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| **Ref.** | **Title** | **Authors** | **Year** | **Methodology** | **Drawbacks** |
| 1 | A Review on Machine Learning-Based Customer Churn Prediction in the Telecom Industry | Sawsan Barham, Nowfal Aweisi, Ala’ Khalifeh | 2023 | Reviewed 33 studies (2019–2022). Techniques: Random Forest (best with 97.4% accuracy), Logistic Regression, Decision Trees, XGBoost. Discusses feature selection and imbalanced data handling. | No empirical validation; lacks discussion on deployment, scalability, computational cost, and interpretability. |
| 2 | Exploratory Data Analysis and Customer Churn Prediction for the Telecommunication Industry | Kiran Deep Singh, Gaganpreet Kaur, Prabh Deep Singh, Vikas Khullar, Ankit Bansal, Vikas Tripathi | 2023 | Used EDA and XGBoost (82.8% accuracy) on real-world data. Emphasized feature selection and retention strategy. | Did not use SMOTE; lacks deep learning model comparison and computational cost discussion. |
| 3 | The Impact of SMOTE and ADASYN on Random Forest and Advanced Gradient Boosting Techniques in Telecom Customer Churn Prediction | Mehdi Imani, Majid Joudaki, Zahra Ghaderpour, Ali Beikmohammadi | 2024 | Applied SMOTE/ADASYN to RF, XGBoost, LightGBM, CatBoost. LightGBM gave 89% F1-score, 95% AUC. ADASYN performed slightly better. | Risk of synthetic noise not evaluated. Minimal impact of hyperparameter tuning discussed. |
| 4 | Customer Churn Prediction in Telecom Sector Using Machine Learning Techniques | Sharmila K. Wagh, A. A. Andhale, K. S. Wagh, J. R. Pansare, S. P. Ambadekar, S. Gawande | 2024 | Used RF, Decision Tree, KNN on IBM Telco dataset. Applied SMOTE. RF achieved 99% accuracy. Included survival analysis and Cox model. | Accuracy may indicate overfitting. Synthetic data may distort reality. No computational complexity analysis. |
| 5 | Predicting Customer Churn in Telecom Industry: A Machine Learning Approach for Improving Customer Retention | Abhikumar Patel, Amit G Kumar | 2023 | Dataset: 2,666 rows, 20 features. Models: Naive Bayes (Bernoulli, Gaussian), SVM, KNN, Decision Tree, RF, XGBoost. XGBoost achieved 94%. Used SMOTE. | Overfitting not addressed. Scalability and computational cost not analyzed. |
| 6 | Telecom Customer Churn Prediction Using Enhanced Machine Learning Classification Techniques | Goldy Verma | 2024 | Compared DT, RF, KNN on Kaggle dataset. RF scored best at 82%. Highlighted tenure and charges as key churn factors. | No class imbalance handling. Lacks interpretability discussion. |
| 7 | Customer Churn Prediction Using Synthetic Minority Oversampling Technique | Aishwarya H M, Soundarya B, Bindhiya T, C Christlin Shanuja, S Tanisha | 2023 | Used SMOTE with GBM (95.13%), RF, DT, and Logistic Regression. Identified tenure and charges as churn drivers. | Synthetic data may distort reality. No computational cost or interpretability discussion. |
| 8 | Churn Prediction of Customer in Telecom Industry using Machine Learning Algorithms | V. Kavitha, S. V Mohan Kumar, M. Harish, G. Hemanth Kumar | 2020 | Used RF, XGBoost, Logistic Regression on Kaggle dataset. RF achieved 93%. Preprocessing included feature selection, normalization. | Logistic Regression underperformed. Interpretability and hyperparameter impact not discussed. |
| 9 | Customer Churn Prediction Based on Interpretable Machine Learning Algorithms in Telecom Industry | Liwen Ou | 2022 | Used RF, DT, Extra Trees on IBM Telco. RF: 82.3%, Extra Trees: 82.5%. Highlighted key features via importance scores. | Did not address imbalance. Ensemble models’ complexity not explored. |
| 10 | Machine Learning-Based Telecom-Customer Churn Prediction | Pushkar Bhuse, Aayushi Gandhi, Parth Meswani, Riya Muni, Neha Katre | 2020 | Compared RF, SVM, XGBoost, Ridge, DNN. RF achieved 90.96%. Used grid search for tuning. Feature selection performed. | Deep learning not optimized. No SMOTE or imbalance handling. Computational cost not discussed. |