No vs Yes)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.1411134

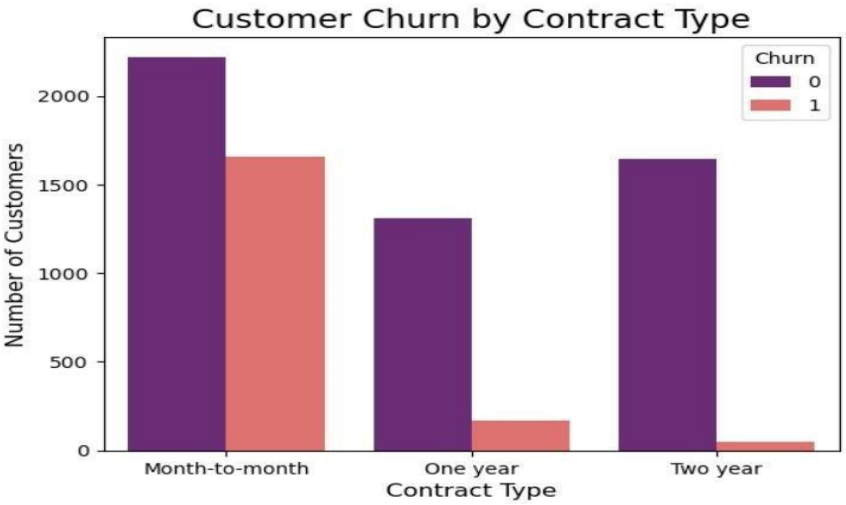

Fig 2. Customer Churn by Contract type

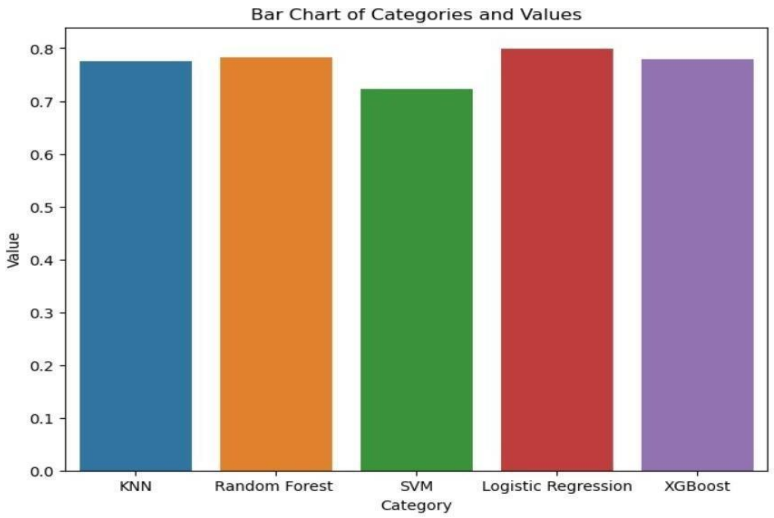

Fig 3. Model Comparison

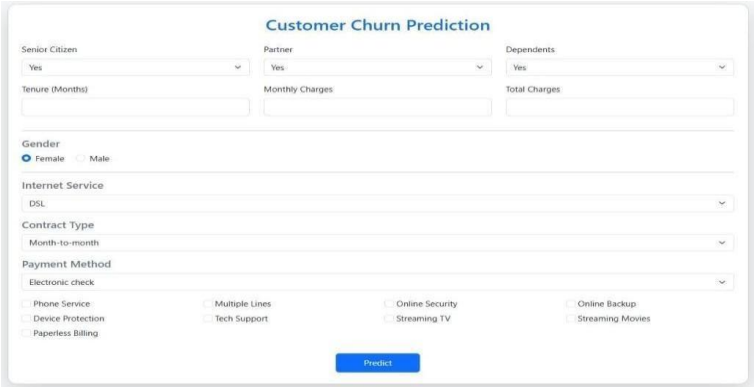

Fig 4. Customer Churn Prediction Input Form (Web Interface)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.1411134

Fig 5. Prediction Result – Customer will CHURN

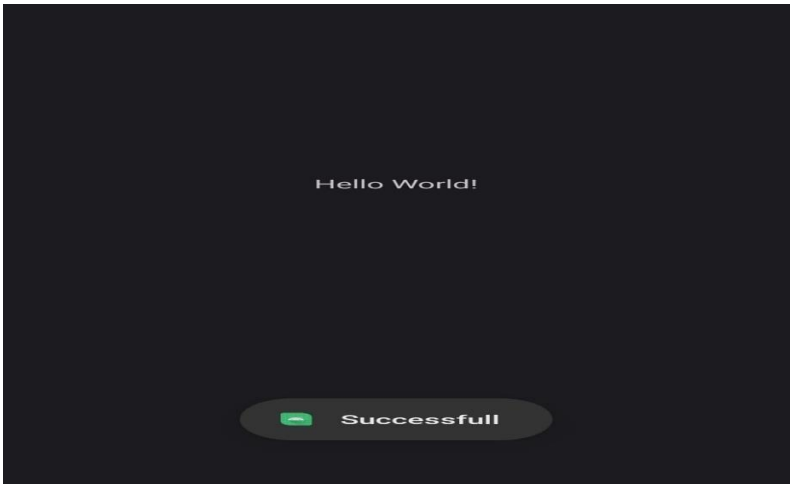

Fig 6. Android Success Notification

Fig 7. Android Notification – Discount Alerts (Telecom App)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.1411134

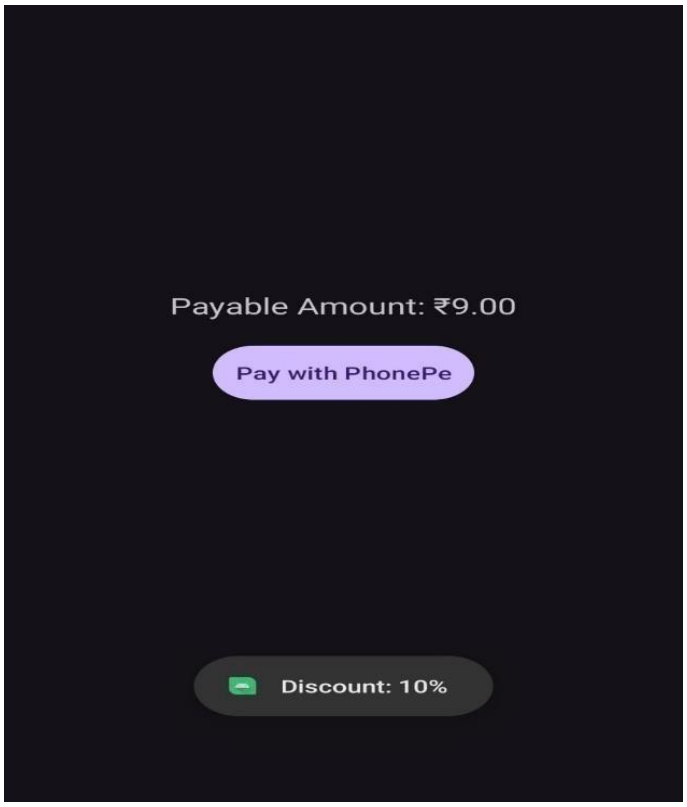

Fig 8. Payment Screen – UPI Interface

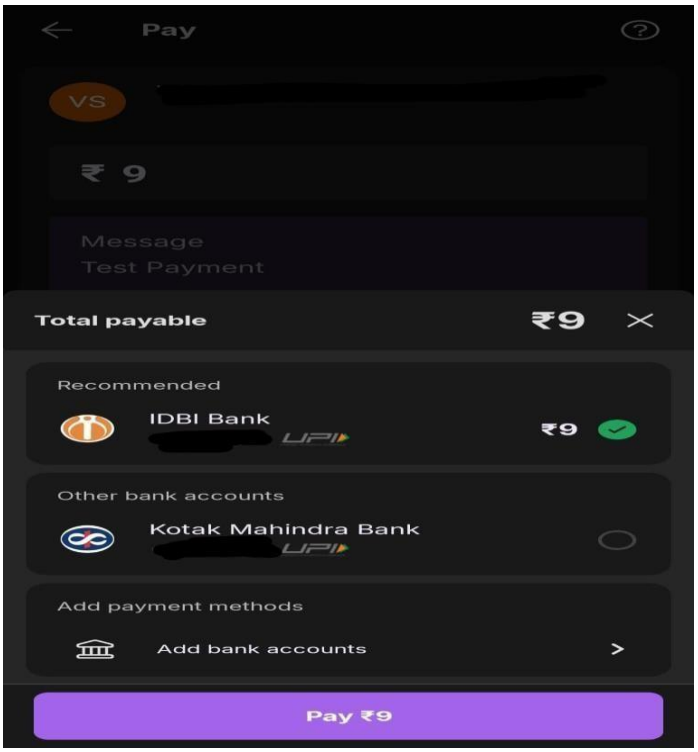

Fig 6. Payment Confirmation with Discount Applied

VI. CONCLUSION AND FUTURE WORK

The Customer Retention and Discount Prediction System effectively tackles the problem of customer attrition in the telecom sector by combining automation, machine learning, and data analytics. The technology gives actionable insights

DOI: 10.17148/IJARCCE.2025.1411134

for retention by identifying users who are likely to stop using services through the analysis of customer behavioral patterns. Instead of concentrating on reactive solutions, this predictive approach helps firms prioritize long-term loyalty and client happiness. The Telecom Customer Churn Dataset, which provides useful data on customer demographics, service usage, and payment patterns, is the foundation of the system. The project generates tailored offers by achieving effective and highly accurate churn prediction using the Logistic Regression model. Customers receive these offers via an integrated cloud-based notification system when they are automatically processed. For the convenience of its users, the Android app offers UPI-based payment alternatives and immediate alerts. This seamless platform integration guarantees prompt client interaction and improves system efficiency. This technology reduces the need for human intervention and enhances operational and decision-making processes through data-driven automation. The study shows how data insights from predictive modeling may be translated into workable retention tactics that have a direct influence on client engagement and company expansion. To sum up, this project emphasizes how crucial it is to combine cloud integration, web technologies, and machine learning to build an intelligent and scalable customer retention framework. It offers tailored recommendations that improve user experience, profitability, and long-term business sustainability in addition to accurately predicting churn.

REFERENCES

[1] *A. Manzoor, M. A. Qureshi, E. Kidney, and L. Longo, "A Review on Machine Learning Methods for Customer Churn Prediction and Recommendations for Business Practitioners", IEEE Access, Vol. 12, pp. 70434–70449, 2024.*

[2] *R. Joshi, et al., "Predictive Analytics for Customer Retention Using Machine Learning", Springer Conference on Smart Computing and Informatics, Springer, 2023, pp. 112–118.*

[3] *A. Kumar and R. Sharma, "Machine Learning Approaches for Predicting Customer Churn in Telecom Sector", International Journal of Advanced Computer Science and Applications (IJACSA), 2021, Vol. 12(5), pp. 110–117.*

[4] *A. Patel and S. Desai, "Deep Learning-Based Customer Churn Analysis in Telecom Domain", International Journal of Scientific Research in Computer Science, 2021, Vol. 9(2), pp. 56–61.*

[5] *S. Verma and P. Gupta, "Churn Prediction in Telecom Industry Using Ensemble Learning", IEEE International Conference on Data Science and Engineering (ICDSE), IEEE, 2020, pp. 88–93.*

[6] *T. Banerjee and M. Sinha, "Telecom Churn Prediction Using Random Forest and Logistic Regression", International Journal of Computer Applications, 2019, Vol. 178(11), pp. 23–29.*

Websites

1. *Firebase Documentation – Cloud Messaging (FCM) Integration Guide*, Google Developers, 2025. Available at: https://firebase.google.com/docs

2. *Kaggle – Telecom Customer Churn Dataset*, Kaggle, 2024. Available at: https://www.kaggle.com/blastchar/telcocustomer-churn

3. *Flask Framework Documentation*, Pallets Projects, 2024. Available at: https://flask.palletsprojects.com/

